Sensor Selection for Fault Diagnostics

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Abstract

In the modern world, systems such as aircraft systems are becoming increasingly complex, often consisting of a large number of components. As no component is perfectly reliable, they can fail, some in many different ways, leading to a large number of potential component failures on complex systems. Component failures can have detrimental effects on the performance of the system, with some component failures even causing system failure, potentially damaging the system, or more importantly, potentially endangering human life. In order to be able to detect component failures on complex systems, the inclusion of sensors is becoming increasingly common. In addition to being able to detect component failures, the sensors can be used to diagnose component failures, with certain symptoms and the resultant sensor readings being produced by certain component failures. Another benefit is that it may also be possible to prevent system failure by detecting component failures early, activating redundant components and enabling the mission to be completed. However, including sensors in the system increases the cost of the system, can add weight to the system and require space for installation, a factor of particular importance for weight critical systems, such as aircraft systems. Therefore, a balance between being able to detect and diagnose failures in systems and the cost, weight and space requirements of the sensors needs to be achieved.

In this thesis, a novel sensor selection methodology is proposed, which is based on a performance metric. Individual sensors, and combinations of sensors are ranked based on their performance of detecting faults and diagnosing failures in the system. In addition to the sensors' detection and diagnostic performance, the metric also considers the effect that the component failures have on the functionality of the system, where sensors that detect critical failures are favoured over sensors that do not detect such failures. The performance metric is then extended to consider the time taken to detect and diagnose component failures, as the sooner component failures are detected, the more likely system failure can be prevented. This is important in a system that operates in a phased mission. In addition, a proposed two-level Genetic Algorithm is used in order to efficiently determine a suitable combination of sensors for larger systems, where an exhaustive calculation of the performance metric for all combinations of sensors is not feasible.

For a simple flow system, a Bayesian Belief Network (BBN) is used to model the effects of component failures, and sensor readings. During the fault diagnostic process, observed

sensor readings can be introduced in the BBN, which then can be used to identify the failed components. However, an alternative system modelling and fault diagnostic technique is proposed as a part of this thesis which can be used on larger systems, and can determine sensor readings and component failures more quickly than the BBN method. This method is based on a series of if-then-else statements in order to determine the effect that the component states have on the performance of the system. The work proposed in this thesis is applied to three example systems: a simple flow system, an example aircraft fuel system and the fuel system for an Airbus A380-800 aircraft.

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Publications

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Chapter 1 - Introduction

1.1. Background and research motivation

Aircraft systems, such as fuel systems, are complex, generally consisting of a large number of components. There can be multiple components of the same type, and also of various different types, such as valves and pumps. There can also be multiple different types of each component and multiple ways each component can fail, which further increases the complexity of the system. As the components are not perfectly reliable, they can fail, and it may affect overall system performance. However, whilst some component failures may have little effect on the system performance, others may cause the system to malfunction or to fail completely. Therefore, it is imperative to be able to detect component failures when they occur. Note that in this thesis “a component failure is detected” means that it is known that a component failure has occurred, but which component has failed does not have to be known.

Therefore, as there are lots of different components on the system, just knowing that there has been a component failure is insufficient and as different component failures have different effects on the system performance, it is imperative to be able to determine exactly which component failure has occurred in order for the appropriate action to be undertaken, such as system reconfiguration, modification of the mission or mission abortion. However, each of these actions have different consequences to the operation of the system. For example, if the mission was aborted whenever a component failure was detected, then the unnecessary financial losses would be significant, but if the mission was not aborted when necessary, the safety of crew, passengers, and people in the vicinity of the aircraft would be at risk. The determination of which component failure has occurred is often referred to as “diagnosing the component failure”, which is how it is also referred to in this thesis, i.e. diagnosing a component failure means knowing exactly which component failure has occurred. This will enable the appropriate action for the specific component failure to be taken. Note, this can also be referred to as the process of isolating the component failure.

In order to be able to detect and diagnose component failures, sensors need to be included on the system in order to monitor the performance of the system. If the sensor readings produced by the sensors deviate from their expected readings (the sensor readings produced during normal operating conditions), a component failure has been detected. Note, the specific component failure may not be determinable without additional information obtained from physical inspection of the system as some component failures may produce the same set of symptoms.

However, whilst sensors can be used to detect failures, they also have associated costs, such as the additional fuel costs from the added weight, the cost of any additional maintenance, and the purchase and installation costs of the sensor. Therefore, a balance between the performance of the selected sensors and the cost of the selected sensors needs to be achieved.

1.2. Research aims and objectives

The aim of the research presented in this thesis is to be able to detect and diagnose as many different component failures as possible, whilst only using a minimal number of sensors on the system. This aim can be categorised into three objectives.

The first objective is to develop a sensor selection methodology in order to determine which combination of sensors is the most suitable solution to be installed on a system. This is achieved by proposing a measure of performance, referred to as a performance metric, which can be used to distinguish between the relative merits of each combination of sensors. The performance metric considers the probability of component failures that the sensors detect, the ease of diagnosis of the detected component failures, and the effect that the component failures have on system performance, i.e. causes system failure. A sensor, or combination of sensors, with a high performance metric, will be able to detect a large percentage of the component failures, (including a large percentage of the component failures that cause system failure), and be able to diagnose a large percentage of the component failures with a high probability of successful diagnosis.

The second objective is to develop a system modelling and fault diagnostics methodology to enable failures of components in the system to be detected and diagnosed. The proposed method can model systems accurately, and output the sensor readings for each combination of component failure. It can also use observed sensor readings to determine which components are most likely to have failed. This is done by outputting the probability of each component being in a failed state, with the component (or components) with the highest probability of being in the failed state being the actual failure. Note, as it is probabilistic, unless a component is definitely in a failed state (i.e. 100% probability), it may not be diagnosed correctly, it may just be the most likely component failure to have occurred. It should also be the case that the higher the factor of the performance metric that considers the ease of diagnosis, the easier the diagnosis of failures.

The third objective is to develop an optimisation technique to enable the determination of suitable combinations of sensors efficiently when it is not feasible to calculate the performance metric for all combinations of sensors exhaustively. This is particularly useful for large systems which can have a large number of possible sensors. The proposed method involves applying a Genetic Algorithm to a set of randomly generated combinations of sensors, in which a number of genetic operators are applied to the combinations of sensors in order to obtain a more suitable solution. It does this by favouring good combinations of sensors in each generation and applying the genetic operators so that a better combination can be obtained in the following generations.

1.3. Thesis outline

Chapter 2 presents a review of literature relevant to the research presented in this thesis. The section begins with an overview of sensor selection techniques, outlining a number of performance metric based approaches, before continuing with a brief overview of importance measures. The next section of the chapter presents a number of fault diagnostic techniques, including Bayesian Belief Networks, Fault Trees, FMEA and Digraphs. The next section of the chapter presents an overview of optimisation techniques, focusing primarily on Genetic Algorithms, as this is the most suitable method for the application, presented in this thesis. The section concludes with a summary of the most suitable techniques in the literature for the work presented in the thesis.

Chapter 3 of the thesis introduces a proposed methodology for sensor selection and fault diagnostics. The chapter begins by introducing an example system which is used to develop the proposed methodology. The performance metric used for sensor selection is proposed next, followed by the fault diagnostic methodology. The section concludes with an application of the methodology to the example system and an analysis of its effectiveness.

Chapter 4 of the thesis introduces a larger example system in order verify the scalability of the methodology. The modifications to the methodology are applied including the automation of the sensor selection and fault diagnostic processes. The chapter finishes with an analysis of the application of the methodology, concluding that the system modelling technique does not scale up sufficiently for larger systems.

Chapter 5 of the thesis presents an alternative system modelling approach that will enable the application of the methodology to significantly larger systems. The alternative modelling technique also requires modifications to the fault diagnostic technique, which are presented next. The alternative methodology is applied to the system and presented next, which is followed by an application of the originally proposed methodology to the same system. The chapter concludes with a comparison of the two methodologies, demonstrating that the alternative methodology presented in this chapter is the more suitable solution.

Chapter 6 of the thesis presents an extended version of the alternative methodology in order to consider time dependence of the component failures. The system considered in this chapter is a real aircraft fuel system, the fuel system from the Airbus A380-800. In order to do this, a proposed mission for a new, significantly larger example system is presented, in which component failures can occur at various points of time in the mission. The next section of the chapter presents the time-dependent sensor performance metric, which considers the effect of the time taken to detect and diagnose component failures, and the time of failure occurrence in the mission. As the system considered in this chapter is significantly larger than the systems considered in Chapters 3, 4, and 5, a proposed two-level Genetic Algorithm based optimisation technique is applied to the sensor selection process, which is introduced next. The chapter continues by applying the proposed time-dependent methodology to the example system, before concluding with an analysis of the effectiveness of the methodology.

Chapter 7 of the thesis summarises and concludes the work presented in the thesis. The chapter concludes with a discussion of potential future research avenues that could be investigated.

Chapter 2 - Literature Review

In this chapter, a review of literature is presented in order to identify potential modelling techniques and sensor selection methods that are suitable inspiration for the methodology, proposed in this thesis. This chapter begins with an overview of sensor selection techniques, outlining a number of performance metric based approaches, and a brief overview of importance measures used in reliability assessment. The chapter continues by presenting fault diagnostic techniques, including Bayesian Belief Networks (BBNs), failure modes and effects analysis (FMEA), Fault Trees (FTs), and Digraphs. In the penultimate section of this chapter, an overview of optimisation techniques is also presented, focusing on Genetic Algorithms. In the final section of this chapter, a summary of the most suitable techniques is presented.

2.1 Sensor selection

In an ideal case, as many sensors as possible would be installed on a system in order to be able to detect and diagnose component failures. However, sensors cost money, add weight to the system, and require space for installation, usually resulting in limits being placed on the number of sensors that can be installed on a system. Therefore, a sensor selection process needs to be applied, such that the chosen combination of sensors can detect and diagnose the most component failures in the system.

In order to determine the most suitable combination of sensors, a number of factors can be considered. These factors are:

- The cost of the selected sensors, i.e. less expensive sensors will be favoured,
- The size and weight of the sensors, i.e. sensors that are smaller and lighter will be favoured,
- The reliability of the sensor, i.e. sensors that are less likely to fail are favoured,
- The number of different component failures that can be detected by the selected sensors, i.e. the sensors that detect a higher number of component failures will be favoured,
- The ease of diagnosis of component failures using the selected sensors, i.e. sensors that can distinguish between failures easily will be favoured,

- The effect the component failures have on the unreliability of the system, i.e. sensors that detect component failures that cause the system to fail will be favoured.

In this section, a number of different sensor selection techniques are discussed, with the majority of this section presenting examples of sensor selection techniques in the literature. The final part of this section introduces importance measures, which are typically used to measure the relative importance of components to the functionality of the system. However, they could be modified in order to apply them during the process of sensor selection, and therefore, a brief overview of some importance measures is presented. The section concludes with a brief summary of the sensor selection techniques.

2.1.1. Sensor selection methods

There are many different approaches for selecting the optimal sensor suite, however, in order to be able to compare sensor performance on the system, a measure of performance needs to be defined, as a criterion for selecting sensors. Different methods have different ways of referring to the measure of performance, including utility function, cost-benefit function, and information metric. For simplicity and to avoid confusion, they will all be referred to as a performance metric.

A simple version of a performance metric is to consider which sensor detects the most component failures. Snooke (2009) and Kang & Golay (2000) use a fault symptom matrix to determine which component failures each sensor can detect. A fault symptom matrix is basically a table, with each column corresponding to a different component failure, and each row corresponding to each sensor. If the sensor can detect a specific component failure then the corresponding element of the matrix is entered (with a "1" or "0", or a tick or a cross). After the entire matrix has been completed for all possible component failures, the row with the most elements entered will be the sensor that can detect the most component failures. When considering combinations of sensors, the selected sensors can be stored in a new matrix, with an additional row at the bottom to represent the combination of sensors. If any of the elements in each column have been completed, then the element in the final row of that column can be entered, and the number of elements in that row can be used to determine the number of component failures detected by that combination of sensors. Whilst this approach is a straight forward way to determine the best sensor, or the best combination of sensors, it does not appear to consider the probability of each component failure occurrence, the effect that the failures have on the system, or the ease of diagnosis. However, if the matrix was completed with the probability of the component failure (instead of a “1” or a tick), then the sensor that detects the highest percentage of component failures could be selected, instead of the sensor that detects the highest number of different component failures.

Snooke (2009) applies a fault symptom matrix based method to an aircraft fuel system for an unspecified twin engine aircraft. The method uses an automated failure mode and effects analysis (FMEA) technique to successfully diagnose all 184 possible faults in the system. The failures are diagnosed by comparing observed symptoms to the FMEA document and determining which failures can produce the observed symptoms. Note, the FMEA method is discussed in section 2.2.2.1. The authors also develop a tool to aid an engineer with the diagnosis of failures in the system, which they demonstrate using the fuel system example. For the selection of sensors on the system, the authors propose choosing additional sensors to the combination of sensors based on the number of additional faults that an additional sensor can detect. The author states that this may not result in the best possible combination of sensors as each additional sensor is added to the previous combination, and therefore, a sensor that is included may detect a smaller number of additional failures, than if one of the sensors from the combination was removed, and two sensors added as a pair. As an example, consider a combination of sensors that can detect all failures on a system apart from 10 component failures. If there are three potential sensors that can be added to the system, sensors A, B and C, each of which detect some of the 10 component failures that cannot be detected by the current sensor combination. If sensor A can detect failures 1 – 7, (i.e. 7 failures), sensor B can detect failures 4 – 9, (i.e. 6 failures), and sensor C can detect failures 1 – 4 and 10, (i.e. 5 failures), then the method would initially add sensor A, (as this would detect 7 additional failures), and then add sensor B, (as this would detect another 2 additional failures). However, if sensor A could be removed, and then sensor B and C added instead, then all 10 failures would be detected. This could be avoided by improving the search using methods such as backtracking heuristics, as suggested by the authors.

The method proposed by Kang & Golay (2000) uses a combination of system-oriented hierarchies, a fault symptom matrix and sensor selection and feasibility study in order to determine a suitable combination of sensors. The method begins by breaking the system down into sections in order to determine the failure modes of each section, (and therefore, the whole), of the system. Next, a fault symptom matrix is constructed, enabling the determination of the causes of the symptoms of the system. The sensor selection criteria and the feasibility of each of the sensors are then determined, before analysis of available sensor data is completed, enabling the determination of a suitable sensor network. The data analysis includes obtaining the data on the system operation (sensor readings), processing the data using techniques such as Fast Fourier Transform, and then combining it with data from other sensors, so that a detailed interpretation of the systems status can be obtained. The fault symptom matrix allows the sensors to be selected based on which component failures are detected by each sensor, i.e. by matching the observed sensor readings to the faults using the matrix. Sensors can then be selected based on which sensors are most useful for fault detection and diagnostics, whilst also ruling out sensors that are impractical to use. The work in the paper is applied to a turbine generator for a power plant system, where the sensors monitor the pressure, flow, temperature and vibration in the system, among other parameters, so that component failures in the system can be detected and diagnosed. This leads to many different types of sensors being considered, where it is likely that not all types of sensors are included in the sensor suite. In the conclusion section of the paper, the authors state that some power plant system experts believe that the method could be extended for complete system coverage, in order to consider other complex rotating machinery, such as reactor coolant pumps and emergency diesel generators.

Pourali & Mosleh (2012) present a method for determining the best combination of sensors by modelling the system using BBNs. The 18 step Bayesian sensor placement optimisation technique can be summarised as: determining the characteristics of the system, (the failure modes, etc.), develop the BBN of the system, determine the possible sensors, determine the sensor readings for component failures, and finally choose the optimum sensor placement. The method does not present a specific performance metric to be used for sensor selection, but does give two example utility functions, presented in Equations (2.1) and (2.2) respectively. In the paper, the performance metric U_I is defined as a monetary scale where its expected values represent a decision maker's preferences.

$$U_I(\theta) = \sum_j ln\left[\pi\left(\theta_j \middle| E, \varepsilon\right)\right]\pi\left(\theta_j \middle| E, \varepsilon\right) - \sum_j ln\left[\pi_0\left(\theta_j\right)\right]\pi_0\left(\theta_j\right) \tag{2.1}$$

$$U_I(\theta) = \sum_j \frac{1}{\sigma^2_{\theta_j}} \tag{2.2}$$

where θ is the unknown of interest, E is the evidence, ε is the observation, π_0 is the prior knowledge about lower level components, π is the calculated posterior at system level, and σ is the uncertainty. Whilst the method proposed is useful in that any performance metric can be used in the methodology, the aim of the work presented in this thesis is to develop a specific performance metric for sensor selection. The method is applied to a system health monitoring system for a power transformer system, and for this application, the performance metric is chosen such that it is dependent on the uncertainty about the unknown of interest. The performance metric chosen for this example is the example performance metric given in Equation (2.2). The introduction of uncertainty into the performance metric is useful for when there are unknown parameters in the system.

Spanache et al. (2004) propose a performance metric based on the sensors' ability to diagnose failures, considering the number of non-discriminable faults, (faults that cannot be discriminated between, i.e. produce the same symptoms), and the cost of the sensors. The ratio between these values is the evaluation efficiency: the higher the value, the better the sensor combination. This formula is presented in Equation (2.3), where ε is the evaluation efficiency, D is the number of non-discriminable faults, and C_i is the cost of sensor i.

$$\varepsilon = \frac{D}{\sum_{i=1}^{n} C_i} \tag{2.3}$$

The cost factor in this paper considers the price, installation costs, and reliability of the sensor, and is presented in Equation (2.4).

$$C_i = P_i + I_i - R_i \tag{2.4}$$

where P_i is a representation of the price of the sensor, I_i is a representation of a measure of the ease of installation/replacement of the sensor, and R_i is a representation of the sensors' reliability, as specified by the supplier. The authors also use a fault symptom matrix as their proposed fault diagnostic technique, and use a Genetic Algorithm (GA) based optimisation technique in order to not have to calculate the efficiency for all combinations of sensors. Note that an overview of optimisation techniques, such as GA, are presented in section 2.3 of this thesis. The authors present an example application to a Damadics Benchmark actuator which is used in the evaporation station in a sugar factory in Poland. They successfully determine the optimal combination of sensors exhaustively (since the system is small), and using the GA. However, the authors do state that the difference in time between exhaustively obtaining the optimal combination of sensors and obtaining it using the GA will increase as the number of sensors increase.

Santi et al. (2005) also use a GA based optimisation technique in order not to have to calculate their performance metric for all of the combinations of sensors. The authors also introduce time dependence in their performance metric, considering the time taken to detect the component failure after its occurrence. To do this they make the performance metric proportional to the time taken to reach the detection threshold by the chosen sensor combination, divided by the minimum time taken to reach the detection threshold by any combination of sensors, where the detection threshold is defined as the minimum deviation of measurements from multiple sensors for reliable hardware fault detection. They also consider the risk reduction of the system which is a measure of the reduction of risk of system failure by diagnosing the failure within an acceptable amount of time. Finally, the authors consider the sensors' ability to discriminate between failures, i.e. the probability of correct diagnosis of component failures. However, the value used in the performance metric is the minimum probability of correct diagnosis, and could result in unreliable results if one sensor reading can be obtained by many different component failures, all of which could potentially have a very low probability of occurrence. This may reduce the performance metric of the combination of sensors and change the optimal combination of sensors. The performance metric proposed by the authors could be adapted such that it includes the probability of each of the component failures occurrence that are being diagnosed, therefore, the above issue would not occur. In this paper, the authors present an example application of the metric to a boost stage rocket developed for the Next Generation Launch Technology program. The authors achieve a performance metric value of 0.62, which the authors believe is reasonable considering the level of design definition of the system. They state that most of the metric reduction from its ideal value of 1.0 is due to fault diagnosis issues rather than detection, i.e. there are component failures that cannot be diagnosed correctly with complete confidence.

A performance metric for aircraft systems was developed by Maul et al. (2008), which is applied to a subsystem of a space shuttle main engine. The performance metric consists of three terms: a utility cost term, a diagnosability performance factor and a user-specified penalty term. The cost term considers various factors of the sensors, such as the cost of the sensors, the weight of the sensors, the power requirements, etc. The cost term is an average of the values for each of the sensors in the sensor combination. The diagnosability performance factor considers the detection of failures by the sensors, the discrimination between the component failures, and a term to represent the relative weighting values of the sensors, such as the relative fault criticality, and the relative importance of each the failures. However, the final factor in the performance metric is a user specified penalty factor, which penalises the sensor selection if the number of sensors in the suite exceeds the desired amount. This factor requires user specified terms, such as a normalising term for the penalty function, and a term that dictates the weight of the penalty term, as well as the difference between the number of sensors in the sensor combination and the desired number of sensors. As some of the terms in the penalty term are user specified, subjectivity is introduced into the methodology. This is undesirable as different applications of the same methodology on the same system, but carried out by different analysts, may result in a different selection of sensors, and may result in a less than optimal combination of sensors being chosen. The method does not present how the various weighting factors, such as the fault criticality weighting factor or the relative importance of each of the failures, may also require user specification, as the determination of these factors is not discussed in the paper.

Other authors consider cost specific measures of performance, referred to as cost-benefit analysis. Cost-benefit analysis is a common technique used to evaluate the safety of systems, and is often used to assess improvements proposed to the system, i.e. if this component is replaced, what is the benefit to the reliability of the system, or if an additional sensor is added to the system, what is the benefit to the fault detection ability of the sensor suite. Cost-benefit analysis uses a mathematical function to determine whether the additional cost of the modification required is worth the benefit observed by the modification to the system. However, the function is usually case-specific and is based on system dependent factors, such as the vulnerabilities of sections of the system or the potential risk to life, and as a result the cost-benefit function has to be manually determined for each application. This results in some subjectivity being embedded in the method, with different analysts potentially proposing different functions for the same application. On the positive side, this does introduce flexibility into the method, as the proposed cost-benefit function can consider the specific factors that the analyst considers to be important. For example, one analyst may think that changing one factor may change the reliability of the system linearly, and as a result, make the reliability of the system directly proportional to the factor, but a different analyst may think that changing the same factor may change the reliability of the system non-linearly, and make the system reliability proportional to the factor to a power.

One particular application of cost-benefit functions for sensor selection is presented by Lambert & Farrington (2007), who propose a function to determine the best placement of sensors for detection of air contaminants. The authors define their cost-benefit function as the potential risk avoided ($/year) divided by the annual cost ($/year), i.e. the larger the value, the better the combination of sensors. This also means that the value of the function can be any value, and therefore there is no reference point on how good the sensor selection is, except in comparison to other combinations of sensors. In their method, they consider a number of factors, such as the average travel time to safety, the population density, the number of vulnerable people, the cost of the sensors and their maintenance, and the cost saved by not having to treat people who would otherwise become infected. The authors present a cost-benefit function that the authors published in an earlier paper, (Lambert & Farrington, 2006), and extend the function with multiple iterations, each time considering additional factors, such as a constant benefit factor, an exponential exposure term, and factors to consider external source of funding. The different versions of the same function are for specific cases, such as if there is exponential intensity or exposure, or if there is an external source of funding available for a specific region. As the authors present a number of different versions of the same function, it suggests that there can be some subjectivity in determining which function is the best solution.

Each of the measures of performance are similar in that they all consider how many of the component failures can be detected and diagnosed. A numerical value representing how useful each of the combinations of sensors are is a common approach, and is therefore also developed in this thesis.

2.1.2. Importance measures

Component importance measures are a measure of the effect that each of the component failures have on the functionality of the system, and the importance measures could be adapted to consider the performance of sensors on the system. Therefore, an overview of component importance measures is presented in the following section. They have a numerical value between 0 and 1, allowing the components to be ranked accordingly. Components that have an importance measure of 1 result in system failure when they fail, and components that have an importance measure of 0 have no effect on the probability of system failure when they fail. Importance measures are typically used to help to identify the sections of the system that are more likely to cause system failure, so that increased frequency of maintenance can be scheduled, or a system redesign can be undertaken. There are a number of different importance measures, but the most common are Birnbaum’s measure of importance, the Criticality measure of importance, and the Fussell-Vesely measure of importance.

2.1.2.1. Birnbaum's measure of importance

Birnbaum's importance (BI) measure is defined as the probability that component i is critical to system failure, i.e. the probability that the system changes from the working state to the failed state when component *i* fails, (Andrews & Beeson, 2003). Note, this is often referred to as the occurrence of basic event i, which represents component i failing. Birnbaum's importance measure is presented in Equation (2.5), where Q_{sys} is the system unreliability, and q_i is the probability of basic event *i* occurring, i.e. $Q_{sys}(q_i = 1)$ is the system unreliability given that component i is in its failed state, and $Q_{sys}(q_i = 0)$ is the system unreliability given that component *i* is in its working state.

$$BI = Q_{sys}(q_i = 1) - Q_{sys}(q_i = 0) \tag{2.5}$$

2.1.2.2. Criticality measure of importance

The Criticality importance (CR) measure can be considered as a generalisation of Birnbaum's importance measure, as it normalises BI's measure by the ratio of the probability of the basic event *i* and of system failure, (Borgonovo, 2007). The CR measure is presented in Equation (2.6), (Borst & Schoonakker, 2001).

$$CR = \frac{Q_{sys}(q_i = 1) - Q_{sys}(q_i = 0)}{Q_{sys}} q_i = \frac{BI}{Q_{sys}} q_i \tag{2.6}$$

The CR measure determines whether the failure of the system is a result of the failure of the component, i.e. if the system has failed, what is the probability that the failure of the component has caused it. Borgonovo (2007) states that as the CR measure considers the probability of component failure, it enables the discrimination among components that have the same BI, as the importance measure is proportional to the probability of component failure.

2.1.2.3. Fussell-Vesely measure of importance

The Fussell-Vesely importance measure is one of the most commonly used importance measures, (Cheok et al., 1998). It is presented in Equation (2.7), (Borst & Schoonakker, 2001).

$$FV = \frac{Q_{sys} - Q_{sys}(q_i = 0)}{Q_{sys}} \tag{2.7}$$

The Fussell-Vesely importance measure considers the effect that individual components have on system unreliability, i.e. it calculates the decrease in the system unreliability by making the component perfectly reliable. The importance measure subtracts the probability of system failure given that basic event *i* has not occurred from the probability of system failure. The importance measure is then normalised by the probability of system failure.

2.1.2.4. Example

In this section, two simple example systems are presented, each consisting of two components, the first with the two components in series, and the second with the two components in parallel. The two components, component 1 and component 2, have reliabilities of p_1 and p_2, respectively, where $p_1 > p_2$. Note, $q_1 = 1 - p_1$.

For a series system, the reliability of the system is equal to p_1p_2, i.e. if either component fails, the system fails. This results in $Q_{sys} = p_1q_2 + q_1p_2 + q_1q_2$. The BI measure for component 1 is presented in Equation (2.8). Note, in Equations (2.8) – (2.13), the corresponding importance measure for component 2 can be determined by changing p_1 with p_2 and q_1 with q_2.

$$\begin{aligned} BI(1) &= Q_{sys}(q_1 = 1) - Q_{sys}(q_1 = 0) \\ &= (0q_2 + 1p_2 + 1q_2) - (1q_2 + 0p_2 + 0q_2) = p_2 \end{aligned} \tag{2.8}$$

Likewise, BI for component 2 is equal to p_1. Therefore, as $p_1 > p_2$, component 2 is the more important component. The same is the case for the criticality importance measure ($p_1(1 - p_2) > p_2(1 - p_1)$), with the criticality importance measure presented in Equation (2.9) for component 1, i.e. component 2 is the more important component.

$$CR(1) = \frac{BI(1)}{p_1q_2 + q_1p_2 + q_1q_2} q_1 = \frac{p_2(1 - p_1)}{1 - p_1p_2} \tag{2.9}$$

The Fussell-Vesely importance measure for component 1 is presented in Equation (2.10), and as before component 2 is the more important component ($(1 - p_2) > (1 - p_1)$), i.e. it has the higher value of the importance measure.

$$FV(1) = \frac{Q_{sys} - Q_{sys}(q_1 = 0)}{Q_{sys}} = \frac{p_1 q_2 + q_1 p_2 + q_1 q_2 - q_2}{p_1 q_2 + q_1 p_2 + q_1 q_2} = \frac{p_1 p_2 - (1 - p_2)}{p_1 p_2} \tag{2.10}$$

In all three importance measures, the component that is the least reliable, is the most important component to the system. This is because if any component in the system fails, the system fails, therefore, the system is only as reliable as its least reliable component.

A similar example is presented in Equations (2.11), (2.12) and (2.13), respectively for a parallel system. Note, for a parallel system, in order for the system to fail, both of the components must fail, i.e. $Q_{sys} = 1 – (p_1 + p_2 – p_1p_2)$.

$$\begin{aligned} BI(1) &= Q_{sys}(q_1 = 1) - Q_{sys}(q_1 = 0) = (1 - (p_2)) - (1 - (1 + p_2 - p_2)) \\ &= 1 - p_2 \end{aligned} \tag{2.11}$$

$$CR(1) = \frac{BI(1)}{1 - (p_1 + p_2 - p_1 p_2)} q_1 = \frac{(1 - p_2)(1 - p_1)}{1 - (p_1 + p_2 - p_1 p_2)} \tag{2.12}$$

$$\begin{aligned} FV(1) &= \frac{Q_{sys} - Q_{sys}(q_1 = 0)}{Q_{sys}} = \frac{1 - (p_1 + p_2 - p_1 p_2) - (1 - (1 + p_2 - p_2))}{1 - (p_1 + p_2 - p_1 p_2)} \\ &= \frac{1 - (p_1 + p_2 - p_1 p_2)}{1 - (p_1 + p_2 - p_1 p_2)} = 1 \end{aligned} \tag{2.13}$$

For parallel components using the BI measure, the most important component is the component with the highest reliability and therefore, to improve a parallel system, the most reliable component should be improved. This is because both components need to fail in order for the system to fail, and therefore, as the more reliable component is less likely to fail, improving this component's reliability further will reduce the probability of system failure. For the CR importance measure, all components in a parallel system are equally important, suggesting that the CR importance measure is not the most suitable importance measure for parallel systems. For the FV importance measure, all components have a measure of 1. This is because the FV measure considers the effect of making one of the components perfectly reliable, and therefore, the system cannot fail, suggesting that the FV importance measure is not the most suitable importance measure for parallel systems.

2.1.3. Summary

Overall, the work of Pourali & Mosleh (2012) presents a generic methodology that could be used for the selection of sensors. This methodology could be extended to incorporate an optimisation technique, like Spanache et al. (2004) and Santi et al. (2005). This means that exhaustive calculation of the performance metric for all combinations of sensors would not have to be completed.

A number of the other authors present performance metrics that could be used as inspiration for a new performance metric. The fault symptom matrix used by Snooke (2009) and Kang & Golay (2000) is a useful first step to determine which sensors can detect which component failures, this would also help with the construction of the BBN in the methodology presented by Pourali & Mosleh (2012). The performance metrics presented by Spanache et al. (2004), Santi et al. (2005), and Maul et al. (2008), all have good features, for example, the discrimination between the failures in Spanache et al. (2004), the time dependence factor in Santi et al. (2005) and considering a large number of factors in Maul et al. (2008), respectively. However, all of the methodologies have drawbacks, for example, Santi et al. (2005) has a factor that could result in an unreliable performance metric if the probability of some of the component failures is low, and Spanache et al. (2004) and Maul et al. (2008) have factors that result in the performance metric being subjective.

The cost-benefit function presented by Lambert & Farrington (2007) is very thorough and considers all possible factors for their application, but it is too application specific to be able to be applied for an aircraft fuel system. Therefore, this methodology is not considered further in this study.

2.2. Fault diagnostic techniques

In this section of the literature review, an overview of a number of fault diagnostic techniques is presented. This section is split into three subsections, the first of which presents an overview of Bayesian Belief Networks, the fault diagnostic technique applied in Chapters 3, and 4 of this thesis. The second section is an overview of a number of other fault diagnostic techniques, including FMEA, Fault Trees and Digraphs. The final section is a summary of this section, presenting the reasons why Bayesian Belief Networks are selected in this study as the fault diagnostic technique.

2.2.1. Bayesian Belief Networks

Bayesian Belief Networks (BBNs), also known as Bayes nets, or Causal networks, are acyclic probabilistic graphical models, built using data and/or expert knowledge. They were named in 1985 by Judea Pearl, (Pearl, 1985), but are based on Bayesian probability, first proposed in Bayes' rule in the 1700s by Thomas Bayes, (Bayes, 1763). The networks consist of a number of variables, represented by nodes, and connected by edges. Each variable has a finite number of discrete states, each with a finite probability of the variable being in each state. The edges represent the relationship between the variables, where the state of one variable affects the probability of each of the state occurrence of the other variable. Note, the networks are acyclic as each variables state probabilities affects the connected variables state probabilities, and would result in a never ending cycle of updating of event probabilities if the network was cyclic. The probability of each state is entered into a conditional probability table (CPT), which is used to calculate the probability of other nodes being in each of their states. Note, the relevant equations are presented in section 2.2.1.1. Each column in the CPT must add up to 100% probability, i.e. the node has to be in one of the states, but the CPT can be completed using numerical values that do not add up to 100, and the network will calculate the probability of each state accordingly. For example, if there is a column with two "1"s in it, each state will have 50% probability, or if there is a column with two "1"s, and a "2", the state's corresponding to "1", will have a 25% probability, and the state corresponding to "2" will have a 50% probability. The variables are often referred to as parent and child nodes, with the state of the child nodes dependent on the state of the parent nodes. Note, each parent node can have multiple child nodes, and each child node can have multiple parent nodes.

BBNs are used to model real systems and can therefore be used to determine the probability of a specific event occurring. An example network is presented in Figure 2.1 that can be used to determine the probability of car headlights being on at various times of the day and year.

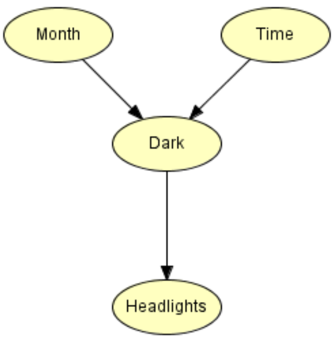


Figure 2.1 BBN for headlights example

The three nodes in the network, “Month”, “Time”, “Dark”, each represent the factors that affect whether or not the headlights will be on, which is represented by the node, “Headlights”. The headlights being on is usually dependent on whether it is dark or not, but other factors, such as the driver forgetting to turn them on/off, the headlights being broken, or whether it is raining or foggy will also affect them. Therefore, the conditional probability table for the “Headlights” node can be completed accounting for these factors, for example, the probability that the headlights are on, given that it is dark, is 98%. The CPT is presented in Table 2.1, where the states along the top represent the states of the “Dark” node, and the states along the left hand side represent the states of the “Headlights” node.

Table 2.1 CPT for the headlight node

Dark	Yes	No
On	0.98	0.1
Off	0.02	0.9

Table 2.2 CPT for the Dark node

Month	April							
Time	0:00	1:00	2:00	3:00	4:00	5:00	6:00	7:00
Dark	1	1	1	1	1	1	0	0
Not Dark	0	0	0	0	0	0	1	1

Continued…

Month	April							
Time	8:00	9:00	10:00	11:00	12:00	13:00	14:00	15:00
Dark	0	0	0	0	0	0	0	0
Not Dark	1	1	1	1	1	1	1	1

Continued…

Month	April							
Time	16:00	17:00	18:00	19:00	20:00	21:00	22:00	23:00
Dark	0	0	0	0	1	1	1	1
Not Dark	1	1	1	1	0	0	0	0

Whether it is dark or not is dependent on the time of day and the time of year, as it is darker for longer each day in the winter than it is in the summer. In order to do represent this using the BBN nodes, the "Month" node has 12 states, one for each month, each with equal probability. Note, all months are assumed to be the same length for simplicity. The "Time" node is assigned 24 states, one for each hour of the day, and therefore, each with equal probability. The CPT for the "Dark" node is presented in Table 2.2. As the CPT for the "Dark" node consists of 288 columns, (a column is required for each combination of month, and time of day, 12×28), only a section of the CPT (for one month, April) is presented. Note, it is assumed to be either dark or not dark in full hour steps for every day of each month.

Bayesian Belief Networks can have evidence of observed variables introduced to the network, and it will update the probability of the states of other variables. In the headlights example, evidence such as the time of day and month could be introduced to the network, and the updated probability of the headlights being on can then be calculated. Alternatively, evidence that the headlights are either on or off, and the time of day could be introduced, and the probability of each of the months could be updated. The updated probabilities of the corresponding node for both of these cases are presented in Tables 2.3 (Headlights) and 2.4 (Months), respectively. In the first example, the time of day is set to 7:00, and the month is set to be January. Using Bayes' Theorem, this results in a 98% probability that the headlights are on. In the second example, the headlights are set to on, and the time of day is set to 7:00, and this results in a 33.11% probability that it is either January or December, and a 3.38% probability for each of the other months. Therefore, if the desired information is the probability of it being January, the answer is 33.11%.

Bayesian Belief Networks can be used for fault diagnostics by using evidence obtained by observing symptoms on the system to update the probability of the states of the components. The components that are more likely to be in the failed state can be repaired or replaced as required.

Table 2.3 Probability of Headlights being on in January at 7:00

Headlights	Probability
On	98%
Off	2%

Table 2.4 Probability of each month given that the headlights are on and it is 7:00

Month	Probability
January	33.11%
February	3.38%
March	3.38%
April	3.38%
May	3.38%
June	3.38%
July	3.38%
August	3.38%
September	3.38%
October	3.38%
November	3.38%
December	33.11%

2.2.1.1. Bayesian probability

In BBNs, a problem is modelled by considering a list of variables X_1, X_2, ..., X_n, and the joint probability is represented by $P(X_1, X_2, ..., X_n)$. In order to calculate the probabilities of each of the variables states, Bayes' rule is used. Bayes' rule is stated in Equation (2.14), where X_1 and X_2 are events and $P(X_2)$ is not equal to 0, $P(X_1)$ is the probability of observing event X_1, $P(X_2)$ is the probability of observing event X_2, and $P(X_1 \mid X_2)$ and $P(X_2 \mid X_1)$ are the probabilities of observing event X_1 given that X_2 is true, and of observing event X_2 given that X_1 is true, respectively, (Koski & Noble, 2009)). Note, if X_1 and X_2 are mutually exclusive, $P(X_1 \text{ or } X_2) = P(X_1) + P(X_2)$, and if X_1 and X_2 are independent, $P(X_1 \mid X_2) = P(X_1)$.

$$P(X_1 \mid X_2) = \frac{P(X_2 \mid X_1)\, P(X_1)}{P(X_2)} \tag{2.14}$$

In Bayesian probability the joint probability function is defined in terms of the conditional probability in the form presented in Equation (2.15), with the generalisation presented in Equation (2.16).

$$P(X_1 \cap X_2) = P(X_1 \mid X_2)\, P(X_2) \tag{2.15}$$

$$P(X) = \sum_i P(X \mid X_i)\, P(X_i) \tag{2.16}$$

For a network with *n* nodes, the joint distribution can be written using the chain rule, as presented in Equation (2.17).

$$P(X_1 \cap X_2 \cap \dots \cap X_n) = P(X_n \mid X_{n-1}, \dots, X_2, X_1) \dots P(X_2 \mid X_1)\, P(X_1) \tag{2.17}$$

For example, the joint distribution for the headlights example, given before is presented in Equation (2.18), where *M* represents the Month node, *T* represents the Time node, *D* represents the Dark node, and *H* represents the Headlights node.

$$P(X_M \cap X_T \cap X_D \cap X_H) = P(X_M)\, P(X_T)\, P(X_D \mid X_M, X_T) P(X_H \mid X_D) \tag{2.18}$$

The probability of an event can be calculated using Bayes' rule (Equation (2.14)), where X_1 is the set of variables of interest, and X_2 is the evidence introduced to the network. This rule can be expressed differently, in the form presented in Equation (2.19), where *Y* is a set of all variables excluding the variables of interest (X_1), and the variables that have had evidence introduced.

$$P(X_1 \mid X_2) = \frac{P(X_2 \mid X_1)\, P(X_1)}{P(X_2)} = \frac{\sum_Y P(X_1, X_2, Y)}{\sum_{X_1} \sum_Y P(X_1, X_2, Y)} \tag{2.19}$$

If the example presented in Table 2.3 is considered, the conditional probability that the headlights are on given that it is January at 7:00 can be expressed by *P(Headlights = On | Month = January, Time = 7:00).* Substituting this expression into the left hand side of Equation (2.19), results in the formula presented in Equation (2.20), where for brevity, *P(Headlights = On | Month = January, Time = 7:00) = A.*

$$A = \frac{N}{D} \tag{2.20}$$
$$= \frac{\sum_{Dark} P(Headlights \ = On, Month \ = January, Time = 7{:}00, Dark)}{\sum_{Month} \sum_{Time} \sum_{Dark} P(Headlights, Month \ = January, Time = 7{:}00, Dark)}$$

The numerator (*N*) of Equation (2.20) can be evaluated to give the solution presented in Equation (2.21), with the denominator (*D*) evaluated to give the solution presented in Equation (2.22). When Equation (2.21), and Equation (2.22) have been evaluated, the probability that the headlights are on given that it is January at 7:00 can be determined, and is presented in Equation (2.23).

$$N = P(Headlights = On \cap Month = January \cap Time = 7{:}00 \cap Dark = Dark) + P(Headlights = On \cap Month = January \cap Time = 7{:}00 \cap Dark = Not\,Dark) = 0.003403 + 0 = 0.003403 \tag{2.21}$$

$$D = P(Headlights = On \cap Month = January \cap Time = 7{:}00 \cap Dark = Dark) + P(Headlights = Off \cap Month = January \cap Time = 7{:}00 \cap Dark = Dark) + P(Headlights = Off \cap Month = January \cap Time = 7{:}00 \cap Dark = Dark) + P(Headlights = Off \cap Month = January \cap Time = 7{:}00 \cap Dark = Not\,Dark) = 0.003403 + 0 + 0.000069 + 0 = 0.003472 \tag{2.22}$$

$$A = \frac{N}{D} = \frac{0.003403}{0.003472} = 0.98 \tag{2.23}$$

In the second example, the example presented in Table 2.4 is considered, the conditional probability that it is January given that the headlights are on and it is 7:00 can be expressed by *P(Month = January | Headlights = On, Time = 7:00).* Again, this is substituted for the left hand side of Equation (2.19), and is represented by *A* in Equation (2.24), as in Equation (2.20). As before, the numerator (*N*) and the denominator (*D*) are calculated in Equations (2.25) and (2.26), respectively, with the probability that it is January given that the headlights are on and it is 7:00 presented in Equation (2.27). Note, in Equation (2.26), all months other than January are referred to as "Not January" for brevity.

$$A = \frac{N}{D} = \frac{\sum_{Dark} P(Headlights = On, Month = January, Time = 7:00, Dark)}{\sum_{Month} \sum_{Time} \sum_{Dark} P(Headlights = On, Month, Time = 7:00, Dark)} \quad (2.24)$$

$$N = P(Headlights = On \cap Month = January \cap Time = 7:00 \cap Dark = Dark) + P(Headlights = On \cap Month = January \cap Time = 7:00 \cap Dark = Not\,Dark) = 0.003403 + 0 = 0.003403 \quad (2.25)$$

$$D = P(Headlights = On \cap Month = January \cap Time = 7:00 \cap Dark = Dark) + P(Headlights = On \cap Month = January \cap Time = 7:00 \cap Dark = Not\,Dark) + P(Headlights = On \cap Month = Not\,January \cap Time = 7:00 \cap Dark = Dark) + P(Headlights = On \cap Month = Not\,January \cap Time = 7:00 \cap Dark = Not\,Dark) = 0.003403 + 0 + 0.003403 + 0.003472 = 0.010278 \quad (2.26)$$

$$A = \frac{N}{D} = \frac{0.003403}{0.010278} = 0.3311 \quad (2.27)$$

In the next section, the different methods of constructing BBNs are discussed, including construction from scratch, and construction from Fault Trees.

2.2.1.2. Construction of BBNs

As BBNs for systems can be large, potentially consisting of a large number of nodes, a method of construction of BBNs needs to be determined. Romesis & Mathioudakis (2006) state ‘it is common belief that, there is no “best” method for construction or inference with a BBN, only a “most suitable” one, with respect to the information available in each case’. The authors construct BBNs by following a three step methodology; acquire information that describes the specific diagnostic problem, define the relationships between the variables, and map out the structural elements of the network. The authors apply the proposed methodology to a gas turbine in order to diagnose failures in the gas path. The authors state that the proposed methodology has a strong diagnostic ability, due to the accuracy in the modelling of the relationships between variables that is achieved because of the proposed construction method of the BBN.

Lampis & Andrews (2009) and Khakzad et al. (2011) propose constructing BBNs using Fault Trees. However, one major problem with constructing Bayesian Belief Networks using Fault Trees, is that Fault Trees have to be constructed for each possible system failure mode, potentially taking a long time and a lot of resources. Lampis & Andrews (2009) outline the steps of the method, beginning with making a binary node for each of the basic events in the Fault Tree. The binary nodes have two states, one for the event occurring, and one for the event not occurring, and are often referred to as root nodes. The CPTs for the root nodes are completed using the probability of event occurrence. The next step outlined is to introduce more binary nodes, one for each of the logic gates in the system, which can be connected to the root nodes, as in the Fault Tree. The logic gates can be represented using the CPTs for the nodes. An AND gate would have the CPT presented in Table 2.5, and the OR gate would have the CPT presented in Table 2.6. For a simple Fault Tree where event A and event B are the inputs to the gate, and event C is the output, both event A and event B need to be in the "True" state for event C to occur if the gate is an AND gate, and at least one of event A or event B must be in the "True" state for event C to occur if it is an OR gate. Finally, the top event of the Fault Tree can be represented using a final binary node.

Table 2.5 CPT for event C, an output of an AND gate with the inputs event A and event B

Event A	True		False	
Event B	True	False	True	False
True	1	0	0	0
False	0	1	1	1

Table 2.6 CPT for event C, an output of an OR gate with the inputs event A and event B

Event A	True		False	
Event B	True	False	True	False
True	1	1	1	0
False	0	0	0	1

Khakzad et al. (2011) state that BBNs can produce a more reliable measure of component importance than can be obtained from the minimal cut sets of a fault tree. This is because they output the probability of the states of the components, enabling more accurate prediction of which failure events have occurred. Also, as events in Fault Trees can either occur or not occur, the Fault Trees can contain less information, or be significantly larger than the corresponding BBNs, which can consist of more than two states per node, as is the case for the "Month" node in the example presented earlier. Santoso et al. (1999) highlight that BBNs require expert knowledge to construct, with values in the CPTs of the root nodes being completed using available data, or expert knowledge if data is not available. This means that it is more difficult for computers to construct BBNs than it is for them to construct Fault Trees.

2.2.1.3. Advanced Bayesian networks

There are a number of modifications that can be made to BBNs to consider more complex systems, the first of which is hierarchical BBNs. Gyftodimos et al. (2002) state that hierarchical BBNs consist of two parts, a structural part and a probabilistic part. The structural part of the network considers the system as a whole, with the probabilistic part being a series of smaller sub-networks. The sub-networks model small sections of the system that are independent of each other. The authors present an example of playing golf, with two sub-networks, one considering the weather, and one considering the finances required to play golf. The two factors in the example are independent, the weather does not influence the players' finances, and the players' finances does not influence the weather. However, as the hierarchical BBNs require the different sub-networks to be independent, complex systems, such as aircraft fuel systems, can be harder to model as different sections of the system typically influence each other and are therefore not independent. Therefore, the components of the system could be in the main network, with sub-networks used to calculate fuel flow in specific sections of the system.

Dynamic BBNs, another extension to BBNs, are time dependent, with the probability of the states of each of the variables changing as time progresses. A number of authors have used dynamic BBNs to model systems, with Vileiniskis et al. (2016) modelling a three phase separator used in offshore oil processing facilities over three time steps. The authors create three instances of the network, with the outputs of one instance used to update the initial values of the next instance. Other authors, such as Murphy (2002), use dynamic BBNs to generalise other modelling techniques, such as hidden Markov models and Kalman filter models, by enabling better representation of state space, instead of as single data points.

2.2.1.4. Summary

In summary, Bayesian Belief Networks are an effective system modelling and fault diagnostic technique. The ability to introduce evidence to the network enables the determination of component state occurrence probability. This could enable sensors to be modelled in the system, and sensor readings could be introduced to the network as evidence, enabling prediction of component states. As discussed in section 2.2.1.2, there are a couple of ways to construct Bayesian Belief Networks, and whilst there is the benefit of using pre-constructed Fault Trees as the basis for the networks, only using binary nodes may not be the most efficient method of modelling complex systems with multiple states for each component. Hierarchical and dynamic BBNs are extensions to conventional BBNs that have been applied by a number of authors. A potential problem with hierarchical BBNs is that they require each of the sub-networks to be independent, which may not be the case with complex systems. However, this problem could be avoided by using component nodes in the main network, enabling all sub-networks to consider their states. A possible solution for introducing time dependence is to create multiple instances of the network, an instance for each time step. However, as this method requires multiple instances of the network, it could end up being computationally intensive.

2.2.2. Other fault diagnostic techniques

There are a number of other fault diagnostic techniques that can be used for the diagnosis of failures in systems. In this section, an overview of FMEA, Fault Trees and Digraphs is presented. A discussion comparing the benefits of these fault diagnostic techniques and BBNs is presented in section 2.2.3.

2.2.2.1. FMEA

Failure Mode and Effects Analysis (FMEA) is a technique that was first developed by the aerospace industry in the 1960s, (Liu et al., 2013), and it has been widely used in a number of different applications. The technique considers individual component failures in the system and the effect of each of their failures on the systems performance, (Ostrom & Wilhelmsen, 2012). A document is typically created that contains all of the failures and the observed symptoms, which can be updated as previously unobserved failures arise. If a failure is detected on a system, the observed symptoms can be compared with the document, enabling prediction of failure occurrence.

FMEA can be modified to include the probability of each of the failures occurring. When the probability of events is included, it is typically referred to as FMECA, Failure Mode, Effects and Criticality Analysis, (Ostrom & Wilhelmsen, 2012). The created document could also be used to highlight sections of the system that are more susceptible to failure, and therefore, improvements to the system could be introduced in order to reduce the risk of failure.

One of the main shortfalls with FMEA and FMECA is that it generally only considers the effects of individual failures and not combinations of failures, (Xiao et al., 2011). This could result in symptoms being observed that are not in the document and the fault diagnostic process being ineffective. This could be the case when two component failures occur, but neither component failure can be detected if it is the only component failure to occur. In this case, other fault diagnostic techniques, such as BBNs, would be more likely to be able to diagnose the component failures.

2.2.2.2. Fault Trees

Fault Trees are a commonly used reliability assessment technique, which were first proposed by Watson in 1961, (Andrews & Beeson, 2003), to be used for the Minuteman Intercontinental Ballistic Missile, (Ostrom & Wilhelmsen, 2012). Fault Trees are used in the modelling of system failure modes and the component failures that can cause the system to fail. There are three types of events used in Fault Trees: the top event, intermediate events and basic events, (Andrews & Moss, 2002). In each Fault Tree there is only one top event, (usually system failure), but there can be many intermediate and basic events. Basic events typically correspond to component failures, and intermediate events correspond to the operation of sections of the system. In between each of the events in the Fault Tree, there are logic gates. There are a number of different logic gates, (Andrews & Moss, 2002), but the two most common are the AND and OR gates. The third most common logic gate is the NOT gate, which is used in non-coherent Fault Trees. An example of each of the three gates is presented in Figure 2.2.

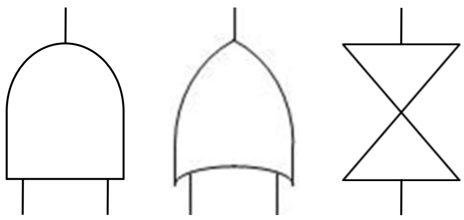


Figure 2.2 a. AND logic gate, b. OR logic gate, c. NOT logic gate

An example (Andrews & Moss, 2002) of a Fault Tree for the brakes on a bicycle is presented in Figure 2.3. Starting from the top event and working down, for the brakes on a bicycle to not operate, both the front and rear brake need to have failed. As both of the events need to have occurred, an AND gate is used. For the front brakes not to work, at least one of three basic events needs to occur, the brake blocks need to be worn so that they cannot slow the wheel, the cable connecting the brakes to the lever is broken, or the lever is broken. As only one of the three events needs to occur for the front brakes to fail, an OR gate is used. The same is the case for the rear brakes.

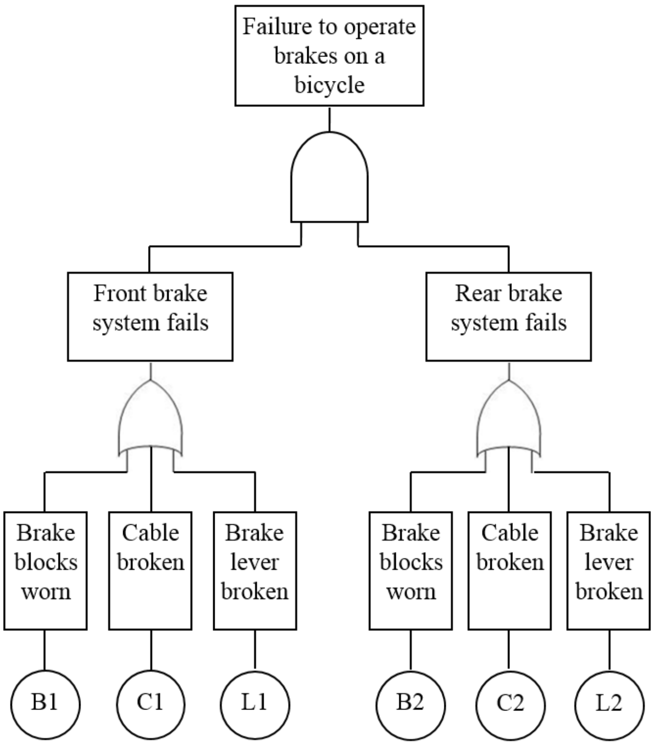


Figure 2.3 Fault Tree for the failure of bicycle brakes (Andrews & Moss, 2002)

Fault Trees that include NOT logic are called non-coherent Fault Trees. A number of authors, (Bartlett et al., 2006), (Hurdle et al., 2008), and (Contini & Matuzas, 2011), claim that whilst coherent Fault Trees are easier to construct and use, non-coherent Fault Trees can be used to provide more information about the system. The NOT gate is used when the system can only fail if it requires one of the components to be in its working state for the system to fail. An example of this is a water tank that is supposed to stop filling up when the water level in the tank reaches a certain level. However, if the water level sensor (LS) has failed, and the tap (T) supplying the water has not failed, the water level will keep on increasing, and the water will overflow, causing the system to fail. The Fault Tree for this system is presented in Figure 2.4.

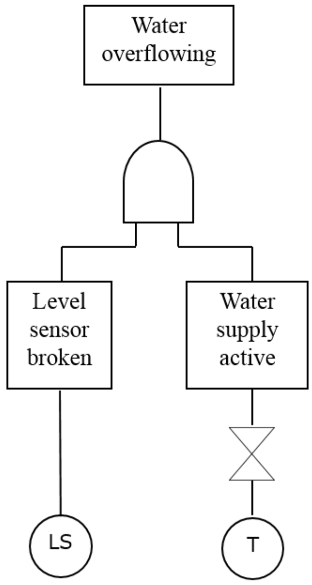


Figure 2.4 Non-coherent Fault Tree for a water tank overflowing

A benefit of analysing systems using Fault Trees is that they aid in the deduction of minimal cut sets. Minimal cut sets are combinations of basic events that if they all occur, the top event will occur. Note, if any of the basic events in the minimal cut sets do not occur, the top event will not occur, (Clark & Verwoerd, 2012). For the bicycle brakes example presented before, the minimal cuts sets are {B1, B2}, {B1, C2}, {B1, L2}, {C1, B1}, {C1, C2}, {C1 L2}, {L1, B2}, {L1, C2} and {L1, L2}. If any of the minimal cut sets occur, the bicycles brakes will fail. A general rule for minimal cut sets, is that the lower the number of basic events in the minimal cut set, the more important the components are to the operation of the system. However, this is not always the case if a minimal cut set consists of a larger number of component failures which are more likely to occur than a minimal cut set that consists of a smaller number of component failures, but are less likely to occur.

Fault Trees can be analysed qualitatively or quantitatively. Qualitative analysis of Fault Trees consists of determining the minimal cut sets and the minimal path sets of the Fault Tree. A path set is a set of basic events, that if none of the events occur, the top event also does not occur. The minimal path set is the minimum set of basic events that need to have not occurred for the top event to not occur. For the bicycle example presented before, the minimal path sets are {B1, C1, L1}, {B2, C2, L2}, i.e. at least one set of brakes works. Quantitative analysis of Fault Trees aims to determine the probability of the top event, or the predicted time to failure of the top event. This can be calculated using the minimal cut sets, i.e. if the probability of the basic events in the minimal cut sets is known, the probability of the top event can be calculated, or if the time to failure for the basic events is known, the time to the top event is the highest of the basic events, (Lee et al., 1985).

A disadvantage of using Fault Trees is the time taken to construct and analyse them. For large systems, with a large number of components, the Fault Tree can become extremely large, and can take a long time to construct. In addition, if the trees are too large, it may not be possible to model the system exactly, in which case approximations are utilised. However, approximations introduce inaccuracy to the model and may not result in exact solutions. As a result, a number of authors have suggested methods of constructing Fault Trees and analysing their solutions more easily. Examples include constructing Fault Trees from Digraphs, (Lapp & Powers, 1977), converting a probabilistic graph into Fault Trees, (Camarda & Trentadue, 1978), and analysing the trees by simplifying them using Faunet reduction or by modularisation, (Reay & Andrews, 2002).

Fault Trees are used for diagnostics by following the logic gates from the top of the Fault Tree down to the basic events, i.e. determining which basic events could have occurred to result in the top event.

2.2.2.3. Digraphs

Digraphs, like BBNs, model systems using a directed graph. The variables in the graph are represented by circular nodes, and are connected by arrows, which are referred to as edges. The edges represent the relationships between the variables and are weighted according to the strength of the relationships. By convention the strength of the relationships can be one of five values, +10, +1, 0, -1, and -10. The relationships that are considered to be strong relationships are indicated by ±10, and the relationships that are considered to be moderate relationships are indicated by ±1. 0 is used to represent that the relationship between two variables is null.

Alternatively, Allen (1984) suggests that the values could be used to represent a change in the normal operating behaviour such as change in the amount of flow through a pipe. For example, 0 can represent no change in behaviour, and ±1 and ±10 can represent varying amounts of change to the flow through pipe. A problem with this is that if, for example, 0 represents normal flow, -1 is a moderate reduction in flow, and -10 is a large reduction in flow, then it is not possible to represent no flow in the pipe, therefore, inaccuracies are introduced.

Another suggestion by Allen (1984) is that flow through pipes could be modelled by having a weighting of 0 for no flow through the pipe, and positive weightings representing flow in one direction, and negative weightings representing flow in the opposite direction. A problem with this suggestion is that it is not clear how to represent the normal flow through the system, as there are only two weightings for each direction of flow, but a minimum of three weightings are required: normal flow, below normal flow, and above normal flow.

A more recent suggestion by Bartlett et al. (2006) is to introduce an additional weighting of ±5 to increase the accuracy of the relationships. In order to do this they modify the definition of ±1 to a small deviation, and introduce a new definition of a moderate deviation, i.e. ±5. Whilst this does increase the accuracy of the modelling of the system, for some applications, it could make the relationships between variables more subjective.

Digraphs can be used to diagnose component failures by initially identifying deviations between the expected system behaviour and the observed system behaviour. The deviations can then be back traced through the system in order to diagnose the component failure. Back tracing is completed until a non-deviated node is observed or no further back tracing can be carried out, (Bartlett et al., 2006). An example Digraph for part of the main tank from Bartlett et al. (2006) is included in Figure 2.5 to show the form of a Digraph.

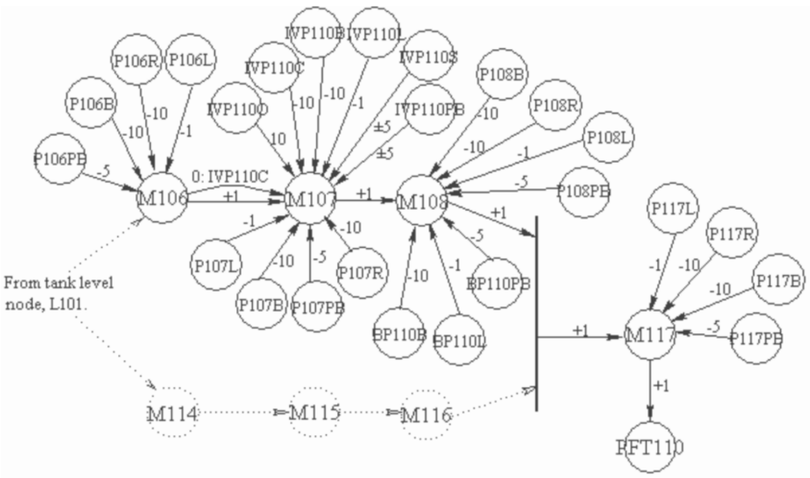


Figure 2.5 Example Digraph

2.2.3. Summary

In this section, an overview of a number of fault diagnostic techniques is presented. The section focused on BBNs with other techniques also included, such as FMEA, Fault Trees and Digraphs, and discussed briefly. BBNs have the ability to handle multiple failure modes for each component efficiently and they can update the probability of event occurrence based on the introduction of evidence. This evidence could be introduced in the form of sensor readings from the system's sensors, and the resultant component state probability could be determined in order to be able to diagnose the component failures. One problem with BBNs is that as they require expert knowledge to construct, they are difficult for computers to construct accurately, and therefore, they need to be constructed manually.

In section 2.2.1.2 the construction of BBNs by converting Fault Trees is discussed. Construction in this way would require a fault tree to be produced for every possible reading of each of the sensors, a large number of Fault Trees would have to be produced for larger systems. This is because the logic gates in the fault trees can only output two variables, for example, 1 or 0, they cannot represent fuel systems which can have multiple states well. For example, a pipe can have multiple different fuel flow rates passing through it, or no flow at all, resulting in many different sensor readings. Therefore, for each different sensor reading a new Fault Tree needs to be constructed. When all the Fault Trees have been constructed, they need to be combined to create the BBN. This can introduce inefficiency into the BBN as a large number of nodes may be introduced, with potentially multiple nodes doing the same, or similar, things. This may cause some confusion in understanding how the BBN works as there may be multiple nodes with similar functionality. If the BBNs are constructed from scratch, these nodes can be combined so that there is minimal repetition of nodes, therefore reducing the inefficiency and potentially reducing the risk of confusion in understanding how the BBN works. This will also reduce the risk of making incomplete changes if modifications are required in the future. If the BBN has many similar nodes, multiple nodes may need to be changed to implement the modifications, as opposed to minimal changes if there is minimal repetition of nodes in the network. Therefore, the BBNs constructed in this work will be constructed from scratch, and not by constructing Fault Trees for the system and converting them into a BBN.

The use of BBNs instead of the other fault diagnostic techniques discussed, including Fault Trees, Digraphs and FMEA, can be justified by considering the construction process, as discussed in the previous paragraph. As stated in the previous paragraph, a Fault Tree needs to be constructed for every possible sensor reading of each of the sensors, making this method of system modelling potentially inefficient. Digraphs also do not model the systems well as subjectivity is required to determine the strengths of the relationships between the nodes. It is also not clear how varying amounts of fuel flow through the system would be represented, particularly in sections where fuel can flow in multiple directions. In addition, FMEA and FMECA generally only consider individual component failures, making them unsuitable for considering systems which can potentially still function after component failure occurrence, and can hence tolerate multiple failures. Therefore, BBNs offer the most suitable solution for fault diagnostics for the systems presented in this thesis.

2.3. Optimisation techniques

The Oxford English dictionary defines optimisation as "the action of making the best or most effective use of a situation or resource", i.e. an optimisation technique aims to achieve the best result possible, whilst only using a reduced amount of resources, such as time or computing power. Optimisation techniques typically (but not always) involve doing fewer calculations to determine the best solution and, as a result, may not always result in the best possible solution, but they usually result in a good solution. In this section, a brief overview of optimisation techniques is presented, followed by a description of the GA, an optimisation technique that is applied in Chapter 6 of this thesis.

2.3.1. Overview of optimisation techniques

Optimisation techniques are used to find the best possible solution to a particular problem. In order to determine what the best solution is, an objective function needs to be defined. An objective function is a mathematical representation of how suitable the solution is, which can be maximised (or minimised) in order to determine the most suitable solution. Note, there can be more than one optimal solution, i.e. multiple different combinations of variables that result in the same value of the objective function, in which case it does not matter which solution is chosen. In more advanced systems, there can be multiple objectives, such as minimising cost, maximising performance, minimising the safety risk, etc. This results in the best solution being the best trade-off of the values of all objective functions. The objective functions can be subject to constraints, for example, available budget, and therefore, even if there is a better solution which costs more money than the operator's budget, then a suboptimal solution will have to be selected.

There are two main types of optimisation techniques: local optimisation and global optimisation. Venter (2010) states that most local optimisation techniques are gradient based, where the gradient information can be used to obtain the optimum solution. Consider a graph representing the fitness value of a set of variables, the graph will have one peak, and by comparing the value of the objective function to the previously calculated values, the maximum value can be obtained, starting from any initial set of variables. However, iteratively calculating the objective function for all possible solutions can be computationally intensive, and it could result in having to exhaustively calculate the objective function for all combinations. Therefore, local optimisation is typically focused on a particular range of possible solutions, i.e. some prior knowledge of a potentially suitable solution is required. For example, if the graph representing the fit of the objective function example introduced above is considered, the range of x axis values, in which the best solution lies, would be known. Instead of finding the maximum value of the objective function by calculating the objective function, the first derivative of the objective function could be calculated, when the resultant values are equal to 0, a peak or trough in the graph has been found. Peaks and troughs can then be distinguished by taking the second derivative of the objective function; if the value is negative, a peak has been found, i.e. a maximised solution, (Haupt & Haupt, 2004).

Global optimisation techniques can also often be presented in a graphical form as discussed above. However, instead of there being one peak as in the case of local optimisation techniques, there are multiple peaks, each with potentially different magnitudes. There may not be an observable pattern to the peaks and therefore in order to ensure the best solution is achieved the full range of parameters needs to be investigated, since if it is not then a suboptimal solution may be selected. Genetic Algorithms are one type of global optimisation technique and are applied to a number of systems and processes, including railway bridge asset management (Yianni, 2017), firewater deluge systems (Andrews & Bartlett, 2003), and system health monitoring system design, ((Maul et al., 2008) and (Jin et al., 2003)). An overview of Genetic Algorithms is presented in the next section.

2.3.2. Genetic Algorithms

Genetic Algorithms are based on the principal of natural selection, where species that are stronger, or have more desirable features, are more likely to reproduce than species with weaknesses, or ones that have features that are not desirable. This principal was proposed by Darwin in the 19th century, (Darwin, 1859). An example of natural selection is that if something caused plants close to the ground to die out, the giraffes with longer necks would be able to reach more food that is on taller plants than giraffes with shorter necks. Therefore, the giraffes with longer necks have more access to food, and are more likely to survive. When the giraffes reproduce, it is more likely that the parents will both have longer necks as there are more of these around, resulting in a higher probability that their offspring also have longer necks. After a number of generations, all, or nearly all, of the giraffes will have long necks.

Genetic Algorithms were initially proposed by Holland (1975). They are considered to be an effective optimisation technique, as they are attempting a wide range of solutions (known as a population), and not just one potential solution, (Samhouri, 2009). They apply an objective function to a set of potential solutions, calculate the best solution out of the available options, and then apply various methods to change the solutions in order to potentially achieve a better solution. An objective function is a measure of how suitable the solution is for the problem, and will be discussed in section 2.3.2.2. The details of the algorithm are presented in section 2.3.2.1. and a number of example applications are presented in section 2.3.2.3.

2.3.2.1. The algorithm

The GA begins with a population of strings, each of which represent a potential solution to the problem to be solved, (Goldberg, 1989). In natural selection, the strings represent the chromosomes of the animal. Each of the chromosomes contain a number of different genes which affect the features of the animal. Therefore, each of the elements of the string provides different information on the potential solutions for the problem that is to be solved. The ability of each member of the population to achieve the desired task is calculated by an objective function, which measures how suitable the solution is at solving the problem. The best members of the population can then have genetic operators applied to them in order to try and achieve a better solution. Applying the operators to the populations results in a new population of potential solutions. This is known as the next generation. This can be repeated a number of times (a number of generations) until the solution for all of the members of the population converges to the best solution. The operations that can be applied to each population include: selection, crossover, elitism and mutation. Note, not all of the operators need to be applied in the algorithm, and the objective function for each new generation will only be calculated after all operators have been applied.

The **selection** operator, as applied by Le (2014), ensures that the best solution from each generation are preserved and are not removed, which could potentially result in the next generation being less optimal than the previous generation. For example, if there are 100 members in the population, the 30 best solutions are preserved and become the first 30 members of the next generation. Note, this selection operation does not need to be applied, and is a modification to the standard Genetic Algorithm aimed at improving the result of the optimisation process. The remaining 70 members of the population can then be determined randomly, where they are weighted to favour the members of the population that have a higher objective function. For example, all 100 of the members of the population are used as a mating pool, where the members with a higher objective function are more likely to be selected. Note, as it is weighted selection, each member can be selected multiple times. These solutions are then paired, for crossover. Again, these pairs are weighted to favour the solutions with the higher objective functions, i.e. a random member is selected for crossover, and is mated with another randomly selected member. Note, as before, as with the initial weighted selection process, the selection of individuals to be paired is also weighted meaning multiples of the same member can be selected.

The **crossover** operator is then applied to each of the 35 pairs, (70 members). In each pair a random point (or points), in the string is selected, and the values in the pairs of strings are swapped at this point. For example if each solution is a binary string *n* digits long, then at some point between any two digits, the strings can be split into two, and the second half of each pair swapped. For example, if the two strings are "0000000" and "1111111", and crossover is applied after the third element, then the new strings will be "0001111" and "1110000". This will generate a number of different solutions which may be better than the previous best solution. An example of crossover with two crossover points could be the two strings, "0000000" and "1111111", to "1100011" and "0011100", where crossover has occurred after the second and fifth element of the string. The two examples of crossover discussed in this paragraph are presented in Figure 2.6. The genetic operators will result in a new population of 100 members, the best 30 members from the previous generation, and 70 new members. The objective function can then be calculated for each of the members.

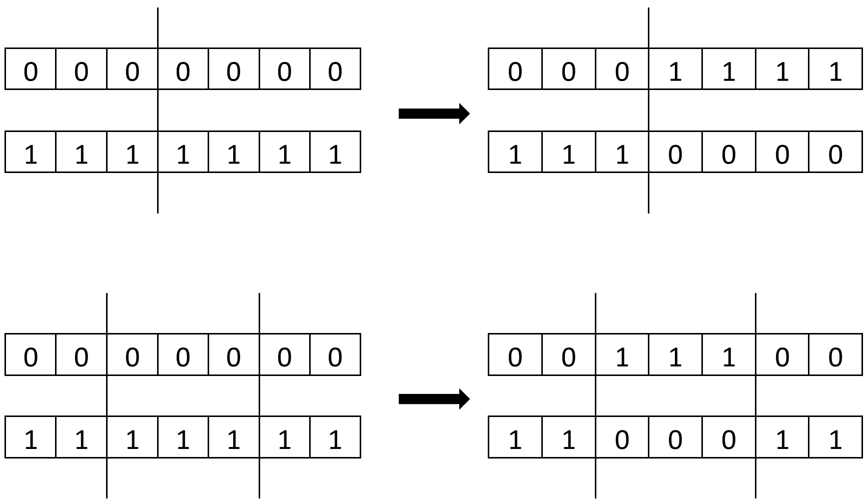


Figure 2.6 One and two point crossover

Once the objective function has been calculated for each of the members, the **elitism** operation can be applied, as also used by Le (2014). This determines the best solutions and preserves them. It typically preserves a smaller amount of solutions than during the selection operation. All other solutions have the **mutation** operation applied to them. In this operation, every digit in each of the strings has a probability of swapping from a "0" to a "1", or a "1" to a "0". This probability is low, typically 1% or less, and therefore is not likely to change a large number of solutions, (Goldberg, 1989). This mutation operation enables potential solutions that were not in the previous generation to be considered. For example, in all of the solutions for the previous generation, there may have been no solutions with a "1" as the last digit in the string. Therefore, this would have not been considered, but with mutation there is a chance that one of the solutions will have its last digit changed to a "1". If the mutation rate is too low, there is too small a chance that a digit will mutate, but if the mutation rate is too high, it will become too close to random selection and the best solution may never be obtained.

The next generation is populated after each of the four operations. The objective function can then be calculated for each of the members and the operations start again, producing another new generation. It is likely that the optimal solution produced by each generation will increase and will eventually converge on the best solution. When the value of the objective function has converged, the algorithm is stopped. Kilsby (2017) suggests that the results have converged when the change in the mean value of the objective functions is less than 0.1% for each additional generation. A summary of the algorithm is presented in Figure 2.7.

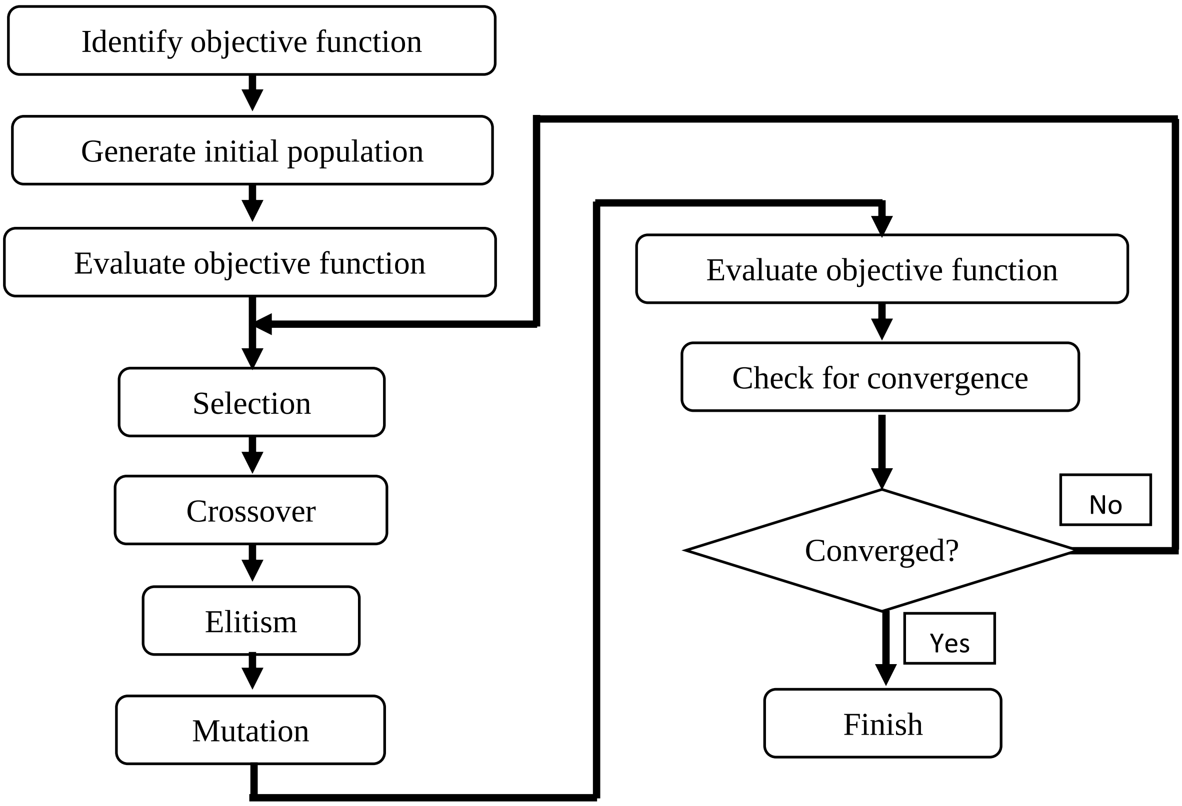


Figure 2.7. Flowchart of the Genetic Algorithm

2.3.2.2. The objective function

The objective function is a measure of how suitable a solution is for completing the desired task. This objective function can be directly related to the desired information to be obtained, or it can be a representation of the desired information. For example, the aim of the Genetic Algorithm could be to minimise the cost of completing a task, in which case the objective function could be the cost of completing the task. Alternatively, the aim of the Genetic Algorithm could be to maximise the performance of a system, in which case the objective function could be a performance metric, such as a sensor performance metric.

The objective function can be subject to a constraint, resulting in a penalty factor applied to the objective function if the constraint is broken. The constraint could be applied if the cost of a potential solution is above a certain threshold, or if the solution requires a large number of a specific asset that is not available. Therefore, the penalty factor could be applied such that it reduces the objective function by a small amount, (or a large amount), depending on the constraint, and how unsuitable the potential solution is. Goldberg (1989) states that they usually use a penalty function that is a square of the violation of the constraint.

The objective function can be modified such that it is more sensitive to smaller changes in the fit of the population. This helps to prevent the algorithm getting stuck at a close to optimal solution. For example, if all the values of the objective function are in a similar range, it is unlikely to result in the best possible solution being selected. This can be achieved by applying a scaling function, (Goldberg, 1989), to the objective function, such that smaller differences appear larger and are therefore more likely to be chosen than they would be with smaller differences. Alternatively, making the objective function non-linear, (such as exponential), will also result in smaller differences of performance having greater effect on the objective function, resulting in a higher probability of a better solution being selected.

2.3.2.3. Problems with Genetic Algorithms

In this section, some of the problems with Genetic Algorithms are discussed. Note, this is not an exhaustive list, and only a few examples are presented.

A problem experienced in many cases during the application of Genetic Algorithms is premature convergence, where the algorithm converges to a solution which is sub-optimal because some members in the population become too dominant in later generations, (Fogel, 2014). In order to prevent this, it is important to ensure the initial population is divergent enough so that a large number of potential solutions can be reached, or increasing the mutation rate will help to prevent premature convergence. Alternatively, applying the optimisation process multiple times will result in a higher probability of getting the true optimal solution.

Another potential problem with the application of the Genetic Algorithm is the need to manually choose the necessary parameters, (Lim, 2014). These parameters include the selection rate, population size, mutation rate, number of crossover points, the number of elite members, etc. Whilst there are a number of different examples of these parameters detailed for each individual application of the algorithm, the parameters are case dependent and it may be difficult to determine the most suitable for the application being considered.

2.3.3. Summary

In this section, an overview of optimisation techniques is presented, primarily focussing on the Genetic Algorithm. An overview of the algorithm is presented, detailing each of the individual steps. Note, some of the steps are additions to the algorithm (selection and elitism), and are not in the core Genetic Algorithm, but as they are applied in the work presented in Chapter 6 of this thesis, they have been presented in this chapter. The section is completed with a brief overview of a couple of problems that are experienced in the application of Genetic Algorithms.

The Genetic Algorithm is a useful optimisation technique that has been used for a large number of different research topics. The method is proven to determine optimal (or close to optimal) solutions significantly more efficiently than exhaustive search methods, (Goldberg, 1989). The method is also computationally simple, but is a powerful search tool for finding better solutions, which is not reliant on a large number of assumptions about the search space, (Goldberg, 1989). Also, as the performance metric for each of the combinations of sensors will not be represented on a clear graph with multiple peaks, with neighbouring combinations of sensors potentially having very different performance metrics, a typical gradient based optimisation technique cannot be used, but a Genetic Algorithm can. In addition, the binary string representation can be used to represent a combination of sensors easily, in which a selected sensor could be represented by "1" and an unselected sensor could be represented by "0". This enables the genetic operators to be applied to the combinations of sensors without having to introduce additional complexity. The suitability of the potential solutions are calculated using an objective function in Genetic Algorithms. For the performance metric based sensor selection method proposed in this thesis, the performance metric could be used as the objective function, enabling the performance metric to be the influencing factor for the selection of combinations of sensors in each generation of the algorithm.

2.4. Summary

In this chapter, an overview of sensor selection methods, fault diagnostic techniques and optimisation techniques are presented. The sensor selection methods presented in this chapter consider performance metric based evaluations of the sensors in order to determine the best sensor or group of sensors. The authors consider a number of factors, such as the detection of failures, the ability to diagnose the failures, the effect of the failures on the system, the cost of the sensor, the weight of the sensor and the reliability of the sensor. Some of the authors consider multiple factors, but all of the methodologies presented have potential drawbacks, such as subjectivity in the metric in the form of a penalty factor. Some authors use an optimisation technique in order not to have to calculate the performance metric exhaustively.

In the second section of this chapter, an overview of fault diagnostic techniques is presented. The selected methodology for system modelling and fault diagnostics for the work presented in this thesis is BBNs. BBNs have the ability to consider multiple failure modes for each component and the ability to determine the probability of event occurrence based on evidence that can be introduced in the system. Whilst there are benefits to the other fault diagnostic techniques presented in this section, they all have drawbacks, as discussed before. Therefore, BBNs are the most suitable solution for the work presented in this thesis, and are therefore used in Chapters 3 and 4.

As applied by a number of authors discussed in the sensor selection section of the methodology, optimisation techniques are a useful tool in order not to have to calculate the performance metric for all combinations of sensors exhaustively. Therefore, an overview of optimisation techniques is presented, focusing on Genetic Algorithms. The authors that applied optimisation techniques to their sensor selection methodology, also applied a Genetic Algorithm based approach, and it is a suitable method for the work presented in this thesis. Therefore, when the number of combinations of sensors becomes excessive, a Genetic Algorithm based optimisation technique is applied.

Chapter 3 - Proposed methodology for sensor selection and fault diagnostics

A method for sensor selection and fault diagnostics was developed in this thesis in order to determine which sensors are most suitable for this purpose. This method takes ideas from the literature discussed in the previous chapter, the literature review. The method proposes a new measure of sensor performance, different to other measures of sensor performance that have been suggested by other authors, including Maul et al. (2008), and Spanache et al. (2004), for the selection of sensors. The method also applies a similar methodology for fault diagnosis to that suggested by Lampis & Andrews (2009) based on Bayesian Belief Networks.

This chapter begins by introducing an example system, which is used later in the chapter in order to demonstrate an application of the methodology to this system. After the introduction of the system, the proposed methodology is presented, and the chapter concludes by analysing the methodology, evaluating its effectiveness and suggesting potential modifications to it. These modifications are utilised in all further applications of the methodology, presented in Chapters 4, 5 and 6 of this thesis.

3.1. System description and failure effects

An example system is introduced in this section and used to demonstrate the application of the proposed methodology. A schematic of the system is shown in Figure 3.1.

This system consists of seven components: two pumps, (P1 and P2) and five valves, (V1, V2, V3, V4 and V5). The flow of the liquid in the system is from the left of the system to the right of the system. The liquid then passes out of the system via the drain, which is represented by the down arrow at the right hand side of the system. There are eleven potential sensor locations on the system. In order to determine which sensor locations are the best, flow sensors are positioned in each of the possible locations. Sensors S1 – S10 are positioned either side of each of the valves and sensor S11 is positioned before the drain, as shown in Figure 3.1. The sensors do not affect the flow of fuel in the system, only measure the flow of fuel. The system is a simple representation of an aircraft fuel system, and the liquid represents aircraft fuel. The system can be separated into four sections: section one consists of the two pumps, valves V1 and V2, and sensors S1 – S4, section two consists of valve V3 and sensors S5 and S6, section three consists of valves V4 and V5, and sensors S7 – S10, and section four consists of sensor S11.

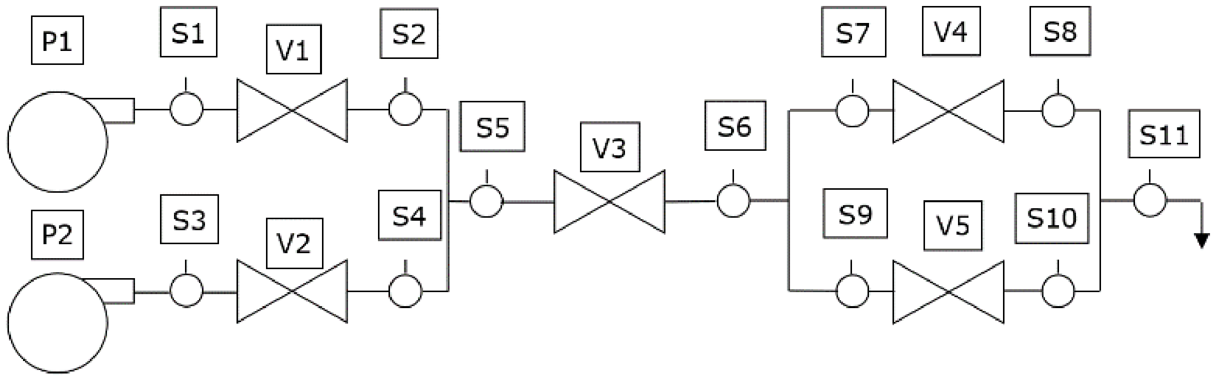


Figure 3.1 Schematic of example system

When the system is operating normally, each of the pumps, P1 and P2, supply fuel to the system at a constant rate. This constant rate is represented by “1” in Table 3.1. The fuel from each of the pumps passes through the adjacent valve, valve V1 and V2 respectively, before combining and passing through valve V3. The quantity of fuel passing through valve V3 is represented by “2” in Table 3.1. This fuel then splits equally and passes through the next two parallel lines, i.e. through valves V4 and V5. The flow of fuel through these two valves, valves V4 and V5, is equal to the same rate of fuel flow through valves V1 and V2, i.e. “1”. Finally, the fuel is combined again, and exits the system by passing through the drain. Therefore, the flow through the drain will be equal to the flow through valve V3, “2”.

In Table 3.1, the sensor readings for each combination of considered component failures are given. In the first row of the table, case 0, the system is working under normal operating conditions, i.e. no component failures. The sensor readings are as introduced above, with “1” representing the standard amount supplied by each pump, “2” being double this amount, and “0.5” being half of this amount. Sensor readings “E” and “N” represent the line empty, and the line full of fuel but no flow of fuel, respectively.

Each component in the system can be in one of two states, the working state or the failed state. The valves are defined to be working when they are not restricting the flow of fuel in any way, i.e. no blockage is present. The valves are defined to be failed when they are restricting the flow of fuel through it, i.e. the valve is blocked or closed. For this system, no partial blockages of valves are considered and no control systems for pumps and valves are modelled, i.e. the valves are controlled to be fully open and the pumps are working on. The pumps are defined to be working when they are supplying the constant rate of fuel introduced above, “1”, and are defined to be failed when they are not supplying any fuel to the system.

For this system, the pumps either supply the constant rate of fuel ("1") introduced above, or they supply no fuel to the system ("0"), i.e. there are no intermediate amounts of fuel (between "0" and "1"), or amounts of fuel greater than "1" that can be supplied to the system. It is assumed that sensors are perfectly reliable.

Table 3.1 Sensor readings produced by failure combinations

No.	Failures	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11
0	*No fault*	1	1	1	1	2	2	1	1	1	1	2
1	P1	N	N	1	1	1	1	0.5	0.5	0.5	0.5	1
2	P2	1	1	N	N	1	1	0.5	0.5	0.5	0.5	1
3	V1	N	N	1	1	1	1	0.5	0.5	0.5	0.5	1
4	V2	1	1	N	N	1	1	0.5	0.5	0.5	0.5	1
5	V3	N	N	N	N	N	E	E	E	E	E	E
6	V4	1	1	1	1	2	2	N	N	2	2	2
7	V5	1	1	1	1	2	2	2	2	N	N	2
8	P1 P2	E	E	E	E	E	E	E	E	E	E	E
9	P1 V1	E	N	1	1	1	1	0.5	0.5	0.5	0.5	1
10	P1 V2	E	E	N	E	E	E	E	E	E	E	E
11	P1 V3	N	N	N	N	N	E	E	E	E	E	E
12	P1 V4	N	N	1	1	1	1	N	N	1	1	1
13	P1 V5	N	N	1	1	1	1	1	1	N	N	1
14	P2 V1	N	E	E	E	E	E	E	E	E	E	E
15	P2 V2	1	1	E	N	1	1	0.5	0.5	0.5	0.5	1
16	P2 V3	N	N	N	N	N	E	E	E	E	E	E
17	P2 V4	1	1	N	N	1	1	N	N	1	1	1
18	P2 V5	1	1	N	N	1	1	1	1	N	N	1
19	V1 V2	N	E	N	E	E	E	E	E	E	E	E
20	V1 V3	N	N	N	N	N	E	E	E	E	E	E
21	V1 V4	N	N	1	1	1	1	N	N	1	1	1
22	V1 V5	N	N	1	1	1	1	1	1	N	N	1
23	V2 V3	N	N	N	N	N	E	E	E	E	E	E
24	V2 V4	1	1	N	N	1	1	N	N	1	1	1
25	V2 V5	1	1	N	N	1	1	1	1	N	N	1
26	V3 V4	N	N	N	N	N	E	E	E	E	E	E
27	V3 V5	N	N	N	N	N	E	E	E	E	E	E
28	V4 V5	N	N	N	N	N	N	N	E	N	E	E

Only up to two component failures can occur at the same time, i.e. combinations of three or more component failures are not considered. This is because of a low probability of such events occurring, as for illustration purposes, components are assumed to have a probability of failure of 0.05, as further described in section 3.4. Note, these values are higher than they would normally be, but the actual values do not matter, i.e. it only matters that the ratio between the component failure rates are realistic. The combinations of one or two component failures are defined as the "considered failures" in this methodology. Note, the combinations of one component failure are defined as one component failed and all the other components working, and the combinations of two component failures are defined as two components failed and all the other components working. Note, it is assumed that when two components have failed, there is no time delay between the two occurrences, or the sensor readings are taken after the effects of both of the failures have stabilised, and no effects of time delay can be observed. No flow back propagation through valves is modelled, however, the fuel is present in the areas of the system that the fuel can access.

Different component failures will have different effects on the systems performance, with some failures producing more severe or critical effects than others. In some cases, this will stop the system performing as desired and therefore, cause system failure. System failure for this example system is defined to be when there is a reduction of fuel exiting the system through the drain. This occurs when at least one of the pumps cannot supply fuel to the system by failing off, or there being a restriction of flow through the system because of a blockage in the valve. This can be defined by a set of minimal cut sets, {P1}, {P2}, {V1}, {V2}, {V3} and {V4, V5}. Note when either valve V4 or valve V5 (but not both) is blocked, the normal amount of fuel will still pass through the drain, as all the fuel can pass through the opposite path to the blocked valve. Therefore, this does not cause system failure.

The sensor readings in Table 3.1 can be determined by considering the supply of fuel to the system from the pumps, and the paths that the fuel can and cannot take in order to pass through the drain valve. This will enable the flow of fuel through each of the sensors to be determined, hence producing the sensor readings given in the table. Each of the sensor readings can be calculated independently, they do not rely on information provided by other sensors to determine the sensor readings produced. Therefore, if additional sensors were introduced to the system, or some of the sensors were removed from the system, each of the sensors would still produce the same sensor readings as given in Table 3.1. However, if the pumps supplied fuel to the system at different rates, the sensor readings produced would be different to the five sensor readings given in the table and there would be more than five sensor readings produced if the pumps could output fuel at more than one rate.

The sensor readings can be produced automatically by using a BBN model of the system to represent the different component failures that can occur. This BBN model is presented in section 3.3 of this thesis, and it produces the same sensor readings as given in the table.

If case 1 from Table 3.1 is taken as an example, "pump P1 failed", there will be supply of fuel to the system from pump P2 only. Therefore, sensors S3, S4, S5 and S6 will measure the amount of fuel, "1". This will then pass through the two parallel lines equally, resulting in sensors S7, S8, S9 and S10 measuring "0.5", with sensor S11 measuring "1" as the supply of fuel combines. Sensors S1 and S2 both measure "N" because there will be no flow of fuel in the pipe. They will not measure "E", because despite there being no flow of fuel in the pipe, there will be fuel in the pipe, as there is no blockage stopping the fuel getting to these two sensors. In comparison, if case 9 is taken as a second example, "pump P1 failed" and "valve V1 failed", as valve V1 is blocked, there can be no supply of fuel to sensor S1, resulting in it measuring "E". All other sensor readings in case 9 are the same as for case 1.

Each of the combinations of sensor readings in Table 3.1 will be used in order to determine the best sensors for the purpose of fault detection and failure identification. During the fault diagnostic process, sensor readings which correspond to a component failure can be introduced to the diagnostic model, and therefore, if the model diagnoses the component failures that were introduced correctly, the fault diagnostic model can be verified.

3.1.1. Summary of assumptions

In this section a summary of all assumptions for this system is presented.

- Each component has one working state and one failed state. Pumps can supply a fixed quantity of fuel (represented by "1"), or supply no fuel, and for valves, they can either let all fuel pass through unrestricted (i.e. no resistance), or let no fuel pass through. There can be no supply of fuel other than "1" and "0", and there are no partial blockages of valves.
- The probability of each component being in the failed state is 0.05.
- Only up to two component failures can occur at the same time, i.e. combinations of three or more component failures are not considered.
- The volume flow rate of fuel remains constant throughout the system, i.e. the same quantity of fuel supplied to the system per time interval must also exit the system via

the drain per time interval. Therefore there is no resistance to the flow of fuel by any of the components (except for valve failures), connecting pipes, sensors, or the drain, i.e. the pipes and the drain cannot be blocked.

- When the line splits in two, (such as after valve V3), the fuel will split equally along all the clear lines, i.e. the lines that do not have blocked valves in them.
- All sensor readings are measured when the system is operating in the steady state, i.e. the flow of fuel has stabilised after the component failures.
- The sensors are perfectly reliable, they cannot fail, and they always measure the flow of fuel through them correctly.
- The sensors can distinguish between the line being empty, and therefore no flow of fuel, and there being fuel in the line, but no flow of fuel.
- System failure is when there is a reduction in fuel flow passing through the drain.

In the next section, the sensor selection process is proposed.

3.2. Performance metric methodology for sensor selection

The proposed sensor selection methodology aims to select the best combination of sensors to use on the system. The most suitable sensors are determined by using a performance metric. This performance metric considers three factors: the probability of failure occurrences that can be detected by the sensors, the ease of diagnosing the component failures, and the effects the component failures have on the system performance, i.e. how likely the detected failures are to cause the system to fail.

The three factors are chosen because it is desirable to be able to detect as many of the component failures as possible, it is desirable to be able to diagnose which component failure has occurred in each case as easily as possible, and it is more desirable to detect the component failures that are more likely to cause system failure than the ones that are not. There are other factors that could be considered in the performance metric, such as the reliability of the sensor, the weight of the sensor, the size of the sensor, and the cost of the sensor. However, for the work presented in this thesis, the sensors are assumed to be perfectly reliable, the sensors are all of the same type, and are therefore the same weight, size and cost. Therefore, the potential additional terms would have little benefit for the applications presented in this thesis. However, a penalty factor could be introduced to the performance metric if the methodology was to be applied to other systems that require multiple different types of sensors with different failure rates, weights, sizes, or costs.

For faults to be detected, a sensor reading that has deviated from what would be expected under normal operating conditions needs to be recorded. Note, in the process of detection, it does not matter what the deviated sensor reading is, it only matters that the sensor records a deviated sensor reading. The ability to distinguish between each deviated sensor reading, and isolate the component failure, is considered in the diagnostic term of the performance metric, section 3.2.2. The value of the performance metric is limited to a maximum value of 1 and a minimum value of 0, where the larger the performance metric the better the suitability of the sensor. The performance metric is limited to this range of values in order to have a reference point. In the following description of the methodology, sensor s can refer to an individual sensor or a group of sensors, i.e. the rules are general in terms of individual sensors and groups of sensors.

3.2.1. Detection term

As stated above, for a fault to be detected by a sensor, the sensor reading produced by the sensor must deviate from the sensor reading expected during normal system behaviour. It is worth noting that for a group of sensors, only one of the sensors is required to deviate from its normal sensor reading for the group of sensors to be able to detect the failure, i.e. it is not necessary for all the sensors to deviate from their normal sensor readings for the fault to be detected.

$$DE_{\{s\}} = \frac{P_d}{P_{md}} \tag{3.1}$$

The detection term is given in Equation (3.1). This term, $DE_{\{s\}}$, is equal to the ratio between the probability of occurrence of any of the detected failures, and the probability of occurrence of any of the considered failures in the system. The term P_d is expressed as the sum of probabilities of the considered failures' occurrence that sensor s can detect. The term P_{md} is expressed as the sum of probabilities of the considered failures' occurrence that can be detected by at least one sensor out of all the possible sensors on the system, i.e. the maximum that can be detected. It is worth noting that on some systems, not all combinations of component failures will be able to be detected by any of the sensors. These are called hidden failures, and this would result in P_{md} being less than the sum of probabilities of all the considered failures' occurrence.

$DE_{\{s\}}$ will be maximised to 1, when sensor s can detect all of the considered failures that are possible to detect. $DE_{\{s\}}$ would equal 1 if all of the sensors are positioned on the system, and it may equal 1 with fewer sensors. $DE_{\{s\}}$ will be minimised to 0, when sensor s cannot detect any of the failures that can occur on the system. In this case, the sensor would have no use in terms of detection and could therefore be dismissed.

3.2.2. Diagnostic term

The diagnostic term considers the probability of the failure being diagnosed correctly, using the information provided by sensor s.

$$DI_{\{s\}} = \frac{\sum_{i=1}^{nrs} P_{mli}}{\sum_{i=1}^{nrs} P_{sri}} \tag{3.2}$$

The diagnostic term, $DI_{\{s\}}$, is given in Equation (3.2). The term is the ratio between the sum of the probability of most likely failure occurrence and the sum of the probability for all the failure occurrence, across all the readings for sensor s. This term consists of two terms for each deviated sensor reading i that can be produced by sensor s. The first of these two terms is P_{sri}, which is defined as the probability that a deviated sensor reading i of sensor s occurs. For some of the combinations of deviated sensor readings, multiple different combinations of component failures can be their reason for occurrence. For each of these sensor readings, there will be a combination of component failures that will have the highest probability of occurrence, and therefore the most likely to have caused the deviated sensor reading. This is represented by P_{mli} and this term is therefore equal to the probability of the most likely combination of component failures that can cause the reading i of sensor s. In Equation (3.2), these terms are summed over the number of different deviated readings of sensor s, nrs. Note, in cases where only one combination of component failures can produce the sensor reading i, $P_{mli} = P_{sri}$. Also note, if there are n (more than 1) different combinations of component failures that produce sensor reading i, and have the same probability of occurrence, if the probability is the highest of all combinations of component failures that can produce sensor reading i, then it does not matter which combination of component failures is selected as the most likely failure. This is because each of the n combinations of component failures have equal probability of occurrence, and this will reduce the value of the diagnostic term, as P_{mli} will have a maximum value of P_{sri}/n, if there are no other combinations of component failures that produce sensor reading i. Therefore, this will make the diagnostic term lower, and hence sensor s less valuable than sensors which have a P_{mli}/P_{sri} closer to 1.

$DI_{\{s\}}$ is, therefore, the ratio between the sum of the probability of most likely failure occurrence and the sum of the probability for all the failure occurrence, across all the readings for sensor s. If there are multiple different deviated sensor reading combinations that can be produced by sensor s, then the diagnostic term will be equal to a weighted ratio of the probability of the most likely component failure occurrence for each sensor reading and the probability of all deviated sensor readings occurrence. This term is weighted with respect to the probability of each of the deviated sensor readings, with deviated sensor readings that have a higher probability of occurrence having a greater influence on the diagnostic term than those with a lower probability of occurrence. The weighting is needed so that the diagnostic term does not become unrepresentatively large when, for example, a sensor can produce two deviated sensor readings, a sensor reading that can be produced by only one combination of component failures, i.e. $P_{mli1} = P_{sri1}$, but with a low probability of occurrence, and a second sensor reading that can be produced by many different combinations of component failures, i.e. $P_{mli2} < P_{sri2}$ but with a significantly higher probability of occurrence i.e. $P_{sri1} + P_{sri2} \approx P_{sri2}$. Without the weighting, the first sensor reading would have a greater influence on the diagnostic term as it has a higher ratio, but with the weighting, the second sensor reading will have a greater influence on the diagnostic term, as it is significantly more likely to occur.

For this term to be maximised to 1, a different sensor reading would need to be produced for each component failure or combination of component failures detected by sensor s. This is unlikely to occur for most sensors, and would therefore usually result in a value of less than 1, as it is common for multiple different component failures to produce the same symptoms, as is also the case with this example system. This term will be close to 0, when there are many different component failure combinations that produce the same sensor reading and have the same probability of occurrence.

3.2.3. Criticality term

The criticality term considers the effect that each of the component failures have on the system's performance, and favours sensors which can detect a higher percentage of component failures that have severe effects on the system performance.

The criticality term is based on one of the importance measures discussed in Chapter 2. This importance measure is the Fussell-Vesely importance measure. It was selected over the other importance measures, such as Birnbaum's importance measure and the Criticality importance measure, because it could be adapted to consider sensors, and groups of sensors, relatively easily. In these calculations, the equivalent of a component being in a failed state in the context of sensors, was for the sensor to be producing a deviated sensor reading, and the equivalent of a component being in a working state, was for the sensor to be producing a non-deviated sensor reading. The Birnbaum's importance measure and the Criticality importance measure could not be easily adapted to consider sensors because of the first term of the importance measures, $Q_{sys}(q_i = 1)$. The term would need to be adapted to consider cases where one sensor's sensor reading has deviated, but another sensor's sensor reading has not. This is not a requirement for the Fussell-Vesely importance measure.

The Fussell-Vesely importance measure, given in Equation (2.7), considers the effect that individual components have on the system unreliability. The importance measure calculates the decrease in the system unreliability by making the component perfectly reliable. The importance measure takes the probability of system failure with component j working as normal away from the probability of system failure. It is then normalised by the probability of the system failure.

Note, this Fussell-Vesely importance measure can be applied to groups of components due to an equivalent form for minimal cut sets. In this case, the term representing the probability of system failure with component j working, is replaced by the probability of system failure with components j_a, j_b, j_c, etc. working.

In order for the term to be applied to sensors, the probability of system failure given that component j has not failed is replaced by the probability of system failure given that sensor s produces the non-deviated sensor reading. Note, for combinations of sensors, all sensors should produce the non-deviated sensor readings that would be expected under normal system operation behaviour.

$CR_{\{s\}}$, the criticality term, is given in Equation (3.3), where Q_{sys} is the probability of system failure with no additional knowledge of any of the component states, and $Q_{sys}(q_s = 0)$ is the probability of system failure given that the non-deviated reading of sensor s occurs.

$$CR_{\{s\}} = \frac{Q_{sys} - Q_{sys}(q_s = 0)}{Q_{sys}} \tag{3.3}$$

This term will be equal to its maximum value, 1, when sensor s can detect all of the critical component failures and it will be equal to its minimum value, 0, when sensor s cannot detect any of the critical component failures. Note, the ratio of the probability of failures that are critical to system performance, and the probability of all failures is not considered in this factor, thus this term can be close to its maximum or close to its minimum, regardless of the detection term. This is because the critical component failures are a subset of all of the component failures, and can therefore be a small (or large) proportion of the component failures. However, the detection term cannot be 1, without the criticality term also being 1, and the criticality term cannot be non-zero, if the detection term is equal to 0. This is because if all the component failures are detected, i.e. the detection term is equal to 1, then all the critical component failures must be detected too (as they are a subset of all the component failures), resulting in the criticality term being equal to 1, and if none of the component failures are detected, i.e. the detection term is 0, then none of the critical component failures can be detected (as they are a subset of all the component failures), hence the criticality term is equal to 0.

3.2.4. Discussion

Now that the three terms have been introduced, a performance metric that consists of the three factors needs to be determined. If each of the three terms are considered to be equally important, then the performance metric can be the average of the three terms. This is shown in Equation (3.4).

$$I_{\{s\}} = \frac{1}{3}\left(\frac{P_d}{P_{md}} + \frac{\sum_{i=1}^{nrs} P_{mli}}{\sum_{i=1}^{nrs} P_{sri}} + \frac{Q_{sys} - Q_{sys}(q_s = 0)}{Q_{sys}}\right) \tag{3.4}$$

However, this could be considered unrepresentative of how good the sensors are, if one of the terms is significantly higher or lower than the other two, making the average value to be unrepresentative of how good the sensor actually is. As an example, if a sensor s only detects one component failure, then the diagnostic term will be equal to 1, because if the sensor reading deviates, then this failure has definitely occurred. However, if the probability of this failure occurring is low, the other two terms in the performance metric will be significantly lower. The performance metric in this case may be significantly higher than the performance metric expected for such a sensor that detects a low percentage of component failures.

The same effect would occur if the probability of a critical failure was comparatively low, in comparison to the probability of a non-critical failure occurring. If the sensor detected all of the critical failures but none of the other failures, then this could again result in a performance metric that is significantly higher than is expected for a sensor that detects a low percentage of component failures.

In some situations, it may be desirable to favour a specific term, but it is reasonable to assume that a balance of the three terms will be desirable for most situations. Therefore, a potential solution is to use the performance metric suggested in Equation (3.4), to determine multiple combinations of sensors that can be considered as suitable groups of sensors, for example the top *X*% of sensor combinations, where *X* can be chosen based on the number of sensor combinations. These combinations could then be studied in more detail, looking at the individual terms of the metric, and selecting the best combination of sensors for a specific application. For example, the detection term could be favoured for low safety-risk systems, such as a car engine, where the car could pull over safely on the side of the road. The diagnostic term could be favoured for systems where system down-time is expensive, requiring the repair work to be completed as quickly as possible, such as a train engine, where the train would block the rail line, delaying other services. The criticality term could be favoured for safety critical systems, where it is dangerous not to detect the critical component failures, and therefore cannot react as quickly as required, such as an aircraft engine, where emergency rerouting may need to be applied immediately. This could be achieved by looking for the best sensor combination with all three terms above a certain threshold, or with one term as high as possible, or any other way that might be desired for a specific system. The proposed sensor selection methodology allows for such conditions to be satisfied, and the system analyst will have the ability to do this when designing the system.

In the following section, the methodology for system modelling and fault diagnostics is introduced. This is presented because the selected sensors are included in the system model in order to verify that they can be used for fault detection and failure diagnosis, i.e. before they would be applied to a real system.

3.3. Fault Diagnostic methodology and the BBN model

The construction process of the fault diagnostic model and how the model can be used to diagnose component failures is introduced in this section. BBNs are used as a fault diagnostic technique because of the ability to introduce evidence to the nodes within the network. BBNs are constructed using a number of nodes, each with a number of discrete states. The probability of each of the states is obtained from a conditional probability table, CPT. The relationship between nodes can be controlled using CPTs. The states of one node, known as a parent node, will affect the states of another node, known as a child node, that it is connected to. Note, it is common to have multiple parent nodes for each child node, and each node can be a parent node to multiple child nodes. This evidence will update the probability of each state for each of the connected nodes. Therefore, sensor readings can be introduced to the nodes representing sensors in the network as evidence, and the connected nodes representing component state probabilities will be updated, enabling prediction of which components have/have not failed.

The BBNs in this work, are constructed using the software, "HUGIN Researcher". The software is intuitive to use with a simple, drag-and-drop method of positioning the nodes. The nodes can be connected using arcs added in the same way, and the CPTs can be completed by selecting the nodes and entering the values into the tables. When the network is complete, it can be "compiled", and this instructs the network to calculate the probabilities of each of the states for the nodes, based on the information provided in the CPTs.

1. The BBN models of the system should be constructed by creating a node for each of the components that appear in the system. Each of these nodes will have a number of states, a state for each of the possible states that the component can be in. The values in the CPTs for these nodes should be the probability that each of the components is in the corresponding state. This will introduce the reliabilities of the components in the network. For the example system introduced in this chapter, there are seven nodes present, one node for each component. Each of these nodes has two states, a "working" state and a "failed" state. The probability of each of the component states is taken from the probability of each of the components being in the failed state presented in section 3.1.

2. The next step is to introduce any intermediate nodes required to the network. The intermediate nodes can be used to consider a group of components in the same section of the system. They could be used to determine the supply of fuel from a particular subsection of the system, or whether there is a clear path for the fuel to pass through a subsection of the system. The CPTs for these intermediate nodes will consider the states of the connected parent nodes, i.e. components' nodes, and output the desired information, i.e. flow through a subsection of the system. Note, if the system is

particularly large, multiple levels of intermediate nodes can be introduced, with some intermediate nodes as the child nodes of the component nodes, and then additional nodes as the child node of the intermediate nodes.

3. The final step in the construction process of the network is to introduce a node for each of the sensors that can be positioned on the system. These are the child nodes of the intermediate nodes and are connected to them using their CPTs accordingly. Each sensor node should have a state for each of the sensor readings that can be produced by the sensor. For systems that can produce many different sensor readings, sensor readings can be grouped for the number of states in the node to be kept to a reasonable number, if desired. For example, if there are one hundred different flow rates that can be recorded by the sensor, between 1 and 100 units per time interval, then this could be grouped in to ranges of 1-10 units per time interval, 11-20 units per time interval, etc. Therefore, rather than having 100 potential sensor readings, and therefore 100 states for the sensor node, there are only 10 ranges of sensor readings, and only 10 states.

Intermediate nodes are not required to be included in the network, and could therefore be omitted if desired. However, if there are no intermediate nodes included in the network, the sensor nodes would have to consider more combinations of component states than if the intermediate nodes were included. The number of entries in the CPTs is equal to the product of the number of states for each of the parent nodes to the child node, multiplied by the number of states in the child node. Therefore, the more parent nodes there are, and the more states they have, the larger the CPTs for the child (sensor) nodes are. Let’s consider another simple example system in order to demonstrate the positive effect of introducing intermediate nodes to a network.

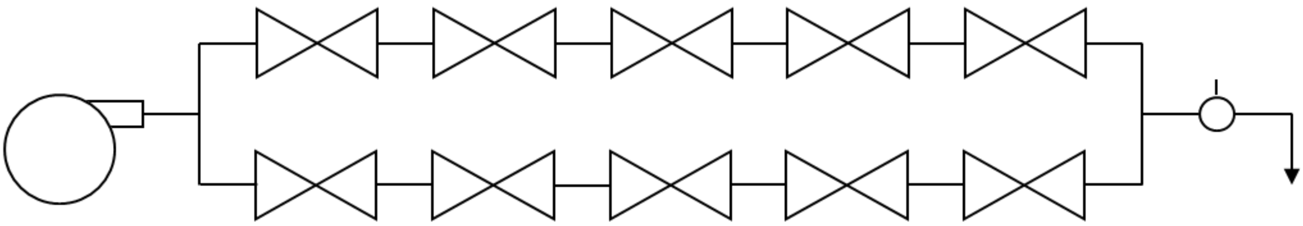


Figure 3.2 Example system

The system shown in Figure 3.2, consists of one pump, which supplies fuel to a drain via two parallel pipes, each of which have five valves positioned in series, with a sensor positioned immediately before the drain. If each of the components have two possible states, working and failed, then if there are no intermediate nodes included in the network, i.e. the eleven component nodes connected to one sensor node, the number of elements in the CPT for the sensor would be equal to 4096 $\left(= \left(2^{11}\right) \times 2\right)$. Note, the ($\times$ 2) factor is to account for the sensor having two states: flow, or no flow. In addition to this, there would be 22 $(= 11 \times 2)$ elements in the CPTs of the component nodes, as each of the eleven components has an element for the probability that it is in the working state, and an element for the probability that it is in the failed state. However, if two intermediate nodes are introduced to the network, one for each of the parallel paths in the network, each considering the five valves on the corresponding path, then this can be reduced to 144 ($= \left(2^5 + 2^5 + 2^3 \right) \times 2$), $\left(2^5\right)$ for the two intermediate nodes, and $\left(2^3\right)$ for the sensor node, plus the 22 $(= 11 \times 2)$ for each of the component nodes, which is a significant reduction. The sensor node in this case would have three parents, the pump node, and the two intermediate nodes, each of which has two states, hence the (2^3) elements per possible sensor state. Note, the ($\times$ 2) factor in each case is to account for there being two states for each of the intermediate nodes, and the sensor node.

Whilst there is clearly a benefit to introducing intermediate nodes to the network, in some cases they may not be necessary, as the additional work and the increase in number of nodes in the network may outweigh the benefit of reducing the number of elements in the CPTs. It may be beneficial to have fewer nodes in the network, with larger CPTs, rather than more nodes, with slightly smaller CPTs. Therefore, the number of intermediate nodes introduced to the network should be balanced with the number of elements in the CPTs, so that a good compromise is achieved.

When the BBN of the system has been constructed, the network should be “compiled” and it can then be used to diagnose component failures that occur on the system. To do this, sensor readings, in the form of evidence, need to be introduced to the network. When a sensor reading is recorded on a real system, this can be inputted into the BBN by selecting that state for the sensor to be in. The BBN will then use this information to update the probabilities of each component being in the different states. The component, with the highest probability of being in the failed state is identified, and can be inspected, and repaired or replaced as appropriate. Note, “inspected” refers to manually investigating whether the component is functioning, and “repaired or replaced” refers to returning the component to full functionality, i.e. so it operates as it would do normally. The exact failures might not be identified with 100% certainty as multiple failures may produce the same symptoms. However, evidence that the inspected component is in its working state, if that is the case, could also be introduced to the BBN. The BBN software will then automatically update the probability of the state of each of the components, and can, therefore suggest the next component, or components, to inspect. This will be the component, or group of components, with the highest probability of being in the failed state. This can be repeated until the failed component is found, which can then be repaired or replaced, and the system can return to normal operating behaviour.

In the next section of this chapter, the proposed methodology will be applied to the example system introduced at the start of this chapter in section 3.1.

3.4. Application of the proposed methodology

For the application of the methodology, the reliability of the components needs to be known. Such values are needed for calculating the performance metric and to determine the most likely cause of the symptoms during the fault diagnostic process. For this system, it is assumed that all the components are equally reliable, for example, the probability of component failure, A, is equal to 0.05, i.e. $P(A) = 0.05$. The probability that only one component is failed, (and all of the other components are working) and the probability that only two components are failed, (and all of the other components are working), are equal to $P(A)\cdot(1 - P(A))^6$ and $P(A)^2\cdot(1 - P(A))^5$ respectively. These values are the probabilities of the events, defined in Table 3.1.

3.4.1. Sensor selection

The methodology starts with calculations of the best value of the performance metric. It is possible to calculate the best achievable performance metric. Assuming that there are no restrictions applied for the number of sensors positioned on the system, the maximum performance metric value will be achieved when all of the possible sensors are included in the system. Therefore, the best performance metric value obtained by considering all 11 sensors on the system, and applying Equation (3.4), is equal to 0.8961. The three terms: the detection term, the diagnostic term and the criticality term are equal to, 1, 0.6883, and 1, respectively.

The values of these terms indicate that all of the failures that have been considered on the system can be detected, as $DE_{\{s\}} = 1$, and as all component failures can be detected, then all of the critical component failures will also be detected, therefore, $CR_{\{s\}} = 1$. As the diagnostic term is less than 1, this means that it will not be possible to diagnose every component failure exactly, and for some component failures it may take a number of inspections to find the failure. Note, inspecting the component means manually determining the state of the component by an engineer.

3.4.1.1. Results of the sensor selection

The performance metric was calculated for all combinations of up to three sensors in this section. The performance metric and its terms are given in Tables 3.2, 3.3 and 3.4 for combinations of one, two and three sensors, respectively. The sensors are ranked according to the value of the performance metric. For the combinations of two and three, only one sensor combination for each rank are given in the table, with the full ranking given in Appendix A. There are multiple sensors, or multiple combinations of sensors, with the same performance metric. This is because of the symmetry in the system, i.e. there are two parallel lines that have the same components and sensors on them in all but the central section of the system. Therefore, any failure detected by one sensor, will have an equivalent failure which can be detected by the equivalent sensor on the opposite line of the system. For example, if cases 1 and 2 from Table 3.1 are studied, it can be seen that sensor S1 detects the failure of pump P1, and sensor S3 detects the failure of pump P2, the corresponding pump and sensor on the opposite parallel line. However, it is possible that a different value of the performance metric is produced, if, for example, two components in the parallel lines have different failure probabilities due to their age or usage.

Table 3.2 Ranking of individual sensors

Rank	Sensor	$I_{\{s\}}$	$DE_{\{s\}}$	$DI_{\{s\}}$	$CR_{\{s\}}$
1	S7	0.8062	0.9740	0.5067	0.9512
	S8	0.8062	0.9740	0.5067	0.9512
	S9	0.8062	0.9740	0.5067	0.9512
	S10	0.8062	0.9740	0.5067	0.9512
2	S5	0.6688	0.7532	0.3362	1.0000
	S6	0.6688	0.7532	0.3362	1.0000
3	S11	0.6667	0.7532	0.3276	1.0000
4	S1	0.3901	0.4740	0.2740	0.5665
	S2	0.3901	0.4740	0.2740	0.5665
	S3	0.3901	0.4740	0.2740	0.5665
	S4	0.3901	0.4740	0.2740	0.5665

Table 3.3 Ranking of combinations of two sensors

Rank	Sensor	$I_{\{s\}}$	$DE_{\{s\}}$	$DI_{\{s\}}$	$CR_{\{s\}}$
1	S1 S7	0.8684	0.9870	0.6513	0.9754
2	S2 S7	0.8663	0.9870	0.6447	0.9754
3	S5 S7	0.8398	1.0000	0.5195	1.0000
4	S7 S9	0.8377	1.0000	0.5130	1.0000
5	S8 S10	0.8355	1.0000	0.5065	1.0000
6	S7 S8	0.8084	0.9740	0.5133	0.9512
7	S1 S3	0.7186	0.7532	0.5345	1.0000
8	S1 S11	0.7121	0.7532	0.5086	1.0000
9	S2 S4	0.7100	0.7532	0.5000	1.0000
10	S5 S6	0.6710	0.7532	0.3448	1.0000
11	S5 S11	0.6688	0.7532	0.3362	1.0000
12	S1 S2	0.3944	0.4740	0.3014	0.5665

Table 3.4 Ranking of combinations of three sensors

Rank	Sensor	$I_{\{s\}}$	$DE_{\{s\}}$	$DI_{\{s\}}$	$CR_{\{s\}}$
1	S1 S3 S7	0.8939	1.0000	0.6818	1.0000
2	S1 S3 S8	0.8918	1.0000	0.6753	1.0000
3	S1 S4 S7	0.8896	1.0000	0.6688	1.0000
4	S1 S4 S8	0.8874	1.0000	0.6623	1.0000
5	S1 S8 S10	0.8853	1.0000	0.6558	1.0000
6	S2 S4 S8	0.8831	1.0000	0.6494	1.0000
7	S1 S2 S7	0.8706	0.9870	0.6579	0.9754
8	S2 S7 S8	0.8684	0.9870	0.6513	0.9754
9	S1 S7 S8	0.8555	0.9870	0.6119	0.9754
10	S5 S6 S7	0.8398	1.0000	0.5195	1.0000
11	S5 S8 S10	0.8377	1.0000	0.5130	1.0000
12	S8 S10 S11	0.8355	1.0000	0.5065	1.0000
13	S2 S5 S6	0.7276	0.7532	0.5704	1.0000
14	S1 S2 S3	0.7208	0.7532	0.5431	1.0000
15	S1 S3 S11	0.7186	0.7532	0.5345	1.0000
16	S1 S2 S6	0.7165	0.7532	0.5259	1.0000
17	S1 S2 S4	0.7143	0.7532	0.5172	1.0000
18	S2 S4 S6	0.7121	0.7532	0.5086	1.0000
19	S2 S4 S5	0.7100	0.7532	0.5000	1.0000
20	S5 S6 S11	0.6710	0.7532	0.3448	1.0000

As discussed above, the best possible performance metric can be achieved by including all of the sensors on the system. However, in this example, this value of the performance metric can be achieved by some combinations of four sensors, therefore, it is unnecessary to consider combinations of five or more sensors, as there would be no further benefit to the process of failure diagnostics and fault detection. However, due to the large number of combinations of four sensors, the performance metric was not calculated for all combinations, and therefore the ranking of these combinations is not given. However, the combinations of four sensors that have the maximum performance metric are:

- S1 S2 S3 S7
- S1 S2 S3 S9
- S1 S3 S4 S7
- S1 S3 S4 S9

If the values of the performance metric and the terms of the performance metric for the combinations of three sensors ranked first are compared with the values of the terms for the maximum achievable performance metric, it can be seen that the benefit of introducing the fourth sensor is comparatively small, with an improvement of only 0.0065 made in the diagnostic term, and an improvement of 0.0022 made in the performance metric. This improvement is an order of magnitude smaller than the improvement between the combinations of two sensors ranked first, and the combinations of three sensors ranked first, 0.0305 for the diagnostic term and 0.0255 for the performance metric. Therefore, as the addition of a fourth sensor results in a comparatively small improvement in performance metric, but the additional calculation time to obtain the performance metric for all combinations of four sensors is significant, they were not considered in the rest of the application of the methodology, i.e. 3 sensors are considered. If the process was automated, the calculation of the performance metric for all combinations of four sensors would be feasible to complete as the performance metrics would be calculated quickly.

3.4.1.2. Discussion

If the individual terms in the performance metric are studied, it suggests that considering the individual terms, as opposed to just the performance metric, is beneficial, as previously suggested. As an example, in Table 3.2, the sensors ranked first, sensors S7, S8, S9 and S10, have a criticality term of 0.9512, but the sensors ranked second and third, sensors S5 and S6, and sensor S11, have a higher criticality term of 1. Therefore, this enables the analyst to select one of the sensors ranked second if it is possible to only use a single sensor on the system, and it is imperative to be able to detect as many as possible of the component failures that are critical to system performance.

Similar conclusions can be made when the values in Table 3.3, the table for combinations of two sensors, are studied. The combinations of sensors ranked third have detection and criticality terms of 1, where the combinations of sensors ranked higher than this have lower detection and criticality terms. The diagnostic term for the combination of sensors ranked third is significantly lower than the combination of sensors ranked second, hence the lower performance metric, resulting in the lower ranking. As before, the system design constraints may require as many as possible of the component failures to be detected, at the expense of the ability to diagnose them, and, therefore, the analyst will most likely select one of the combinations of sensors ranked third.

By comparing the values of the performance metric terms in Tables 3.2 and 3.3, it can be concluded that there is generally a smaller benefit by introducing a second sensor in close proximity to the first selected sensor, than there is by introducing a second sensor not in close proximity to the first sensor. For example, the performance metric for sensor S7 is 0.8062, but the performance metric for sensors (S7 S8) is 0.8084, which gives a small improvement of 0.0022. In this case, only one term in the performance metric improves, the diagnostic term, with the other two terms staying the same. These two sensors are positioned either side of the same valve, V4. However, when any other sensor from another section of the system is chosen, the increase in performance metric is an order of magnitude greater, with the next lowest performance metric for a combination of two sensors which includes sensor S7, given by (S7 S9), with a performance metric of 0.8377, which gives an improvement of 0.0315. Note, (S7 S10) and (S7 S11) have the same performance metric. However, including a sensor that is a greater distance away from sensor S7 than sensor S9, such as sensor S1 or S3, with multiple components between the two selected sensors, results in an even greater improvement of the performance metric of 0.0622 to 0.8684. Therefore, this suggests that generally sensors should not be selected which are in close proximity to each other, as it is likely that the sensors that are in close proximity will provide similar information on what is happening in the system. This could be useful if there are restrictions on the number of sensors and only a small selection is possible. There will, of course, be exceptions to this rule, but if there is limited time available to determine the best sensor combinations, and an exhaustive approach is not possible, then this rule could be used as a guide in order to try and determine the best combination as quickly as possible.

It can be seen that the performance metric increases as the amount of sensors increases. This is expected, because it should not be possible for a combination of *n* sensors to detect and diagnose failures better than the same combination of *n*+1 sensors. However, there is a diminishing return for each additional sensor considered, with the difference, for example, between the maximum performance metric for the combinations of three and four sensors being less than the difference between the maximum performance metric for the combinations of two and three sensors. The same is true for the difference in the value of the performance metric for combinations of two and three sensors, and combinations of one and two sensors. This is expected, and therefore it demonstrates the motivation to find the correct balance between the performance metric and the cost of adding additional sensors to the system.

The selection of sensors to be used for system monitoring and fault diagnostics later in this chapter was chosen to be the combination of sensors, (S1 S3 S7). This combination of sensors has the highest performance metric for any combination of three sensors, as shown in Table 3.4. The locations of these sensors are such that there is one sensor positioned next to each of the pumps, before the valve on the same line of the system, and a sensor positioned before a valve in the third section on the system. Note, as discussed above, the third sensor in the group could be positioned on either of the parallel lines, as the system symmetry will mean that they are equally beneficial to the detection of faults and diagnosis of failures. This is reflected in Appendix A, Table A.2, by the fact that sensors (S1 S3 S7) and (S1 S3 S9) have the same performance metric. Using these three sensors on the system enables the flow throughout the whole system to be determined. This is because the sensors next to each of the pumps, sensors S1 and S3, inform the analyst what fuel is being supplied to the system, and the sensor in the final section of the system, sensor S7 or S9, informs the analyst which valve the fuel is passing through, if at all, in the third section of the system. Therefore, if there is a deviation in the operating behaviour of the system, this combination of sensors will be able to detect it.

In the next section, the effect of changing the component failure rates on the sensor selection rates is presented.

3.4.1.3. The effect of changing the component failure probabilities on the sensor selection

In order to determine the effect that changing the probability of the component failures has on the selection of sensors, different component failure probabilities were assigned to each of the components and the performance metrics calculated accordingly. The pumps are assumed to have a probability of failure of 0.1, and the valves are assumed to have a probability of failure of 0.01, i.e. pump failures are significantly more likely to occur. Note, these probabilities are only used in this subsection of the thesis, with the probability of component failures given in section 3.1 used in the rest of the chapter. Only one combination of component failure probabilities is considered as it is not possible to exhaustively consider all component failure probabilities.

The resultant performance metrics are given in Tables 3.5, 3.6, and 3.7 for the combinations of one, two, and three sensors, respectively. As before, only one combination of sensors for each rank is given in Tables 3.6 and 3.7, with all of the combinations given in Appendix A in Tables A.3 and A.4, respectively.

By comparing the ranking of the individual sensors in Table 3.2 and Table 3.5, it can be observed that they are very similar. The only difference is that in Table 3.2, sensors S5 and S6 have the same performance metric and hence ranking, but in Table 3.5 they have slightly different performance metrics, resulting in a different ranking. This is because the pumps and valve failures have different failure probabilities in this example, so the component with the highest probability of being in the failed state is different for these two sensors, which is not the case with the normal failure probabilities. Nonetheless, the general ranking is broadly similar. It is also worth noting that the terms in each of the performance metrics are generally similar. There are however, exceptions to this, e.g. the diagnostic term for sensors S1 – S4 are 0.2740 in Table 3.2 and 0.8104 in Table 3.5, significantly higher. If the first deviated sensor reading for sensor S1 in Table 3.1 is considered, the sensor reading “N”, the probability of the failure of pump P1 is at least an order of magnitude greater than all of the other component failures that produce the same deviated sensor reading. Therefore, if this symptom is observed, it is significantly more likely to be this component failure that has occurred than any of the other component failures, resulting in the higher diagnostic term. The same is the case with the other deviated sensor reading of sensor S1, “E”. The probability of failure of both of the pumps P1 and P2, is an order of magnitude greater than the probability of failure of the other two combinations of component failures that can produce the same symptoms, i.e. pump P1 and valve V1, or pump P1 and valve V2.

The ranking of combinations of two and three sensors is broadly similar to that given in Tables 3.3 and 3.4, respectively. There are obviously some exceptions as sensor combinations that don’t detect as many component failures, but detect the component failures that are more likely to occur, have a higher performance metric and are therefore ranked higher. An example of this is the combination of sensors (S1 S3), which was ranked 7th in Table 3.4, but is ranked

3rd in Table 3.6. In this case, the detection term of the performance metric increases from 0.7532 to 0.9321. The opposite of this also happens with sensors ranking lower than before when they do not detect the component failures that are most likely to occur. For example, the sensors (S2 S7 S8) were ranked 8th in Table 3.4 but are ranked 14th in Table 3.7. The effect of the component failures having different probabilities of occurrence has also resulted in a larger number of rankings, as it resulted in combinations that detected the same number of component failures having different diagnostic terms, as discussed briefly above. For example, the combinations of sensors ranked 3rd and 7th in Table 3.7 are all ranked 3rd in Table 3.4. This has resulted in 28 different rankings in Table 3.7, as opposed to the 20 in Table 3.4.

Another observation is that the maximum achievable performance metric for each amount of sensors has increased, going from 0.8062 to 0.8212 for individual sensors, from 0.8684 to 0.9641 for combinations of two sensors, and from 0.8939 to 0.9738 for combinations of three sensors. This increase is because of the increase in the diagnostic term. This is predominantly because of the difference in probability of failure for the pumps P1 and P2, and the valves V1 and V2. If the cases numbered 1 and 3 (or 2 and 4) in Table 3.1 are considered for the best combination of three sensors, (S1 S3 S7), this sensor reading combination is the most likely to occur because the probability of pump failure is an order of magnitude greater than any other failure, and therefore this term will have the most effect on the diagnostic term in the performance metric. Note, this deviated sensor reading, along with the deviated sensor reading for cases numbered 2 and 4, was also one of the most likely to occur using the original probabilities of failure. However, the ratio with the new probabilities is 10:1 that if the sensor reading is produced, the pump will have failed and not the valve, whereas before it was 1:1. This makes the P_{mli} term significantly higher in comparison to P_{sri}, resulting in the higher diagnostic term, and the higher performance metric.

The work in this subsection suggests that the selection of the sensor combinations is not affected too highly by the components having a different failure probability, as the best combination of sensors in both cases is the same. It is not possible to definitely say that the combination of sensors (S1 S3 S7) is the best combination of three sensors for all probabilities of component failures without calculating the performance metric for a number of different probabilities of component failures. However, as this combination of sensors produces the highest number of deviated sensor reading combinations, it is likely that if it is not the best, it will still be one of the best combinations of sensors. It is also unlikely that the components' probability of failure would change drastically in comparison to the probability of other components failing during the operation of the system, as there would be regularly scheduled maintenance or part replacement for aircraft systems in order to satisfy safety criteria, i.e. it is not expected that one component degrades significantly faster or slower than other components in the system.

Table 3.5 Ranking of individual sensors with different component failure rates

Rank	Sensor	$I_{\{s\}}$	$DE_{\{s\}}$	$DI_{\{s\}}$	$CR_{\{s\}}$
1	S7	0.8212	0.9918	0.4872	0.9886
	S8	0.8212	0.9918	0.4872	0.9886
	S9	0.8212	0.9918	0.4872	0.9886
	S10	0.8212	0.9918	0.4872	0.9886
2	S5	0.7938	0.9321	0.4820	1.0000
3	S6	0.7825	0.9321	0.4459	1.0000
4	S11	0.7824	0.9321	0.4455	1.0000
5	S1	0.4723	0.5124	0.8104	0.4895
	S2	0.4723	0.5124	0.8104	0.4895
	S3	0.4723	0.5124	0.8104	0.4895
	S4	0.4723	0.5124	0.8104	0.4895

Table 3.6 Ranking of combinations of two sensors with different component failure rates

Rank	Sensor	$I_{\{s\}}$	$DE_{\{s\}}$	$DI_{\{s\}}$	$CR_{\{s\}}$
1	S1 S7	0.9641	0.9959	0.9059	0.9944
2	S2 S7	0.9629	0.9959	0.9022	0.9943
3	S1 S3	0.9234	0.9321	0.8991	1.0000
4	S1 S5	0.9208	0.9321	0.8910	1.0000
5	S1 S6	0.9197	0.9321	0.8873	1.0000
6	S1 S11	0.9196	0.9321	0.8870	1.0000
7	S2 S6	0.9184	0.9321	0.8833	1.0000
8	S2 S5	0.9183	0.9321	0.8829	1.0000
9	S5 S7	0.8417	1.0000	0.5251	1.0000
10	S5 S8	0.8416	1.0000	0.5247	1.0000
11	S6 S7	0.8304	1.0000	0.4911	1.0000
12	S8 S10	0.8302	1.0000	0.4907	1.0000
13	S7 S8	0.8227	0.9918	0.4917	0.9886
14	S5 S6	0.7939	0.9321	0.4823	1.0000
15	S5 S11	0.7938	0.9321	0.4820	1.0000
16	S6 S11	0.7825	0.9321	0.4459	1.0000
17	S1 S2	0.4749	0.5124	0.8252	0.4895

Table 3.7 Ranking of combinations of three sensors with different component failure rates

Rank	Sensor	$I_{\{s\}}$	$DE_{\{s\}}$	$DI_{\{s\}}$	$CR_{\{s\}}$
1	S1 S3 S7	0.9738	1.0000	0.9214	1.0000
2	S1 S3 S8	0.9737	1.0000	0.9211	1.0000
3	S1 S5 S7	0.9713	1.0000	0.9139	1.0000
4	S1 S5 S8	0.9712	1.0000	0.9135	1.0000
5	S1 S6 S7	0.9700	1.0000	0.9101	1.0000
6	S1 S8 S10	0.9699	1.0000	0.9097	1.0000
7	S1 S4 S7	0.9692	1.0000	0.9076	1.0000
8	S1 S4 S8	0.9691	1.0000	0.9072	1.0000
9	S2 S4 S7	0.9688	1.0000	0.9063	1.0000
10	S2 S4 S8	0.9687	1.0000	0.9060	1.0000
11	S1 S2 S7	0.9654	0.9959	0.9097	0.9943
12	S1 S2 S8	0.9654	0.9959	0.9097	0.9943
13	S1 S7 S8	0.9642	0.9959	0.9063	0.9943
14	S2 S7 S8	0.9630	0.9959	0.9025	0.9943
15	S2 S4 S6	0.9358	0.9321	0.9391	1.0000
16	S1 S2 S3	0.9236	0.9321	0.8999	1.0000
17	S1 S3 S5	0.9235	0.9321	0.8995	1.0000
18	S1 S3 S11	0.9234	0.9321	0.8991	1.0000
19	S1 S2 S6	0.9210	0.9321	0.8914	1.0000
20	S1 S2 S4	0.9208	0.9321	0.8910	1.0000
21	S1 S6 S11	0.9197	0.9321	0.8873	1.0000
22	S2 S5 S6	0.9184	0.9321	0.8833	1.0000
23	S2 S4 S5	0.9183	0.9321	0.8829	1.0000
24	S5 S6 S7	0.8417	1.0000	0.5251	1.0000
25	S5 S8 S10	0.8416	1.0000	0.5247	1.0000
26	S6 S7 S8	0.8344	1.0000	0.5033	1.0000
27	S8 S10 S11	0.8343	1.0000	0.5030	1.0000
28	S5 S6 S11	0.8048	0.9321	0.5175	1.0000

In the next section, the construction of the BBN fault diagnostics model will be discussed. In the remainder of this chapter, the probability of each of the component failures is assumed to be 0.05.

3.4.2. Construction of the Fault Diagnostics Model

As discussed before, the fault diagnostics model is a BBN model of the system. The model was created using the software "HUGIN Researcher", and it includes intermediate nodes, in order to minimise the number of elements in the CPTs.

3.4.2.1. BBN development

Following the methodology outlined in section 3.3, a node for each of the components was introduced (the top of Figure 3.3). The CPTs for each of these nodes consist of one column with two rows, one element for each of the states that the component can be in. Therefore, for the working state, the element of the CPT is 0.95, and for the failed state, the element of the CPT is 0.05, which is the probability of each component failure as stated in section 3.1.

The next step in the BBN development process is to introduce intermediate nodes to the network. These nodes are to determine the flow of fuel at various points in the system. These points are: the supply of fuel that will pass through Valve V1 from Pump P1 (Supply 1 node in Figure 3.3), the supply of fuel that will pass through Valve V2 from Pump P2 (Supply 2 node in Figure 3.3), the supply of fuel coming from both Valve V1 and V2 (Supply node in Figure 3.3), and finally, whether there is a clear path for the fuel to pass through the final section of the system before it reaches the drain, i.e. whether the fuel pass through Valve V4 and/or Valve V5, (Section 3 node in Figure 3.3).

Finally, a node for each of the possible 11 sensors in the system can be introduced to the BBN. These nodes are connected to the intermediate nodes and component nodes, as required. Using the states from these nodes, the CPTs for the sensor nodes can be completed and the sensor reading states can be added to the sensor nodes, where each row in the CPTs corresponds to a sensor reading that can be produced by the corresponding sensor.

The benefits of introducing the intermediate nodes, discussed earlier, becomes evident in this BBN. For example, for sensors from S5 to S11, the only information required from the first section of the system is whether there is a supply of fuel, and how much is being supplied, if any. Therefore, if there is only supply from one of the pumps, it is not necessary to know whether the fuel is supplied from pump P1 or pump P2, as it would produce the same symptoms for these sensors in both situations. Therefore, not keeping this information results in a smaller CPT for each of these sensors, as without this node in the BBN there would be 16 combinations of states for the four nodes in this section, but with this node, the number of combinations of states can be reduced to 3. These 3 states are: Full Supply (FS, "2"), Partial Supply (PS, "1") and No Supply (NS). This process results in the CPTs for each of these sensor nodes to have less than a quarter of the elements that they would have without it. Table 3.8 demonstrates how these 16 combinations can be reduced to 3 states shown in the last column, and Table 3.9 gives the resultant CPT for sensor S11. In this CPT, the section 3 node represents what paths are available through the third section of the system as introduced in section 3.1, and the supply node represents the supply of fuel that is coming out of the first section of the system. The CPTs for the Supply 1, Supply and Section 3 nodes are given in Tables 3.10, 3.11 and 3.12 respectively. Note, the CPT for the Supply 2 node is the same as that for the Supply 1 node except the parents of the node are pump P2 and valve V2, instead of pump P1 and Valve V1.

Table 3.8 Reduction of states by introducing an intermediate node for the first section of the system

Component States				Intermediate
Pump P1	Pump P2	Valve V1	Valve V2	Node States
On	On	Open	Open	Full Supply
On	On	Open	Closed	Partial Supply
On	On	Closed	Open	
On	Off	Open	Open	
On	Off	Open	Closed	
Off	On	Open	Open	
Off	On	Closed	Open	
On	On	Closed	Closed	No Supply
On	Off	Closed	Open	
On	Off	Closed	Closed	
Off	On	Open	Closed	
Off	On	Closed	Closed	
Off	Of	Open	Open	
Off	Off	Open	Closed	
Off	Off	Closed	Open	
Off	Off	Closed	Closed	

Table 3.9 CPT for sensor S11

Section 3	V4 open, V5 open						V4 open, V5 blocked					
Valve 3	Open			Blocked			Open			Blocked		
Supply	FS	NS	PS	FS	NS	PS	FS	NS	PS	FS	NS	PS
E	0	1	0	1	1	1	0	1	0	1	1	1
1	0	0	1	0	0	0	0	0	1	0	0	0
2	1	0	0	0	0	0	1	0	0	0	0	0
Section 3	V4 blocked, V5 open						V4 blocked, V5 blocked					
Valve 3	Open			Blocked			Open			Blocked		
Supply	FS	NS	PS	FS	NS	PS	FS	NS	PS	FS	NS	PS
E	0	1	0	1	1	1	1	1	1	1	1	1
1	0	0	1	0	0	0	0	0	0	0	0	0
2	1	0	0	0	0	0	0	0	0	0	0	0

Table 3.10 CPT for Supply 1 node

Pump P1	On		Off	
Valve V1	Open	Closed	Open	Closed
Supply	1	0	0	0
No Supply	0	1	1	1

Table 3.11 CPT for the Supply node

Supply 1	Supply		No Supply	
Supply 2	Supply	No Supply	Supply	No Supply
Full Supply	1	0	0	0
Partial Supply	0	1	1	0
No Supply	0	0	0	1

Table 3.12 CPT for the Section 3 node

Valve 4	Open		Closed	
Valve 5	Open	Closed	Open	Closed
V4 open, V5 open	1	0	0	0
V4 open, V5 blocked	0	1	0	0
V4 blocked, V5 open	0	0	1	0
V4 blocked, V5 blocked	0	0	0	1

Note, for sensors S1 – S6 and sensor S11, the number of elements in the CPTs could have been reduced even further, by introducing an alternative node for Section 3, containing two states: there is a path through the section or there is no path through the section. In this process, the state which describes whether there is a path through the section would incorporate the three states of, "V4 open, V5 open", "V4 open, V5 blocked" and "V4 blocked, V5 open" states and the state which describes there is not a path through the section incorporates the "V4 blocked and V5 blocked" state. This is possible because it is not necessary for these sensors to know the path(s) that the fuel is passing through, only whether there is a flow of fuel or not. However, this step was not implemented because it has a smaller reduction in the number of elements in the CPTs than the other intermediate nodes. If this network was to be constructed again, this step would possibly be implemented as the reduction in the size of the CPTs provided is greater than the additional CPT required to include it. Full CPTs for the sensor nodes S1 – S10 are given in Appendix B, Tables B.1 – B.10 for reference.

The complete structure of the BBN is given in Figure 3.3.

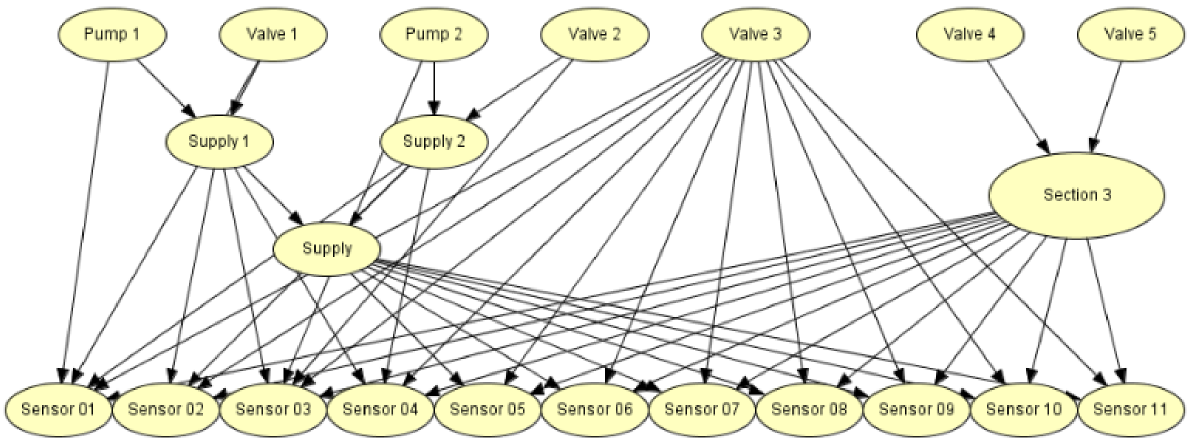


Figure 3.3 BBN of the example system

3.4.2.2. Discussion

The sensor nodes, such as "Sensor 01", in the BBN are used to represent the sensors that can be positioned in the system. They represent the sensor readings accurately, as a state can be added to the sensor node for each possible sensor reading that can be produced by this sensor. However, as mentioned earlier, if there are a large number of different sensor readings for each sensor, it might be desirable to group the sensor readings into ranges of readings, in order to keep the number of states for the nodes reasonable, i.e. preventing the number of elements in the CPTs from becoming too large. However, this will reduce the accuracy of the sensor modelling. This step is not required for a system of the size considered in this section.

As discussed previously, the introduction of intermediate nodes to the network, such as "Supply 1", helped to reduce the size of some of the CPTs. However, the number of entries in all of the CPTs of the network for this relatively small example system is still large, around 1400. This highlights the fact that the total number of elements in the CPTs could become very large, which may be impractical for larger systems.

The next step in the application of the methodology is to use the BBN to aid the diagnosis of component failures in this system. This is discussed in the following section.

3.4.3. Fault Diagnostics Process

The developed BBN model can be used to diagnose component failures in the system, by applying the method introduced in section 3.3. As stated previously, the combination of sensors, selected for the diagnosis of component failures, is sensors (S1 S3 S7). All of the component failures given in Table 3.1 are used to carry out the diagnosis of component failures in the system. In each case, the corresponding sensor readings from this table are inserted into the BBN, by adding evidence about the sensor reading to the sensor nodes of the network. The probability that each component is in the failed state is updated, and the diagnostics process can therefore be carried out.

The BBN successfully diagnoses the component failures for each of the 28 considered component failures, detailed in Table 3.1. For some of these combinations, the correct diagnosis was not achieved immediately, but the diagnostics process never resulted in inspecting more than one additional component than the number of components that had failed, i.e. no more than one component that was working was inspected. Therefore, with minimal additional component inspections, the BBN could be used to diagnose the component failures correctly, using the selected sensors.

In the following paragraphs of this section, each of the diagnoses of the combinations of the component failures are discussed. The 28 component failure combinations are grouped into seven different groups, based on how successfully the component failures are diagnosed, with explanations given if the diagnostics are not accurate. These groups, the actual failed components, and the diagnosed failed components are given in Table 3.13.

Table 3.13 Diagnosis of component failures

Case	No.	Actual failure	Diagnosed Failure 1	Probability	Diagnosed Failure 2	Probability	Diagnosed Failure 3	Probability
1	6	V4	V4	100%				
	7	V5	V5	100%				
	8	P1 P2	P1	100%	P2	100%		
	9	P1 V1	P1	100%	V1	100%		
	15	P2 V2	P2	100%	V2	100%		
	28	V4 V5	V4	100%	V5	100%		
2	5	V3	V3	95.84%				
	10	P1 V2	P1	100%	V2	95.47%		
	14	P2 V1	P2	100%	V1	95.47%		
3	1	P1	P1	50%	V1	50%		
	2	P2	P2	50%	V2	50%		
	3	V1	P1	50%	V1	50%		
	4	V2	P2	50%	V2	50%		
4	12	P1 V4	V4	100%	P1	50%	V1	50%
	13	P1 V5	V5	100%	P1	50%	V1	50%
	17	P2 V4	V4	100%	P2	50%	V2	50%
	18	P2 V5	V5	100%	P2	50%	V2	50%
	21	V1 V4	V4	100%	P1	50%	V1	50%
	22	V1 V5	V5	100%	P1	50%	V1	50%
	24	V2 V4	V4	100%	P2	50%	V2	50%
	25	V2 V5	V5	100%	P2	50%	V2	50%
5	26	V3 V4	V3	95.84%				
	27	V3 V5	V3	95.84%				
6	11	P1 V3	V3	95.84%				
	16	P2 V3	V3	95.84%				
	20	V1 V3	V3	95.84%				
	23	V2 V3	V3	95.84%				
7	19	V1 V2	V3	95.84%				

The first case given in Table 3.13, refers to the component failure combinations, 6, 7, 8, 9, 15 and 28, from Table 3.1. These component failures are diagnosed correctly, with the BBN predicting 100% probability of these components being failed. Therefore, by inspecting, and then replacing or repairing the components as appropriate, the system will be returned to normal operating behaviour. This will be achieved by inspecting the same number of components as there are failures, i.e. if one component has failed, one component will be inspected, and if two components have failed, two components will be inspected.

The second case given in Table 3.13, refers to the component failure combinations, 5, 10 and 14, from Table 3.1. As in the first case, these components are diagnosed correctly, however, not with 100% probability, i.e. 95.84% for component failure combination 5, and 95.47% for the component failure combinations 10 and 14. In each of the latter two cases, there are two components failed, one diagnosed with 100% probability, and the other with 95.47% probability. The reduction in probability for the component failure combination 5, V3 fails closed, results from the fact that the same symptoms are produced for the component failure number 19, and for the component failure combination 5, and therefore there is a possibility that the component failure combination 19, (V1 and V2), is the actual component failure combination. This case will be discussed further in case seven. For the component failure combinations 10 and 14, the same symptoms can be produced by the combinations of three (or more) component failures, and therefore will not be discussed further, as these are not being considered. Note, this is not the only set of symptoms in Table 3.1 that can be produced by a combination of three (or more) component failures.

The third case given in Table 3.13, refers to the component failure combinations, 1, 2, 3 and 4, from Table 3.1. For these combinations of component failures, the first component selected by the diagnostics process to be inspected will not always be the correct component failure that has occurred. This is true because there are multiple component failures with the same probabilities of occurrence that produce the same symptoms for these three sensors. In each case, the component that is inspected will be the component that has actually failed 50% of the time. Therefore, this will result in the system being returned to the normal operating behaviour after inspecting a maximum of two components, when only one component has failed, i.e. one additional component is being inspected 50% of the time. An example of this is when the selected sensor combination, (S1 S3 S7), produces the sensor reading combination (N 1 0.5). In this case, either pump P1 or valve V1 has failed, both with a probability of 50%. Therefore, there is a 50% probability that the component that has failed is inspected first, i.e. if the component failure is pump P1, there is a 50% probability that this component will be inspected first, but there is also a 50% probability that it is inspected second. It is worth noting that when both the components, P1 and V1, or P2 and V2, are failed, a different set of symptoms is observed, and therefore, it is not part of this case.

The fourth case, given in Table 3.13, refers to the component failure combinations, 12, 13, 17, 18, 21, 22, 24 and 25, from Table 3.1. This case is similar to case 3, except that in addition to there being a 50% chance for two components being in the failed state, another component has definitely failed. Therefore, this process will result in the system being returned to normal operating behaviour after inspecting a maximum of three components, when only two components have failed, i.e. one additional component is inspected 50% of the time.

The fifth case, given in Table 3.13, refers to the component failure combinations, 26 and 27, from Table 3.1. In this case, the diagnosed component is valve V3, but either valve V4 or valve V5 has failed in addition to valve V3. These component failure combinations produce the same symptoms as there would be in the case when only valve V3 has failed, but the probability of these events is significantly lower, and therefore the component failure is predicted to be only valve V3. However, when valve V3 has been inspected, and repaired or replaced as appropriate, the sensor readings will be different than previously observed but they will not match the readings produced under normal operating conditions. It will, therefore, be apparent that there is another component failure. This will then result in case 1, when the correct component failure can be diagnosed correctly. Therefore, the system operation will be returned to normal operation behaviour after inspecting, and repairing or replacing two components, when two components have failed. For this case, the predicted probability that valve V3 is the failed component is not equal to 100%, but it is equal to 95.84%. This situation occurs for the same reason as discussed briefly in the second case, but it will also be further discussed in more detail in the seventh case.

The sixth case, given in Table 3.13, refers to the component failure combinations, 11, 16, 20 and 23, from Table 3.1. This case is similar to the fifth case, where when valve V3 is repaired or replaced as required, it will become apparent that there is a second component failure, because the sensor readings will not return to the expected sensor readings for normal operating behaviour. This situation will then result in the symptoms observed in the third case discussed, where there will be two possible components that could have failed, each with equal probability of failing. Therefore, the system will be returned to normal operation behaviour after inspecting, and repairing or replacing as appropriate, two or three components, when only two components have failed, i.e. inspecting an additional component 50% of the time. As with cases two and five, it is possible that for those symptoms, valve V3 has not failed, and other components have failed instead. This situation results in the probability of valve V3 being failed being equal to 95.84%. As before, this is discussed in more detail in the seventh case.

The seventh, and final case given in Table 3.13, refers to the component failure combination, 19, from Table 3.1. In this case, the BBN predicts the incorrect component failure, it predicts that valve V3 has failed, when, in actual fact, valve V1 and valve V2 have both failed. This is because, whilst both combinations produce the same symptoms, the probability of valve V3 failing, is significantly higher than the probability of both valve V1 and valve V2 failing. Therefore, as valve V3 is more likely to have failed, it is logical to investigate this component, rather than the component failure combination of valve V1 and valve V2. However, when valve V3 is inspected, and it is found not to have failed, this evidence can be introduced into the BBN. This will then update the probability of each of the other components being in the failed state, and therefore result in the correct components being diagnosed, and therefore, inspected, and repaired or replaced as appropriate. The system operation will, therefore, be returned to normal by inspecting three components, when there are only two component failures present in the system.

All of the example cases discussed above, with the exception of the first, result in the diagnostic term being less than 1, i.e. ($DI_{\{s\}} = 0.6818$). This is because some component failure combinations are not diagnosed correctly initially. However, all of the component failure combinations can be diagnosed correctly with no more than one additional component being inspected. In some of these cases, this is because two component failures produce the same symptoms and have an equal probability of occurring, and in other cases, this is because the component failure combination considered, has a lower probability of occurring than another combination of component failures that produces the same symptoms.

If the best combination of four sensors is considered, the additional sensor, either sensor S2 or S4, would result in the component failure combination number 19 being diagnosed correctly on the first attempt. This is the main benefit of introducing the fourth sensor in this example. The introduction of this sensor provides the additional information required to be able to determine that valve V1 and V2 have failed. Note, it is possible that valve V3 has still failed in addition to these two valves, as this would produce the same symptoms, but the combinations of three (or more) component failures are not considered in this thesis.

In the next section, an analysis of how the diagnostics performance of the sensor combinations changes when the diagnostic term of the performance metric changes is given.

3.4.4. Validation of the Diagnostic term

In order to validate that the diagnostic term of the performance metric is favouring combinations of sensors that diagnose component failures more easily, the same combinations of component failures are diagnosed using a number of different combinations of sensors. In order to ensure that the diagnostic term is the only factor that is considered, one combination of sensors from each ranking of three sensors that has a detection and criticality term of 1 is selected, i.e. (S1 S3 S8), (S1 S4 S7), (S1 S4 S8), (S1 S8 S10), (S2 S4 S8), (S5 S6 S7), (S5 S8 S11), and (S8 S10 S11), and is compared with the results of the diagnostic process in the previous section, i.e. for sensor combination (S1 S3 S7). These combinations of sensors are ranked second, third, fourth, fifth, sixth, tenth, eleventh, and twelfth. For each combination of sensors, a table in the form of Table 3.13 is produced, and is given in Appendix C, Tables C.1 – C.9, but summary tables are presented as Table 3.14 – 3.17. Note, a table for the combination of sensors ranked first is given in Appendix C for completeness, in order to add an additional column for clarity that was not included in Table 3.13. This additional column groups each of the combination of component failures into four groups:

- Group 1 is when there is one component failure and it is detected.
- Group 2 is when there are two component failures and they are both detected.
- Group 3 is when there are two component failures, one of which is detected, but the second is only detected when the first component is repaired or replaced.
- Group 4 is when there are two component failures which are detected, but they are diagnosed incorrectly.

Within each of these groups, the combinations of component failures are separated into smaller groups indicated by a letter. For the fourth case, the symptoms are observed, but the diagnostics process suggests the wrong component to inspect, for example, case 7 in Table 3.13. Each of these four groups are presented in Tables 3.14 – 3.17, respectively.

If Table 3.14 is studied, the table for group 1, there is a clear step between the sensors ranked 6th and the sensors ranked 10th. This coincides with the big step in the diagnostic term, with a difference of 0.1299, where the difference in the diagnostic term between the sensors ranked 1st and 6th is 0.0324, less than a quarter of the difference. At this step, between the sensors ranked 6th and the sensors ranked 10th, instead of there being 4 component failures that are in group 1c, for which the probability of diagnosing the component failure is approximately 50%, there are 4 component failures in group 1d, for which the probability of diagnosing the component failure is approximately 25%. In each of the 9 considered rankings, there are three component failures that are in group 1a or 1b, with the sensors ranked 3rd having all three in the group 1a, and all the others having two in group 1a and one in group 1b. As group 1a is 100% probability of the component being in the failed state, it is more desirable to have component failures in group 1a than in group 1b. This would suggest that for this group of failures the combination of sensors ranked 3rd is best, however, as the probability of correct diagnosis for the component failures in group 1b is high (>80%), including the combinations of sensors ranked 1st and 2nd, the benefit of using the combinations of sensors ranked 3rd is small. Therefore, for group 1, the combinations of sensors ranked 3rd is the best, but the combinations of sensors ranked 1st is a close second best, with the combinations of sensors ranked 2nd the third best.

Table 3.14 Summary of the diagnostic performance of sensor rankings for group 1, (one component failure and detected)

	1a	1b	1c	1d
Rank	1 of 1 (100%)	1 of 1 (>80%)	1 of 1 (~50%)	1 of 1 (~25%)
1	2	1 (95.84%)	4 (50%)	0
2	2	1 (91.68%)	4 (50%)	0
3	3	0	4 (50%)	0
4	2	1 (95.47%)	4 (50%)	0
5	2	1 (88.04%)	2 (50%), 2 (51.28%)	0
6	2	1 (95.47%)	4 (51.28%)	0
10	2	1 (95.44%)	0	4 (25.64%)
11	2	1 (95.47%)	0	4 (25.64%)
12	2	1 (81.46%)	0	4 (25.64%)

If Table 3.15 is studied, the table for group 2, it can be concluded that having more in group 2a is better, as both of the component failures are diagnosed 100% correctly. The sensor combination ranked 1st has the most combinations of component failures that fall into this group. The second column, case 2b, results in a higher confidence in the diagnosis of component failure than cases 2c and 2d, as the second component failure in each case has less confidence in diagnosis. If the top three rankings are compared, it can be concluded that the sensor combination ranked 1st is best, followed by the sensor combination ranked 2nd, then by the sensor combination ranked 3rd. Here, the sensor combination ranked 1st is demonstrably better than the sensor combination ranked 3rd, having two additional combinations of component failures in cases 2a and 2b, where the probability of correct diagnosis is higher in comparison to the four additional combinations of component failures in case 2c for the sensors ranked 3^{rd}, i.e. correct diagnosis all the time (and 95% of the time) vs correct diagnosis approximately 50% of the time. The difference between the probability of the components being in the failed state of 50% and 51.28% is negligible in comparison to the difference between the approximately 50% and 100% (and approximately 95%) of cases 2a (and 2b), respectively.

Whilst it is clear that group 2a is more desirable than group 2b, group 2b is more desirable than group 2c, and group 2c is more desirable than 2d, it is not clear exactly where groups 2e, 2f and 2g, fall in terms of how desirable they are, as they could be considered to be better than group 2d as the probability is higher for the second component, but could also be worse than group 2d as the probability for the diagnosis of the first component is not 100%. However, it is clear that group 2e is more desirable than group 2f, and group 2f is more desirable than group 2g, as for group 2e, fewer components are required to be inspected (two), than for groups 2f and 2g (maximum of four). It is also clear that group 2f is more desirable than group 2g as the probability of each of the component failures is higher, although in reality, it has no effect as up to four components will need to be inspected in each case.

As observed with the previous table, there is a clear step between ranks 6 and 10, where at least eight combinations of component failures are in 2c for rankings 6 and higher, and eight combinations of component failures are in 2d for rankings 10 and lower.

It is also clear that, unlike in the first group, there are different amounts of component failures that fall into group 2 for each ranking. For example, the sensor combination ranked 1^{st} has four combinations of component failures in group 2a, two in group 2b, and eight in group 2c i.e. 14 in total, but the sensor combination ranked 3^{rd} has two combinations of component failures in group 2a, twelve in group 2c, and one in group 2e, i.e. 15 in total. This difference in number of combinations for each ranking is because of component failures that fall into group 4, where the sensor combination ranked 1^{st} has an additional combination of component failures than the sensor combination ranked 3^{rd}.

It can be concluded from the discussions in the previous paragraphs that the sensor combination ranked 1^{st} is the best for the combinations of component failures in group 2. The difference between the sensor combinations ranked 1^{st}, 2^{nd} and 3^{rd}, is much larger than the difference observed for the combinations of component failures in group 1.

Table 3.15 Summary of the diagnostic performance of sensor rankings for group 2, (two component failures and both detected)

	2a	2b	2c	2d	2e	2f	2g
Rank	2 of 2 (100%)	2 of 2 (100%, >80%)	2 of 2 (100%, ~50%)	2 of 2 (100%, ~25%)	2 of 2 (~50%, ~50%) but both failed	2 of 2 (~50%, ~50%), two pairs	2 of 2 (~25%) two out of four
1	4	2 (95.47%)	8 (50%)	0	0	0	0
2	3	2 (95.26%)	8 (50%)	0	0	0	0
3	2	0	4 (50%), 8 (51.28%)	0	1 (51.28%)	0	0
4	1	0	4 (50%), 8 (51.28%)	0	1 (51.28%)	0	0
5	1	0	4 (50%), 2 (50.07%), 4 (51.28%)	0	1 (51.28%)	0	0
6	0	0	8 (51.28%)	0	2 (51.28%)	4 (51.28%)	0
10	1	0	0	8 (25.64%)	0	4 (51.28%)	2 (25.64%)
11	0	0	0	8 (25.64%)	0	4 (51.28%)	2 (25.64%)
12	0	0	0	8 (25.64%)	0	0	2 (25.64%)

In Table 3.16, group 3 is presented. These are combinations of component failures where initially it appears as if there is only one component that has failed, but when this component is repaired or replaced, it becomes apparent that there is a second component failure. If Table 3.16 is studied, the six groups, 3a – 3f, can be split into two, 3a – 3c, and 3d – 3f, where in the first set of groups the first component is diagnosed with 100% confidence, and the second set of groups with less than 100% confidence. Within these two sets, they can be grouped into pairs of one from each set based on the probability of the second component being diagnosed correctly, i.e. 3a and 3d, 3b and 3e, and 3c and 3f. For each ranking, there are two combinations of component failures in group 3a or 3d, and four combinations of component failures in group 3b, 3c, 3e or 3f. The most desirable pair is 3a and 3b as these have the highest probability for each of the possible combinations. The only combinations of sensors that produce this pair are the sensors ranked 3rd. However, as with group 1, the benefit of 3a as opposed to 3d, and 3b as opposed to 3e, is minimal as the probability of the first failure in 3d and 3e is high (>80%), therefore the sensor combinations ranked 3rd is the best, but the sensor combinations ranked 1st is a close second best, with the sensor combinations ranked 2nd the third best.

As observed in group 1, there is a clear step between the combinations of sensors ranked 6th and 10th as the four combinations of component failures go from being in group 3b or 3e, to 3c or 3f, i.e. a significant decrease in the probability of correct diagnosis, with having to potentially inspect an additional two components.

Table 3.16 Summary of the diagnostic performance of sensor rankings for group 3, (two component failures, one detected and second detected when first is repaired)

	3a	3b	3c	3d	3e	3f
Rank	1 (+1 delayed) 100%, (100%)	1 (+1 delayed) 100%, (~50%)	1 (+1 delayed) 100%, (~25%)	1 (+1 delayed) >80%, (100%)	1 (+1 delayed) >80%, (~50%)	1 (+1 delayed) >80%, (~25%)
1	0	0	0	2 (95.84%)	4 (95.84%, 50%)	0
2	0	0	0	2 (91.68%)	4 (91.68%, 50%)	0
3	2	2 (50%), 2 (51.28%)	0	0	0	0
4	0	0	0	2 (95.47%)	4 (95.47%, 50%)	0
5	0	0	0	2 (88.04%)	2 (88.04%, 50%), 2 (88.04%, 51.28%)	0
6	0	0	0	2 (95.47%)	4 (95.47%, 51.28%)	0
10	2	0	4 (25.64%)	0	0	0
11	2	0	4 (25.64%)	0	0	0
12	0	0	0	2 (81.46%)	0	4 (81.46%, 25.64%)

Table 3.17 Summary of the diagnostic performance of sensor rankings for group 4, (incorrect diagnosis of some component failures)

	4a	4b	4c	4d	4e	4f
Rank	1 wrong (~95%), followed by 2 of 2 (100%), inspect 3	1 wrong (>80%), followed by 2 of 2 (~50%) inspect 3	1 wrong (>80%), followed by 1 wrong (~50%), followed by 2 of 2 (100%), inspect 4	1 wrong (~95%), followed by 1 (>50%), followed by delayed (~50%), inspect 3/4	1 wrong, then wrong again, then wrong again, then 2 of 2 (100%), inspect 5	wrong, 2 in 4 right; if right: 1 in 2, inspect 3/4. if wrong: 1 right, followed by 1 in 2 right. inspect 4/5
1	1 (95.84%)	0	0	0	0	0
2	0	1 (91.68%, 54.60%)	1, (91.68%), (54.60%)	0	0	0
3	0	0	0	0	0	0
4	1 (95.47%)	0	0	0	0	0
5	0	0	1, (88.04%), (66.72%)	2 (88.04%, 66.72%, 50.12%)	0	0
6	1 (95.47%)	0	0	0	0	0
10	0	0	0	0	0	0
11	1 (95.47%)	0	0	0	0	0
12	0	0	0	0	1 (81.46%, 41.63%, 67.74%)	4 (81.46%, 41.63%) if 2nd insp. right, (50.12%), if 2nd insp. wrong (67.74%, 50.12%)

In Table 3.17, the final group, group 4, is presented. It is undesirable to have any combinations of failures in group 4, as the actual component failure is not one of the components with the highest probability of being in the failed state, resulting in an incorrect diagnosis. Therefore, the combinations of sensors ranked 3rd and 10th are the most desirable for this group as they do not have any combinations of component failures that fall in to this group.

In this group, the most desirable to have is group 4a, followed by 4b, as in both of these cases, only three components will need to be inspected when two components have failed. This is better than a number of groups in group 2 and 3, such as, 2d, 2f, 2g, 3c and 3f, where four or five components may need to be inspected when only two components have failed. Therefore, the combinations of sensors ranked 1st, 4th, 6th and 11th are the next best, but it can be concluded that having component failures in these groups is more desirable than in the groups listed above, 2d, 2f, 2g, 3c and 3f.

Groups 4c and 4d may also require four components to be inspected, so are less desirable than groups 4a and 4b, and groups 4e and 4f may require up to five components to be inspected so are less desirable than groups 4c and 4d.

For each of these groups, there was a ranking of sensor combinations that was determined to be the best, the combinations of sensors ranked 3rd, for groups 1, 3 and 4, and the combinations of sensors ranked 1st for group 2. However, the difference between the two rankings were minimal for groups 1 and 3, with no additional inspections required. Therefore, if the maximum number of inspections required for all of the combinations of component failures that fall into groups 2 and 4 is summed, the effect that group 2 has on the performance metric can be demonstrated. This results in a maximum of 39 inspections for the combination of sensors ranked 1st, and 43 inspections for the combinations of sensors ranked 3rd. The 4 additional inspections result from the fact that more of the component failures have two possible failures that produce the same symptoms. The difference in diagnostic term for the two combinations of sensors is small, as discussed earlier, and therefore the diagnostic term is more affected by this difference than the difference observed in groups 1 and 3, suggesting that the sensor combination ranked 1st is the best. This also suggests that the sensor combinations ranked 2nd is 2nd best, with a maximum number of inspections for all of the combinations of component failures in groups 2 and 4 of 40 despite having two combinations of component failures in group 4 (where the failures are diagnosed incorrectly), i.e. in between the 39 that could be required for the combinations of sensors ranked 1st, and the 43 that could be required for the combinations of sensors ranked 3rd.

This effect is more pronounced when comparing the combinations of sensors ranked 1st and 12th which have a bigger difference in the diagnostic term. In this case, the maximum number inspections for all combinations of component failures is considered, which is equal to 66 for the combinations of sensors ranked 1st, and is equal to 116 for the combinations of sensors ranked 12th, a significant increase. This demonstrates that the diagnostic term favours the combinations of sensors that are better at failure diagnosis.

In the next section, an analysis of the methodology is given, along with an outline of potential improvements to the methodology that are then described in Chapter 4.

3.5. Analysis of the Proposed Methodology

The methodology consists of three steps, sensor selection, system modelling and fault diagnostics. The sensor selection step is completed by using a performance metric, a measure of how well the sensor performs at its desired task, i.e. detecting faults and diagnosing failures. The maximum possible performance metric can be calculated initially, therefore removing the risk of the analyst looking for improvements that cannot be obtained, which will also prevent resources from being wasted, be it computational, or man-hours. For example, for this system, without the knowledge of the maximum performance metric, combinations of five sensors could have been calculated unnecessarily, as the best result can be achieved by some combinations of four sensors.

An observation that was made when applying the methodology to the example system was that the BBN model of the system could be used to aid the calculation of the performance metric. It means that the metric could be calculated automatically using a computer script. This script could introduce component states to the BBN in the form of evidence, compile the network and record the resultant sensor readings, and the probability of the evidence introduced. The computer script could repeat this process automatically for all considered combinations of component failures. Using the recorded sensor readings, and probability of the evidence introduced, the performance metric could be calculated. This process would be of particular use for complex systems with a large number of components, or a large number of component failure modes. This will be completed in Chapter 4 of this thesis. Note, when introducing component state evidence to the network using HUGIN Researcher, all components must have evidence introduced, not just the failed components, in order for the BBN to calculate the correct values. This is because the sensor readings are dependent on all of the component states, and without evidence for all of the component states being introduced, the sensor readings will not always have 100% probability because the state of the component without evidence introduced could affect the state of the sensor reading.

A key benefit of the proposed methodology is that it is general, i.e. it can be applied to a large number of different types of systems. For the performance metric, the requirements are that the symptoms of component failures must be observable using sensors, and the probabilities of the component failures must be known. For the diagnostic process, a BBN can be constructed for any system, as long as it is acyclic, i.e. it does not have any loops in the system. This is because BBNs must be acyclic as otherwise a node's state will depend on its own state, producing an infinite loop of updating the probability of observing each of the node's states.

3.5.1. Sensor selection

In section 3.2.4 of this thesis, it was suggested that the performance metric, given in Equation (3.4), should be used as a guide to reduce the number of sensor combinations considered, with the final selection of sensors based on individual terms. The benefits of this process will be greater for larger systems than they are for this, relatively small, example system. It gives the analyst better control over the selection of the sensors, and enables them to ensure that they get the sensor combination which suits the application best. This process will also reduce the risk that a sensor combination that has one term significantly lower than desired is selected, resulting in a more suitable sensor combination.

3.5.2. Modelling the system

The system modelling technique, BBNs, produces a good representation of the example system, with each component state and sensor state included in it. Each of the components and sensors are assigned a node in the network, so that they can each have evidence introduced to the model as desired. The relationship between the components and sensors is controlled by the CPTs, with the desired sensor states output for the corresponding component states.

The example system is a simple system, where partial failures, such as partial blockages and degraded pumps, are not considered and therefore the model does not account for these situations arising. However, further failure models could be added, but it would increase the number of elements in the CPTs, increase the number of nodes in the network and therefore, result in a larger network. As mentioned briefly in section 3.4.2, even for this relatively small system, the network is large, with approximately 1400 entries in the CPTs. It highlights a potential scalability issue that may arise when the method is applied to significantly larger systems. When the BBN models cannot be scaled to model larger systems, alternative system modelling techniques must be considered, as discussed in Chapter 5.

3.5.3. Fault diagnostics

The fault diagnostic process was shown to successfully diagnose all of the component failures considered on the system. However, in some cases, components were not diagnosed correctly initially, but the method required no more than one additional component to be inspected than was actually failed in order for the system to be returned to normal operating behaviour by repairing or replacing the failed components.

One of the main benefits of using the BBN as the fault diagnostics model, is that the BBN software automatically outputs the probability that each component is in the failed state. Therefore, the analyst could set a threshold probability, such that any component which is above a certain probability of being in the failed state could be taken to the aircraft for repair, along with the component that is most likely to have failed. This would reduce the risk of unnecessary down-time, but would also prevent large amounts of equipment being transported unnecessarily, when the probability of the components being failed is comparatively low. For this example system, if the sensor reading combination produced is that of the first case (for example) in Table 3.1, both replacement components, pump P1 and valve V1, would be taken to the system for repair. This is because if the current component cannot be repaired, it would result in a reduction of system downtime in comparison to taking the components to the system individually, and potentially taking the wrong component first.

3.6. Summary

In summary, this chapter proposes a methodology for sensor selection and system modelling for fault diagnostics. The method is demonstrated by using an example system consisting of seven components: two pumps and five valves. The sensor selection method entails using a newly developed performance metric, which details the sensors that are the best to use, based on their ability to detect faults and diagnose failures. It also considers the effects that these failures have on the operation of the system. It was suggested that the performance metric should be used to narrow down the number of combinations of sensors, and the best combination of sensors for the specific application should be selected based on the three individual terms.

A BBN-based system modelling technique was suggested, in order to be able to diagnose component failures using the selected sensors. A BBN was constructed for the example system, with nodes for each of the components and sensors, and any other nodes, for some parts of the system, depending on its complexity, as required. The model can have sensor readings introduced to the network in the form of evidence, and it is used to update the probability that each of the components have failed. The component failures can then be diagnosed, and system operation can be restored to normal operating behaviour by repairing or replacing the failed components.

There are a number of potential improvements to the methodology that are developed in Chapters 4, 5, and 6. For example, the scalability of the methodology can be tested by applying it to a larger system. This will require some automation, particularly for the sensor selection process, i.e. calculating the performance metric for each combination of sensors. Another extension could be to consider a system that has multiple operation modes, as this process would enable more failure modes to be considered. Finally, a phased mission could be modelled, with the aircraft moving through the different operation modes throughout a mission, such as take-off, cruise, fuel transfer and landing. This process would enable component failures to be inserted into the mission at various times in the mission, with the sensor performance metric considering how quickly the failures can be detected and diagnosed.

Chapter 4 - Application of the proposed methodology to a simplified aircraft fuel system

In this chapter the methodology proposed in Chapter 3 is applied to a more complex system in order to determine its scalability. In comparison to the simple system, analysed in Chapter 3, a larger BBN model is constructed, and more component failures and sensors are considered for this system.

This chapter begins by introducing a simplified aircraft fuel system, (note, that some of the simplifications of the system are later removed in Chapter 5 of this thesis). A simplified aircraft fuel system is introduced in order to demonstrate that the scalability of the BBN is not suitable for systems that are significantly larger, and an alternative modelling technique is then presented in Chapter 5. The simplifications include ignoring the redundant sections of the system and ignoring the operation modes that are not used frequently. The next step describes the application of the methodology to the system, i.e. model the system, select the sensors, and diagnose component failures. The chapter concludes with a discussion of the results of the application of the methodology to this system.

4.1. System description

The system introduced in this section can be found in Moir & Seabridge (2011). This system is a "typical fighter aircraft" fuel system. Therefore, it is not an accurate representation of any physical aircraft fuel system, but it has the main features of operation for this type of system. Four different operation modes of the system are presented: engine feed, fuel transfer, fuel jettison, and refuel. Each of these schematics are given in Figures 4.1 – 4.4, respectively. The engine feed operation mode is presented in Figure 4.1, the fuel transfer operation mode is presented in Figure 4.2, the fuel jettison operation mode is presented in Figure 4.3, and the refuel operation mode is presented in Figure 4.4. In the figures, the dashed lines represent the path of the fuel round the system in each of the operation modes.

Each of the operation modes is active during different phases of the mission, and each mode is intended to complete a different task. For example, during the engine feed operation mode, fuel should be supplied to the engine and this process occurs during the flight. During the fuel transfer operation mode, fuel should be transferred from the wing tanks to the fuselage tanks, where it can then be supplied to the engine. The system is in this operation mode when the aircraft is in the cruise phase of the mission, and the fuel level in the fuel tanks becomes lower than a set limit. This process will, therefore, replenish the engine supply tanks. The fuel jettison operation mode should only be activated in emergency situations. This operation mode jettisons fuel from the system when an emergency landing is required, and is activated in order to bring the aircraft weight down to a safe landing weight. The final operation mode, refuel, is normally active before the aircraft takes off (although it can be active mid-flight for some aircraft), during which the tanks are refilled from an external source so that the aircraft can start a new mission, or complete the current mission.

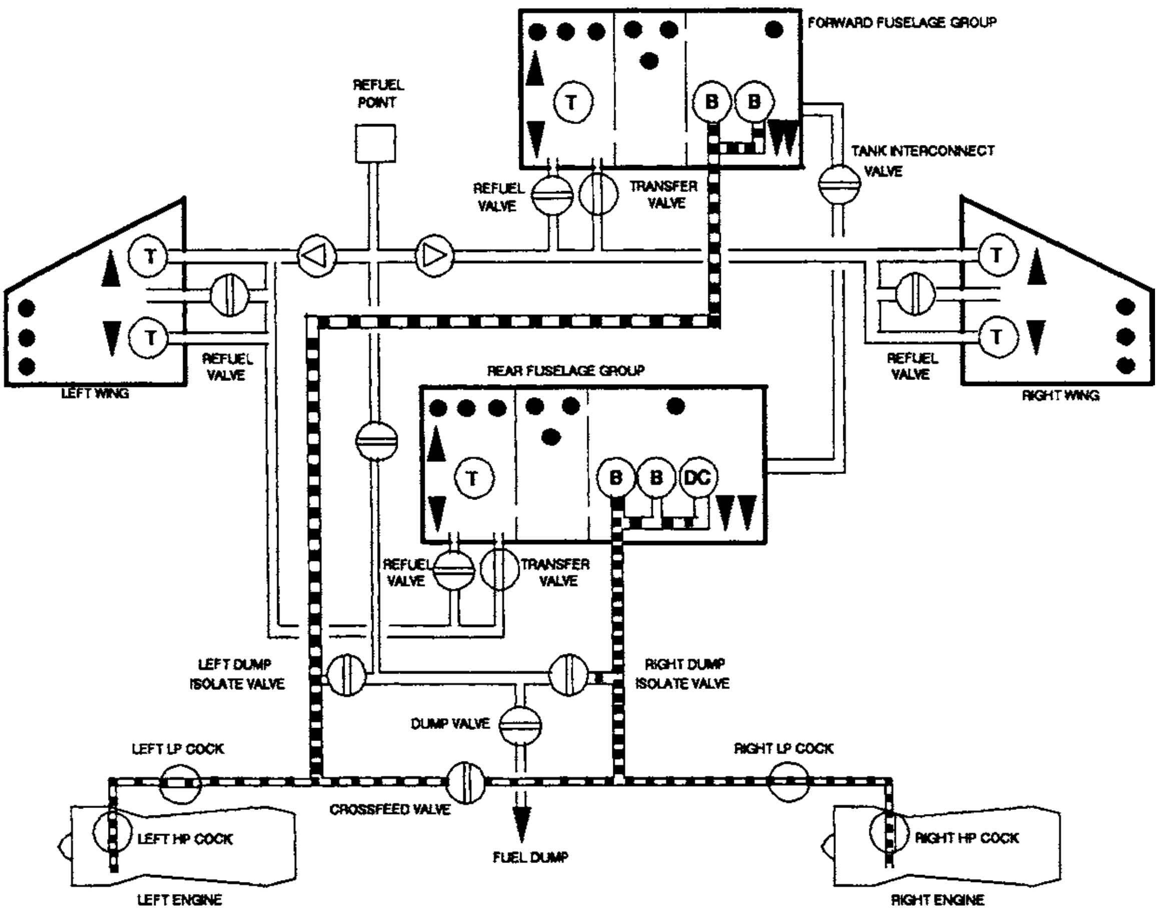


Figure 4.1 Schematic of the fuel system in engine feed mode from Moir & Seabridge (2011)

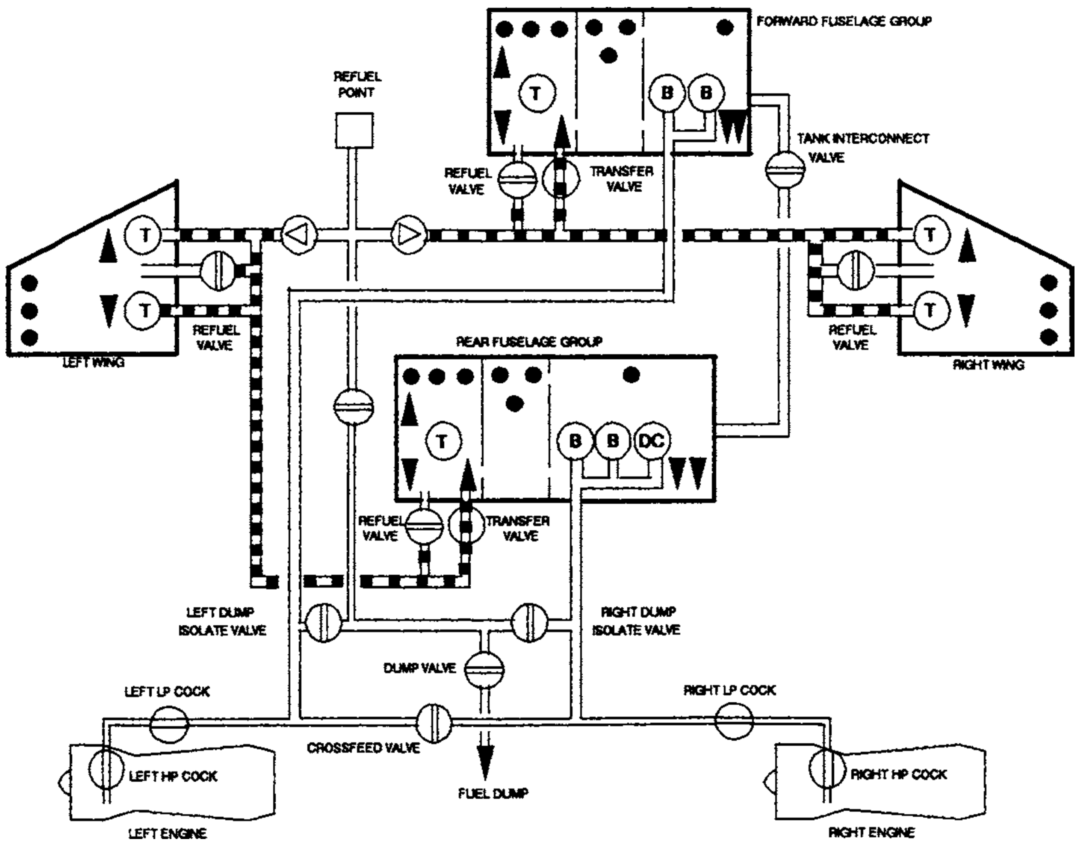


Figure 4.2 Schematic of the fuel system in the fuel transfer operation mode from Moir & Seabridge (2011)

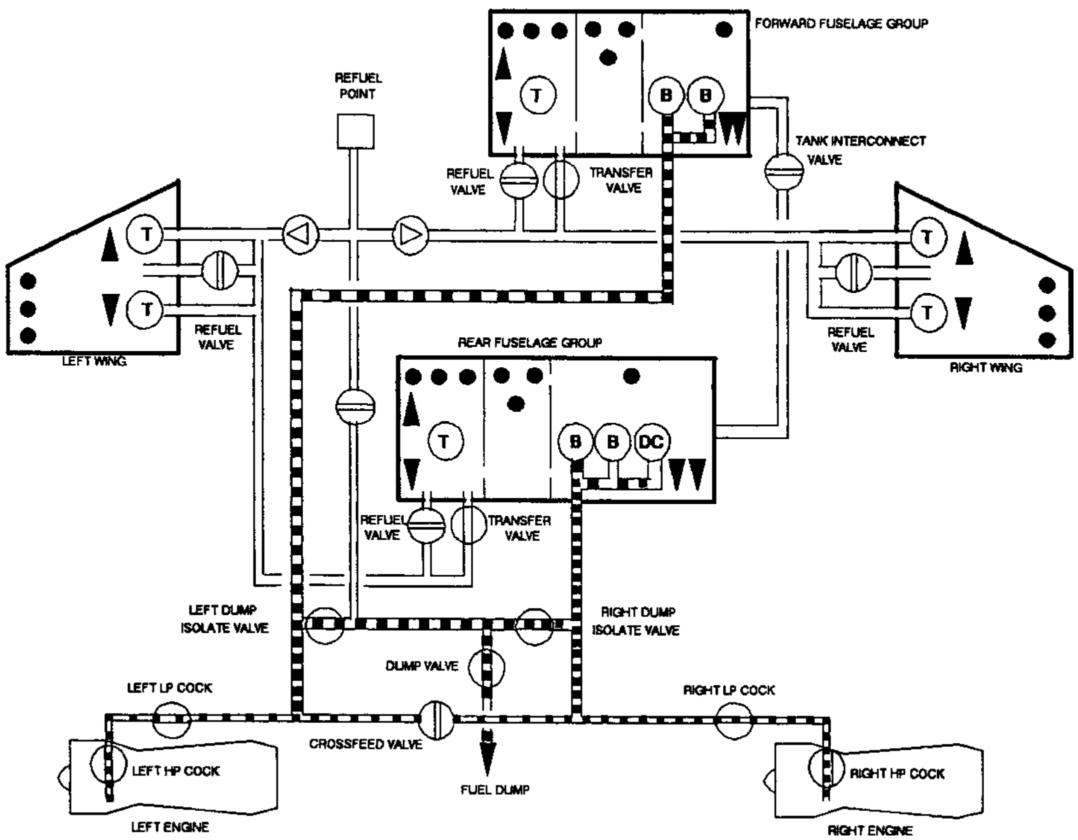


Figure 4.3 Schematic of the fuel system in the fuel jettison operation mode from Moir & Seabridge (2011)

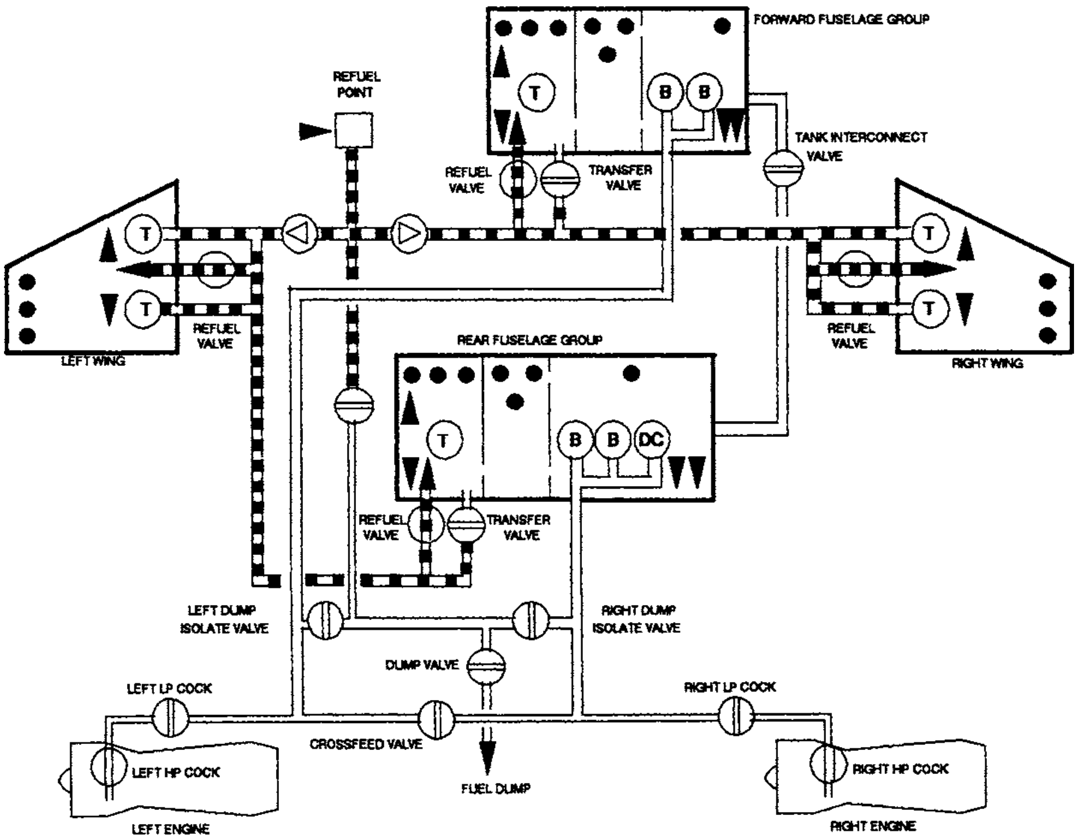
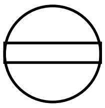
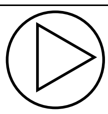


Figure 4.4 Schematic of the fuel system in the refuel operation mode from Moir & Seabridge (2011)

In the schematics, there are four types of components, with multiple components of each type in the system. The four types of components are booster pumps, transfer pumps, valves and one-directional valves (1D valves). "DC" shows that the pumps require a DC power supply and for simplicity the DC power supply is not considered in this work.

Booster pumps are used to supply fuel to the engine, whereas transfer pumps are used to transfer fuel from one tank to another. The valves (two-directional and one-directional) are used to control the flow of fuel around the system. When the two-directional valves are open, they will allow the fuel to flow in either direction, and no fuel can pass when the valves are closed or blocked. The one-directional valves allow the flow in one direction only, which is the direction of the point of the triangle, as shown in Figure 4.4. Note, that one-directional valves can fail blocked, i.e. fuel cannot pass through in either direction, and can fail open, i.e. fuel can pass through in both directions and does not prevent the flow of fuel in the opposite direction to which it is desired. For the analysis, all of the components in the system are labelled in Figure 4.5 with descriptions of the components given in Table 4.1.

Table 4.1 Component descriptions for the components in the fuel system

Type	Symbol	Description	Name	Number
Transfer pump	T	Transfer Pump Left wing Top	TPLT	1
		Transfer Pump Left wing Bottom	TPLB	2
		Transfer Pump Right wing Top	TPRT	3
		Transfer Pump Right wing Bottom	TPRB	4
		Transfer Pump Forward Fuselage	TPFF	5
		Transfer Pump Rear Fuselage	TPRF	6
Booster Pump	B	Booster Pump Forward fuselage Left	BPFL	7
		Booster Pump Forward fuselage Right	BPFR	8
		Booster Pump Rear fuselage Left	BPRL	9
		Booster Pump Rear fuselage Right	BPRR	10
Valve		Refuel Valve Left Wing	RVLW	11
		Refuel Valve Right Wing	RVRW	12
		Refuel Valve Forward Fuselage	RVFF	13
		Refuel Valve Rear Fuselage	RVRF	14
		Transfer Valve Forward Fuselage	TVFF	15
		Transfer Valve Rear Fuselage	TVRF	16
		Left Dump isolate Valve	LDV	17
		Right Dump isolate Valve	RDV	18
		Dump Valve	DV	19
		Cross-feed Valve	CV	20
		Refuel Point Valve	RPV	21
		Left Low-Pressure cock	LLP	22
		Left High-Pressure cock	LHP	23
		Right Low-Pressure cock	RLP	24
		Right High-Pressure cock	RHP	25
		Tank Interconnect Valve	TIV	26
1D Valve		One-directional Valve Left	NVL	27
		One-directional Valve Right	NVR	28

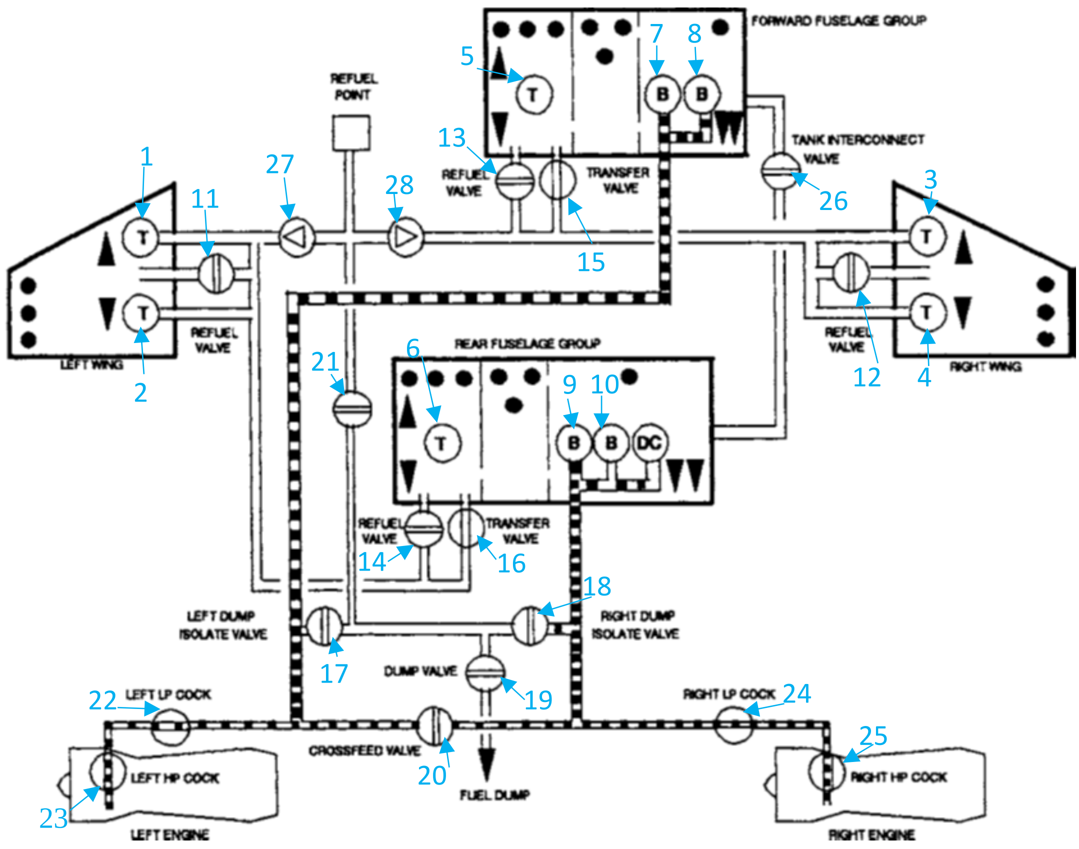


Figure 4.5 Schematic of the fuel system with the components numbered

Since the system has multiple operation modes, its components can be in a number of working (and failed) states. For example, in the fuel transfer operation mode, a transfer pump should be on, transferring fuel to a fuselage tank, but in the engine feed operation mode, it should be off, not transferring fuel to a fuselage tank. Alternatively, in the fuel jettison operation mode, the dump valve should be open, allowing fuel to pass through it and exit the system, but in the other operation modes, it should be closed, not allowing fuel to pass through it. Therefore, multiple component failure modes can occur, for example, pumps fail on, pumps fail off, valves fail open, and valves fail closed. This is an additional level of complexity considered in comparison to the simple system discussed in Chapter 3. The working states of the components in each operation mode are summarised in Table 4.2.

There are a number of components in this system that are redundant. For example, there are ten pumps, four of which are secondary pumps, such as TPLB, TPRB, BPFR and BPRR, which are only used if the primary pump has failed. Therefore, if there are primary pump failures present on the system, none of these pumps are on. However, in the fuel jettison operation mode, BPFR and BPRR are operational at the same time as BPFL and BPRL so that fuel can be jettisoned from the system as quickly as possible.

Table 4.2 Component normal working state for each operation mode

Component		Working state for each operation mode			
Name	Number	Engine Feed	Fuel Transfer	Fuel Jettison	Refuel
TPLT	1	Off	On	Off	Off
TPLB	2	Off	Off	Off	Off
TPRT	3	Off	On	Off	Off
TPRB	4	Off	Off	Off	Off
TPFF	5	Off	Off	Off	Off
TPRF	6	Off	Off	Off	Off
BPFL	7	On	Off	On	Off
BPFR	8	Off	Off	On	Off
BPRL	9	On	Off	On	Off
BPRR	10	Off	Off	On	Off
RVLW	11	Closed	Closed	Closed	Open
RVRW	12	Closed	Closed	Closed	Open
RVFF	13	Closed	Closed	Closed	Open
RVRF	14	Closed	Closed	Closed	Open
TVFF	15	Open	Open	Open	Closed
TVRF	16	Open	Open	Open	Closed
LDV	17	Closed	Closed	Open	Closed
RDV	18	Closed	Closed	Open	Closed
DV	19	Closed	Closed	Open	Closed
CV	20	Closed	Closed	Closed	Closed
RPV	21	Closed	Closed	Closed	Closed
LLP	22	Open	Open	Open	Closed
LHP	23	Open	Open	Open	Open
RLP	24	Open	Open	Open	Closed
RHP	25	Open	Open	Open	Open
TIV	26	Closed	Closed	Closed	Closed
NVL	27	Open	Open	Open	Open
NVR	28	Open	Open	Open	Open

Other components, TPFF, TPRF, CV, and TIV, are also redundant components. These components are only to be used if the other components that are used to transfer fuel in the fuel transfer operation mode have failed in the system. This is used to enable the transfer of fuel around the system, when there are component failures that result in fuel not being transferred to the fuselage tanks as desired (i.e. TPLT off, TPRT off, TPLB off, TPRB off, TVFF closed and TVRF closed). As a result these components are always in the off/closed state in Table 4.2, (with the exception of BPFR and BPRR in the fuel jettison operation mode, as discussed before). Note, it is assumed that if a component fails and there is a secondary or redundant component to do the same task, then the secondary or redundant pump, or valve, will automatically activate or open respectively. This occurs in order for the system to function as normal if it is possible to do this using the redundant components, i.e. the fuel will still be supplied to the engine, or transferred to the fuselage tanks as desired.

In order to calculate the performance metric, and to be able to diagnose the component failures in the system, each component failure needs a probability assigned to it. As there is no available data on component reliabilities, the values are assumed to be those presented in Table 4.3. Note, these values are higher than they would normally be, but the actual values do not matter, it only matters that there is a realistic ratio between the component failure probabilities. The table summarises the probability of being in the working and failed states for each type of component. The second column in this table gives the desired state for the component, which corresponds to the types of states the components are required to be in across the different operation modes, given in Table 4.2.

The probabilities of each component failure mode are also required to determine when the system is critical for each operation mode. The component failures that are critical are different for each operation mode. For example, for the engine feed operation mode, the critical system failure occurs if there is no fuel supplied to both engines, or if fuel is exiting through the dump valve. For the fuel transfer operation mode, the critical failure occurs if no fuel is transferred from both of the wing tanks to the respective fuselage tanks, or if fuel is exiting through the dump valve. For the fuel jettison operation mode, the critical failure occurs if no fuel is jettisoned from the system. For the refuel operation mode, the critical failure occurs if any of the tanks are not refilled.

The minimal cut sets for each of the operation modes can be determined by considering which combinations of component failures cause the system to fail, i.e. what combination of component failures have to occur to cause the system to fail. For example, what combination of component failures have to occur in order for there to be no supply of fuel to the engines.

The minimal cut sets for the engine feed operation mode are:

- {LLP closed, RLP closed}
- {LHP closed, RLP closed}
- {LLP closed, RHP closed}
- {LHP closed, RHP closed}
- {LDV open, DV open}
- {RDV open, DV open}
- {BPFL off, BPFR off, RLP closed}
- {BPFL off, BPFR off, RHP closed}
- {BPRL off, BPRR off, LLP closed}
- {BPRL off, BPRR off, LHP closed}
- {BPFL off, BPFR off, BPRR off, BPRL off}

The minimal cut sets for the fuel transfer operation mode are:

- {TVFF closed, TVRF closed}
- {TPLT off, TPLB off, TVFF closed}
- {TPRT off, TPRB off, TVRF closed}
- {NVL open 2 way, RPV open, DV open}
- {NVR open 2 way, RPV open, DV open}
- {TPLT off, TPLB off, TPRT off, TPRB off}

The minimal cut sets for the fuel jettison operation mode are:

- {DV closed}
- {LDV closed, RDV closed}
- {BPFL off, BPFR off, RDV closed}
- {BPRL off, BPRR off, LDV closed}
- {BPFL off, BPFR off, BPRL off, BPRR off}

The minimal cut sets for the refuel operation mode are:

- {NVL closed}
- {NVR closed}
- {RVLW closed}

- {RVRW closed}
- {RVFF closed}
- {RVRF closed}

Table 4.3 Component state probability

Component type	Desired state	Component states and their probabilities			
Valve	-	Working Open	Failed Open	Failed Closed	Working Closed
	Working Open	0.998	0.001	0.001	0
	Working Closed	0	0.001	0.001	0.998
Pump	-	Working On	Failed On	Failed Off	Working Off
	Working On	0.990	0.005	0.005	0
	Working Off	0	0.005	0.005	0.990
1D Valve	-	Working (1 way)	Failed open (2 way)	Failed (Closed)	
	Working (1 way)	0.991	0.008	0.001	

In order to be able to detect the faults and diagnose component failures, flow sensors need to be positioned on the system. There are 33 possible sensor locations, which are shown in Figure 4.6, where a sensor is placed next to each component. Note, the sensors do not affect the flow of fuel through the system, only measure the flow of fuel through the system. These sensors are numbered from S1 to S29, with the remaining four sensors numbered, S1a, S12a, S15a and S16a, respectively. These four sensors are positioned next to the secondary pumps in the system, and the corresponding primary pump has a sensor, numbered in the same way, i.e. S1, S12, S15 and S16. For example, the primary pump TPLT has sensor S1 positioned next to it, and the corresponding secondary pump, TPLB, has sensor S1a positioned next to it. The reason for this is presented in the next section of this chapter, section 4.2.

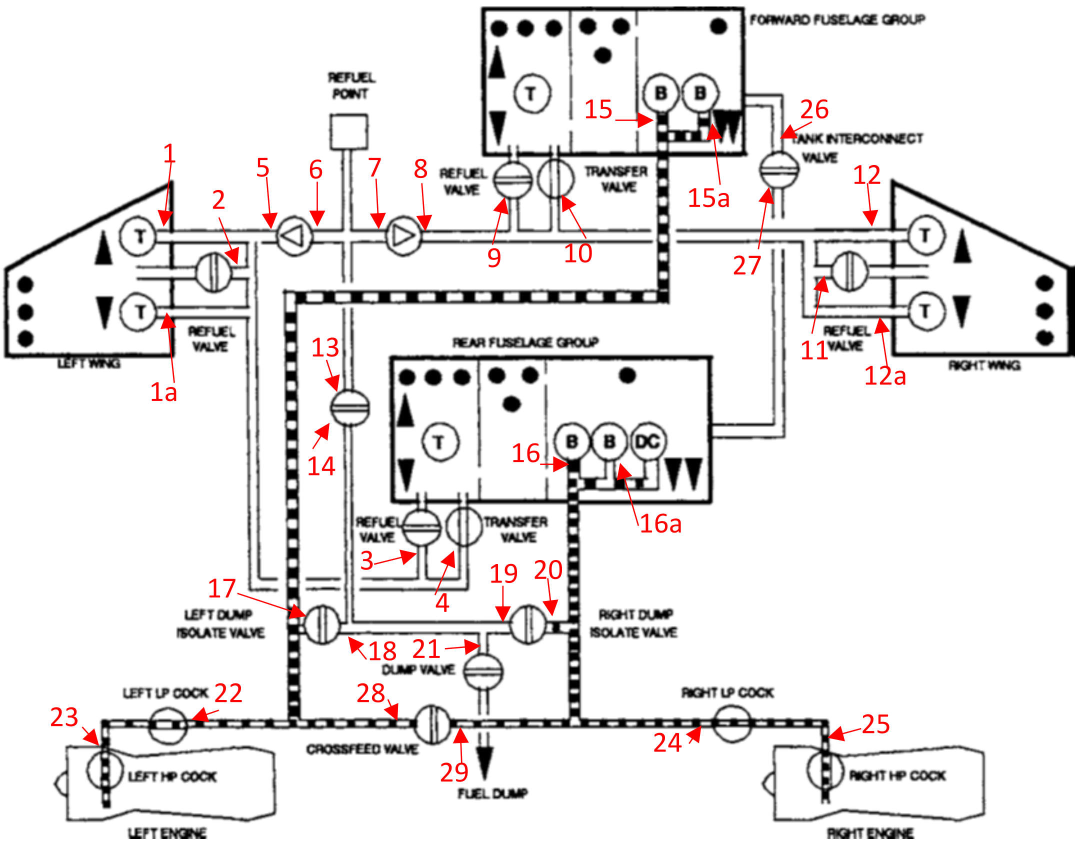


Figure 4.6 Schematic of the fuel system with sensor locations labelled

The state of sensor readings for each of the operation modes are given in Table 4.4. As before, the sensor readings represent the system in a steady state, i.e. when all the effects of the component failures have stabilised. Only the sensor readings for normal operating behaviour have been included in this table, because of the number of different component failures that can occur for this larger system. The sensor readings for all of the individual component failures for the engine feed and the fuel transfer operation modes are presented in Tables D.1 and D.2 in Appendix D, respectively. A full table of all considered component failures (individual failures and combinations of 2 component failures), like the ones presented in Table 3.1 is not given, as there are approximately 1600 combinations per operation mode. As in the simple system example, the pumps supply a standard amount of fuel to the system, “1”, when pipes are empty the sensors read “E”, and when there is no flow of fuel but the pipes have fuel in them the reading is “N”. Note, for valves in the centre of the system, such as NVL, NVR, LDV, and RDV, flow of fuel from the centre outwards is positive, e.g. “1”, and for valve RPV, flow from the top of the schematic downwards is positive, with the opposite being negative in each case, e.g. "-1". The refuel rig is assumed to supply fuel to the system at twice the rate that the pumps supply fuel to the engines. In reality, this value is likely to be significantly higher, but it is assumed to be of this value for simplicity.

Table 4.4 Sensor readings for each operation mode

Operation mode	S1	S1a	S2	S3	S4	S5	S6	S7	S8	S9	S10
Engine feed	E	E	E	E	E	E	E	E	E	E	E
Fuel transfer	1	N	N	N	1	N	E	E	N	N	1
Fuel jettison	E	E	E	E	E	E	E	E	E	E	E
Refuel	N	N	1	1	N	1	1	1	1	1	N

Continued…

Operation mode	S11	S12	S12a	S13	S14	S15	S15a	S16	S16a	S17	S18
Engine feed	E	E	E	E	E	1	N	1	N	N	E
Fuel transfer	N	1	N	E	E	E	E	E	E	E	E
Fuel jettison	E	E	E	E	N	1	1	1	1	-1	-1
Refuel	1	N	N	N	E	E	E	E	E	E	E

Continued…

Operation mode	S19	S20	S21	S22	S23	S24	S25	S26	S27	S28	S29
Engine feed	E	N	E	1	1	1	1	E	E	N	N
Fuel transfer	E	E	E	E	E	E	E	E	E	E	E
Fuel jettison	-1	-1	2	1	1	1	1	E	E	N	N
Refuel	E	E	E	E	E	E	E	E	E	E	E

The sensor readings in Table 4.4, like with Table 3.1, can be determined by considering the supply of fuel to the system from the pumps, and what paths the fuel can and cannot take in order to pass into the tanks or engines. The flow of fuel through each of the sensors is determined, hence producing the sensor readings presented in the table. Information provided by other sensors is not required to determine the sensor readings for each sensor, resulting in the same sensor readings produced by a particular sensor regardless of whether there are other sensors positioned on the system or not.

Also, as in Chapter 3, the sensor readings can be produced automatically by using a model of the system to represent the different component failures that can occur. This model is presented in section 4.3 of this thesis, and it produces the same sensor readings as given in the table, and in Tables D.1 and D.2 from Appendix D.

In the next section a number of simplifications are applied to this system in order to increase the complexity of the system gradually, as the scalability of the methodology is investigated. The discussed simplifications are re-introduced to the system in Chapter 5 in order to demonstrate the scalability of the alternative modelling technique presented in Chapter 5.

4.2. Simplifications

A number of simplifications are applied to the system, the first of which is that two of the system operation modes are removed and no longer considered. The two operation modes that are ignored are the fuel jettison and the refuel operation modes. The fuel jettison operation mode is ignored because it would only be activated in an emergency, and is therefore not very common, and when it is activated, a failure will most likely have already been detected in another operation mode. The refuel operation mode is ignored because in the refuel process it should be possible to detect a problem via the refuel rig. If the refuel rig does not output the expected amount of fuel, it is clear that there has been a component failure, or a failure of the refuel rig. In addition, this failure would occur whilst the aircraft is on the ground, minimising the corresponding risk. Therefore, these two operation modes are not considered for this system as the failures would be detected in other operation modes, or by external sources.

The next simplification that is applied to the system is to ignore the redundant components, outlined in the previous section. These components are the secondary pumps, such as TPLB, TPRB, BPFR, and BPRR, which are off in the two chosen operation modes, and other components that are used to move fuel around the system when there has been a component failure, i.e. TPFF, TPRF, CV, and TIV, are also off (for pumps) or closed (for valves) in the two chosen operation modes. Removing these eight components from the system, considerably reduces the number of combinations of component states that can occur for each operation mode, down to approximately 800 for individual component failures and combinations of two component failures. The redundant components are only used if there has been a related failure in the system, but if they are active when they should not be, it is unlikely that they will have a negative effect on the system. This is because these components are designed to move the fuel around the system when it is not possible to do so normally, and therefore moving fuel around the system using the redundant components as well as the normal components is unlikely to be critical to the systems performance. The only combination that could result in the system being critical is if TIV and either TPFF or TPRF failed, as this could result in the fuel level in one of the fuselages dropping too low to supply fuel to the engine when desired. However, the system could be prevented from becoming critical by opening the cross-feed valve and supplying both engines from the one tank. The reduced set of components is given in Table 4.5, in the same format as Table 4.1. Note, the components are re-numbered.

Table 4.5 Component descriptions for the components in the fuel system

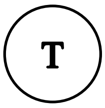
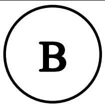
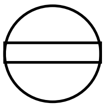
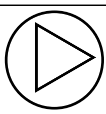
Type	Symbol	Description	Name	Number
Transfer pump		Transfer Pump Left wing Top	TPLT	1
		Transfer Pump Right wing Top	TPRT	2
Booster Pump		Booster Pump Forward fuselage Left	BPFL	3
		Booster Pump Rear fuselage Left	BPRL	4
Valve		Refuel Valve Left Wing	RVLW	5
		Refuel Valve Right Wing	RVRW	6
		Refuel Valve Forward Fuselage	RVFF	7
		Refuel Valve Rear Fuselage	RVRF	8
		Transfer Valve Forward Fuselage	TVFF	9
		Transfer Valve Rear Fuselage	TVRF	10
		Left Dump isolate Valve	LDV	11
		Right Dump isolate Valve	RDV	12
		Dump Valve	DV	13
		Refuel Point Valve	RPV	14
		Left LP cock	LLP	15
		Left HP cock	LHP	16
		Right LP cock	RLP	17
		Right HP cock	RHP	18
1D Valve		One-directional Valve Left	NVL	19
		One-directional Valve Right	NVR	20

Figure 4.7 and Table 4.6, are restatements of Figure 4.5 and Table 4.2 respectively, with the reduced number of components.

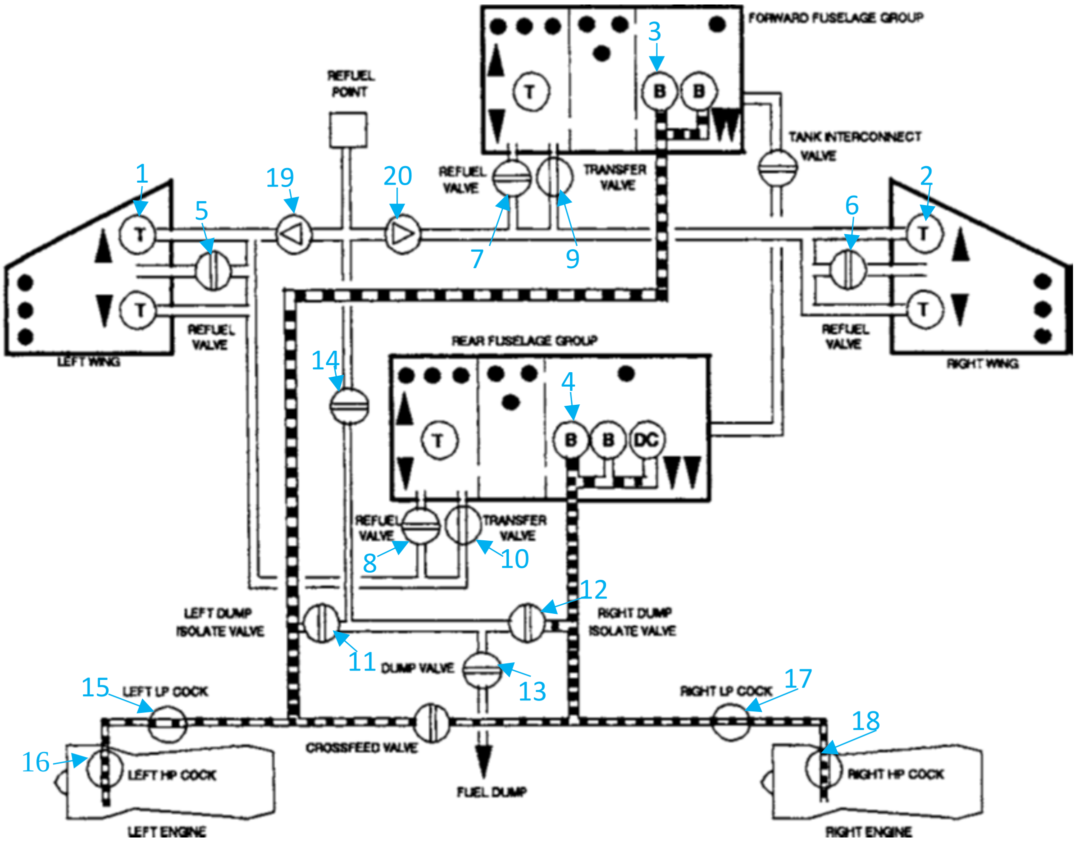


Figure 4.7 Schematic of the fuel system with the components numbered, for the engine feed operation mode

A consequence of reducing the number of components considered in the system is that some sensors are no longer required. This is because some of the sensors will never be able to measure the flow of fuel, they will only measure whether there is fuel in the pipe or not. The sensors that can therefore be removed, are the sensors next to the ignored components, i.e. S1a, S12a, S15a, S16a, S26, S27, S28 and S29. This reduces the number of sensors that can be used on the system from 33 to 25 sensors. The schematic with the reduced number of sensors is given in Figure 4.8. The sensor readings for each of the 25 sensors are the same as those for each operation mode in Table 4.4. This is because none of the removed components are used in normal operating conditions for the chosen operation modes, as previously stated.

Table 4.6 Component working state for each operation mode

Component		Operation mode normal working state	
Name	Number	Engine Feed	Fuel transfer
TPLT	1	Off	On
TPRT	2	Off	On
BPFL	3	On	Off
BPRL	4	On	Off
RVLW	5	Closed	Closed
RVRW	6	Closed	Closed
RVFF	7	Closed	Closed
RVRF	8	Closed	Closed
TVFF	9	Open	Open
TVRF	10	Open	Open
LDV	11	Closed	Closed
RDV	12	Closed	Closed
DV	13	Closed	Closed
RPV	14	Closed	Closed
LLP	15	Open	Open
LHP	16	Open	Open
RLP	17	Open	Open
RHP	18	Open	Open
NVL	19	Open	Open
NVR	20	Open	Open

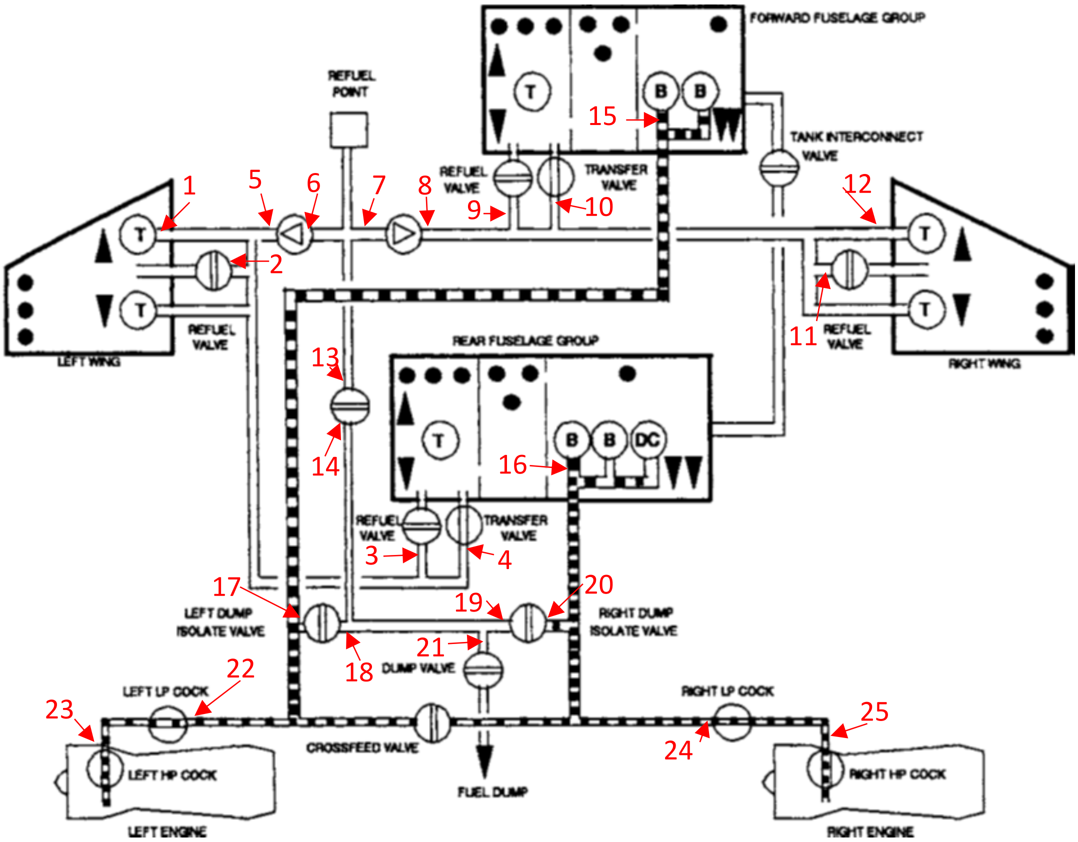


Figure 4.8 Schematic of the fuel system with the sensor locations labelled for the engine feed operation mode

In the next section, a full summary of the assumptions is presented.

4.2.1. Summary of assumptions

- Each component has up to two working states and up to two failure modes. Pumps can supply a fixed quantity of fuel (represented by "1"), (working on or failed on), or supply no fuel, (working off or failed off), and valves can either let all fuel pass through without restriction (i.e. no resistance), (working open or failed open) or let no fuel pass through, (represented by "0"), (working closed or failed closed). One-directional valves can allow flow to pass through in one direction, (working one way), two directions, (failed two way), or not at all, (failed closed). There can be no supply of fuel other than "1" or "0", and no partial blockages of valves are modelled.
- There are two operation modes considered, engine feed and fuel transfer.
- The probabilities of each component being in each state for each operation mode are summarised in Table 4.3.
- Only up to two component failures can occur at the same time, i.e. combinations of three or more component failures are not considered.
- No redundant sections on the system are considered.
- The flow rate of fuel is constant throughout the system, i.e. the same quantity of fuel supplied to the system per time interval must also exit the system via an engine or into a tank per time interval. Therefore, there is no resistance to the flow of fuel by any of the components, connecting pipes or the drain, i.e. the pipes and the drain cannot be blocked.
- When the pipe line splits in two, the fuel will split equally along all the clear lines, i.e. the lines that do not have any blocked valves in them.
- The fuel will exit the system at equal rates through all available paths.
- All sensor readings are measured when the system is operating in the steady state, i.e. the flow of fuel has stabilised after the occurrence of component failures.
- The sensors are perfectly reliable, they cannot fail and they always measure the flow of fuel correctly.
- The sensors can distinguish between the line being empty ("E"), and, therefore, no flow of fuel is present, and also the line being full, but still no flow of fuel ("N").

- System failure is defined as when there is no supply of fuel to either of the engines in the engine feed operation mode, and when there is no transfer of fuel to the fuselage tanks in the fuel transfer operation mode.

The proposed system modelling and sensor selection methodology can now be applied to the system, and will be presented in the following sections.

4.3. Modelling the system

As suggested in section 3.5 of this thesis, a BBN model of the system is produced before the sensor selection process takes place, as the BBN can be used to automate the performance metric calculation. As before, the BBN is constructed using the software, "HUGIN Researcher".

4.3.1. BBN development

The methodology outlined in section 3.3 of this thesis is applied and the complete BBN is given in Figure 4.9.

As the BBN consists of a large number of nodes, it is not possible to view all the relationships between the nodes in one figure, therefore, the relationships between the nodes in the network are presented in Appendix F, Figures F.1 to F.28. The method normally begins by introducing nodes for each of the components in the system. However, in this case, as the component state is dependent on the operation mode of the system, an additional node, which is the parent node of all the component nodes, is required. This node is the "operation mode" node at the top of Figure 4.9. The CPT for the operation mode node can be completed by considering the duration and the criticality of each mode. However, as the system is considered in the two operation modes individually, the values in this CPT do not matter. The CPTs for the component nodes can be completed by using the probabilities given in Table 4.3 for the desired states of the components given in Table 4.6. The CPTs for the components are presented in Tables E.1 – E.5 in Appendix E.

These component nodes can then be connected to several intermediate nodes, which are the next set of nodes to be introduced in to the network. As the system is quite complex, there is a relatively large number of intermediate nodes. The intermediate nodes in this network can be grouped into three groups: exits, supply, and supply per exit. The exits group of intermediate

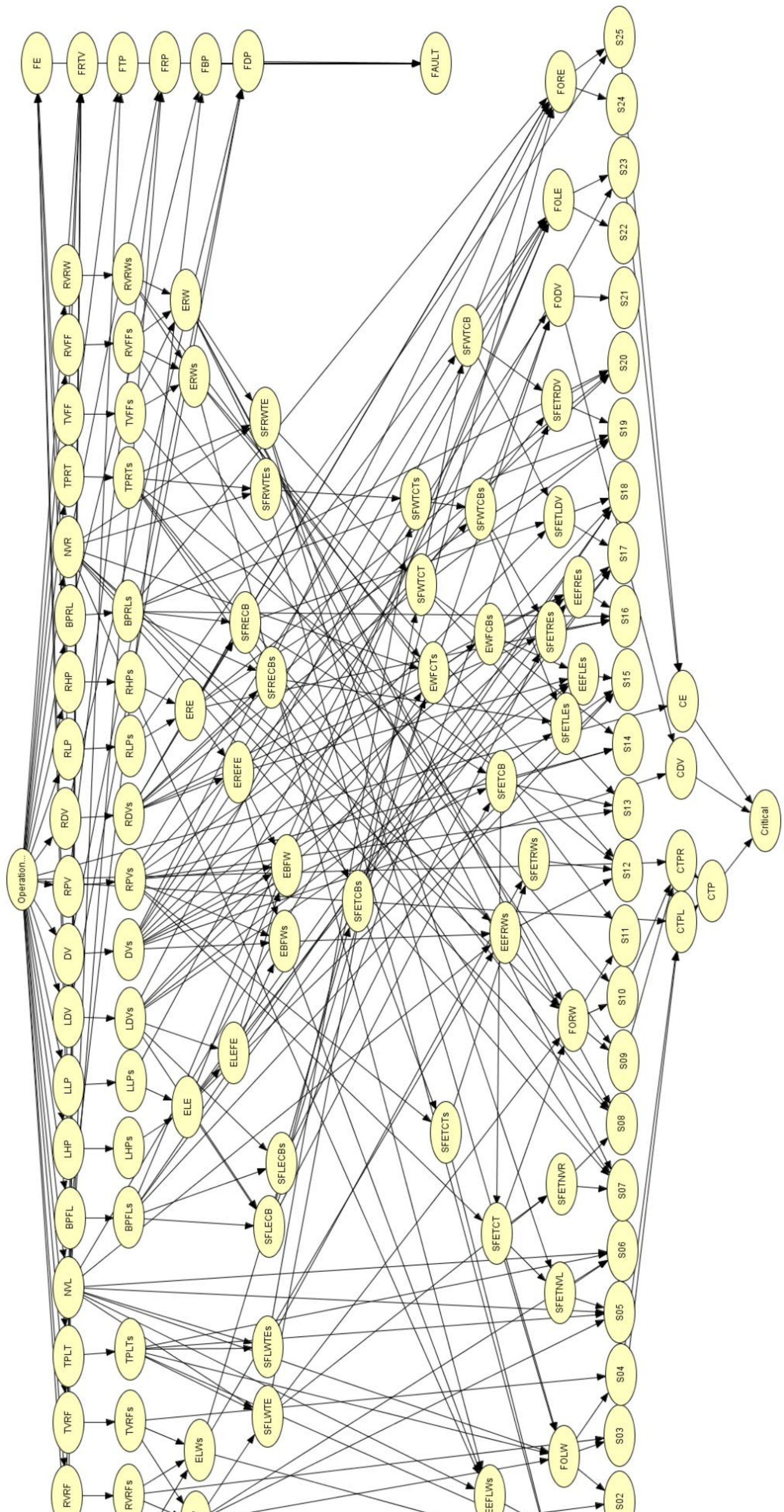


Figure 4.9 BBN of the aircraft fuel system

nodes groups all components that can let fuel pass into one of the tanks, into the engines, or out of the system. There are multiple exit intermediate nodes, one for each section of the system, as well as for combinations of sections of the system grouped together. For example, an intermediate node representing a section of the system is ELE (exit left engine), and an example of an intermediate node that considers a group of sections of the system together is EBFW (exit bottom from wings). This node groups the exits for the engines and the dump valve together, and considers whether RPV is open and fuel from the top of the system can pass through one of the exits. There are multiple supply intermediate nodes, and they consider how much fuel is supplied to the system by the pumps. For example, SFRWTE (supply from right wing to elsewhere) considers whether the fuel supplied from the pumps in the right wing can exit the system elsewhere in the system (i.e. whether the fuel can pass out of the right wing). As with the exit nodes, some of the supply nodes consider supply from multiple sections of the system. An example of one of these nodes is SFWTCT (supply from wings to centre top) and considers whether the fuel in each wing can pass into the centre of the system, i.e. in the area between NVL, NVR and RPV. The final group of intermediate nodes, supply per exit, determines how much fuel is supplied per exit that the fuel can pass through. Therefore, these nodes can be used to determine what the sensor readings are. An example of a node in this group is FOLE (fuel out left engine), which considers the amount of fuel that is in the system, and the number of exits from the system the fuel can pass through. This will, therefore, result in the amount of fuel that is supplied to the left engine. For some sensors, it is not important to know where the supply of fuel is coming from and where else it is exiting the system, just how much fuel is supplied and the number of exits available. For example, for the FOLE node (fuel out left engine), it does not matter which valve the fuel is exiting the system from in the wings, it just matters how many exits there are that the fuel will exit the system (as the fuel splits equally between all available exits). Using this information, the fuel passing through the sensors, and, therefore, the sensor readings, can be determined.

The next step is to introduce nodes for each of the sensors, the row towards the bottom of the figure. These nodes can be connected to the intermediate nodes as required, in order to determine the sensor readings. However, unlike in the example system discussed in Chapter 3 of this thesis, there is a large number of potential sensor readings for each of the sensors. For example, there are 9 exits in the system and a maximum supply of fuel to the system of 4, and therefore any fraction of fuel with a numerator up to 4 and a denominator up to 9 can pass through each of the sensors positioned next to each of the exits. For each possible sensor reading, a state is required for the sensor node. This would, therefore, increase the number of the entries in the CPTs for these sensor nodes dramatically. As a result of this, some of the sensor readings were grouped into ranges. For sensors positioned next to pumps, the flow sensor can measure three readings: “E”, “1”, and “N”, where “1” is the normal amount of fuel to be supplied by a pump, as outlined earlier. For sensors positioned next to valves, the sensor readings are: “E”, “<1” (i.e. the flow of fuel is less than the normal value), “1” (i.e. the normal amount of fuel to pass through the valve), “>1” (i.e. the flow of fuel is greater than the normal value), and “N”. The only exception to this is S21, which has the middle three sensor readings, (<1, 1, and >1) grouped together, as for the considered operation modes, there is no “normal” amount of fuel to pass through the valve as DV should always be closed in the two considered operation modes. Finally, the sensors which are positioned next to valves that can have fuel flowing through in both directions, have the sensor readings, “E”, “+ve” (i.e. all the rates of flow of fuel from the centre of the system outwards, or downwards for S13 and S14 grouped together), “–ve” (i.e. all the rates of flow of fuel inwards towards the centre of the system, or upwards for S13 and S14 grouped together), and “N”. Note, the sensors positioned next to NVL and NVR, fall into this last category as they can fail allowing flow in either direction.

There are two additional sections in this network that were not discussed in the methodology presented in section 3.3 of this thesis. These sections are introduced because in addition to failure diagnostics, this BBN is to be used to calculate the performance metric. The first of these sections is a section that contains nodes to determine whether the system is critical for each combination of component failures, to be used for the calculation of the criticality term of the performance metric. This mode considers the states of each of the components and determines whether the system is critical or not.

The second additional section is a series of fault nodes, which output the probability that there is a fault in the system based on the sensor readings. This can be used during the diagnostics process to check whether there has been a component failure in the system, rather than having to check all the sensor readings for a deviation. These nodes are not required in the network, they are supplementary nodes to make it easier to tell whether there has been a component failure during manual inspection of the network, such as when checking whether the network has been constructed correctly.

4.3.2. Discussion

As in the example system discussed in Chapter 3, the BBN is able to represent the flow of fuel throughout the system. However, in this situation, due to the size of the network, the sensor readings have been grouped into ranges, therefore reducing the accuracy of the model. This process also reduces the accuracy of the fault diagnostic process, illustrated in section 4.5. It is possible to include a state for every sensor reading, but the network would become large.

Even with this grouping of sensor readings, the total number of elements in the CPTs is approximately 80,000, which is comparatively large, as the example system discussed in Chapter 3, which contains 7 components and 11 sensors, has approximately 1400 elements in the CPTs. However, the introduction of intermediate nodes has dramatically reduced the number of elements in the network. For comparison, the same system was modelled independently using significantly fewer intermediate nodes in the network, 10 instead of 63, and the number of elements in the CPTs in this network was approximately 10,000,000. This network is given in Figure 4.10. For clarity, in this section, Figure 4.9 will be referred to as "network A" and Figure 4.10 will be referred to as "network B". In the following sections, network B will not be referred to unless explicitly stated, and therefore, "the network", or "the BBN" will refer to network A.

As with Figure 4.9, the BBN consists of a large number of nodes, and it is therefore not possible to view all the relationships between the nodes in one figure. Therefore, the relationships between the nodes in the network are presented in Appendix F, Figures F.29 to F.33.

Network B in Figure 4.10 consists of 69 nodes, in comparison to the 122 nodes in network A. Network B represents the same system as network A, but instead of multiple levels of intermediate nodes, just one level of intermediate nodes is used in network B, with a few extra intermediate nodes included for specific purposes. If the intermediate nodes in network B are compared to the intermediate nodes in network A, the intermediate nodes, ETS and EBS, are the exits in the top section (i.e. wings and fuselages) and bottom section (i.e. engines and dump valve), respectively. The intermediate node SF considers the supply in the system, and the intermediate node PTC considers the paths along which the fuel can pass through the system. Using these four nodes (and in some cases a couple of component nodes), the fuel passing through any sensor in the system can be determined. These four nodes provide the same information as all the intermediate nodes in network A, but the intermediate nodes in network A are separated into more nodes, in order to consider smaller sections of the system and result in smaller CPTs.

Both networks execute in similar times i.e. the introduction of additional intermediate nodes does not slow the execution of the network. As expected, the networks do take significantly longer to execute than the network for the system discussed in Chapter 3.

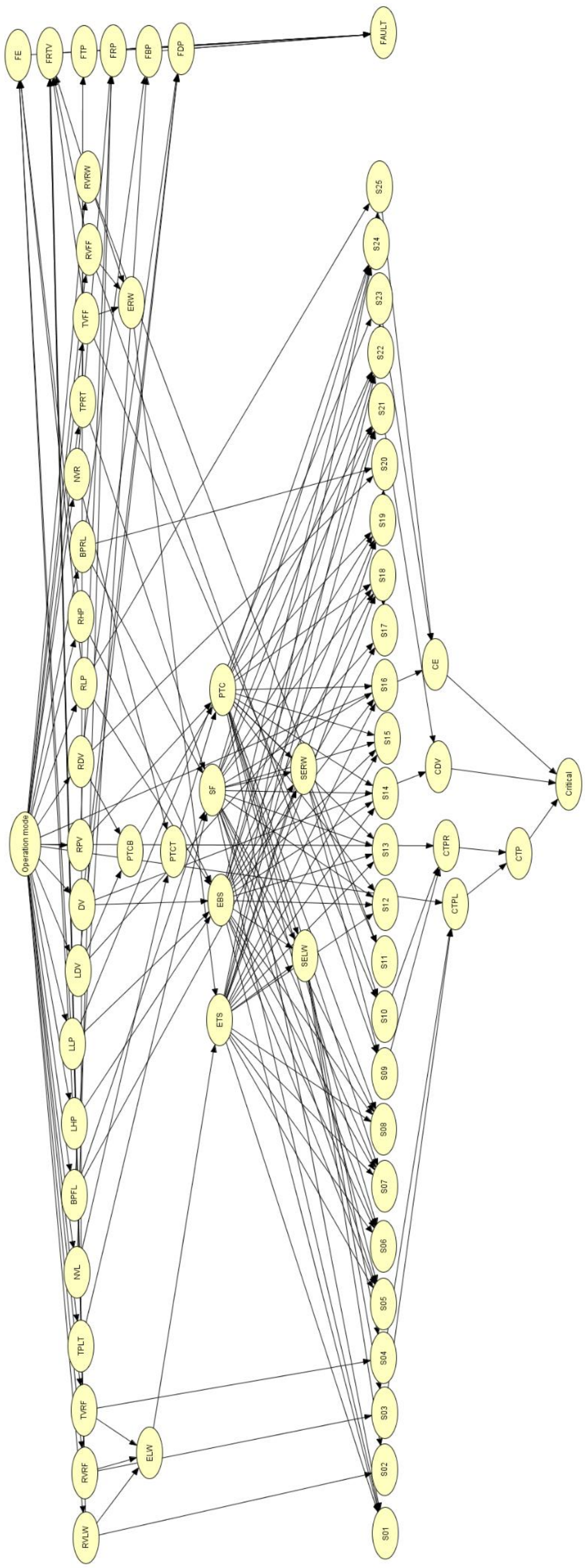


Figure 4.10 BBN of the aircraft fuel system with fewer intermediate nodes

However, this simplified system is still comparatively small for an aircraft fuel system. Therefore, it is likely that the BBN method used to model the system may not be suitable for modelling on significantly larger systems, and an alternative methodology may need to be considered, as discussed in Chapter 5. However, if a BBN is not used to model the system, an alternative fault diagnostic technique will need to be developed, which is also presented in Chapter 5.

4.3.2.1. Verification of the BBN

In order to ensure that the BBN is modelling the system correctly, the network needs to be verified. This is to ensure that the sensor readings are produced correctly for each considered combination of component failures. As the CPTs for each of the nodes are manually entered, and the CPTs contain a lot of elements, it is inevitable that errors arise, often simply due to mistyping. For example, some could have the wrong state selected for the particular set of parent states, or some could have two states selected when only one can be selected.

The verification of the network can be completed using three methods. The first of these methods is to compare the sensor readings produced by the BBN (network A) for each of the combinations of component failures, with the sensor readings produced by network B for the same combination of component failures. If the two sets of sensor readings do not match, then there is an error in one or both of the networks, and the CPTs for the corresponding nodes must be inspected in order to find the errors. Note, the error may be in one of the parent nodes' CPTs, which would then be inspected if an error is not found in the nodes' CPT.

The second verification technique is to introduce evidence to the BBN that the sensor produces a specific reading and then studying the sensor readings of the other sensors in the system. This can highlight errors in the CPTs when combinations of sensor readings occur that are impossible. For example, if sensor S17 indicates fuel is moving through it, i.e. "+ve" or "–ve", but sensor S18 does not, there is an error in the CPTs as they should be the same if there is fuel passing through. Alternatively, if sensor S1 indicates that there is fuel in the pipe, but sensor S2 indicates that there is no fuel in the pipe, there is an error in the CPTs as they are both situated in the same pipe.

The final verification technique is to manually determine what the sensor readings should be for each combination of component failures, and compare them with the sensor readings produced by the BBN for the same combination of component failures.

By applying the three verification techniques, the network should produce the correct sensor readings for each of the considered combinations of component failures and the network can be relied upon for modelling the system. Note, there may be further minor errors in the system that would only become apparent when combinations of three or more component failures are considered, but these should not significantly affect the performance of the model for this application, as these component failures are not considered in this study.

In the next section, the best combination of sensors is selected using the BBN model to automatically calculate the performance metric.

4.4. Sensor selection

As with the example system discussed in Chapter 3, all combinations of one and two component failures are considered for each operation mode. Also as before, a combination with one component failure is defined as one component has definitely failed (the probability of failure is 1), and all other components have definitely not failed (the probability of failure is 0), and a combination with two component failures is defined as two components have definitely failed, and all other components have definitely not failed. No situations with more failures are considered due to their low probability of occurrence and the large number of combinations. The probabilities of each event are equal to the probability of the failed components being in the corresponding failure mode (as shown in Table 4.3), multiplied by the probability of all the other components being in the working state.

As there are a large number of combinations of component failures considered, approximately 800 per operation mode, it is desirable to automate the sensor selection process. Also, as there are significantly more considered sensors, 25 sensors instead of 11 sensors as used on the system in Chapter 3, the number of combinations of sensors is also significantly higher, with approximately 15,000 combinations with 1, 2, 3 and 4 sensors, with it increasing exponentially, (approximately 53,000 combinations with 5 sensors, approximately 177,000 combinations with 6 sensors), after that up until half the maximum number of sensors, where the number of combinations decreases again, according to the formula presented in Equation (4.1), where *r* is the number of sensors selected and *n* is the total number of sensors.

$$\binom{n}{r} = \frac{n!}{r!\,(n-r)!} \tag{4.1}$$

In addition to this, the number of different sensor reading combinations also increases. For example, if there is a combination of three sensors, each with three different sensor readings, the maximum number of different combinations of sensor readings is 27 (3^3). However, if there is a combination of five sensors, each with three sensor readings, the maximum number of different combinations of sensor readings is 243 (3^5), which is a significant increase. Note, it is unlikely that every single possible combination of sensor readings will be produced and, therefore, the actual number of different combinations of sensor readings is lower than this.

Therefore, a C++ script was written in order to automatically produce the sensor readings for all the combinations of component failures used in the BBN, and then use these sensor readings to automatically calculate the performance metric for each combination of sensors. The next section outlines this C++ script.

4.4.1. Automating the sensor selection

The C++ script uses the BBN model of the system in order to determine the sensor readings for component states. To do this, three input text files are required, the first of which is a list of the sensors in the system. It provides the C++ script with the information that it needs to determine which nodes in the network correspond to the sensors in the system. The benefit of using this input file, is that if some sensors are to be omitted for an external reason, such as their reliability or cost, they can be removed from the input file, and no modifications are required in the code. The second input file is a list of the components in the system. It provides the C++ script with the information that it needs to determine which nodes in the network correspond to the components in the system. The final input file is the component state combinations, the states of each of the components for all combinations of considered component failures (one or two failures). There are two versions of this file, one for each operation mode because the working state for some components is different for each operation mode. These files consist of approximately 800 lines, one for each combination of component failures, made up of 20 integer values. Each integer value corresponds to a component, and indicates the state number that the component is in for that combination of component failures. The first line of the component state input files corresponds to the component states when there are no component failures in the system. It is used so that a reference set of sensor readings can be produced, in order to determine whether there is a failure present in the system.

The first step in the C++ script, is to set the operation mode to the desired state, and then to set the states of all the components in the system, using the first line of the component state file, i.e. the working state. The C++ script will then execute the BBN, and the states of all the nodes in the network will be determined. The sensor nodes states are recorded, i.e. the sensor readings are stored in a vector, the state of the criticality node is stored in a vector for the calculation of the criticality term of the performance metric, and the probability of the event is stored in a vector for the calculation of the performance metric. This process can be repeated for all the combinations of component failures, and then repeated for the other operation mode.

The C++ script can then calculate the performance metric. In order to do this, a combination of sensors needs to be selected. The corresponding sensor readings for each combination of component failures can be compared to the first set of sensor readings recorded, i.e. the “no fault” sensor readings. If the sensor readings are different, then the probability of that combination of component failures should be summed with the probability of the other component failures that are detected by the sensors in order to calculate the detection term (Equation (3.1)) of the performance metric. Note, as before, only one sensor needs to have deviated from the “no fault” sensor reading for the component failure to be detected. This should be repeated for all combinations of component failures. The next step is to group the detected combinations of failures into groups of the same sensor readings. The diagnostic term (Equation (3.2)) can then be calculated using the highest probability for each of the combinations of component failures for each combination of sensor readings, and the sum of the probabilities for each of these combinations of sensor readings. Finally, the criticality term (Equation (3.3)) can be calculated by finding the combinations of failures that are critical and comparing these sensor readings to the “no fault” sensor readings. If they are the same then the probability can be summed in order to find the second term in the numerator of the criticality term. The first term in the numerator, (and the denominator), of the criticality term can be calculated by summing the probability of all critical failures. These terms can be used to calculate the criticality term, and therefore calculate the performance metric. This process should be repeated for all considered combinations of component failures.

A number of different criteria can be applied to the sensor selection process via the C++ script. For example, the sensor combination with the highest criticality term can be selected, or the sensor combination with the highest detection term can be selected. Alternatively, the calculation of the performance metric can be stopped after all combinations with the same number of sensors when the desired performance metric has been achieved, i.e. not to continue calculating the performance metric for combinations of sensors with any additional sensors than the combination of sensors that can achieve the desired performance metric.

A flowchart of the sensor selection code is presented in Figure 4.11.

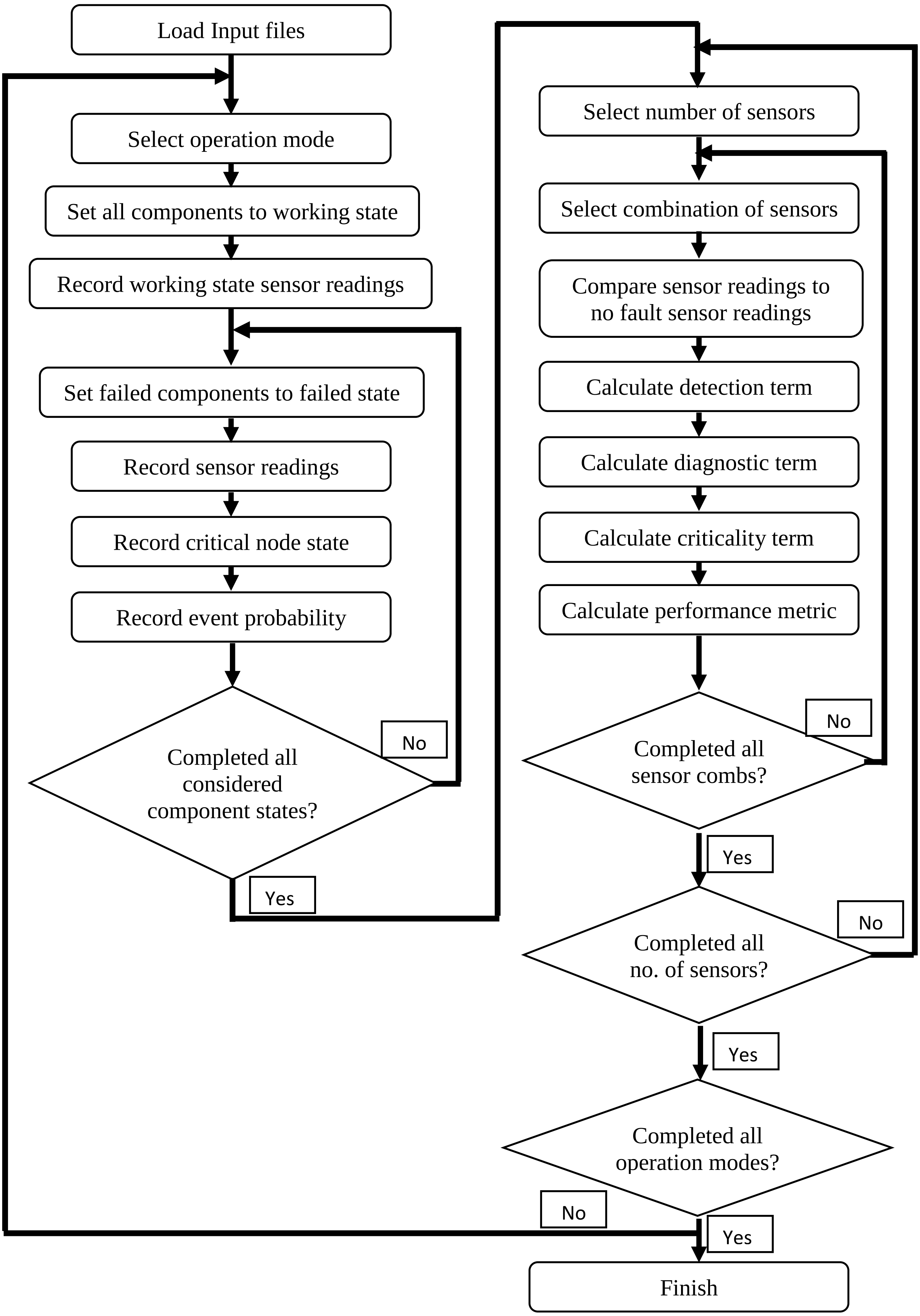


Figure 4.11 Flowchart of the sensor selection code

4.4.2. Sensor selection results

There are some hidden failures in this system, which means that there are some component failures that cannot be detected by any of the sensors in the system. The hidden failures are failures of components that are not used in the selected operation mode, or are components failing in their normal operating state for the selected operation mode. This phenomenon affects the performance metric, as the P_{md} term in the detection term is smaller than the probability of all of the component failures considered in the system. As the hidden failures are different for each operation mode, the P_{md} term is different for each operation mode, 0.0257 for the engine feed operation mode, and 0.0412 for the fuel transfer operation mode. This corresponds to detecting 31.0669% (345/800) and 49.8419% (402/800) of the failures for the engine feed and the fuel transfer operation modes, respectively. These values are calculated using the sum of the probabilities of detected failures, divided by the sum of the probabilities of all considered failures. Note, for both operation modes, all of the critical component failures that are considered in the system can be detected. Also note, if a phased mission was considered, the number of hidden failures would reduce as some of the failures that are hidden in one operation node are observable in the other operation mode. A summary of the hidden failures is presented in Table 4.7.

Table 4.7 Hidden component failure states for each operation mode

Number	Operation mode	Component	Hidden failure
1	Engine Feed	BPFL	On
2	Engine Feed	BPRL	On
3	Engine Feed	RVLW	Open
4	Engine Feed	RVRW	Open
5	Engine Feed	RVFF	Open
6	Engine Feed	RVRF	Open
7	Engine Feed	NVL	2 way
8	Engine Feed	NVR	2 way
9	Engine Feed	TPLT	Off
10	Engine Feed	TPRT	Off
11	Engine Feed	TVFF	Closed
12	Engine Feed	TVRF	Closed
13	Fuel Transfer	TPLT	On
14	Fuel Transfer	TPRT	On

15	Fuel Transfer	LDV	Open
16	Fuel Transfer	RDV	Open
17	Fuel Transfer	BPFL	Off
18	Fuel Transfer	BPRL	Off
19	Fuel Transfer	LLP	Closed
20	Fuel Transfer	LHP	Closed
21	Fuel Transfer	RLP	Closed
22	Fuel Transfer	RHP	Closed
23	Both	TVFF	Open
24	Both	TVRF	Open
25	Both	DV	Open
26	Both	RPV	Open
27	Both	LLP	Open
28	Both	LHP	Open
29	Both	RLP	Open
30	Both	RHP	Open
31	Both	RVLW	Closed
32	Both	RVRW	Closed
33	Both	RVFF	Closed
34	Both	RVRF	Closed
35	Both	LDV	Closed
36	Both	RDV	Closed
37	Both	DV	Closed
38	Both	RPV	Closed
39	Both	NVL	Closed
40	Both	NVR	Closed

The performance metric was calculated using the C++ script for the combination of all sensors on the system, in order to determine the maximum achievable performance metric for each operation mode. This maximum performance metric for the engine feed operation mode is equal to 0.9713, with a detection term of 1, a diagnostic term of 0.9139, and a criticality term of 1, and the maximum performance metric for the fuel transfer operation is equal to 0.9865 with a detection term of 1, a diagnostic term of 0.9595, and a criticality term of 1.

The performance metric for all combinations of sensors, starting at one sensor and gradually increasing by one was calculated until the detection term reached 1, which was achieved for combinations of five sensors for each operation mode. No combinations with more than five sensors were considered, since the number of combinations increases as the number of sensors increases, and the performance metrics are close to the maximum performance metrics. The maximum performance metric for combinations of five sensors is presented in the following paragraphs.

The performance metric for each individual sensor and the terms of the performance metric, for each of the operation mode, are given in Tables 4.8 and 4.9 respectively.

Table 4.8 Ranking of individual sensors for the example aircraft fuel system in the engine feed operation mode

Rank	Sensor	$I_{\{s\}}$	$DE_{\{s\}}$	$DI_{\{s\}}$	$CR_{\{s\}}$
1	S22	0.6829	0.2717	0.7964	0.9806
	S23	0.6829	0.2717	0.7964	0.9806
	S24	0.6829	0.2717	0.7964	0.9806
	S25	0.6829	0.2717	0.7964	0.9806
2	S15	0.6764	0.2716	0.7964	0.9612
	S16	0.6764	0.2716	0.7964	0.9612
3	S17	0.6103	0.1944	0.9288	0.7076
	S20	0.6103	0.1944	0.9288	0.7076
4	S5	0.3775	0.1959	0.9365	0
	S8	0.3775	0.1959	0.9365	0
5	S4	0.3753	0.1959	0.9300	0
	S10	0.3753	0.1959	0.9300	0
6	S1	0.3750	0.1959	0.9291	0
	S12	0.3750	0.1959	0.9291	0
7	S2	0.3728	0.1959	0.9226	0
	S3	0.3728	0.1959	0.9226	0
	S9	0.3728	0.1959	0.9226	0
	S11	0.3728	0.1959	0.9226	0
8	S6	0.3263	0.0030	0.9760	0
	S7	0.3263	0.0030	0.9760	0
9	S14	0.1930	0.0773	0.4638	0.0388
	S18	0.1930	0.0773	0.4638	0.0388
	S19	0.1930	0.0773	0.4638	0.0388
	S21	0.1930	0.0773	0.4638	0.0388
10	S13	0.1677	0.0030	0.5000	0

Table 4.9 Ranking of individual sensors for the example aircraft fuel system in the fuel transfer operation mode

Rank	Sensor	$I_{\{s\}}$	$DE_{\{s\}}$	$DI_{\{s\}}$	$CR_{\{s\}}$
1	S4	0.8119	0.5737	0.8620	1.0000
	S10	0.8119	0.5737	0.8620	1.0000
2	S5	0.7589	0.5023	0.9400	0.8344
	S8	0.7589	0.5023	0.9400	0.8344
3	S1	0.6916	0.1450	0.9299	1.0000
	S12	0.6916	0.1450	0.9299	1.0000
4	S2	0.6377	0.1443	0.9345	0.8344
	S3	0.6377	0.1443	0.9345	0.8344
	S9	0.6377	0.1443	0.9345	0.8344
	S11	0.6377	0.1443	0.9345	0.8344
5	S6	0.4413	0.3843	0.9397	0
	S7	0.4413	0.3843	0.9397	0
6	S23	0.3506	0.1210	0.9307	0
	S25	0.3506	0.1210	0.9307	0
7	S15	0.3503	0.1211	0.9298	0
	S16	0.3503	0.1211	0.9298	0
	S22	0.3503	0.1211	0.9298	0
	S24	0.3503	0.1211	0.9298	0
8	S17	0.3500	0.1211	0.9289	0
	S20	0.3500	0.1211	0.9289	0
9	S13	0.2841	0.3843	0.4680	0
10	S14	0.1027	0.0006	0.3076	0
	S18	0.1027	0.0006	0.3076	0
	S19	0.1027	0.0006	0.3076	0
	S21	0.1027	0.0006	0.3076	0

The combinations of sensors with the highest performance metric for combinations of five sensors are also given in Tables 4.10 and 4.11 for the engine feed, and the fuel transfer operation modes respectively. Note, all combinations in each of the tables have the same performance metric. The performance metric for the engine feed operation mode is 0.9468, with a detection term of 1, a diagnostic term of 0.8405, and a criticality term of 1. The performance metric for the fuel transfer operation mode is 0.9773, with a detection term of 0.9982, a diagnostic term of 0.9337, and a criticality term of 1. The highest performance metric for the fuel transfer operation mode, does not have a detection term of 1, which can be achieved by some combinations of five sensors. However, for these combinations, the performance metric is 0.9706, with a detection term of 1, a diagnostic term of 0.9117, and a criticality term of 1, and is less than the maximum performance metric that can be achieved using five sensors. These combinations are given in Table 4.12.

Table 4.10 Combinations of five sensors with the highest performance metric for the engine feed operation mode, I = 0.9468, DE = 1, DI = 0.8405, CR = 1

Sensors	Sensors continued
S1 S10 S14 S22 S24	S4 S12 S14 S22 S24
S1 S10 S14 S22 S25	S4 S12 S14 S22 S25
S1 S10 S14 S23 S24	S4 S12 S14 S23 S24
S1 S10 S14 S23 S25	S4 S12 S14 S23 S25
S1 S10 S15 S18 S24	S4 S12 S15 S18 S24
S1 S10 S15 S18 S25	S4 S12 S15 S18 S25
S1 S10 S15 S21 S24	S4 S12 S15 S21 S24
S1 S10 S15 S21 S25	S4 S12 S15 S21 S25
S1 S10 S16 S19 S22	S4 S12 S16 S19 S22
S1 S10 S16 S19 S23	S4 S12 S16 S19 S23
S1 S10 S16 S21 S22	S4 S12 S16 S21 S22
S1 S10 S16 S21 S23	S4 S12 S16 S21 S23
S1 S10 S18 S22 S24	S4 S12 S18 S22 S24
S1 S10 S18 S22 S25	S4 S12 S18 S22 S25
S1 S10 S18 S23 S24	S4 S12 S18 S23 S24
S1 S10 S18 S23 S25	S4 S12 S18 S23 S25
S1 S10 S19 S22 S24	S4 S12 S19 S22 S24
S1 S10 S19 S22 S25	S4 S12 S19 S22 S25
S1 S10 S19 S23 S24	S4 S12 S19 S23 S24
S1 S10 S19 S23 S25	S4 S12 S19 S23 S25
S1 S10 S21 S22 S24	S4 S12 S21 S22 S24
S1 S10 S21 S22 S25	S4 S12 S21 S22 S25
S1 S10 S21 S23 S24	S4 S12 S21 S23 S24
S1 S10 S21 S23 S25	S4 S12 S21 S23 S25

Table 4.11 Combinations of five sensors with the highest performance metric for the fuel transfer operation mode, I = 0.9773, DE = 0.9982, DI = 0.9337, CR = 1

Sensors	Sensors continued
S2 S4 S10 S15 S16	S4 S9 S10 S15 S16
S2 S4 S10 S15 S24	S4 S9 S10 S15 S24
S2 S4 S10 S16 S22	S4 S9 S10 S16 S22
S2 S4 S10 S22 S24	S4 S9 S10 S22 S24
S3 S4 S10 S15 S16	S4 S10 S11 S15 S16
S3 S4 S10 S15 S24	S4 S10 S11 S15 S24
S3 S4 S10 S16 S22	S4 S10 S11 S16 S22
S3 S4 S10 S22 S24	S4 S10 S11 S22 S24

Table 4.12 Combinations of five sensors with the highest performance metric for the fuel transfer operation mode that detects all of the component failures, I = 0.9706, DE = 1, DI = 0.9117, CR = 1

Sensors	Sensors continued
S4 S6 S10 S15 S16	S4 S7 S10 S15 S16
S4 S6 S10 S15 S24	S4 S7 S10 S15 S24
S4 S6 S10 S16 S22	S4 S7 S10 S16 S22
S4 S6 S10 S22 S24	S4 S7 S10 S22 S24

In the next section, a discussion on the selections of sensors is presented.

4.4.3. Discussion

A conclusion that was made earlier in Chapter 3 can also be confirmed by the work completed on this system. It is better to consider the three terms individually rather than the overall performance metric for the final selection of sensors. In Table 4.8 for the engine feed operation mode, the individual sensors ranked 8th, S6 and S7, have a performance metric significantly higher than the five sensors ranked lower, despite detecting significantly fewer component failures (*DE* = 0.0030) than four of these other sensors (*DE* = 0.0773), with the fifth sensor detecting the same number of failures. The reason the performance metric is higher for these two sensors is that the diagnostic term is nearly 1, (*DI* = 0.9760), the highest of all individual sensors for the engine feed operation mode. It makes the performance metric, which is an average of the three terms, higher than the other five sensors with a lower diagnostic term, therefore, the results can be misleading. This is also evident by the combinations of five sensors for the fuel transfer operation mode, when the combinations of sensors (Table 4.11) that have the highest performance metric do not have the maximum detection term, but other combinations of sensors (Table 4.12) which have a lower performance metric, do have the maximum detection term. As the difference between the performance metrics in these two cases is relatively small, the analyst may decide to select one of the combinations of sensors that can detect all of the component failures, i.e. $DE = 1$, and, therefore, sacrifice some of the ability to diagnose component failures, i.e. to have a lower diagnostic term. Note, this is the case in the work presented in this chapter.

Also, as was the case for the example system discussed in the previous chapter, it is generally better to select sensors from different parts of the system, i.e. not in close proximity to each other. Although the performance metric for all combinations of two sensors are not provided in this thesis for brevity, for illustration consider the combinations of two sensors with the highest performance metric for the engine feed operation mode: (S22, S24), (S22, S25), (S23, S24), and (S23, S25). The performance metric in this case is equal to 0.7810, an increase of 0.0981 (from 0.6829 in Table 4.8) over each of the individual sensors. Each of these pairs contains a sensor near each engine. However, if other combinations are considered, such as, (S22, S23), and (S24, S25), i.e. both sensors are near the same engine, the increase in the performance metric is 0.0439, i.e. it is a significantly smaller increase than the one from the combinations of sensors with one sensor near each engine. In this situation, the increase in performance metric for the four sensor combinations above, (S22, S24), (S22, S25), (S23, S24), and (S23, S25), comes from an increase in all three of the terms (but mainly the detection term), from 0.2717 to 0.5416 for the detection term, from 0.7964 to 0.8014 for the diagnostic term and from 0.9806 to 1 for the criticality term, respectively. However, the increase in the performance metric for the other too sensor combinations, (S22, S23), and (S24, S25), comes from the increase in the diagnostic term only, from 0.7964 to 0.9282, with the other two terms staying exactly the same as for the individual sensors, (S22), (S23), (S24), and (S25). This smaller increase for the two sensor combinations, (S22, S23), and (S24, S25), is in line with a proposed rule that it is generally better to select sensors in different sections of the system, than to select sensors in close proximity.

The 25 sensors can be grouped into six sections based on their location on the system, and these groups are given in Table 4.13. Each section of the system is separated by a valve in the system, either NVL, NVR, LDV, RDV, or RPV. The six sections are labelled in Figure 4.12.

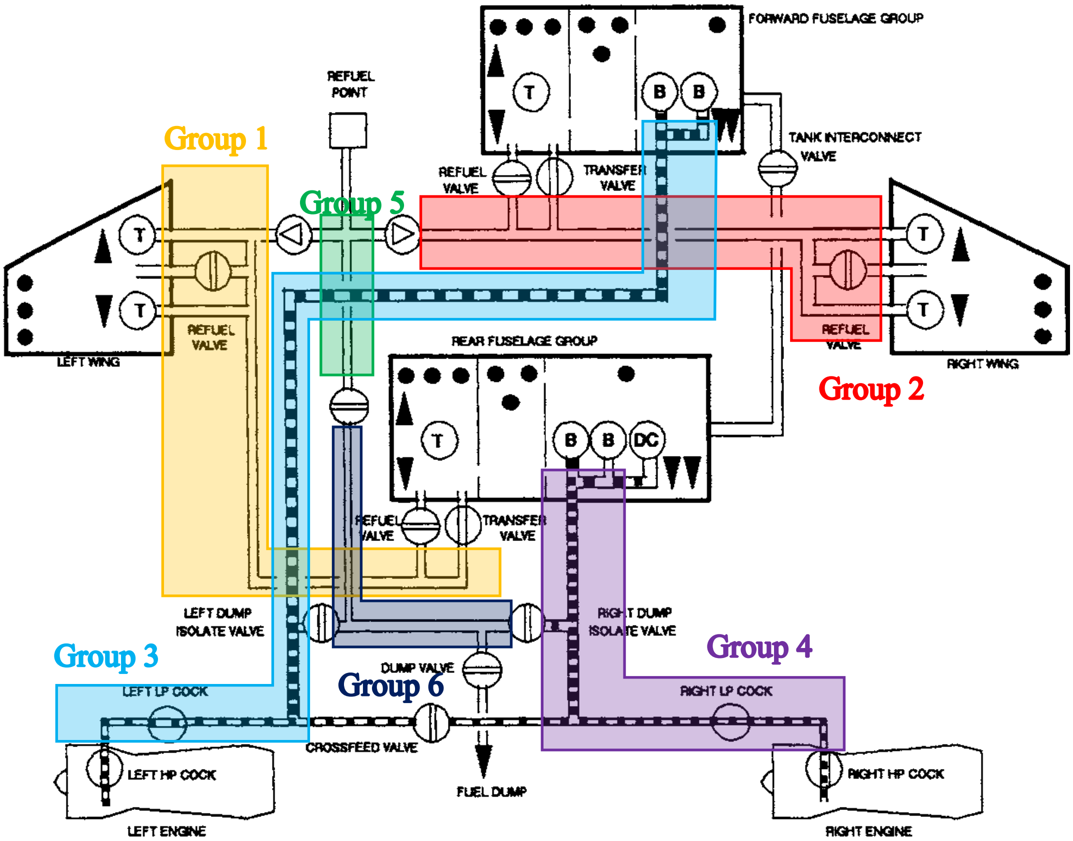


Figure 4.12 Sections of the system labelled

Each of the combinations of five sensors that can detect all the component failures given in Tables 4.10 and 4.12, contains one sensor from five of the six sections of the system. For both operation modes, the combinations of sensors each consist of a sensor from one of the four corner sections of the system, groups 1, 2, 3, and 4, and a sensor from either group 6 or group 5, for the engine feed and fuel transfer operation modes respectively. For example, the first combination of sensors in Table 4.10 is the sensor combination (S1, S10, S14, S22, S24), which are sensors from groups 1, 2, 6, 3, and 4, respectively, and the first combination of sensors in Table 4.12 is the sensor combination (S4, S6, S10, S15, S16), which are sensors from groups 1, 5, 2, 3, and 4, respectively.

There, are however, in all but group 6, sensors that are not included in any of the combinations of sensors, given in Table 4.10 and 4.12, for either operation mode. This is because for each operation mode, there is another sensor in the same section of the system that would result in a higher performance metric for the combination of sensors. The sensors that are not selected also have lower individual performance metrics than the selected sensors in the groups. It also suggests that it is better to select sensors in different parts of the system than from the same part of the system, as discussed before. The combinations of sensors for each operation mode are not the same, with the sensors in groups 1 and 2 different for each operation mode, either S1 and S10 or S4 and S12, for the engine feed operation mode, and S4 and S10 for the fuel transfer operation mode. Another way the combinations of sensors for each operation mode is different is that in the engine feed operation mode the combination has a sensor from group 6, but the fuel transfer mode has a sensor from group 5. In each case, this is the group that is in closer proximity to the sections of the system that are operational in each operation mode. It means that the best combination of sensors for both operation modes cannot be selected by looking at the values of the performance metrics as calculated by the C++ script. In order to select the best combination of sensors, the duration of each operation mode and its importance to the operation of the system needs to be considered. It would require the information on an example mission for the system to be considered. Note, this is considered in Chapter 6. As the system is considered in a steady state, a fixed point in time condition, the two operation modes, and therefore two sensor selections, are considered individually, where one combination of sensors from Table 4.10, and one combination of sensors from Table 4.12, will be used to diagnose component failures in the corresponding operation mode.

For simplicity, the first combination of sensors is selected from each table, i.e. (S1, S10, S14, S22, S24), and (S4, S6, S10, S15, S16), respectively.

Table 4.13 The sensors grouped by the sections of the system

Group	Included sensors				Not included sensors		
1	S1	S4			S2	S3	S5
2	S10	S12			S8	S9	S11
3	S15	S22	S23		S17		
4	S16	S24	S25		S20		
5	S6	S7			S13		
6	S14	S18	S19	S21			

One major observation from this application of the methodology, is the fact that the sensors cannot detect all of the failures that can occur on the system, only approximately 31% and 50% for the two operation modes, respectively, (as shown in section 4.4.2). However, it is because the remaining failures have no effect on the system performance, and therefore do not produce any symptoms. This is because either a particular component has failed in the state it is supposed to be in, such as failed open for a valve that should be open, or that a particular component is in a section of the system which is not in use in this operation mode. Therefore, in the current selection of the type and location of sensors there is no way that these component failures can be observed by any of the sensors considered on the system. It is, therefore, not a shortfall of the proposed methodology, the component failures are not observable.

As discussed before, there are diminishing returns when the number of sensors is increased. The performance metrics for a larger number of selected sensors increases by a smaller amount, as each additional sensor is introduced to the system. As before, it adds to the motivation to find the balance between the cost of additional sensors in the system, and the benefit that they add to the detection of fault, and the diagnostics of failures on the system. The performance metrics for the best combination including up to five sensors is given for each operation mode in Table 4.14. Note, only one combination of sensors is given for each number of sensors, with multiple combinations having the same performance metric. The final row in the table presents the maximum performance metric achievable for all sensors on the system. The diminishing return for each additional sensor can be observed in the % difference columns for each operation mode.

Table 4.14 Best performance metric for each number of sensors

	Engine feed			Fuel transfer		
Number	Sensors	$I_{\{s\}}$	% diff.	Sensors	$I_{\{s\}}$	% diff.
1	S22	0.6829	0	S4	0.8119	0
2	S22 S24	0.7810	14.37	S4 S10	0.8831	8.77
3	S5 S22 S24	0.8594	10.04	S4 S10 S15	0.9268	4.95
4	S1 S10 S22 S24	0.9313	8.37	S4 S10 S15 S16	0.9696	4.62
5	S1 S10 S14 S22 S24	0.9468	1.66	S2 S4 S10 S15 S16	0.9773	0.79
25	All sensors	0.9713	2.59	All sensors	0.9865	0.94

In the next section, the automation of the fault diagnostics process will be introduced, and applied to the system using the sensors selected for each operation mode.

4.5. Fault diagnostics

The selected sensors for fault diagnostics are the first combination of five sensors from Tables 4.10 and 4.12 for the engine feed and fuel transfer operation mode, respectively, i.e. for the engine feed operation mode the selected sensors are (S1, S10, S14, S22, S24) and for the fuel transfer operation mode the selected sensors are (S4, S6, S10, S15, S16). In order to show the effectiveness of the selected sensors, they can be used in the BBN to diagnose the component failures in the system. For each operation mode, each of the combinations of component failures used to calculate the performance metrics are used as example failures to test the fault diagnostic process. Note, as discussed before, there are some component failures that cannot be detected, and therefore cannot be diagnosed for each operation mode. This results in the maximum percentage of component failures that can be detected of approximately 31% and 50%, for the engine feed and fuel transfer operation modes respectively. The fault diagnostic technique is demonstrated by inputting sensor readings corresponding to a component failure and comparing the diagnosed component failure to the actual component failure. This results in all of the component failures being diagnosed. In order to diagnose the combinations of component failures, a C++ script was written to automate the fault diagnostic process.

4.5.1. Automating the fault diagnostics

As in the sensor selection script described in section 4.4.1, this C++ script integrates with the BBN model of the system to get the desired information on the state of each component. As before, three input files are introduced to the script, an input file that contains a list of components, and an input file that contains a list of selected sensors, and the final input file contains the sensor readings for the selected sensors for each of the combinations of component failures.

As before, the first step in the C++ script is to choose the operation mode. The first line of the sensor readings file (the sensor readings for the first combination of component failures) can then be introduced to the nodes, corresponding to sensors, and the BBN can be compiled, as before. The script can then check the probability of each state for each component and output them to a text file. The script also determines which components are more likely to be in one of the failure modes than in the working state, and also outputs this information to a text file. The components that are more likely to be in one of the failure modes are the components that are predicted to have failed, and caused deviations in sensor readings. Therefore, if a component failure is detected, the C++ script will output the most likely component failure to have occurred. This process can be repeated for each of the failures, before repeating the whole process with the other operation mode.

Note, that the reason that the third input file contains the sensor readings for multiple combinations of component failures, is in order to verify that the fault diagnostic process can be used for multiple different combinations of component failures. If the fault diagnostic process was to be used on a real system, only one combination of sensor readings would be introduced, those observed on the system, and the component failure would be diagnosed so that the appropriate action can be taken on the real system.

A flowchart of the fault diagnostics code is presented in Figure 4.13.

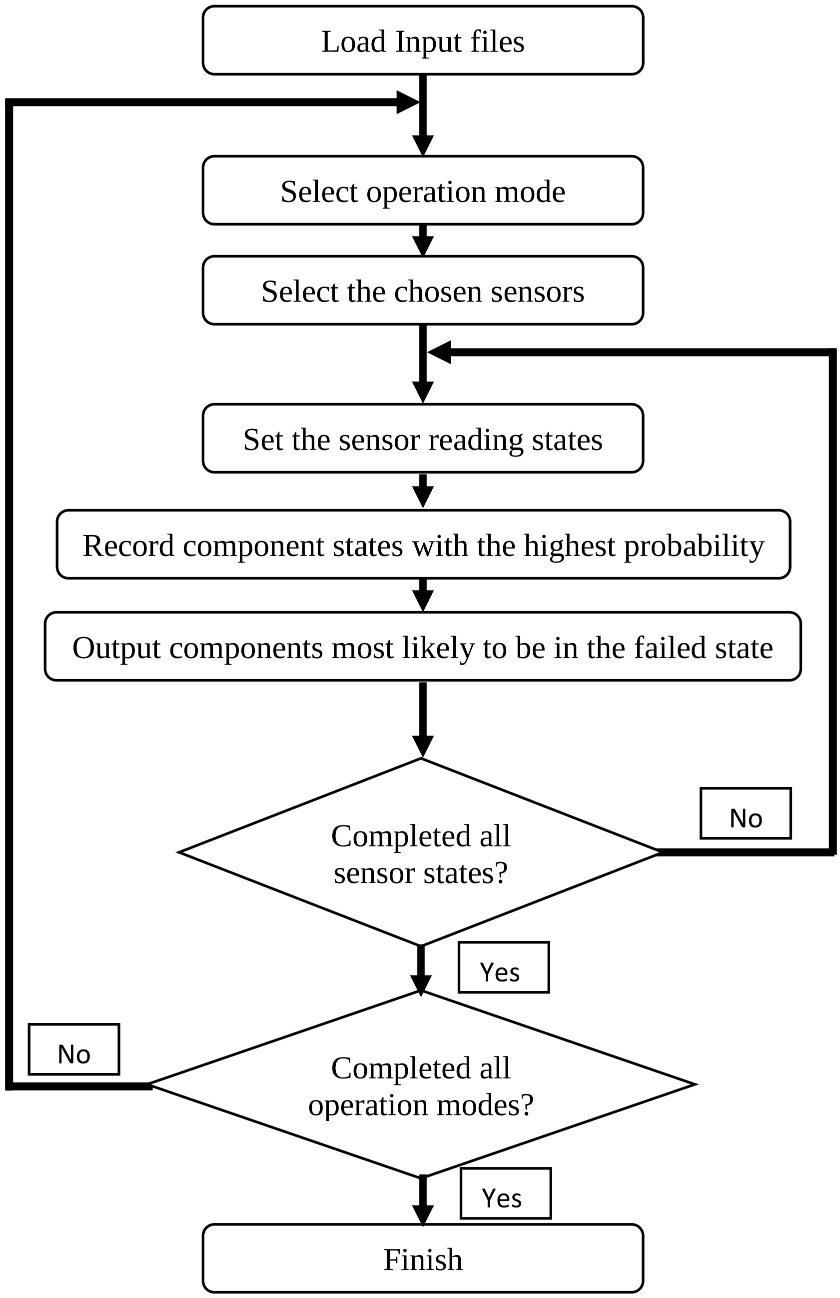


Figure 4.13 Flowchart for fault diagnostics code

4.5.2. Fault diagnostics results

Each of the combinations of component failures used to calculate the sensor performance metric are used to test the diagnostic process, i.e. 800 per operation mode. The results of each of these combinations can be grouped together into cases which consist of combinations of component failures that have the same effect on the system. There are 12 cases for the engine feed operation mode and 16 cases for the fuel transfer operation mode. The cases are presented in Tables 4.15 and 4.16 for the engine feed, and fuel transfer operation modes, respectively. As there are two failure modes for each component, the bracketed word in these tables indicates the mode that the component has failed in, for example, TPLT (On) represents TPLT failed on. Note, (Off) represents failed off, (Op) represents failed open, (Cl) represents failed closed, and (2 way) represents the one directional valve allowing the flow through in both directions.

In the two tables, all of the combinations of component failures are not given, as there are 345 and 402 combinations of component failures that are detected for each operation mode, respectively, and the higher number of combinations for the fuel transfer operation mode results in the higher number of cases. One of each set of failure combinations within each case is presented. For example, in case 3 of Table 4.15, there are multiple combinations of component failures where there are two component failures in the system where one of them is TPLT failed on and the other is not diagnosed, and therefore, rather than stating TPLT failed on multiple times, only one example is given. The number of component failures that each case represents is given in the third column of the tables. The second column in the tables, for example, 1 of 2, represents the number of component failures that are diagnosed (i.e. 1) of the number of component failures in the event considered (i.e. 2).

The accuracy of the diagnostics for each case is discussed after the tables for each operation mode. Note, in the discussion of each of the cases in the table below, when the confidence is approximately 50%, this means that there are two potential component failures that could have caused the sensor reading and are equally likely to have occurred. It is also possible that both of the component failures have occurred, but this situation is discussed in more detail during individual cases.

Table 4.15 Diagnostics of component failures for the engine feed operation mode

Case	Number Diagnosed	Number Represented	Diagnosed failure 1	Probability	Diagnosed failure 2	Probability	Diagnosed failure 3	Probability	Diagnosed failure 4	Probability
1	1 of 1	1	TPLT (On)	100%						
		1	TPRT (On)	100%						
		1	BPFL (Off)	100%						
		1	BPRL (Off)	100%						
2	1 of 1	2	LDV (Op)	50.0025%	RDV (Op)	50.0025%				
		2	LLP (Cl)	50.0025%	LHP (Cl)	50.0025%				
		2	RLP (Cl)	50.0025%	RHP (Cl)	50.0025%				
3	1 of 2	27	TPLT (On)	100%						
		25	TPRT (On)	100%						
		29	BPFL (Off)	100%						
		29	BPRL (Off)	100%						
4	1 of 2	52	LDV (Op)	50.0025%	RDV (Op)	50.0025%				
		56	LLP (Cl)	50.0025%	LHP (Cl)	50.0025%				
		56	RLP (Cl)	50.0025%	RHP (Cl)	50.0025%				
5	2 of 2 (one delayed)	2	BPFL (Off)	100%	LLP (Cl)	50.0025%	LHP (Cl)	50.0025%		
		2	BPRL (Off)	100%	RLP (Cl)	50.0025%	RHP (Cl)	50.0025%		
6	1 of 2 (one incorrect)	2	LDV (Op)	50.0025%	RDV (Op)	50.0025%				
		2	LLP (Cl)	50.0025%	LHP (Cl)	50.0025%				

Case	Number Diagnosed	Number Represented	Diagnosed failure 1	Probability	Diagnosed failure 2	Probability	Diagnosed failure 3	Probability	Diagnosed failure 4	Probability
		2	RLP (Cl)	50.0025%	RHP (Cl)	50.0025%				
7	2 of 2	1	RPV (Op)	100%	LDV (Op)	100%				
		1	RPV (Op)	100%	RDV (Op)	100%				
		1	DV (Op)	100%	LDV (Op)	100%				
		1	DV (Op)	100%	RDV (Op)	100%				
		1	BPRL (Off)	100%	LDV (Op)	100%				
		1	BPFL (Off)	100%	RDV (Op)	100%				
		1	BPFL (Off)	100%	BPRL (Off)	100%				
		1	TPLT (On)	100%	TPRT (On)	100%				
		1	TVRF (Cl)	100%	TPLT (On)	100%				
		1	TVFF (Cl)	100%	TPRT (On)	100%				
		1	BPFL (Off)	100%	TPLT (On)	100%				
		1	BPFL (Off)	100%	TPRT (On)	100%				
		1	BPRL (Off)	100%	TPLT (On)	100%				
		1	BPRL (Off)	100%	TPRT (On)	100%				
8	2 of 2 (one delayed)	1	BPFL (Off)	100%	LDV (Op)	50.0025%	RDV (Op)	50.0025%		
		1	BPRL (Off)	100%	RDV (Op)	50.0025%	LDV (Op)	50.0025%		

Case	Number Diagnosed	Number Represented	Diagnosed failure 1	Probability	Diagnosed failure 2	Probability	Diagnosed failure 3	Probability	Diagnosed failure 4	Probability
9	2 of 2	1	TPLT (On)	100%	NVL (2 way)	99.9999%				
		1	TPRT (On)	100%	NVR (2 way)	99.9999%				
10	2 of 2	1	LLP (Cl)	50.0025%	LHP (Cl)	50.0025%				
		1	RLP (Cl)	50.0025%	RHP (Cl)	50.0025%				
		1	LDV (Op)	50.0025%	RDV (Op)	50.0025%				
11	2 of 2	4	LLP (Cl)	50.0025%	LHP (Cl)	50.0025%	RLP (Cl)	50.0025%	RHP (Cl)	50.0025%
		4	LLP (Cl)	50.0025%	LHP (Cl)	50.0025%	LDV (Op)	50.0025%	RDV (Op)	50.0025%
		4	RLP (Cl)	50.0025%	RHP (Cl)	50.0025%	LDV (Op)	50.0025%	RDV (Op)	50.0025%
12	2 of 2	2	BPRL (Off)	100%	LLP (Cl)	50.0025%	LHP (Cl)	50.0025%		
		2	BPFL (Off)	100%	RLP (Cl)	50.0025%	RHP (Cl)	50.0025%		
		2	TPLT (On)	100%	LLP (Cl)	50.0025%	LHP (Cl)	50.0025%		
		2	TPLT (On)	100%	RLP (Cl)	50.0025%	RHP (Cl)	50.0025%		
		2	TPLT (On)	100%	LDV (Op)	50.0025%	RDV (Op)	50.0025%		
		2	TPRT (On)	100%	LLP (Cl)	50.0025%	LHP (Cl)	50.0025%		
		2	TPRT (On)	100%	RLP (Cl)	50.0025%	RHP (Cl)	50.0025%		
		2	TPRT (On)	100%	LDV (Op)	50.0025%	RDV (Op)	50.0025%		
		2	TPRT (On)	100%	RVRW (Op)	50.0025%	RVFF (Op)	50.0025%		

Table 4.16 Diagnostics of component failures for the fuel transfer operation mode

Case	Number Diagnosed	Number Represented	Diagnosed failure 1	Probability	Diagnosed failure 2	Probability	Diagnosed failure 3	Probability	Diagnosed failure 4	Probability
1	1 of 1	1	NVL (2 way)	100%						
		1	NVR (2 way)	100%						
		1	TVFF (Cl)	100%						
		1	TVRF (Cl)	100%						
		1	BPFL (On)	100%						
		1	BPRL (On)	100%						
		1	TPLT (Off)	100%						
		1	TPRT (Off)	100%						
2	1 of 1	2	RVLW (Op)	50.0025%	RVRF (Op)	50.0025%				
		2	RVRW (Op)	50.0025%	RVFF (Op)	50.0025%				
3	1 of 2	26	NVL (2 way)	100%						
		26	NVR (2 way)	100%						
		27	TVFF (Cl)	100%						
		27	TVRF (Cl)	100%						
		25	BPFL (On)	100%						
		25	BPRL (On)	100%						
		27	TPLT (Off)	100%						
		27	TPRT (Off)	100%						

Case	Number Diagnosed	Number Represented	Diagnosed failure 1	Probability	Diagnosed failure 2	Probability	Diagnosed failure 3	Probability	Diagnosed failure 4	Probability
4	1 of 2	52	RVLW (Op)	50.0025%	RVRF (Op)	50.0025%				
		52	RVRW (Op)	50.0025%	RVFF (Op)	50.0025%				
5	2 of 2 (one delayed)	2	NVL (2 way)	100%	RVLW (Op)	50.0025%	RVRF (Op)	50.0025%		
		2	NVR (2 way)	100%	RVRW (Op)	50.0025%	RVFF (Op)	50.0025%		
		2	TVFF (Cl)	100%	RVLW (Op)	50.0025%	RVRF (Op)	50.0025%		
		2	TVRF (Cl)	100%	RVRW (Op)	50.0025%	RVFF (Op)	50.0025%		
		2	TPLT (Off)	100%	RVLW (Op)	50.0025%	RVRF (Op)	50.0025%		
		2	TPRT (Off)	100%	RVRW (Op)	50.0025%	RVFF (Op)	50.0025%		
6	1 of 2 (one incorrect)	2	RVLW (Op)	50.0025%	RVRF (Op)	50.0025%				
		2	RVRW (Op)	50.0025%	RVFF (Op)	50.0025%				
7	2 of 2 (one incorrect)	2	NVL (2 way)	100%	TPRT (Off)	71.3792%	RVRW (Op)	50.0025%	RVFF (Op)	50.0025%
		2	NVR (2 way)	100%	TPLT (Off)	71.3792%	RVLW (Op)	50.0025%	RVRF (Op)	50.0025%
8	1 of 2 (one incorrect)	2	NVL (2 way)	90%	NVR (2 way)	90%				
9	2 of 2	1	TVFF (Cl)	100%	NVR (2 way)	100%				
		1	TVRF (Cl)	100%	NVL (2 way)	100%				
		1	TVFF (Cl)	100%	BPFL (On)	100%				
		1	TVFF (Cl)	100%	BPRL (On)	100%				
		1	TVRF (Cl)	100%	BPFL (On)	100%				

Case	Number Diagnosed	Number Represented	Diagnosed failure 1	Probability	Diagnosed failure 2	Probability	Diagnosed failure 3	Probability	Diagnosed failure 4	Probability
		1	TVRF (Cl)	100%	BPRL (On)	100%				
		1	TVFF (Cl)	100%	TPLT (Off)	100%				
		1	TVRF (Cl)	100%	TPRT (Off)	100%				
		1	TVFF (Cl)	100%	TVRF (Cl)	100%				
		1	BPFL (On)	100%	TPLT (Off)	100%				
		1	BPFL (On)	100%	TPRT (Off)	100%				
		1	BPRL (On)	100%	TPLT (Off)	100%				
		1	BPRL (On)	100%	TPRT (Off)	100%				
		1	BPFL (On)	100%	BPRL (On)	100%				
		1	TPLT (Off)	100%	TPRT (Off)	100%				
		1	BPFL (On)	100%	NVL (2 way)	100%				
		1	BPRL (On)	100%	NVL (2 way)	100%				
		1	BPFL (On)	100%	NVR (2 way)	100%				
		1	BPRL (On)	100%	NVR (2 way)	100%				
10	2 of 2	1	TVFF (Cl)	100%	NVL (2 way)	99.9%				
		1	TVRF (Cl)	100%	NVR (2 way)	99.9%				
11	2 of 2	1	RVLW (Op)	50.0025%	RVRF (Op)	50.0025%				
		1	RVRW (Op)	50.0025%	RVFF (Op)	50.0025%				

Case	Number Diagnosed	Number Represented	Diagnosed failure 1	Probability	Diagnosed failure 2	Probability	Diagnosed failure 3	Probability	Diagnosed failure 4	Probability
12	2 of 2 (one delayed)	1	TPLT (Off)	100%	TVRF (Cl)	100%				
		1	TPLT (Off)	100%	NVL (2 way)	100%				
		1	TPRT (Off)	100%	TVFF (Cl)	100%				
		1	TPRT (Off)	100%	NVR (2 way)	100%				
13	2 of 2	1	NVL (2 way)	90%	NVR (2 way)	90%				
14	2 of 2	1	NVL (2 way)	100%	TPLT (Off)	71.3792%				
		1	NVR (2 way)	100%	TPRT (Off)	71.3792%				
15	2 of 2	2	BPFL (On)	100%	RVLW (Op)	50.0025%	RVRF (Op)	50.0025%		
		2	BPRL (On)	100%	RVLW (Op)	50.0025%	RVRF (Op)	50.0025%		
		2	BPFL (On)	100%	RVRW (Op)	50.0025%	RVFF (Op)	50.0025%		
		2	BPRL (On)	100%	RVRW (Op)	50.0025%	RVFF (Op)	50.0025%		
		2	TVFF (Cl)	100%	RVLW (Op)	50.0025%	RVRF (Op)	50.0025%		
		2	TVRF (Cl)	100%	RVRW (Op)	50.0025%	RVFF (Op)	50.0025%		
		2	TPRT (Off)	100%	RVLW (Op)	50.0025%	RVRF (Op)	50.0025%		
		2	TPLT (Off)	100%	RVRW (Op)	50.0025%	RVFF (Op)	50.0025%		
		2	BPFL (On)	100%	LLP (Cl)	50.0025%	LHP (Cl)	50.0025%		
		2	BPRL (On)	100%	RLP (Cl)	50.0025%	RHP (Cl)	50.0025%		
16	2 of 2	4	RVLW (Op)	50.0025%	RVRF (Op)	50.0025%	RVRW (Op)	50.0025%	RVFF (Op)	50.0025%

The first case in Table 4.15 consists of component failures where one component has failed, and it has been diagnosed correctly with 100% confidence. These cases consist of failures of the transfer pumps and the booster pumps. The component failures in this case, and also the component failures in the second case, consist of only one component failure, and, therefore, are significantly more likely to occur than the combinations of two component failures described below. Therefore, it is important that these failures are diagnosed correctly.

The second case in Table 4.15 consists of component failures where one component has failed, but there are two possible component failures that can produce the same symptoms, and, therefore, they are diagnosed correctly with approximately 50% confidence in each case. These cases consist of failures of the left and right dump valves, the left and right low-pressure cocks, and the left and right high-pressure cocks. The probability that one component has failed in each case is slightly above 50%, because the same symptoms are also produced if both components are failed, and, therefore, each component is slightly more likely to have failed than not failed. The situation of both components failing is case number ten in Table 4.15.

The third case in Table 4.15 is combinations of component failures that have two components failed, but only one of the component failures can be diagnosed with 100% confidence. In each combination, the first component failure is one of the component failures given in the first case, and the second component failure is a hidden failure, and is, therefore, not detected. Each of these hidden component failures are not normally detected, when they are the only component that has failed, and therefore, the presence of the first failure is not making the second failure hidden.

The fourth case in Table 4.15 is similar to the third case, except instead of the first component failure being one of the component failures from case one, it is one of the component failures from case two. Therefore, one of the two component failures can be diagnosed with a confidence of approximately 50%.

The fifth case in Table 4.15 describes combinations of component failures that have two components failed, and both of the component failures can be diagnosed. The first component failure (booster pumps) is diagnosed with 100% confidence upon first inspection. However, the second component failure (the valves from case two) is not detected, and can, therefore, not be diagnosed until the first component failure has been repaired or replaced. This second component failure can then be diagnosed as one of the other two possible component failures with a confidence of approximately 50%. In other words, the sensor readings produced by both component failures are the same as the sensor readings produced by just the first component failure. Therefore, in the diagnostic process it is assumed that there is only one component that has failed. However, when the first failed component has been repaired or replaced, the sensor readings do not return to the readings produced under normal operating conditions, and the second component failure can therefore be detected, and can be diagnosed.

The sixth case in Table 4.15 is when the diagnostics process produces an incorrect diagnosis. In this case, each combination of component failures consists of one of the components in the failure mode given in the table, (such as one of the valves in case two), and therefore diagnosed correctly, but the second component has actually failed in the components other failure mode, i.e. if the component failure mode in the table is the failed open mode, then the second component is in the failed closed mode, and vice versa. However, this second failure is a hidden failure, so it will still appear like the component is functioning as normal. Therefore, whilst the diagnostic process is suggesting a component is in a different failure mode than it is, this component failure mode would not normally be detected.

The seventh case in Table 4.15 are combinations of component failures that consist of two failed components, and both components are diagnosed correctly with 100% confidence. These cases consist of combinations of the components that are grouped into case one, (such as the transfer and booster pumps), as well as a few other combinations of component failures, (including the components RPV, DV, LDV, RDV, TVRF and TVFF). These other combinations of component failures consist of component failures that are hidden, but can be detected when they both occur together, such as DV and LDV both in the failed open mode.

The eighth case in Table 4.15 are combinations of component failures that have two components failed, and both are diagnosed correctly. However, the second component failure is only observed after the first component (the booster pumps) has failed. This second component (LDV or RDV) failure will be diagnosed with approximately 50% confidence. However, in each of the cases, the second option (diagnosed failure 3 column) corresponds to the second failure in the fifth and sixth row of the seventh case. Therefore, it cannot be the second option for the second component failure, as the failure would have been diagnosed immediately, and must be the first option (diagnosed failure 2 column). The fault diagnostics process does not highlight this, but there will only be a maximum of one additional component inspected, i.e. maximum of three components inspected for two component failures.

The ninth case in Table 4.15 are combinations of component failures that have two components failed, and one is diagnosed correctly with 100% confidence, (transfer pump failure), and the second component is diagnosed correctly with a confidence of 99.9999%, (one directional valves). In order for this second component not to be the component that has failed, at least 3 different components would have to have failed. Instead of NVL failing two way, TVRF would need to fail closed, TPRT would need to fail on, and either RVRW and/or RVFF would need to fail open, in order for these symptoms to occur. This is extremely unlikely as it would require four component failures to occur for this to arise, and, therefore, it results in the very high confidence for the second component being failed.

The tenth case in Table 4.15 was discussed in the paragraph about the second case. In this case, both components have failed, so it is actually diagnosing the component failures 100% correctly, but the fault diagnostic process states that each component has a probability of being failed of approximately 50%.

The eleventh case in Table 4.15 are combinations of component failures that have two components failed, and for each component failure there are two potential options that are equally likely. Therefore, each pair is diagnosed correctly with a confidence of approximately 50%. This would result in approximately 25% probability that the correct pair of failed components is selected when the first two components are inspected.

The twelfth and final case in Table 4.15 is combinations of component failures that have two components failed and both component failures are diagnosed, one with 100% confidence, and one with approximately 50% confidence. However, unlike the fifth case, both component failures are detected and diagnosed upon first inspection, and the first component is not required to be repaired or replaced before the second component can be detected.

The first case in Table 4.16 consists of combinations of one component failure which are diagnosed correctly with 100% confidence. This is the same as the first case for the engine feed operation mode, consisting of failures of the transfer and booster pumps (the other failure mode for each component), and some other components, such as NVL, NVR, TVFF and TVRF.

The second case in Table 4.16 consists of combinations of one component failure (such as the refuel valves) which are diagnosed correctly with approximately 50% confidence, and this is the same as the second case for the engine feed operation mode. The confidence being slightly above 50% is for the same reason as discussed before, i.e. both components can fail and cause the same symptoms, but in this case only one component has failed. The case in which both of the possible components are failed is case eleven for this operation mode.

The third case in Table 4.16 consists of combinations of two component failures, but combinations in which only one of the component failures is diagnosed with 100% confidence, (the same component failures as in the first case), with the second component failure in each of the combinations a hidden failure. This case is the same as the third case for the engine feed operation mode.

The fourth case in Table 4.16 consists of combinations of two component failures, but only one of the component failures in each combination is diagnosed with approximately 50% confidence, (the same component failures as in the second case). The second component failure in each case is a hidden failure, and therefore not detected or diagnosed. This is the same as the fourth case for the engine feed operation mode.

The fifth case in Table 4.16 consists of combinations of two component failures, but the second component failure is only observable after the first component failure has been repaired or replaced. The first component failure (including failures of the one directional valves, the transfer valves and the transfer pumps) is diagnosed with 100% confidence, and the second component failure (including failures of the refuel valves) is diagnosed with approximately 50% confidence. This case corresponds to the fifth case for the engine feed operation mode.

The sixth case in Table 4.16 is one of the cases for this operation mode that the diagnostics process produces an incorrect diagnosis. The components in this case are the refuel valves. In this case, one of the components in each combination of component failures has failed in the failure mode given in the table, and therefore diagnosed correctly, but the other component has failed in the components other failure mode. However, this second failure is normally a hidden failure, so the sensor readings produced suggest the component is functioning as normal. Therefore, although the diagnostic process is suggesting a component is in a different failure mode than it is in, this component failure would not normally be detected. This case corresponds to the sixth case for the engine feed operation mode.

The seventh case in Table 4.16 is combinations of component failures that consist of two failed components, but the second component in each combination is diagnosed incorrectly. The first component is diagnosed to have failed with 100% confidence, but the second component is diagnosed to have failed with approximately 71% confidence, (note the other two components are predicted to be working). However, when the first component is repaired or replaced, and the second component has been inspected and found to not be failed, then it will result in the probability of other components being in the failed state changing. This results in the second component failure being diagnosed with approximately 50% confidence. For example, NVL and TPRT are inspected, NVL is found to be failed but TPRT is found to be working. This evidence will then result in the diagnostic process outputting that RVRW and RVFF have failed with a probability of approximately 50%. This case does not have a corresponding case for the engine feed operation mode.

The eighth case in Table 4.16 are also combinations of two component failures but one of the component failures is diagnosed incorrectly. In this case, one of the 1D valves in each combination of components is in the failed 2 way failure mode as given in the table, but the other 1D valve is in the failed blocked failure mode. The failed blocked failure mode is less likely to occur but results in the same symptoms, hence the incorrect diagnostics. However, in this case, the same component will still have to be inspected, so the correct failure will likely be observed, and can, therefore, be repaired or replaced, as required. This case does not have a corresponding case for the engine feed operation mode.

The ninth case in Table 4.16 is combinations of two component failures where both are diagnosed with 100% confidence. This case corresponds to the seventh case for the engine feed operation mode. The failures include the transfer valves, the one directional valves, the booster pumps, and the transfer pumps.

The tenth case in Table 4.16 is combinations of two component failures and one is diagnosed with 100% confidence (transfer valves), and the second is diagnosed with 99.9% confidence (1D valves). This is the same as the ninth case for the engine feed operation mode, albeit with a slightly lower confidence.

The eleventh case in Table 4.16 was discussed in the paragraph about the second case. In this case, both components have failed, so it is diagnosing the component failures 100% correctly, but the fault diagnostic process states that each component has a probability of being failed of approximately 50%.

The twelfth case in Table 4.16 are combinations of two component failures and both are diagnosed with 100% confidence, but the second component (transfer valves and 1D valves) only becomes observable after the first component (transfer pumps) has been repaired or replaced. This case does not have a corresponding case for the engine feed operation mode, but is similar to case five for both of the operation modes, except that in the fuel transfer operation mode the second failure is diagnosed with 100% confidence.

The thirteenth case in Table 4.16 are combinations of two component failures and both are diagnosed correctly, but only with 90% confidence. (The components are the 1D valves). This is because one of the components can be in the other failure mode and the same sensor readings would be produced. This case does not have a corresponding case for the engine feed operation mode.

The fourteenth case in Table 4.16 are combinations of two component failures, with both component failures diagnosed correctly. However, the first component failure (1D valves) is diagnosed with 100% confidence, but the second component failure (transfer pumps) is diagnosed with approximately 71% confidence. This case is also not observed for the engine feed operation mode.

The fifteenth case in Table 4.16 are combinations of two component failures with both component failures diagnosed correctly. The first component failure (booster pumps, transfer pumps or transfer valves) is diagnosed with 100% confidence, but the second component failure (refuel valves, high-pressure cocks, and low-pressure cocks) is only diagnosed with approximately 50% confidence. This case corresponds to the twelfth case for the engine feed operation mode.

The sixteenth and final case in Table 4.16 are combinations of two component failures with both component failures diagnosed correctly. (The components in this case are the refuel valves). However, the diagnostics of both component failures has approximately 50% confidence for each pair of component failures. This case corresponds to the eleventh case for the engine feed operation mode.

The next section contains a discussion about how successful the application of the fault diagnostic methodology on this system is, whilst also highlighting some of the drawbacks observed during the application of the methodology.

4.5.3. Discussion

All of the combinations of component failures listed above that do not have 100% confidence in the diagnosis of the failed components, result in a diagnostic term of less than 1. It is possible to get a higher diagnostic term by using more sensors, as stated earlier, and it would also increase the confidence with which some of the combinations of component failures are diagnosed. For example, if sensor S23 was added to the selection of sensors for the fuel transfer operation mode, giving 6 sensors, (S4, S6, S10, S15, S16, S23), case 15 in Table 4.16 would have higher confidence in the diagnostics of the failure, as the fault diagnostic process will be able to distinguish between the failures of component LLP and LHP. For the component failures, BPFL (On) and LLP (Cl), S23 will measure the sensor reading “E”, but for the component failures, BPFL (On) and LHP (Cl), S23 will measure the sensor reading “N”. Note, all other sensors will record the same sensor reading. As the detection and criticality terms are 1 for both operation modes, it is not possible to improve on these terms.

As detailed in the results section, the fault diagnostic process works as desired and diagnoses all of the component failures that can be detected. However, there was a number of combinations of component failures where a wrong component failure was diagnosed, case six for the engine feed operation mode, and cases six, seven and eight for the fuel transfer operation mode. However, when additional evidence is introduced, the second component failure can be diagnosed (if possible) and it can be dealt with as necessary, i.e. repaired or replaced.

There are also some component failures that are not diagnosed until one of the component failures is repaired. Therefore, this process would increase the repair time of the system, as the engineer would have to delay the process of dealing with the second component, as it would only be diagnosed after the first failure is addressed. This is because the additional component failure results in the same symptoms as the symptoms produced by the first component failure, and therefore the same sensor readings are produced for both failures. In each of these cases, the probability of the two components failing is less than the probability of just one component failing, as the components are more likely to be working than failed, hence the diagnostics process predicting only one component failure initially.

There was also a large number of combinations of component failures that were not detected (455 for the engine feed operation mode and 398 for the fuel transfer operation mode), and a large number of combinations of component failures where only one of the two component failures was detected (280 for the engine feed operation mode, and 320 for the fuel transfer operation mode). This is because of the comparatively large number of hidden failures, i.e. failures that have no effect on the system's performance in that operation mode, and are therefore not observable. These component failures are the failed component being in sections of the system that are not used in the operation mode, or the component failing in the same failure mode as their working state, i.e. failed open if it is supposed to be working open. From studying Tables 4.15 and 4.16, it is clear that generally the individual component failures that are hidden remain as hidden failures when combined with a non-hidden failure to form a combination of two component failures, with a couple of exceptions. The exceptions to this observation are given in case seven of Table 4.15, i.e. the combinations of component failures including RPV failed open, and DV failed open, and case fifteen of Table 4.16, i.e. the combinations of component failures including LLP failed closed, LHP failed closed, RLP failed closed, and RHP failed closed. These component failures are only observable when both component failures occur. Note, a full summary of the hidden failures was presented in Table 4.7.

For some of the combinations of component failures that can be diagnosed correctly, additional components will be inspected which have not failed. However, whenever there is a combination of component failures, of which one of the component failures can be diagnosed, no more than one additional component that has not failed will be inspected. Note, this is the case for combinations of one, and combinations of two component failures. If there is a combination of component failures in which two component failures can be diagnosed, no more than two additional component failures that has not failed will be inspected. In other words, if there is one diagnosable component failure, no more than two components need to be inspected, and if there are two diagnosable component failures, no more than four components need to be inspected. Note, in some cases, there will be no need to inspect so many additional components.

4.6. Discussion

One of the techniques introduced in this chapter, which was applied successfully to an example system, was the automation of the sensor selection and fault diagnostic processes. The automation of this methodology made it possible to calculate the performance metric for a large number of combinations of sensors, which would not be feasible to be done manually. For the diagnostic process, the diagnosis time is also greatly reduced in comparison to manually diagnosing component failures, but as in a real system only one combination of sensor readings would be introduced, automating the diagnostic process would not provide a big advantage. However, for the testing of the diagnostic process, where approximately 800 combinations of sensor readings are attempted to be diagnosed for each operation mode, automating the diagnostic process is beneficial.

As discussed in this chapter, each of the steps of the methodology is applied successfully to the system. One of the potential problems observed in this application is that the size of the BBN grows quickly as the size of the system increases. It was discussed during the development of the BBN model (section 4.3.1) that it was not possible to consider exact sensor readings because the size of the network would become too large, and the sensor readings had to be grouped into ranges. This process resulted in less accurate modelling of the system than desired. Despite this reduction in accuracy of the model, the network was still comparatively large. This large network resulted in the network compiling comparatively slowly, (approximately 10 seconds instead of approximately 0.1 seconds for the system presented in Chapter 3), resulting in the sensor readings being determined and the faults being diagnosed significantly slower than before. Whilst the BBN method can be applied to a system of this size, it appears that it would not be feasible to apply it to a significantly larger system. Therefore, in the next chapter, an alternative modelling technique is introduced which enables a more accurate modelling of the system, quicker determination of the sensor readings, and quicker fault diagnostics. This will also require a new fault diagnostic technique to be introduced, as the BBN model used to diagnose the component failures will no longer be constructed.

Another of the potential problems that could be drawn from this application is that as the number of potential sensors increases, the number of combinations of sensors increases, and, therefore, the required number of performance metric calculations increases, i.e. the computation time increases. In addition to the increase in the number of combinations of sensors, the number of sensor readings per sensor is higher than for the simple system discussed in the previous chapter, further increasing the computation time to calculate the performance metric for each combination of sensors. Whilst excessive computation time has not been a problem for this system, it could potentially be a problem for larger systems which may have more potential sensor locations. The same sensor selection method is applied to the system discussed in the next chapter, i.e. the example system discussed in this chapter with some of the simplifications removed from the system model. At the end of the next chapter, a discussion about whether an optimisation process needs to be introduced during the sensor selection process is given, or if the exhaustive approach applied thus far can be used on larger systems.

4.7. Summary

In summary, in this chapter the proposed methodology is applied to a simplified version of the aircraft fuel system introduced by Moir & Seabridge (2011). For this system, combinations of one and two component failures are considered in two different operation modes: engine feed and fuel transfer. Each of the 20 components have two potential failure modes. Of these component failures, approximately 31% of the failures in the engine feed operation mode, and approximately 50% of the failures in the fuel transfer operation mode can be detected by at least one of the 25 potential sensors that could be introduced to the system. As a result, the performance metric of each combination of five (and fewer) sensors was calculated for both operation modes, and the best combination of five sensors that can detect all of the observable component failures is selected for each of the operation modes. This process was completed using a C++ script, instead of the manual calculation applied in Chapter 3.

In order to calculate the performance metrics for each combination of sensors, and select the combinations of sensors, a BBN model of the system was constructed. This model was able to simulate all of the combinations of component failures, and could therefore be used to determine the sensor readings for each of the sensors. However, due to the long compiling time of the network, and the requirement of grouping the sensor readings to prevent the network getting too large, an alternative modelling technique is proposed in the next chapter. The method of the performance metric calculation can still be used, if the alternative modelling technique outputs sensor readings in the same format as they are by the BBN method.

As with the previous system, the BBN was used to successfully diagnose all of the component failures that can be detected, with only one or two additional components being inspected that have not failed. However, if the BBN is not going to be used to model the system, an alternative diagnostic process that does not use the BBN will also need to be introduced, as investigated in the next chapter.

Chapter 5 - Proposed methodology for fault diagnostics using simulation

In this chapter, an alternative but related system modelling and fault diagnostics approach to the BBN approach, is proposed. The alternative method is developed in order to achieve the better model scalability required when dealing with large systems. This method is described as an evolution of the BBN based method, drawing on techniques developed during the construction of BBNs for use in the construction of simulation based models. This methodology is applied to the system presented in Chapter 4 with the simplifications applied in Chapter 4 removed. In order to demonstrate the accuracy of the proposed fault diagnostic method, a BBN model of the system is produced for comparison. Note, the applications of the two methodologies are completed independently, with no reference to each other in each of the applications, all comparisons between the two methodologies are made in section 5.5, in which the comparisons are separated into the three parts of the methodology, system modelling, selection of sensors, and diagnosis of failures.

This chapter begins by introducing the new methodology for modelling and diagnosing failures in the system. Next, a brief overview of minor modifications to the system presented in section 4.1 is given followed by the newly proposed methodology and the BBN based methodology are applied. The chapter concludes by presenting a comparison of the two methodologies, and detailing why the proposed method is the more suitable solution for large systems.

5.1. The methodology

In order to be able to select sensors and diagnose failures in large systems, a simulation method is proposed as an evolution to BBNs. The sensor selection method is the same as the one presented in Chapters 3 and 4, and will, therefore, not be discussed in this section of the chapter. The method involves calculating the performance metric of all combinations of sensors. The sensor selection process will be presented in the application of the methodology presented in section 5.3.

5.1.1. Modelling the System using flow simulation

The model of the system is completed using a similar process to that proposed for the construction of the BBNs in section 3.3, i.e. considering the quantity of fuel supplied using the pumps, considering the exits that the fuel can pass through in the system, and the sections of the system that the fuel can pass between. The method is effectively a streamlined version of the BBNs' conditional probability tables, as only the probabilities that are required for the calculation of the performance metric are determined, and not the probability of every state of every node as in the BBN method. In addition, the simulation method should also be more efficient because it does not require the software "HUGIN Researcher" to determine the probabilities of the sensor states. The probability of each of the states can be calculated directly rather than having to communicate back and forth with the software. In addition, the probability of each state is only calculated from the sensors in the proposed method, but in the BBN, the probability of each state for every node is calculated. The proposed method can be described as an evolution of the BBN based methodology, i.e. a streamlined version of the BBNs' conditional probability tables, as opposed to a new unrelated method, which may require a completely different approach and thought process.

The model is constructed using a C++ script consisting of a number of functions. Each function is used to determine sensor readings for each individual sensor and uses a series of if-then-else statements to determine the sensor readings for each combination of component failures, i.e. a function for each sensor. The if-then-else statements used for determining the sensor readings begin by considering the exits in the system which are closest to the sensor considered, then determining the exits in other sections of the system if there are clear paths between sections of the systems using the components that separate the sections of the system, i.e. NVL, NVR, LDV, RDV and RPV as introduced in section 4.1. The next set of if-then-else statements can be completed by considering the supply to the system, i.e. consider the supply of fuel to the section of the system that the sensor is located in, and then consider the supply from other sections of the system if there are clear paths from these sections of the systems, i.e. using the same components as before, NVL, NVR, LDV, RDV and RPV. A full example of the script for sensor S1 is presented in Appendix G, and a flowchart detailing the steps of the functions to calculate the sensor readings is presented in Figure 5.1.

The if-then-else functions in the simulation code that are used to determine the sensor readings calculate the amount of fuel available in each section of the system, and the number of exits that the fuel can pass through. The amount of fuel moving in the system can be divided by the number of exits and the flow of fuel through each of the exits can be determined. This enables the flow of fuel at each of the pumps, and through each of the exits to be determined. From this, the path which the fuel has to take from the pumps to exit the system can be determined, enabling the flow of fuel past the sensors in the middle of the system to be determined using formulas, i.e. dividing the supply of fuel in the system by the number of exits in the system.

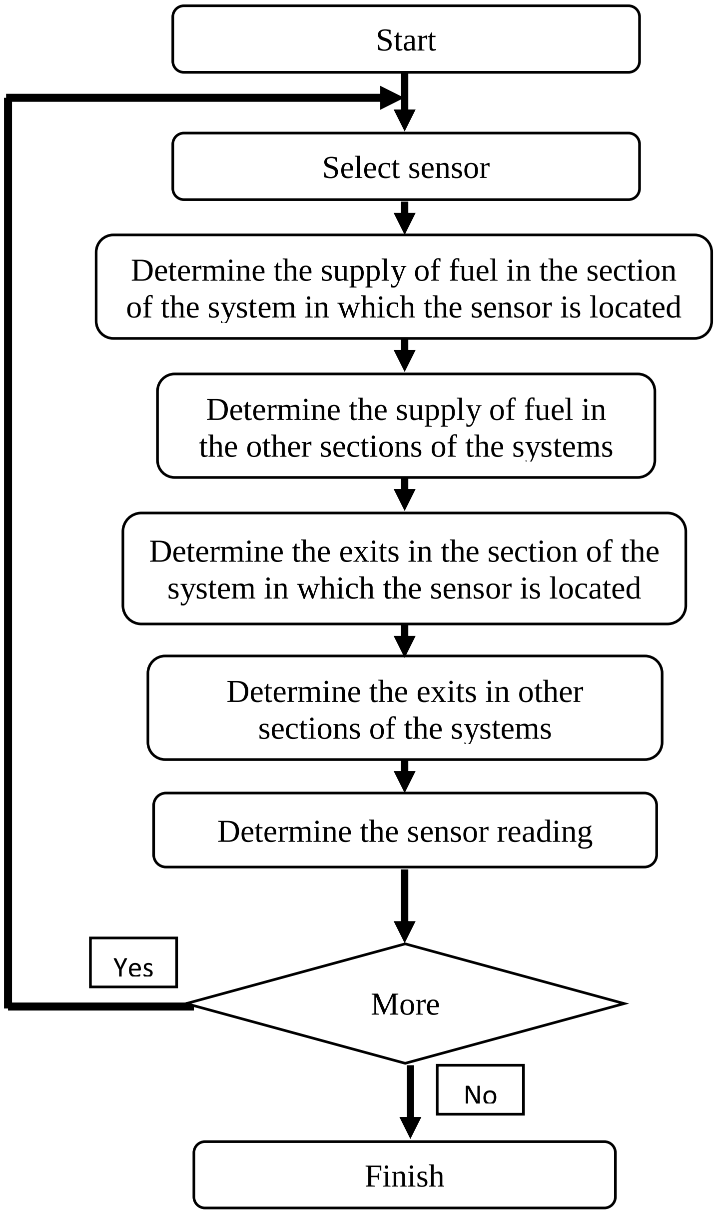


Figure 5.1 Flowchart of the steps of the functions to calculate the sensor readings

The script for the model begins by setting the system operation mode and by introducing the occurrence probability of each of the component states, which depends on the operation mode. The component states for the considered component failure can then be set, and the probability of the considered event can then be calculated, i.e. the product of the component states. Next, each of the functions to calculate the sensor reading can be executed and the resultant sensor readings stored in a vector. The script will then output whether due to the failures, the system is in a critical state, as defined in section 4.1. These steps are repeated for all combinations of component states and are then used for the selection of the sensors using the sensor selection code presented in Chapter 4. A flowchart of the modelling of the system is presented in Figure 5.2. Note, the step in the flowchart, "Calculate the sensor readings for all considered events" corresponds to the flowchart presented in Figure 5.1.

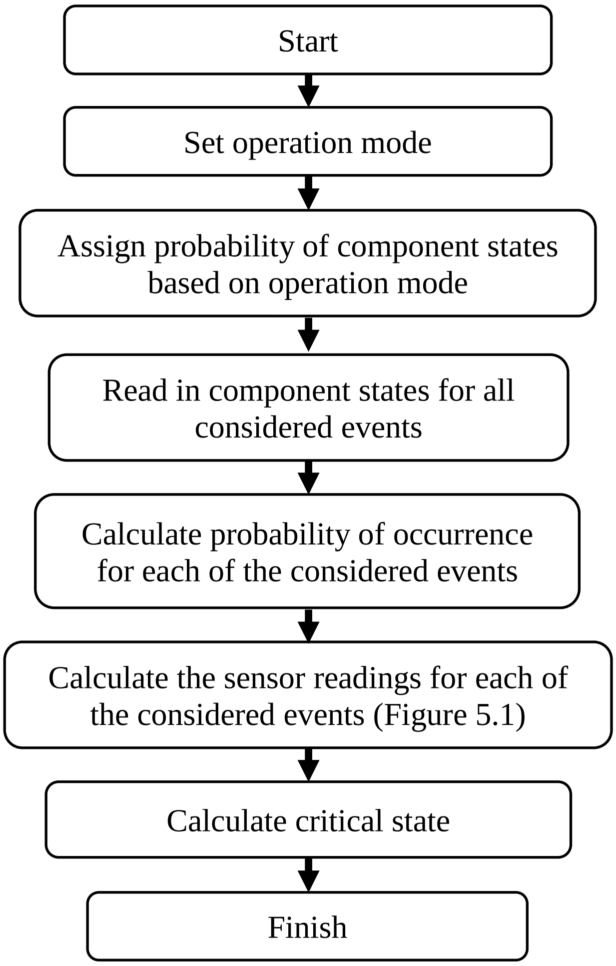


Figure 5.2 Flowchart for the modelling of the system

One of the main benefits of modelling the system in this way, is that instead of having predefined states for the sensor readings (like in the BBN), formulas in the functions are used to calculate the sensor readings. Therefore, any value that can be produced in the real system, can be output by the model rather than having to group the sensor readings into ranges. This also enables the change in the level of fuel in the tanks to be considered, which was not considered in the BBN model constructed in Chapter 4. The change in the level of fuel in the tanks can be calculated by determining the difference between the quantities of fuel exiting, and entering each of the tanks. This is not possible in the BBN as there are ranges of quantities of fuel entering the tanks, so the exact level change cannot be determined.

In the next section, an outline of the diagnostic process using this simulation-based model is presented.

5.1.2. Fault Diagnostics

Using the simulation-based modelling technique requires an alternative fault diagnostics method to be developed, as a BBN is not constructed, and can therefore not be used for fault diagnostics. The alternative fault diagnostic method entails building up a library of sensor readings for a set of possible component failures. The library of sensor readings consists of all of the sensor readings corresponding to the component failures used to calculate the sensor performance metric. The observed sensor readings for the considered failure can then be compared with the readings in the library, and component failures that caused them are identified. A flow chart detailing the steps of the diagnostics process of component failures is presented in Figure 5.3.

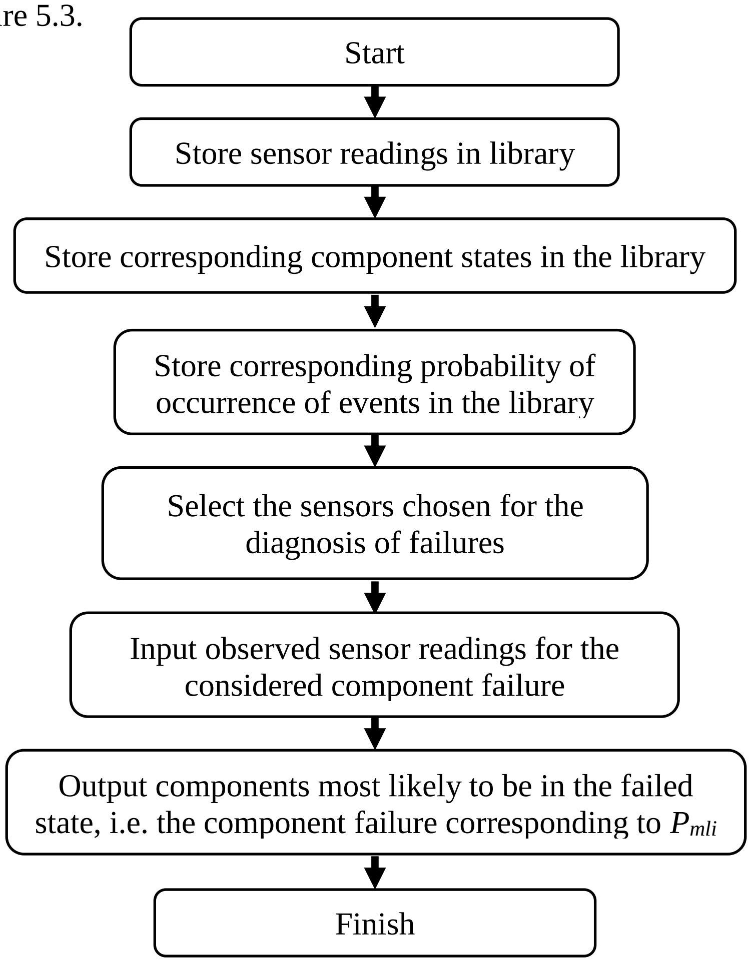


Figure 5.3 Flowchart for the diagnosis of component failures

A potential problem with the proposed fault diagnostics method is when a set of sensor readings that is observed is not in the library, i.e. all failure scenarios would not be considered. As before, only combinations of one or two component failures are considered in this chapter. In addition, a set of sensor readings that is not in the library could be observed if there has been a sensor failure, but these are not considered in this study. However, the C++ script was modified so that it offers potential solutions to these two cases if they were to be considered. If the observed sensor readings do not match any combinations in the library, the C++ script compares the sensor readings observed to the sensor readings in the library progressively ignoring an increasing number of sensors until the observed sensor readings match a case in the library. For example, each of the individual sensors will be removed, then every combination of two sensors will be removed, then every combination of three sensors will be removed, etc. This will suggest potential component failures that may have occurred, or sensors that may have failed.

5.1.3. Summary

In summary, the methodology uses a C++ simulation to model the system by using a series of if-then-else statements to determine sensor readings for each combination of component states. Then the sensor selection process is carried out using the methodology proposed in Chapters 3 and 4, i.e. using the input states for individual and combinations of two component failures in this system. Finally, a library of sensor readings for all combinations of considered component failures is built, and therefore, any considered combination of component failures that can be diagnosed, is diagnosed.

In the next section, the system from Chapter 4 is presented with some modifications.

5.2. System description

The un-simplified version of the system presented in Chapter 4 is used for the application of this methodology in this chapter. The schematic of the system was first presented in Figure 4.1 for the engine feed operation mode, and Figure 4.2 for the fuel transfer operation mode. The application considers the 28 components and 33 sensor locations presented in Figures 4.5 and 4.6, respectively. Note, the components are labelled in Table 4.1. As detailed above, it is possible to consider fuel tank level sensors in the proposed methodology, resulting in an additional 4 level sensors being included, one in each of the tanks, i.e. 37 sensors in total.

As in the previous chapter, the only two operation modes considered are the engine feed and the fuel transfer operation mode. However, there are some minor modifications to the system considered. The fuel transfer operation mode is modified such that the fuel is supplied to the engines at all times. Note that in the previous chapter, no supply was considered to the engines during fuel transfer as this is how the fuel transfer operation mode is presented in the figure, (Figure 4.2). This results in new minimal cut sets for the fuel transfer operation mode, in comparison to those presented in section 4.1. Minimal cut sets for the engine feed operation mode are the same and they are presented in section 4.1. The new set of minimal cut sets for the fuel transfer operation modes can be determined by considering which combinations of component failures cause the system to fail. For example, what combinations of component failures cause no fuel to supplied to the engines, or what combinations of component failures cause no fuel to be transferred around the system. The minimal cut sets are:

- {TPLT off, TPLB off, TPRT off, TPRB off}
- {TPLT off, TPLB off, TPRT off, TPRB off}
- {TVFF closed, TVRF closed}
- {TPLT off, TPLB off, TVFF closed}
- {TPRT off, TPRB off, TVRF closed}
- {NVL open 2 way, RPV open, DV open}
- {NVR open 2 way, RPV open, DV open}
- {BPFL off, BPFR off, BPRR off, BPRL off,}
- {LLP closed, RLP closed}
- {LHP closed, RLP closed}
- {LLP closed, RHP closed}
- {LHP closed, RHP closed}
- {BPFL off, BPFR off, RLP closed}
- {BPFL off, BPFR off, RHP closed}
- {BPRL off, BPRR off, LLP closed}
- {BPRL off, BPRR off, LHP closed}
- {LDV open, DV open}
- {RDV open, DV open}

In the previous chapter, the transfer pumps were assumed to supply fuel at the same rate as the booster pumps. However, if this is the case, the level of fuel in the fuselage tanks will remain constant during the fuel transfer operation mode. Therefore, the transfer pumps are assumed to supply fuel at double the rate of the booster pumps, i.e. “2”, the same notation as used in Chapters 3 and 4 is used in the tables, i.e. “E”, “1”, “2”, “N”, etc. Updated versions of Tables 4.2 (component working states) and 4.4 (sensor readings for each operation mode in the “no fault” condition) are presented in Tables 5.1 and 5.2, respectively.

Table 5.1 Component normal working state for each operation mode

Component Name	Component Number	Engine Feed operation mode	Fuel Transfer operation mode
TPLT	1	Off	On
TPLB	2	Off	Off
TPRT	3	Off	On
TPRB	4	Off	Off
TPFF	5	Off	Off
TPRF	6	Off	Off
BPFL	7	On	On
BPFR	8	Off	Off
BPRL	9	On	On
BPRR	10	Off	Off
RVLW	11	Closed	Closed
RVRW	12	Closed	Closed
RVFF	13	Closed	Closed
RVRF	14	Closed	Closed
TVFF	15	Open	Open
TVRF	16	Open	Open
LDV	17	Closed	Closed
RDV	18	Closed	Closed
DV	19	Closed	Closed
CV	20	Closed	Closed
RPV	21	Closed	Closed
LLP	22	Open	Open
LHP	23	Open	Open
RLP	24	Open	Open
RHP	25	Open	Open
TIV	26	Closed	Closed
NVL	27	Open	Open
NVR	28	Open	Open

Table 5.2 Sensor readings for each operation mode

Operation mode	S1	S1a	S2	S3	S4	S5	S6	S7	S8	S9	S10
Engine feed	E	E	E	E	E	E	E	E	E	E	E
Fuel transfer	2	N	N	N	2	N	E	E	N	N	2

Continued…

Operation mode	S11	S12	S12a	S13	S14	S15	S15a	S16	S16a	S17	S18
Engine feed	E	E	E	E	E	1	N	1	N	N	E
Fuel transfer	N	2	N	E	E	1	N	1	N	N	E

Continued…

Operation mode	S19	S20	S21	S22	S23	S24	S25	S26	S27	S28	S29
Engine feed	E	N	E	1	1	1	1	E	E	N	N
Fuel transfer	E	N	E	1	1	1	1	E	E	N	N

Continued…

Operation mode	LWTL	RWTL	FFL	RFL
Engine feed	0	0	-1	-1
Fuel transfer	-2	-2	1	1

Note, in Table 5.2 LWTL (left wing tank level), RWTL (right wing tank level), FFL (forward fuselage tank level), and RFL (rear fuselage tank level) represent the change in fuel level observed by the level sensors in each of the fuel tanks. For these four sensors, negative values represent the fuel level in the tanks decreasing, 0 represents the fuel level in the tanks remaining constant, and positive values represent the fuel level in the tanks increasing.

In the next section, the methodology proposed in section 5.1 is applied to the system.

5.3. Application of the methodology

The proposed methodology is applied to this system. As in Chapters 3 and 4, all combinations of one and two component failures are considered on the system, which can be in one of the two operation modes. This results in 1568 combinations of component failures for each operation mode. Note, that the probability of each failure event can be calculated using Table 4.3, as before.

5.3.1. Modelling the system

The proposed methodology begins by developing the system model. For comparison, the model was constructed in the form of a C++ script that outputs the sensor readings in the same format as they are outputted by the C++ script that uses the BBN. This enables the same sensor selection script to be used as in Chapter 4.

5.3.1.1. System Model development

As detailed in section 5.1.1, the C++ script begins by choosing the operation mode of the system. The next step is to assign the probability of the states to each component. However, this is dependent on the operation mode, and as a result, this step is completed by using an if-then-else statement. For example, if the system is in the fuel transfer operation mode, then the probability that the component TPLT is in the "working on" state is 0.990, the probability that it is in the "failed on" failure mode is 0.005, the probability that it is in the "failed off" failure mode is 0.005, and the probability that it is in the "working off" state is 0, as it cannot work off in this mode. Alternatively, if the system is in the engine feed operation mode, the probability that the component TPLT is in the "working on" state is 0, the probability that it is in the "failed on" failure mode is 0.005, the probability that it is in the "failed off" failure mode is 0.005, and the probability that it is in the "working off" state is 0.990, as it cannot work on in this mode.

The next step in the methodology is to read in the component states from the input files. These component states are detailed in the form of integer values, each of which indicate the state number the component is in, i.e. for the pumps, state 0 is working on, state 1 is failed on, 2 is failed off, and state 3 is working off; and for the valves, state 0 is the working state, state 1 is failed open, and state 2 is failed closed.

Once the component states for each considered combination of component failures have been stored, the probability of each combination of component failures can be calculated and stored. This is calculated by multiplying the corresponding state probabilities for each of the components. For example, the probability of TPLT being in the failed on failure mode and all other components in the working state for the fuel transfer operation mode, is equal to $0.005\times0.990^{9}\times0.998^{16}\times0.991^{2} = 0.0004344$.

The next step is to calculate the sensor readings for each of the sensors. For each sensor, a function was written which considers the states of each the components used to determine sensor readings. As discussed, an example of the function for sensor S1 is presented in Appendix G. The script in each of the functions follows the same format as presented in the flowchart in Figure 5.1. The determination of the sensor readings is repeated for all sensors, and then for all considered combinations of component failures.

The penultimate step is to determine whether the system fails for each combination of component failures. This is completed by comparing the component states to the minimal cut sets for each operation mode detailed in sections 4.1 and 5.2 for the engine feed and fuel transfer operation modes, respectively. If one of the minimal cut sets is observed, then the system is critical.

The final step is to output the sensor readings, the event probabilities, and the critical state to text files. These are the outputs to be used in the sensor selection code.

5.3.1.2. Discussion

There are a number of benefits to the proposed method for system modelling. The first arises because the flow can be calculated using equations, the flow value can be determined by the model without having to assign a state to a range of values, as would be required using the BBN method. It makes this modelling technique more accurate than that presented in Chapters 3 and 4. Additionally, it enables fuel level sensors to be modelled to record the change of fuel level in each of the tanks. Since fuel tank level sensors are commonly used in real systems, it is desirable to be able to model them.

Another benefit of using this modelling technique is that determining the sensor readings for all 37 sensors for all 1568 combinations of one and two component failures for each operation mode takes around 1 – 2 seconds. This is significantly less than the time (approximately one hour) it took to determine the sensor readings using the BBN for the 800 combinations of one and two component failures, presented in Chapter 4. This means that despite considering more sensors, more combinations of component failures, and achieving a higher level of accuracy in the model, the method is significantly faster, and is therefore, a better option than using the BBN method since larger, more complex systems can be modelled using the proposed method.

In the next section, the selection of sensors to be used for the fault diagnostics process will be presented.

5.3.2. Sensor Selection

The next step of the methodology is to select the sensors to be used for the fault diagnostics process. As in Chapters 3 and 4, all combinations of sensors are considered exhaustively until a suitable combination of sensors is determined. In order to determine suitable combinations, the maximum possible performance metric needs to be calculated for comparison, i.e. when all sensors are considered on the system. The maximum performance metric for the engine feed operation mode is 0.9688, which consists of a detection term of 1, a diagnostic term of 0.9063, and a criticality term of 1. This corresponds to being able to detect 38.9239% (760/1568) of all considered failures for the engine feed operation mode. The maximum achievable performance metric for the fuel transfer operation mode is 0.9751, which consists of a detection term of 1, a diagnostic term of 0.9253, and a criticality term of 1. This corresponds to detecting 53.6849% (1044/1568) of the considered failures for the fuel transfer operation mode. Note, these percentage values are calculated using the sum of the probabilities of detected failures divided by the sum of the probabilities of all considered failures.

As the percentage of detectable failures is less than 100% for both of the operation modes, there are a number of hidden failures. However, like in Chapter 4, none of the hidden failures are critical to system performance, i.e. all of the critical failures are detected, therefore, CR = 1. A summary of hidden failures is presented in Table 5.3.

Table 5.3 Hidden component failures for each operation mode

Number	Operation mode	Component	Hidden failure
1	Engine Feed	RVLW	Open
2	Engine Feed	RVRW	Open
3	Engine Feed	RVFF	Open
4	Engine Feed	RVRF	Open
5	Engine Feed	NVL	2 way
6	Engine Feed	NVR	2 way
7	Engine Feed	TPLT	Off
8	Engine Feed	TPRT	Off
9	Engine Feed	TVFF	Closed
10	Engine Feed	TVRF	Closed
11	Fuel Transfer	TPLT	On

12	Fuel Transfer	TPRT	On
13	Both	BPFL	On
14	Both	BPRL	On
15	Both	TVFF	Open
16	Both	TVRF	Open
17	Both	DV	Open
18	Both	CV	Open
19	Both	RPV	Open
20	Both	LLP	Open
21	Both	LHP	Open
22	Both	RLP	Open
23	Both	RHP	Open
24	Both	TIV	Open
25	Both	TPLB	Off
26	Both	TPRB	Off
27	Both	TPFF	Off
28	Both	TPRF	Off
29	Both	BPFR	Off
30	Both	BPRR	Off
31	Both	RVLW	Closed
32	Both	RVRW	Closed
33	Both	RVFF	Closed
34	Both	RVRF	Closed
35	Both	LDV	Closed
36	Both	RDV	Closed
37	Both	DV	Closed
38	Both	CV	Closed
39	Both	RPV	Closed
40	Both	TIV	Closed
41	Both	NVL	Closed
42	Both	NVR	Closed

If Tables 5.3 and 4.7 are compared, it is observed that there are fewer hidden failures that are only unobservable in one of the operation modes. For example, the primary engine feed pumps (BPFL, BPRL) failing off and the valves to the engines (LLP, LHP, RLP, RHP) failing closed are no longer hidden in the fuel transfer operation mode. This is a result of the components that are used to supply fuel to the engines being active in both operation modes, due to the modification made in section 5.2 (supply of fuel to the engines required in both operation modes). This results in significantly fewer hidden failures that are not observed in the fuel transfer operation mode only, as most of the hidden failures for the fuel transfer operation mode only in Table 4.7 are components that are used to supply fuel to the engines, or are in the engine feed sections of the system. This accounts for eight (numbers 15 – 22) of the ten failures (numbers 13 – 22) that are only hidden in the fuel transfer mode in Table 4.7.

5.3.2.1. Results

The performance metric for all combinations of sensors, starting with one sensor and then gradually increasing the number of sensors, was calculated until the performance metric for combinations of nine sensors was achieved. This resulted in a detection term of 1 for the engine feed operation mode, and 0.9249 (less than 1) for the fuel transfer operation mode. The minimum number of sensors required to detect all the component failures for the fuel transfer operation mode was determined manually by looking through the sensor readings and determining which component failures were not detected by the best combination of nine sensors. The sensors required to detect these failures can be determined, and as a result, the minimum number required to detect them can be determined. This result is twelve sensors, and if the performance metric was to be calculated exhaustively, it would require approximately 3,000,000,000 additional combinations of sensors to be considered, in addition to approximately 176,000,000 combinations of sensors, which the performance metric is already calculated for. This would take in excess of a week, instead of around 8 hours. This suggests that applying an optimisation process to the selection of sensors would be beneficial for future, larger systems, as presented in Chapter 6. The maximum performance metric for each operation mode achieved using nine sensors is presented in the following paragraphs. A combination of nine sensors was selected because a combination of nine sensors can detect all the failures in the engine feed operation mode.

The performance metric and each individual term is presented for the engine feed and fuel transfer operation modes in Tables 5.4 and 5.5, respectively, when individual sensors are considered.

Table 5.4 Ranking of individual sensors for the example aircraft fuel system in the engine feed operation mode using the simulation

Rank	Sensor	$I_{\{s\}}$	$DE_{\{s\}}$	$DI_{\{s\}}$	$CR_{\{s\}}$
1	S23	0.5605	0.1645	0.6836	0.8333
	S25	0.5605	0.1645	0.6836	0.8333
2	S15	0.5445	0.0915	0.8754	0.6667
	S16	0.5445	0.0915	0.8754	0.6667
3	S22	0.5283	0.1645	0.5870	0.8333
	S24	0.5283	0.1645	0.5870	0.8333
4	FFL	0.5095	0.2747	0.5871	0.6667
	RFL	0.5095	0.2747	0.5871	0.6667
5	S17	0.3889	0.00003	1.0000	0.1667
	S20	0.3889	0.00003	1.0000	0.1667
6	S1	0.3519	0.1837	0.8719	0
	S1a	0.3519	0.1837	0.8719	0
	S12	0.3519	0.1837	0.8719	0
	S12a	0.3519	0.1837	0.8719	0
7	S26	0.3230	0.0923	0.8766	0
	S27	0.3230	0.0923	0.8766	0
8	S18	0.2687	0.0365	0.4361	0.3333
	S19	0.2687	0.0365	0.4361	0.3333
9	S14	0.2685	0.0365	0.4357	0.3333
	S21	0.2685	0.0365	0.4357	0.3333
10	S5	0.2089	0.1837	0.4431	0
	S8	0.2089	0.1837	0.4431	0
11	S4	0.2086	0.1837	0.4422	0
	S10	0.2086	0.1837	0.4422	0
12	LWTL	0.2081	0.1822	0.4422	0
	RWTL	0.2081	0.1822	0.4422	0
13	S15a	0.2073	0.1819	0.4401	0
	S16a	0.2073	0.1819	0.4401	0
14	S2	0.2067	0.1837	0.4364	0
	S3	0.2067	0.1837	0.4364	0
	S9	0.2067	0.1837	0.4364	0
	S11	0.2067	0.1837	0.4364	0
15	S28	0.1725	0.0738	0.4438	0
	S29	0.1725	0.0738	0.4438	0
16	S6	0.1675	0.0026	0.5000	0
	S7	0.1675	0.0026	0.5000	0
17	S13	0.0852	0.0026	0.2530	0

Table 5.5 Ranking of individual sensors for the example aircraft fuel system in the fuel transfer operation mode using the simulation

Rank	Sensor	$I_{\{s\}}$	$DE_{\{s\}}$	$DI_{\{s\}}$	$CR_{\{s\}}$
1	FFL	0.5933	0.3659	0.6999	0.7143
	RFL	0.5833	0.3659	0.6999	0.7143
2	S23	0.5057	0.1192	0.6836	0.7143
	S25	0.5057	0.1192	0.6836	0.7143
3	S15	0.5044	0.0663	0.8754	0.5714
	S16	0.5044	0.0663	0.8754	0.5714
4	S22	0.4735	0.1192	0.5870	0.7143
	S24	0.4735	0.1192	0.5870	0.7143
5	S4	0.4243	0.3139	0.8163	0.1429
	S10	0.4243	0.3139	0.8163	0.1429
6	S17	0.3810	0.00002	1.0000	0.1429
	S20	0.3810	0.00002	1.0000	0.1429
7	LWTL	0.3715	0.0924	0.8793	0.1429
	RWTL	0.3715	0.0924	0.8793	0.1429
8	S5	0.3664	0.2104	0.8888	0
	S8	0.3664	0.2104	0.8888	0
9	S6	0.3662	0.2112	0.8875	0
	S7	0.3662	0.2112	0.8875	0
10	S1	0.3193	0.0793	0.7357	0.1429
	S12	0.3193	0.0793	0.7357	0.1429
11	S26	0.3145	0.0669	0.8766	0
	S27	0.3145	0.0669	0.8766	0
12	S2	0.3015	0.0135	0.8910	0
	S3	0.3015	0.0135	0.8910	0
	S9	0.3015	0.0135	0.8910	0
	S11	0.3015	0.0135	0.8910	0
13	S18	0.2485	0.0266	0.4331	0.2857
	S19	0.2485	0.0266	0.4331	0.2857
	S14	0.2483	0.0266	0.4327	0.2857
	S21	0.2483	0.0266	0.4327	0.2857
14	S13	0.2169	0.2112	0.4393	0
15	S1a	0.1913	0.1321	0.4417	0
	S12a	0.1913	0.1321	0.4417	0
16	S15a	0.1907	0.1319	0.4401	0
	S16a	0.1907	0.1319	0.4401	0
17	S28	0.1658	0.0535	0.4438	0
	S29	0.1658	0.0535	0.4438	0

In both operation modes, the sensors ranked in the top 4 are the same, except in a different order. This suggests that there are sensors that are good in both of the operation modes. However, the same is not the case for the sensors towards the bottom of the table, for example, the sensors S1a and S12a are ranked 6^{th} in the engine feed operation mode, but are ranked 15^{th} in the fuel transfer operation mode. This is because different components are used in different operation modes and therefore the sensors can detect different amounts of component failures.

Table 5.6 Combinations of nine sensors with the highest performance metric for the engine feed operation mode using the simulation, I = 0.9676, DE = 1, DI = 0.9028, CR = 1

Sensors	Sensors continued
S1 S12 S14 S15 S16a S23 S25 S26 S27	S1a S12 S14 S15 S16a S23 S25 S26 S27
S1 S12 S14 S15a S16 S23 S25 S26 S27	S1a S12 S14 S15a S16 S23 S25 S26 S27
S1 S12 S14 S15a S16a S23 S25 S26 S27	S1a S12 S14 S15a S16a S23 S25 S26 S27
S1 S12 S15 S16a S18 S23 S25 S26 S27	S1a S12 S15 S16a S18 S23 S25 S26 S27
S1 S12 S15 S16a S19 S23 S25 S26 S27	S1a S12 S15 S16a S19 S23 S25 S26 S27
S1 S12 S15 S16a S21 S23 S25 S26 S27	S1a S12 S15 S16a S21 S23 S25 S26 S27
S1 S12 S15a S16 S18 S23 S25 S26 S27	S1a S12 S15a S16 S18 S23 S25 S26 S27
S1 S12 S15a S16 S19 S23 S25 S26 S27	S1a S12 S15a S16 S19 S23 S25 S26 S27
S1 S12 S15a S16 S21 S23 S25 S26 S27	S1a S12 S15a S16 S21 S23 S25 S26 S27
S1 S12 S15a S16a S18 S23 S25 S26 S27	S1a S12 S15a S16a S18 S23 S25 S26 S27
S1 S12 S15a S16a S19 S23 S25 S26 S27	S1a S12 S15a S16a S19 S23 S25 S26 S27
S1 S12 S15a S16a S21 S23 S25 S26 S27	S1a S12 S15a S16a S21 S23 S25 S26 S27
S1 S12a S14 S15 S16a S23 S25 S26 S27	S1a S12a S14 S15 S16a S23 S25 S26 S27
S1 S12a S14 S15a S16 S23 S25 S26 S27	S1a S12a S14 S15a S16 S23 S25 S26 S27
S1 S12a S14 S15a S16a S23 S25 S26 S27	S1a S12a S14 S15a S16a S23 S25 S26 S27
S1 S12a S15 S16a S18 S23 S25 S26 S27	S1a S12a S15 S16a S18 S23 S25 S26 S27
S1 S12a S15 S16a S19 S23 S25 S26 S27	S1a S12a S15 S16a S19 S23 S25 S26 S27
S1 S12a S15 S16a S21 S23 S25 S26 S27	S1a S12a S15 S16a S21 S23 S25 S26 S27
S1 S12a S15a S16 S18 S23 S25 S26 S27	S1a S12a S15a S16 S18 S23 S25 S26 S27
S1 S12a S15a S16 S19 S23 S25 S26 S27	S1a S12a S15a S16 S19 S23 S25 S26 S27
S1 S12a S15a S16 S21 S23 S25 S26 S27	S1a S12a S15a S16 S21 S23 S25 S26 S27
S1 S12a S15a S16a S18 S23 S25 S26 S27	S1a S12a S15a S16a S18 S23 S25 S26 S27
S1 S12a S15a S16a S19 S23 S25 S26 S27	S1a S12a S15a S16a S19 S23 S25 S26 S27
S1 S12a S15a S16a S21 S23 S25 S26 S27	S1a S12a S15a S16a S21 S23 S25 S26 S27

Table 5.7 Combinations of nine sensors with the highest performance metric for the fuel transfer operation mode using the simulation, I = 0.9479, DE = 0.9249, DI = 0.9187, CR = 1

Sensors
S1a S12a S15a S16a S18 S26 S27 FFL RFL
S1a S12a S15a S16a S19 S26 S27 FFL RFL

The combinations of 9 sensors with the highest performance metric are presented in Table 5.6 for the engine feed operation mode, and in Table 5.7 for the fuel transfer operation mode, respectively. For the engine feed operation mode, this performance metric is 0.9676, with a detection term of 1, a diagnostic term of 0.9028, and a criticality term of 1, and for the fuel transfer operation mode, the performance metric is 0.9479, with a detection term of 0.9249, a diagnostic term of 0.9187, and a criticality term of 1. Note, in Table 5.6 the combinations of sensors are given in two columns for brevity.

In the next section, a discussion on the selections of sensors is presented.

5.3.2.2. Discussion

One thing that can be observed from the performance metrics of the individual sensors, is that the level sensors are a useful addition to the possible types of sensors already considered. This is evident because the level sensors in the front (FFL) and rear (RFL) fuselage tanks are ranked 1st for the fuel transfer operation mode, i.e. they are the best sensors to use if only one sensor can be installed on the system for the fuel transfer operation mode. Note, that they are ranked 4th for the engine feed operation mode. The fuselage tank level sensors are also included in the combinations of nine sensors as can be observed in Table 5.7. In addition, the fuselage tank level sensors are also members of the best combinations of sensors, up to combinations of nine sensors for the fuel transfer operation mode, as presented in Table 5.10 later in this section. However, the level sensors are not included in any of the highest ranking combinations of sensors for the engine feed operation mode.

Other factors that were observed and also discussed in Chapters 3 and 4, are that it is best to select the sensors by considering the individual terms of the performance metric. For example, the sensors ranked 5th for the engine feed operation mode, sensors S17 and S20, have a low detection term (0.00003), and hence detect a small percentage of component failures, but are ranked highly because of the high diagnostic term (1). These individual sensors would not be considered because of the low detection term. Also, as discussed previously, it is generally not beneficial to select two sensors in close proximity to each other, as this typically does not increase the performance metric significantly. If the same example presented in Chapter 4 is considered, the sensor groups consisting of S22 and S23, and S24 and S25 have the same performance metrics value for the engine feed operation mode as sensors S23 and S25 have individually, respectively, i.e. there is no benefit from the additional sensor. In contrast, as shown in Table 5.9, the sensor combination S23 and S25, two sensors from different sections of the system, has a 27.17% increase in performance metric over the two sensors individually.

There are a number of best combinations of nine sensors for each operation mode, 48 combinations for the engine feed operation mode, and two combinations for the fuel transfer operation mode. If Table 5.6 is studied, there are a number of similarities that can be observed, for example, each combination has a pair of sensors, S1 or S1a, and S12 or S12a, one of the sensors, from S14, S18, S19 or S21, one of the sensors, from S15 or S15a and one of the sensors, from S16 or S16a (note, not including the combination S15 and S16), and then the four sensors, S23, S25, S26 and S27. Likewise, if Table 5.7 is studied, despite the fact that there are only two combinations, there is still some symmetry in the results that can be observed, i.e. sensor S18 or S19, the sensor next to LDV or the sensor next to RDV, respectively. The other sensors, despite the first four sensors being the same numbers as for the engine feed operation mode (i.e. 1, 12, 15 and 16), the only combination of sensors that result in the maximum performance metric is using the sensors S1a, S12a, S15a, and S16a. This is because these four sensors selected for the fuel transfer operation mode detect failures that are not detected by the other sensors in the sensor suite, whereas the sensors, S1, S12, S15, and S16, do not detect as many of these failures. Therefore, the combination of S1a, S12a, S15a, and S16a is the only combination that can be selected to achieve the maximum performance metric for the fuel transfer operation mode for combinations of 9 sensors.

In the un-simplified version of the system, sensors S23 and S25 are selected instead of sensors S22 and S24 as in the simplified version of the system. In both cases, the only difference in the terms of the performance metric is the diagnostic terms. This is because of the inclusion of the redundant booster pumps in the model. In the simplified version of the system, sensors S22 and S24 produce the same sensor reading for each of the low and high pressure cocks failing closed and a different sensor reading for the booster pumps failing off. Sensors S23 and S25 produce the same sensor reading for the low pressure cock failing closed and the booster pumps failing off, and a different sensor reading for the high pressure cock failing closed. As the probability of the booster pumps being in the failed state is higher than each of the cocks failing closed, sensors S22 and S24 have a higher diagnostic term. However, in the un-simplified version of the system, because of the redundant booster pumps, the sensors cannot detect the booster pump failing as the redundant pumps automatically activate when the primary pumps fail off. Therefore, as sensors S23 and S25 can distinguish between the low and high pressure cocks failing closed, which sensors S22 and S24 cannot, they are selected in the un-simplified version of the system.

For both operation modes, the sensors are selected from groups of sensors as before. The groups are presented in Figure 5.4, and groups 1 – 6 are the same as presented in Figure 4.12, with three additional groups added. Note, level sensors are grouped together into group 9, but are not displayed on the Figure 5.4 for clarity. Also note, in groups 1 – 4, there are additional sensors in comparison to those presented in section 4.4.3, because of the additional sensors considered in this chapter, sensors S1a, S12a, S15a, and S16a.

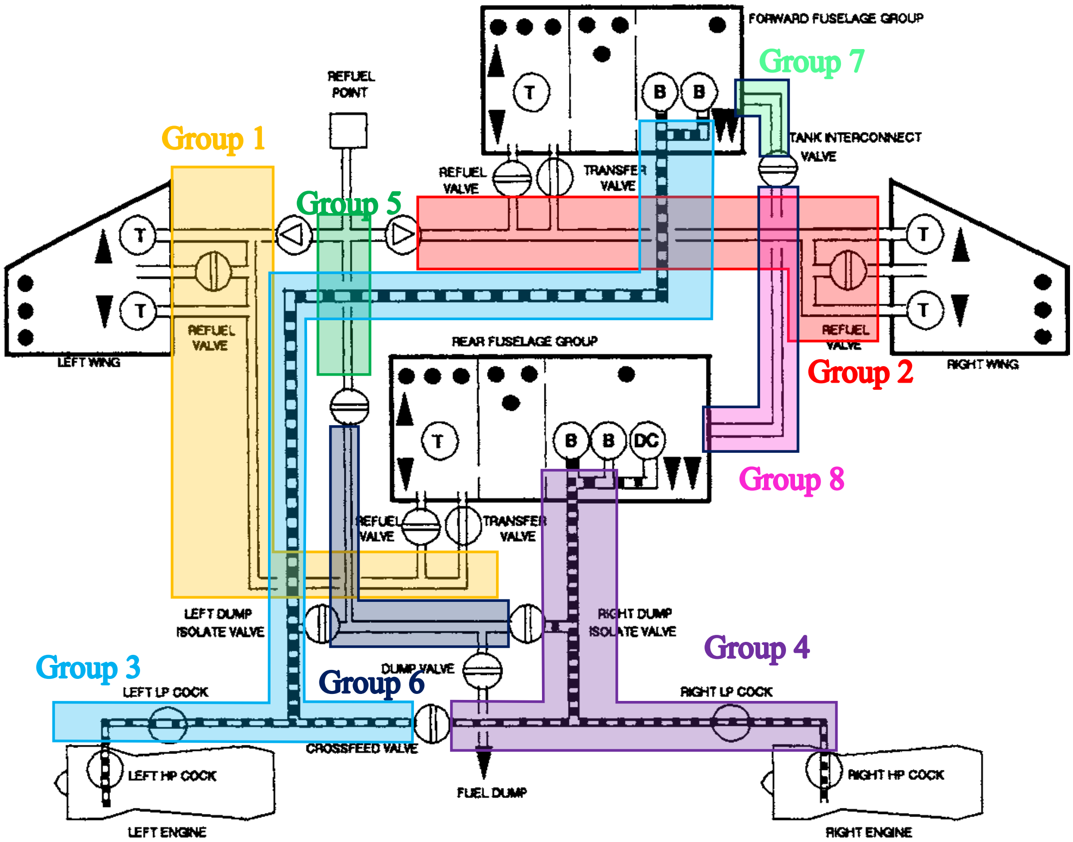


Figure 5.4 Sections of the system labelled

The best combinations of nine sensors for the engine feed operation mode consist of a sensor from each of the groups 1, 2, 6, 7, and 8, and two sensors from each of the groups 3 and

4. As in the previous chapter, no sensor from group 5 is included in the best combination of 9 sensors for the engine feed operation mode. In addition no sensor is included from group 9, with sensors included from each of the other groups. However, group 9, the tank level sensors, could also be split into groups 1, 2, 3 and 4, with the wing tank level sensors in groups 1 and 2, respectively, and the fuselage level sensors in groups 3 and 4, respectively. If this was the case, this would result in the selection of sensors for the fuel transfer operation mode following the same format as the selection of sensors for the engine feed operation mode. Note, the best combination of nine sensors for the fuel transfer operation mode consists of a sensor from each of the groups 1, 2, 3, 4, 6, 7, and 8, and two sensors from group 9, (or one sensor from 1, 2, 6, 7 and 8 and two sensors from group 3 and 4 if the fuel level sensors are split into groups 1 – 4 as suggested). For clarity, each of the groups are presented in Table 5.8, with the "included sensors" representing the sensors that are in the best selection of nine sensors for each operation mode, and the "not included sensors" representing the sensors that are not in the best combinations of 9 sensors for each operation mode.

Table 5.8 The sensors grouped by the sections of the system

Group	Included sensors				Not included sensors		
1	S1	S1a	S4		S2	S3	S5
2	S10	S12	S12a		S8	S9	S11
3	S15	S15a	S23		S17	S22	S28
4	S16	S16a	S25		S20	S24	S29
5					S6	S7	S13
6	S14	S18	S19	S21			
7	S26						
8	S27						
9	FFL	RFL			LWTL	RWTL	

If the performance metric of the best combination of sensors for each number of sensors is compared, it is observed that the increase in performance diminishes as the number of sensors is increased. This is observed in both operation modes, and is presented in the last column of Tables 5.9 and 5.10, respectively. This was also observed in section 4.4.3, and in section 3.4.1.1.

If a phased mission was considered for the system, where the operation mode changes throughout the mission, the two operation modes could be combined and the failures weighted according to the time spent in each operation mode. One combination of sensors could then be chosen using one performance metric. This is considered in Chapter 6.

Table 5.9 Best performance metric for the engine feed operation mode for each number of sensors for the simulation

Number	Sensors	$I_{\{s\}}$	% diff.
1	S23	0.5605	0
2	S23 S25	0.7128	27.17
3	S1 S23 S25	0.7749	8.71
4	S1 S12 S23 S25	0.8379	8.13
5	S1 S12 S23 S25 S26	0.8691	3.72
6	S1 S12 S23 S25 S26 S27	0.9000	3.56
7	S1 S12 S15a S23 S25 S26 S27	0.9307	3.41
8	S1 S12 S15 S16a S23 S25 S26 S27	0.9611	3.27
9	S1 S12 S14 S15 S16a S23 S25 S26 S27	0.9676	0.68
37	All sensors	0.9688	0.12

Table 5.10 Best performance metric for the fuel transfer operation mode for each number of sensors for the simulation

Number	Sensors	$I_{\{s\}}$	% diff.
1	FFL	0.5933	0
2	S23 FFL	0.7049	18.81
3	S18 FFL RFL	0.7945	12.71
4	S23 S25 FFL RFL	0.8262	3.99
5	S15a S16a S18 FFL RFL	0.8561	3.62
6	S1a S15a S16a S18 FFL RFL	0.8795	2.73
7	S1a S12a S15a S16a S18 FFL RFL	0.9025	2.62
8	S1a S12a S15a S16a S18 S26 FFL RFL	0.9253	2.53
9	S1a S12a S15a S16a S18 S26 S27 FFL RFL	0.9479	2.44
37	All sensors	0.9751	2.87

In the next section, the fault diagnostics process is applied to the system using the selected group of sensor for each operation mode.

5.3.3. Fault diagnostics

The selected sensors for fault diagnostics are the first combination of nine sensors obtained using the simulation method from Tables 5.6 and 5.7, for the engine feed and fuel transfer operation mode, respectively. Therefore, the combinations of sensors selected for the engine feed operation mode are (S1, S12, S14, S15, S16a, S23, S25, S26, S27) and the combination of sensors selected for the fuel transfer operation mode are (S1a, S12a, S15a, S16a, S18, S26, S27, FFL, RFL). In order to determine the effectiveness of the selected sensors, they are used to diagnose failures in the system using the method presented in section 5.1.2. As in Chapters 3 and 4, all combinations of component failures that are used to calculate the performance metrics, are used as example failures to test the diagnostic process. As detailed in section 5.3.2, only approximately 39% of the combinations of component failures for the engine feed operation mode can be detected, and only approximately 54% of the combinations of component failures for the fuel transfer operation mode can be detected. However, as the detection term for the combination of sensors for the fuel transfer operation mode is less than 1, only approximately 49.65% of the component failures can be detected for the fuel transfer operation mode, i.e. the detection term multiplied by the sum of the probability of the failures that can be detected in the fuel transfer operation mode, 0.9249×53.6849%.

The fault diagnostic technique is applied by comparing the observed sensor readings to a library of sensor readings for known component failures, and outputting the component failure with the highest probability in each case. The diagnosed failure can then be compared to the actual component failure, in order to assess the accuracy of the fault diagnostic method.

5.3.3.1. Fault Diagnosis Results

Each of the combinations of component failures used to calculate the performance metric are used to test the diagnostic process, i.e. 1568 failures for each operation mode. The results of each of these combinations are grouped together into cases which consist of combinations of component failures that have similar fault diagnostic results, i.e. such as in the first case of Table 5.11. There are 14 cases for the engine feed operation mode, and 14 cases for the fuel transfer operation mode. The cases are presented in Tables 5.11 and 5.12, for the engine feed, and the fuel transfer operation modes, respectively. As in Chapter 4, as there are two failure modes for each of the components, the bracketed word in the tables indicates the mode that the component has failed in, for example, RVLW (Open) represents RVLW failed open. Note, as before (On) represents failed on, (Off) represents failed off, (Open) represents failed open, (Cl) represents failed closed, and (2 way) represents the one directional valve allowing the flow through in both directions.

All combinations of component failures are not presented in the tables, as there are 760, and 840 combinations of failures that are detected for the engine feed and the fuel transfer operation modes, respectively. Instead, only one of each set of combinations of component failures within each case is presented. The number of failure combinations in each case is detailed in the third column of the tables. The second column in the tables, e.g. 1 of 2, represents the number of component failures that are diagnosed, (i.e. 1), of the number of component failures in the considered event, (i.e. 2).

The probability that each component is in the failure mode is presented after each of the component failures. This is equal to the probability of each failure occurrence, divided by the probability of all component failures that produce the observed symptoms, respectively, i.e. P_{mli}/P_{sri}. For example, if the probability is 50%, then there is a 50% likelihood that the component has failed.

The diagnostic results for the engine feed operation mode are presented in Table 5.11, with the component failures in each case explained in the same way as they were explained for Tables 4.15 and 4.16.

The first case in Table 5.11 consists of component failures where one component has failed and it is diagnosed correctly with approximately 90% confidence. The component failures in this case consist of only one component failure, and are therefore, more likely to occur than other combinations of component failures. This case includes component failures for the booster pumps, the transfer pumps, and the low and high pressure cocks.

The second case in Table 5.11 also consists of component failures where only one component has failed, but in this case the probability of each of the component failures is approximately 45%. The component failure is one of the two options presented, and therefore, it is diagnosed correctly. The component failures in this case include the left and right dump valves. It is possible that both of the components can be failed and produce the same set of symptoms, this is detailed in case nine of Table 5.11.

The third and fourth cases in Table 5.11 are combinations of two component failures, but only one of them is diagnosed. The component failures in these two cases are the same as the component failures in cases one and two respectively, but with an additional component failure that is hidden. The additional component failures are component failures that are not normally detected when they are on their own, i.e. the failures are hidden failures regardless of the presence of the diagnosed failure, the diagnosed failure is not causing the second failure to be hidden.

The fifth case in Table 5.11 are combinations of two component failures where both of them are diagnosed. The combinations of component failures in this case consist of a component failure from case one, and a component failure from case two. Therefore, the probability of the first component being failed is 100%, and the probability of the second component being failed is 50%. Note, the reason that the probability of the diagnosis being correct is 100% and 50%, respectively, and not approximately 90% and 45%, respectively, is because the library of observed component failures only consists of combinations of one and two component failures. Therefore, no additional component failure can be observed in this case, but an additional component failure can be in cases one and two, (i.e. cases three and four), hence the lower probability of the diagnosis being correct.

The sixth case in Table 5.11 is when there are two component failures, and both of them are diagnosed. In this case, either the diagnosed failure 1 and diagnosed failure 2, or the diagnosed failure 3 and diagnosed failure 4 has occurred, i.e. TPLB (On) and NVL (2 way), or TPRB (On) and NVR (2 way). The probability of each pair occurring is approximately 38%. This is less than 50% for each pair as there is another combination of component failures that produces the same set of symptoms. This combinations of component failures are presented in case thirteen.

The seventh case in Table 5.11 is when there are two component failures, both of which are diagnosed, but with approximately 60% confidence. This is because there is another combination of component failures that can produce the same symptoms, but the combination is less likely to occur. These combinations of component failures are detailed in case number eleven.

The eighth case in Table 5.11 is combinations of two component failures, and both are diagnosed with 100% confidence, i.e. both of the components have definitely failed. The components that are included in this case are the components CV, TIV, DV, and the component failures that are in case one.

The ninth case in Table 5.11 is a combination of two component failures where both are diagnosed. This case was referred to in the paragraph about the second case, where both of the components have failed, and not just one of the components as the diagnostic process suggests. The component failures are the same as those presented in case two.

The tenth case in Table 5.11 is a combination of two component failures, both of which are diagnosed, but the second component failure will not be diagnosed until after the first component failure has been repaired or replaced. These combinations of component failures include component failures for the transfer pumps, booster pumps, and low and high pressure cocks.

The eleventh case in Table 5.11 was discussed briefly in case seven. This case consists of a combination of component failures that are both diagnosed, but one is incorrect initially. The first component failure is diagnosed correctly, but the second component failure is not diagnosed correctly. However, when further evidence is introduced, the actual second component failure will be diagnosed correctly. As one component failure has already been diagnosed, and the limit of the number of component failures is two, the actual second component failure will be diagnosed correctly with 100% confidence.

The twelfth case in Table 5.11 are combinations of two component failures, but one of the failures is diagnosed incorrectly. The incorrectly diagnosed component is actually in its other failure mode, i.e. failed closed. This component failure is normally hidden, and is therefore, not normally found. This is the same as the sixth case from Table 4.15.

The thirteenth case in Table 5.11 is a combination of two component failures, but the fault diagnostics process outputs two pairs of component failures with approximately 38% probability of being correct, i.e. as in case six. However, the actual combination of component failures is one component from each pair, TPLB (On) and TPRB (On), which produces the same symptoms as the other two combinations, but is less likely to occur. Therefore, the component failures are also diagnosed correctly, but up to four components may be inspected in order to determine the correct combination of component failures.

The final case in Table 5.11 is a combination of two component failures, but is initially diagnosed as one component failure, which has not actually failed. However, when this evidence is introduced, the two component failures are diagnosed correctly with 100% confidence. This is because the two component failures produce the same set of symptoms as the originally diagnosed component failure, but the combination of failures is less likely to occur.

Table 5.11 Diagnostics of component failures for the engine feed operation mode using the simulation

Case	Number Diagnosed	Number Represented	Diagnosed failure 1	Probability	Diagnosed failure 2	Probability	Diagnosed failure 3	Probability	Diagnosed failure 4	Probability
1	1 of 1	2	BPFR (On)	91.8554%						
		2	TPFF (On)	91.8554%						
		2	TPLT (On)	92.1111%						
		2	TPLB (On)	92.3703%						
		2	BPFL (Off)	91.7709%						
		2	LLP (Cl)	91.4312%						
		2	LHP (Cl)	91.5150%						
2	1 of 1	2	LDV (Op)	45.7785%	RDV (Op)	45.7785%				
3	1 of 2	76	BPFR (On)	91.8554%						
		76	TPFF (On)	91.8554%						
		74	TPLT (On)	92.1111%						
		76	TPLB (On)	92.3703%						
		76	BPFL (Off)	91.7709%						
		86	LLP (Cl)	91.4312%						
		66	LHP (Cl)	915150%						
4	1 of 2	72	LDV (Op)	45.7785%	RDV (Op)	45.7785%				
5	2 of 2	4	BPFL (Off)	100%	LDV (Op)	50%	RDV (Op)	50%		
		4	BPFR (On)	100%	LDV (Op)	50%	RDV (Op)	50%		

Case	Number Diagnosed	Number Represented	Diagnosed failure 1	Probability	Diagnosed failure 2	Probability	Diagnosed failure 3	Probability	Diagnosed failure 4	Probability
		4	TPFF (On)	100%	LDV (Op)	50%	RDV (Op)	50%		
		4	TPLT (On)	100%	LDV (Op)	50%	RDV (Op)	50%		
		4	TPLB (On)	100%	LDV (Op)	50%	RDV (Op)	50%		
		4	LLP (Cl)	100%	LDV (Op)	50%	RDV (Op)	50%		
		4	LHP (Cl)	100%	LDV (Op)	50%	RDV (Op)	50%		
6	2 of 2	2	TPLB (On)	38.0860%	NVL (2 way)	38.0860%	TPRB (On)	38.0860%	NVR (2 way)	38.0860%
7	2 of 2	2	TPLT (On)	61.5450%	NVL (2 way)	61.5450%				
8	2 of 2	4	LLP (Cl)	100%	BPFL (Off)	100%				
		4	LHP (Cl)	100%	BPFL (Off)	100%				
		4	LLP (Cl)	100%	BPFR (On)	100%				
		4	LHP (Cl)	100%	BPFR (On)	100%				
		2	LLP (Cl)	100%	CV (Cl)	100%				
		2	LHP (Cl)	100%	CV (Cl)	100%				
		4	LLP (Cl)	100%	TPFF (On)	100%				
		4	LHP (Cl)	100%	TPFF (On)	100%				
		4	LLP (Cl)	100%	TPLT (On)	100%				
		4	LHP (Cl)	100%	TPLT (On)	100%				
		4	LLP (Cl)	100%	TPLB (On)	100%				

Case	Number Diagnosed	Number Represented	Diagnosed failure 1	Probability	Diagnosed failure 2	Probability	Diagnosed failure 3	Probability	Diagnosed failure 4	Probability
		4	LHP (Cl)	100%	TPLB (On)	100%				
		1	LLP (Cl)	100%	RLP (Cl)	100%				
		2	LLP (Cl)	100%	RHP (Cl)	100%				
		1	LHP (Cl)	100%	RHP (Cl)	100%				
		2	LDV (Op)	100%	RPV (Op)	100%				
		2	LDV (Op)	100%	DV (Op)	100%				
		2	TIV (Op)	100%	TPFF (On)	100%				
		2	CV (Op)	100%	BPFR (On)	100%				
		1	TPFF (On)	100%	TPRF (On)	100%				
		4	TPFF (On)	100%	TPLT (On)	100%				
		4	TPFF (On)	100%	TPLB (On)	100%				
		1	TPLT (On)	100%	TPRT (On)	100%				
		4	TPFF (On)	100%	BPFL (Off)	100%				
		4	TPLT (On)	100%	BPFL (Off)	100%				
		4	TPLB (On)	100%	BPFL (Off)	100%				
		4	TPFF (On)	100%	BPFR (On)	100%				
		4	TPLT (On)	100%	BPFR (On)	100%				
		4	TPLB (On)	100%	BPFR (On)	100%				

Case	Number Diagnosed	Number Represented	Diagnosed failure 1	Probability	Diagnosed failure 2	Probability	Diagnosed failure 3	Probability	Diagnosed failure 4	Probability
		2	BPFL (Off)	100%	BPFR (Off)	100%				
		1	BPFL (Off)	100%	BPRL (Off)	100%				
		2	BPFL (Off)	100%	BPRR (On)	100%				
		1	BPFR (On)	100%	BPRR (On)	100%				
9	2 of 2	1	LDV (Op)	45.7785%	RDV (Op)	45.7785%				
10	2 of 2 (one delayed)	2	TPLT (On)	92.1111%	TPLB (On)	92.3703%				
		2	BPFL (Off)	91.7709%	BPFR (On)	91.8554%				
		2	LLP (Cl)	91.4312%	LHP (Cl)	91.5150%				
11	1 of 2 (one incorrect)	2	TPLT (On)	61.5145%	NVL (On)	61.5145%	TPRB (On)	100%		
12	2 of 2 (one incorrect)	2	LDV (Op)	45.7785%	RDV (Op)	45.7785%				
13	2 of 2	1	TPLB (On)	38.0860%	NVL (2 way)	38.0860%	TPRB (On)	38.0860%	NVR (2 way)	38.0860%
14	2 of 2 (one incorrect)	2	TPLB (On)	92.3703%	TPLT (On)	100%	TVRF (Cl)	100%		

Table 5.12 Diagnostics of component failures for the fuel transfer operation mode using the simulation

Case	Number Diagnosed	Number Represented	Diagnosed failure 1	Probability	Diagnosed failure 2	Probability	Diagnosed failure 3	Probability	Diagnosed failure 4	Probability
1	1 of 1	2	BPFR (On)	93.0642%						
		2	TPLT (Off)	93.0642%						
		2	TPFF (On)	93.2381%						
		2	TPLB (On)	93.1511%						
		2	BPFL (Off)	93.1511%						
		2	RVLW (Op)	92.8875%						
		2	TVFF (Cl)	91.2619%						
		2	NVL (2 way)	93.0619%						
2	1 of 1	2	LDV (Op)	46.4437%	RDV (Op)	46.4437%				
3	1 of 2	74	BPFR (On)	93.0642%						
		72	TPLT (Off)	93.0642%						
		72	TPFF (On)	93.2381%						
		74	TPLB (On)	93.1511%						
		72	BPFL (Off)	93.1511%						
		72	RVLW (Op)	92.8875%						
		72	TVFF (Cl)	91.2619%						
		68	NVL (2 way)	93.0619%						
4	1 of 2	69	LDV (Op)	46.4437%	RDV (Op)	46.4437%				

Case	Number Diagnosed	Number Represented	Diagnosed failure 1	Probability	Diagnosed failure 2	Probability	Diagnosed failure 3	Probability	Diagnosed failure 4	Probability
5	2 of 2	2	BPFL (Off)	100%	LDV (Op)	50%	RDV (Op)	50%		
		2	BPRL (Off)	100%	LDV (Op)	50%	RDV (Op)	50%		
		2	BPFR (On)	100%	LDV (Op)	50%	RDV (Op)	50%		
		2	BPRR (On)	100%	LDV (Op)	50%	RDV (Op)	50%		
		2	TPFF (On)	100%	LDV (Op)	50%	RDV (Op)	50%		
		2	TPRF (On)	100%	LDV (Op)	50%	RDV (Op)	50%		
		2	TPLT (Off)	100%	LDV (Op)	50%	RDV (Op)	50%		
		2	TPRT (Off)	100%	LDV (Op)	50%	RDV (Op)	50%		
		2	TPLB (On)	100%	LDV (Op)	50%	RDV (Op)	50%		
		2	TPRB (On)	100%	LDV (Op)	50%	RDV (Op)	50%		
		2	RVLW (Op)	100%	LDV (Op)	50%	RDV (Op)	50%		
		2	RVRW (Op)	100%	LDV (Op)	50%	RDV (Op)	50%		
		2	TVRF (Cl)	100%	LDV (Op)	50%	RDV (Op)	50%		
		2	TVFF (Cl)	100%	LDV (Op)	50%	RDV (Op)	50%		
		4	CV (Cl)	100%	LLP (Cl)	50%	LHP (Cl)	50%		
6	2 of 2	4	BPFL (Cl)	50%	TVFF (Cl)	50%	BPFR (On)	50%	RVRW (Op)	50%
		4	LLP (Cl)	50%	LHP (Cl)	50%	RLP (Cl)	50%	RHP (Cl)	50%
7	2 of 2	6	NVL (2 way)	100%	RPV (Op)	33.3333%	LDV (Op)	33.3333%	RDV (Op)	33.3333%

Case	Number Diagnosed	Number Represented	Diagnosed failure 1	Probability	Diagnosed failure 2	Probability	Diagnosed failure 3	Probability	Diagnosed failure 4	Probability
8	2 of 2	2	NVL (2 way)	88.9582%	BPFR (On)	88.9582%				
9	2 of 2	2	BPFL (Off)	100%	BPFR (Off)	100%				
		1	BPFL (Off)	100%	BPRL (Off)	100%				
		2	BPFL (Off)	100%	BPRR (On)	100%				
		1	BPFR (On)	100%	BPRR (On)	100%				
		2	BPFL (Off)	100%	NVL (2 way)	100%				
		2	BPFL (Off)	100%	NVR (2 way)	100%				
		2	BPFR (On)	100%	NVR (2 way)	100%				
		2	BPFL (Off)	100%	TVRF (Cl)	100%				
		2	BPFR (On)	100%	TVRF (Cl)	100%				
		2	BPFR (On)	100%	TVFF (Cl)	100%				
		2	BPFL (Off)	100%	RVLW (Op)	100%				
		2	BPFL (Off)	100%	TPFF (On)	100%				
		2	BPFL (Off)	100%	TPRF (On)	100%				
		2	BPFL (Off)	100%	TPLB (On)	100%				
		2	BPFL (Off)	100%	TPRB (On)	100%				
		2	BPFL (Off)	100%	TPLT (Off)	100%				
		2	BPFL (Off)	100%	TPRT (Off)	100%				

Case	Number Diagnosed	Number Represented	Diagnosed failure 1	Probability	Diagnosed failure 2	Probability	Diagnosed failure 3	Probability	Diagnosed failure 4	Probability
		2	BPFR (On)	100%	TPFF (On)	100%				
		2	BPFR (On)	100%	TPRF (On)	100%				
		2	BPFR (On)	100%	TPLB (On)	100%				
		2	BPFR (On)	100%	TPRB (On)	100%				
		2	BPFR (On)	100%	TPLT (Off)	100%				
		2	BPFR (On)	100%	TPRT (Off)	100%				
		1	TIV (Op)	100%	TPFF (On)	100%				
		1	TIV (Op)	100%	TPRF (On)	100%				
		1	RPV (Op)	100%	LDV (Op)	100%				
		1	RPV (Op)	100%	RDV (Op)	100%				
		1	LDV (Op)	100%	DV (Op)	100%				
		2	RVRF (Op)	100%	NVL (2 way)	100%				
		1	TVRF (Cl)	100%	TVFF (Cl)	100%				
		2	TVRF (Cl)	100%	NVL (2 way)	100%				
		2	RVLW (Op)	100%	NVL (2 way)	100%				
		2	RVLW (Op)	100%	NVR (2 way)	100%				
		2	RVLW (Op)	100%	TVFF (Cl)	100%				
		2	RVLW (Op)	100%	RVRF (Op)	100%				

Case	Number Diagnosed	Number Represented	Diagnosed failure 1	Probability	Diagnosed failure 2	Probability	Diagnosed failure 3	Probability	Diagnosed failure 4	Probability
		1	RVLW (Op)	100%	RVRW (Op)	100%				
		1	TPFF (On)	100%	TPRF (On)	100%				
		2	TPFF (On)	100%	TPLB (On)	100%				
		2	TPFF (On)	100%	TPRB (On)	100%				
		2	TPFF (On)	100%	TPLT (Off)	100%				
		2	TPFF (On)	100%	TPRT (Off)	100%				
		2	TPLT (Off)	100%	TPRB (On)	100%				
		2	TPLT (Off)	100%	TPLB (Off)	100%				
		1	TPLT (Off)	100%	TPRT (Off)	100%				
		1	TPLB (On)	100%	TPRB (On)	100%				
		2	TPFF (On)	100%	RVLW (Op)	100%				
		2	TPFF (On)	100%	RVRW (Op)	100%				
		2	TPLT (Off)	100%	RVLW (Op)	100%				
		2	TPLT (Off)	100%	RVRW (Op)	100%				
		2	TPLB (On)	100%	RVRW (Op)	100%				
		2	TPFF (On)	100%	TVFF (Cl)	100%				
		2	TPFF (On)	100%	TVRF (Cl)	100%				
		2	TPLT (Off)	100%	TVFF (Cl)	100%				

Case	Number Diagnosed	Number Represented	Diagnosed failure 1	Probability	Diagnosed failure 2	Probability	Diagnosed failure 3	Probability	Diagnosed failure 4	Probability
		2	TPLB (Off)	100%	TVFF (Cl)	100%				
		2	TPFF (On)	100%	NVL (2 way)	100%				
		2	TPRF (On)	100%	NVL (2 way)	100%				
		2	TPLT (Off)	100%	NVL (2 way)	100%				
		2	TPLT (Off)	100%	NVR (2 way)	100%				
		2	TPLB (On)	100%	NVL (2 way)	100%				
		2	TPLB (On)	100%	NVR (2 way)	100%				
10	2 of 2	1	LDV (Op)	46.4437%	RDV (Op)	46.4437%				
11	2 of 2 (one delayed)	2	BPFL (Off)	93.1511%	BPFR (On)	93.0642%				
		2	TPLT (Off)	93.0642%	TPLB (On)	93.1511%				
		2	TVRF (Cl)	91.2619%	TPLT (Off)	93.0642%				
		2	TVRF (Cl)	91.2619%	TPLB (On)	93.1511%				
		2	TVRF (Cl)	91.2619%	RVLW (Op)	92.8875%				
		2	TVRF (Cl)	91.2619%	NVR (2 way)	93.0619%				
12	1 of 2 (one incorrect)	2	LDV (Op)	46.4437%	RDV(Op)	46.4437%				
13	2 of 2 (one incorrect)	2	BPFR (On)	88.9582%	NVL (2 way)	88.9582%	BPFL (Off)	100%	RVLW (Op)	100%
14	2 of 2 (one incorrect)	2	BPFR (On)	93.0642%	BPFL (Off)	100%	RVRW (Op)	100%		
		2	TPLT (Off)	93.0642%	TPLB (On)	100%	RVLW (Op)	100%		

Table 5.12 presents the combinations of component failures for the fuel transfer operation mode. The first case in Table 5.12 consists of component failures where one component has failed and is diagnosed correctly with approximately 90% confidence. The component failures in this case are more likely to occur than other combinations of component failures, as these consist of only one component failure. This case includes component failures for the booster pumps, transfer pumps, transfer valves, refuel valves and 1D valves. This is the equivalent of case one for the engine feed operation mode in Table 5.11.

The second case in Table 5.12 is the equivalent of the second case of the engine feed operation mode. It consists of individual component failures, diagnosed with approximately 45% confidence. The components included in this case are the left and right dump valves, and the failed component is one of the two options presented in the table for this case.

The third and fourth cases in Table 5.12 are the equivalents of the third and fourth cases in the engine feed operation mode. Therefore, they consist of combinations of two component failures, one of which is diagnosed. The third case consists of the component failures from the first case, and the fourth case consists of the component failures from the second case. Both cases also have a hidden failure in each combination of component failures.

The fifth case in Table 5.12 represents combinations of two component failures, both of which are diagnosed. The first component failure is diagnosed with a confidence of 100% and the second component with 50% confidence. This case is the same as the fifth case for the engine feed operation mode. The components in this case are booster pumps, transfer pumps, refuel valves, transfer valves, left and right dump valves, low and high pressure cocks, and the cross-feed valve.

The sixth case in Table 5.12 represents combinations of two component failures, both of which are diagnosed. In this case, there are two pairs of component failures that have 50% probability of being the combinations of component failures to have occurred. For the first row of this case, it can either be the first two component failures or the second two component failures, but for the second row it can be any combination of left and right cocks failed closed.

The seventh case in Table 5.12 consists of combinations of two component failures that are both diagnosed. The first of which is diagnosed with 100% confidence, but the second component can be any of three component failures, all of which are equally likely to occur, and therefore, the probability of each of them is approximately 33.33%. This consists of the components, 1D valves, left and right dump valves, and the refuel point valve.

The eighth case in Table 5.12 consists of combinations of two component failures both of which are diagnosed with approximately 90% confidence. This is because there are other combinations of component failures that can produce the same symptoms but are less likely to occur. These component failures include combinations of the booster pumps and one-directional valves failing.

The ninth case in Table 5.12 consists of combinations of two component failures, both of which are diagnosed with 100% confidence. This corresponds to the eighth case of the engine feed operation mode. The component failures in this case include combinations of failures of booster pumps, transfer pumps, transfer valves, refuel valves, 1D valves, and the dump valves.

The tenth case in Table 5.12 consists of a combination of two component failures. This combination is diagnosed as approximately 45% probability of being LDV failed open, or RDV failed open, but the actual component failure combination is both of the valves failed open. This case is the equivalent of the ninth case in the engine feed operation mode.

The eleventh case in Table 5.12 consists of combinations of two component failures, both of which are diagnosed, but the second component failure is not diagnosed until after the first component failure has been repaired or replaced. The components in this case include the transfer pumps, transfer valves, booster pumps, refuel valves, and the 1D valves. This is the equivalent of case ten for the engine feed operation mode.

The twelfth case in Table 5.12 consists of combinations of two component failures, one of which is diagnosed incorrectly. One of the components in each combination of component failures has failed in a different mode than it is diagnosed to be in, i.e. failed closed. However, this component failure would normally be a hidden failure, and therefore, the presence of the correctly diagnosed component failure is not affecting the diagnosis of this component failure. This is the equivalent of case twelve for the engine feed operation mode.

The thirteenth case in Table 5.12 consists of combinations of two component failures. However, neither of the most likely component failures are the actual component failures present in the system, but when this evidence is introduced, the correct combination of component failures is diagnosed. There is no case for the engine feed operation mode that is the equivalent of this case.

The final case in Table 5.12 consists of combinations of two components, but it is initially diagnosed as one component failure with approximately 90% confidence. However, when evidence is introduced that the component has not failed, the correct combination of component failures is diagnosed correctly with 100% confidence.

In the next section, a discussion about the success of the proposed fault diagnostic technique, is presented.

5.3.3.2. Discussion

The fault diagnostic process successfully diagnoses a large number of combinations of component failures, including all of the individual component failures that can be detected. In both operation modes, the accuracy of the diagnostic process could be improved by including more sensors, as the maximum achievable diagnostic term is not achieved for either operation mode using the 9 sensors. Note that for the fuel transfer operation mode, the detection term of the performance metric can also be increased by including more sensors. This would result in more component failures being detected and diagnosed.

However, there were a number of cases where the correct component failure was not diagnosed initially, but when additional evidence was introduced in the model, the correct component failure was diagnosed in all cases. The cases in which this occurs are cases eleven and fourteen for the engine feed operation mode, and cases thirteen and fourteen for the fuel transfer operation mode. In all cases, no more than four components need to be inspected in order to find the failed components.

As detailed before, there are a number of hidden component failures, 808/1568 for the engine feed operation mode, and 728/1568 (204 of which are because the detection term is less than 1 for the selected combination of 9 sensors) for the fuel transfer operation mode. These hidden component failures consist of components failing in sections of the system that are not being used or there is no sensor included, and components failing in the failure mode that they are supposed to be in during each operation mode. Some of the hidden failures cannot be detected in cases where there are combinations of two component failures. This results in a large number of cases where only one of the two component failures are diagnosed, but as discussed above, the component failure that is not diagnosed correctly would not normally be detected. This affects cases three, four, eleven and twelve for the engine feed operation mode, and cases three, four and twelve for the fuel transfer operation mode.

For both of the operation modes, there are some cases where the second component failure is not detected until after the first component has been repaired or replaced. This would increase the repair time of the system, but as the combination of the two component failures produces the same symptoms as the first component failure on its own, it is unavoidable unless components that are less likely to have failed are to be taken to the system when the system is inspected. The cases in which there are component failures that are only detected after another component failure has been repaired or replaced are case ten for the engine feed operation mode, and case eleven for the fuel transfer operation mode.

5.3.4. Summary

The proposed methodology has been applied to the aircraft system and the results have been presented in this section of the chapter. In order to ensure that the method works as desired, the BBN method, developed in Chapter 4, is also applied to the same system. This will enable the results from both methodologies to be compared, and then the most suitable method to be applied in Chapter 6, when a full aircraft system is considered. This discussion is presented in section 5.5.

5.4. Application of the methodology using BBNs for comparison

In order to verify that the simulation method can be used to determine a good selection of sensors and can diagnose the failures efficiently, the system is modelled using a BBN. The BBN is then used to aid the selection of a sensor suite, and finally, it is used to test the capability to diagnose component failures. As before, a sensor suite is selected for each operation mode independently. Note, as stated before, the applications of the two methodologies are completed independently, with no reference to each other in each application, all comparisons between the two methodologies are made in section 5.5.

5.4.1. Modelling the system

As the system is more complex than the one used in Chapter 4, i.e. the redundant sections of the system are included, a new BBN model for this system is constructed. It is constructed using the same methodology as in Chapter 4 and the same software, "HUGIN Researcher".

5.4.1.1. BBN development

As in section 4.3.1, the methodology described in section 3.3 of this thesis is applied to construct the network. The final BBN is presented in Figure 5.7, with some of the sections of the system labelled, including the components section, the fault section, the critical section, and the sensor section. As the system is similar to the one presented in Chapter 4, but with the redundant sections included, the full development of the BBN is not presented in detail, only the modifications to the BBN are explained. Also, like with Figures 4.9 and 4.10, it is not possible to see all the relationships between the nodes in the BBN in one figure, so the relationships between the nodes are presented in Appendix H, Figures H.1 – H.36.

As discussed in section 5.1.1, the fuel level sensors are not included in the BBN, as in order to prevent the number of entries in the CPTs becoming too large, the sensor readings are grouped into ranges. This means that the change in fuel level, fuel in vs fuel out, cannot be determined, as ranges and not exact values of fuel flow through the system are modelled. In this chapter, some of the sensors have a larger number of ranges of sensor readings included than in Chapter 4. The sensors with additional states are sensors S2, S3, S4, S9, S10 and S11. This is to account for the normal amount of supply passed through them to increase to “2” because of the modification to the output of the transfer pumps, as detailed in section 5.2. The states for these sensors are “E”, “<1”, “1”, “1<flow<2”, “2”, “2<flow<4”, “4”, and “N”. (Note, this also results in sensors S1, S1a, S12, and S12a states changing from “E”, “1”, and “N”, to “E”, “2”, and “N”). The additional sensors S1a and S12a, have the same possible sensor reading states as sensors S1 and S12, the additional sensors S15a and S16a have the same possible sensor readings as sensors S15 and S16, and the additional sensors S26, S27, S28, and S29 have the same possible sensor readings as other sensors that are in the central sections of the system, i.e. between LDV, RDV, NVL and NVR (for example sensor S17, with the sensor readings, “E”, “+ve”, “-ve”, and “N” as in Chapter 4).

A new addition to the BBN is the introduction of sub-networks, which are used to represent a small section of the network, which can be considered in isolation. The sub-networks take nodes from the main network as input nodes, and outputs other nodes, which can then be used in the main network. They are used to aid in the construction of the network, in order to try and keep the network tidier, and easier to understand, as small sections of the system can be considered in isolation. An example of a sub-network in the main network is presented in Figure 5.5, with the sub-network presented in Figure 5.6. This sub-network is used to determine the supply of fuel to the engines from the pumps, i.e. “Pumps to Engines, PE”. This sub-network has a number of input nodes, they include:

- The nodes that represent the booster pumps,
- The supply of fuel, and the number of exits, that is available from the wings, i.e. SFWTB (supply from wings to bottom),
- The nodes that indicate what paths the fuel can take around the system, i.e. PTCB (path to centre bottom) and CV (cross-feed valve),
- The nodes that indicate which engine the fuel can exit through, i.e. ELE (exit left engine) and ERE (exit right engine).

There are also a number of intermediate nodes in the sub-network. They include:

- Nodes that consider whether there is supply from the pumps. Note, this is the pump name followed by a lower case “s”. This is because it does not matter whether the pump is working on, or failed on, it is still supplying the same amount of fuel, and therefore, the size of the CPTs for the child nodes can be reduced.
- For the nodes, SFWTBs and SFWTBe, the amount of fuel supplied (s) from wings to bottom, and the number of exits (e) in the wings are separated into two nodes.
- The nodes, SLPFE and SRPFE, determine the supply of fuel to left/right pumps from elsewhere in the system.
- The final intermediate nodes in the sub-network are EFLP and EFRP, which determine whether there are exits for the fuel from the left and right booster pumps respectively.

Using these intermediate nodes, the sub-network can then determine whether there is a supply of fuel from the booster pumps and then determine if there is an exit that the fuel can pass through. Alternatively, if there is no supply of fuel from the booster pumps, it can then determine whether there is a supply of fuel from elsewhere in the system. These nodes are PLE (pumps to left engine), and PRE (pumps to right engine), and they can then be used to determine the sensor readings for sensors S15 and S15a, and S16 and S16a, respectively, i.e. the sensors next to the booster pumps.

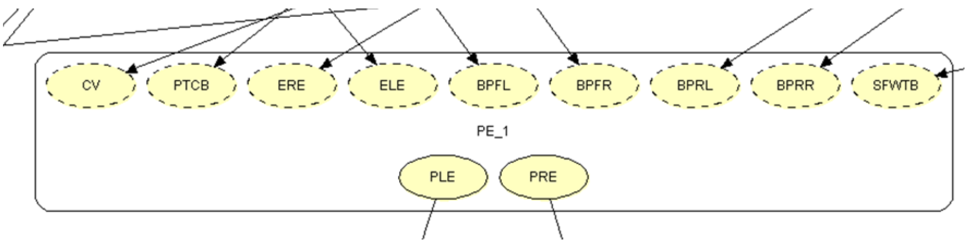


Figure 5.5 Sub-network "pumps to engines, PE" in the main network

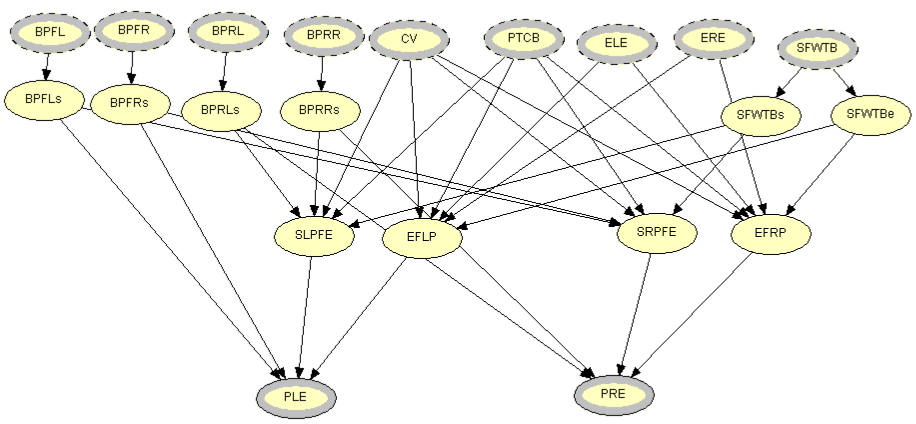


Figure 5.6 Sub-network "pumps to engines, PE"

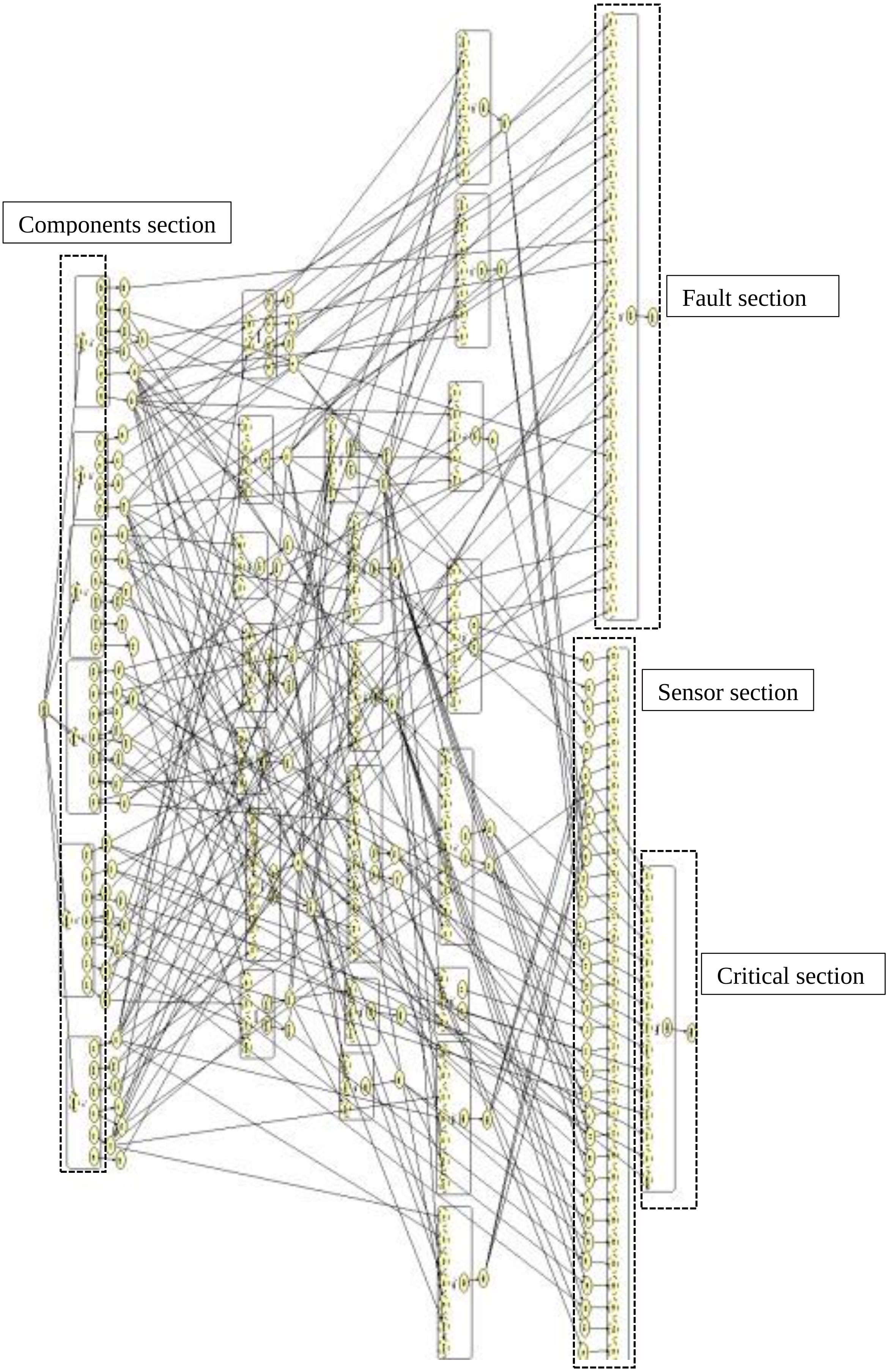


Figure 5.7 BBN of the aircraft fuel system

5.4.1.2. Discussion

As in the examples presented in Chapters 3 and 4, the BBN models the system accurately, representing the flow of fuel throughout the system. Also like in Chapter 4, the sensor readings have been grouped into ranges, and therefore, the accuracy of the model is reduced in comparison to the simulation method presented in section 5.3. However, if the number of different sensor reading ranges was increased, the size of the conditional probability tables would increase further. This would also increase the size of the network, and the time taken to construct it.

By visually comparing the two figures of the full BBNs from each chapter, Figures 4.9 and 5.7, it can be seen that the network for the un-simplified version of the system presented in Chapter 5 is significantly larger than the BBN for the simplified version of the system presented in Chapter 4. This is confirmed numerically as the network presented in this chapter consists of approximately 767,000 entries in the CPTs of the network, and 419 nodes, 108 in the main network, and 311 nodes in the 30 sub-networks. Note, the number of entries in the CPTs includes the number of entries in all of the sub-networks. This is approximately 10 times more entries than in the BBN presented in Chapter 4, despite only a few additional components and sensors being considered. There are approximately 4 times as many nodes in the BBN constructed in this chapter than there are in the BBN in Chapter 4, which consists of 122 nodes. It takes approximately 35 seconds to compile this network, which is significantly slower than the BBN in Chapter 4, which takes approximately 10 seconds to compile. When the combinations of one and two component failures are considered it results in an execution time of approximately 15 hours to produce the sensor readings for all of the considered combinations of component failures for each operation mode. It is clear that it is not feasible to apply the BBN method to a significantly larger system, as the BBN for a system that is only a little bit bigger is 10 times larger, and takes more than three times longer to compile. This was hypothesised in section 4.6 of this thesis.

In the next section, the selection of sensors to be used for the fault diagnostics process is presented.

5.4.2. Sensor Selection

The next step of the methodology is to select the combinations of sensors used for fault diagnostics. As in section 5.3.2, the performance metric for all combinations of sensors is calculated exhaustively until a suitable combination of sensors is determined, but in this section the BBN is used to calculate the performance metrics, (instead of the proposed simulation method). In order to determine which combinations of sensors are suitable, the maximum possible performance metric needs to be calculated for comparison, i.e. when all sensors are considered on the systems. Using the BBN, the maximum achievable performance metric for the engine feed operation mode is 0.9688, which consists of a detection term of 1, a diagnostic term of 0.9063, and a criticality term of 1. This corresponds to being able to detect 38.9239% (760/1568) of all considered failures for the engine feed operation mode. The maximum achievable performance metric for the fuel transfer operation mode is 0.9751, which consists of a detection term of 1, a diagnostic term of 0.9253, and a criticality term of 1. This corresponds to being able to detect 53.6849% (1044/1568) of the considered failures for the fuel transfer operation mode. In each of these cases, the maximum performance metric is lower than that observed in section 5.3.2, but the percentage of failures, i.e. the number of hidden failures, are the same as obtained in the simulation method. As before, these percentage values are calculated using the sum of the probabilities of detected failures divided by the sum of the probabilities of all considered failures.

As in section 5.3.2, the maximum percentage of detectable failures is less than 100% for each of the operation modes, since there are a number of hidden failures. The hidden failures are the same as in section 5.3.2, (Table 5.3), and are therefore, not presented in this section. Note, as before, all critical failures are detected, and therefore, the criticality term, *CR* is equal to 1.

5.4.2.1. Results

As in the application of the methodology presented in section 5.3, all of the component failures can be observed using combinations of nine sensors for the engine feed operation mode, and using combinations of twelve sensors for the fuel transfer operation mode. Therefore, as before, the performance metric for all combinations of sensors up to nine sensors was calculated, as this enables a direct comparison of the two methods. This comparison is presented in section 5.5. The performance metric for each individual sensor and the terms of the performance metric, for each operation mode, are presented in Tables 5.13 and 5.14, respectively, and the maximum performance metrics achieved by combinations of nine sensors are presented in the following paragraphs.

Table 5.13 Ranking of individual sensors for the example aircraft fuel system in the engine feed operation mode using the BBN

Rank	Sensor	$I_{\{s\}}$	$DE_{\{s\}}$	$DI_{\{s\}}$	$CR_{\{s\}}$
1	S23	0.5601	0.1645	0.6825	0.8333
	S25	0.5601	0.1645	0.6825	0.8333
2	S15	0.5445	0.0915	0.8754	0.6667
	S16	0.5445	0.0915	0.8754	0.6667
3	S22	0.5279	0.1645	0.5859	0.8333
	S24	0.5279	0.1665	0.5859	0.8333
4	S1	0.3519	0.1837	0.8719	0
	S1a	0.3519	0.1837	0.8719	0
	S12	0.3519	0.1837	0.8719	0
	S12a	0.3519	0.1837	0.8719	0
5	S26	0.3230	0.0923	0.8766	0
	S27	0.3230	0.0923	0.8766	0
6	S14	0.2685	0.0365	0.4357	0.3333
	S18	0.2685	0.0365	0.4357	0.3333
	S19	0.2685	0.0365	0.4357	0.3333
	S21	0.2685	0.0365	0.4357	0.3333
7	S17	0.2222	0.00003	0.5000	0.1667
	S20	0.2222	0.00003	0.5000	0.1667
8	S5	0.2089	0.1837	0.4430	0
	S8	0.2089	0.1837	0.4430	0
9	S4	0.2086	0.1837	0.4422	0
	S10	0.2086	0.1837	0.4422	0
10	S15a	0.2073	0.1819	0.4401	0
	S16a	0.2073	0.1819	0.4401	0
11	S2	0.2067	0.1837	0.4364	0
	S3	0.2067	0.1837	0.4364	0
	S9	0.2067	0.1837	0.4364	0
	S11	0.2067	0.1837	0.4364	0
12	S28	0.1681	0.0738	0.4307	0
	S29	0.1681	0.0738	0.4307	0
13	S6	0.1655	0.0026	0.4939	0
	S7	0.1655	0.0026	0.4939	0
14	S13	0.0852	0.0026	0.2530	0

Table 5.14 Ranking of individual sensors for the example aircraft fuel system in the fuel transfer operation mode using the BBN

Rank	Sensor	$I_{\{s\}}$	$DE_{\{s\}}$	$DI_{\{s\}}$	$CR_{\{s\}}$
1	S23	0.5053	0.1192	0.6825	0.7143
	S25	0.5053	0.1192	0.6825	0.7143
2	S15	0.5044	0.0663	0.8754	0.5714
	S16	0.5044	0.0663	0.8754	0.5714
3	S22	0.4731	0.1192	0.5859	0.7143
	S24	0.4731	0.1192	0.5859	0.7143
4	S4	0.4242	0.3139	0.8159	0.1429
	S10	0.4242	0.3139	0.8159	0.1429
5	S5	0.3646	0.2104	0.8834	0
	S8	0.3646	0.2104	0.8834	0
6	S6	0.3644	0.2112	0.8821	0
	S7	0.3644	0.2112	0.8821	0
7	S1	0.3193	0.0793	0.7357	0.1429
	S12	0.3193	0.0793	0.7357	0.1429
8	S26	0.3145	0.0669	0.8766	0
	S27	0.3145	0.0669	0.8766	0
9	S2	0.3015	0.0135	0.8910	0
	S3	0.3015	0.0135	0.8910	0
	S9	0.3015	0.0135	0.8910	0
	S11	0.3015	0.0135	0.8910	0
10	S14	0.2483	0.0266	0.4327	0.2857
	S18	0.2483	0.0266	0.4327	0.2857
	S19	0.2483	0.0266	0.4327	0.2857
	S21	0.2483	0.0266	0.4327	0.2857
11	S13	0.2169	0.2112	0.4393	0
12	S17	0.2143	0.00002	0.5000	0.1429
	S20	0.2143	0.00002	0.5000	0.1429
13	S1a	0.1913	0.1321	0.4417	0
	S12a	0.1913	0.1321	0.4417	0
14	S15a	0.1907	0.1319	0.4401	0
	S16a	0.1907	0.1319	0.4401	0
15	S28	0.1614	0.0535	0.4307	0
	S29	0.1614	0.0535	0.4307	0

The combinations of sensors with the highest performance metric for combinations of nine sensors are presented in Tables 5.15 and 5.16 for the two operation modes. Note, all combinations of sensors in each of the tables have the same performance metric. For the engine feed operation mode, this performance metric is 0.9674, with a detection term of 1, a diagnostic term of 0.9022, and a criticality term of 1, and for the fuel transfer operation mode, the performance metric is 0.9388, with a detection term of 0.9123, a diagnostic term of 0.9040, and a criticality term of 1. As in section 5.3.2, the limit of nine sensors was selected because a combination of nine sensors can detect all of the component failures for the engine feed operation mode.

Table 5.15 Combinations of nine sensors with the highest performance metric for the engine feed operation mode using the BBN, I = 0.9674, DE = 1, DI = 0.9022, CR = 1

Sensors
S1 S12 S14 S15a S16a S23 S25 S26 S27
S1 S12 S15a S16a S18 S23 S25 S26 S27
S1 S12 S15a S16a S19 S23 S25 S26 S27
S1 S12 S15a S16a S21 S23 S25 S26 S27
S1 S12a S14 S15a S16a S23 S25 S26 S27
S1 S12a S15a S16a S18 S23 S25 S26 S27
S1 S12a S15a S16a S19 S23 S25 S26 S27
S1 S12a S15a S16a S21 S23 S25 S26 S27
S1a S12 S14 S15a S16a S23 S25 S26 S27
S1a S12 S15a S16a S18 S23 S25 S26 S27
S1a S12 S15a S16a S19 S23 S25 S26 S27
S1a S12 S15a S16a S21 S23 S25 S26 S27
S1a S12a S14 S15a S16a S23 S25 S26 S27
S1a S12a S15a S16a S18 S23 S25 S26 S27
S1a S12a S15a S16a S19 S23 S25 S26 S27
S1a S12a S15a S16a S21 S23 S25 S26 S27

Table 5.16 Combinations on nine sensors with the highest performance metric for the fuel transfer operation mode using the BBN, I = 0.9388, DE = 0.9123, DI = 0.9040, CR = 1

Sensors
S1a S4 S10 S12a S15a S23 S25 S26 S27
S1a S4 S10 S12a S16a S23 S25 S26 S27

In the next section, a discussion on the selections of sensors is presented.

5.4.2.2. Discussion

There are a number of combinations of nine sensors for each operation mode that produce the maximum performance metric, 16 combinations for the engine feed operation mode, and 2 combinations for the fuel transfer operation mode. If Table 5.15 is studied, there are a number of similarities that can be observed, for example, each combination has a pair of sensors, S1 or S1a, and S12 or S12a, one of the sensors, S14, S18, S19, S21, and the six sensors, S15a, S16a, S23, S25, S26 and S27. Likewise, if Table 5.16 is studied, there is still some symmetry observed, i.e. sensor S15a or S16a. However, unlike the engine feed operation mode, the only combination of sensors number 1 and 12 that can be selected is the sensors S1a and S12a, i.e. not the sensors S1 or S12. This will influence the combination of sensors selected if the two operation modes were considered together. As before, the sensors can be separated in to groups, and the selection of sensors is distributed throughout the sections. The groups are the same as for the simulation method, and as presented in Figure 5.4. Note, as there are no level sensors considered in the application of the method using BBNs, there are only 8 groups considered. Each of these groups are presented in Table 5.17, with the included sensors representing the sensors that are in the best selection of sensors for each operation mode and each number of sensors up to 9, and the column entitled, “not included sensors” representing the sensors that are not in the selection. Also note, in groups 1 – 4, there are additional sensors in comparison to those presented in section 4.4.3 because of the additional sensors considered in this chapter. The additional sensors are sensors S1a, S12a, S15a, and S16a. The additional sensors to each of the groups are the same as the additional sensors to each of the groups presented in section 5.3.2.

The combinations of nine sensors with the highest performance metric for the engine feed consist of combinations of one sensor from the groups, 1, 2, 6, 7, and 8, and two sensors from the groups 3 and 4. Note, no sensor is selected from group 5 as was the case in Chapter 4. This is because the sensors in this section are the least useful in the detection and diagnosis of failures in the engine feed operation mode. The combination of nine sensors with the highest performance metric for the fuel transfer operation mode consist of one sensor from groups 7, and 8, and two sensors from groups 1 and 2, and depending on the selection of sensors, two sensors from group 3 or 4, and one from the other. Also, as in the applications presented in

Chapter 4, no sensor is selected from group 6, but there is also no sensor selected from group 5 either, unlike in the combination of sensors selected for the fuel transfer operation mode presented in Chapter 4.

As discussed in further detail in Chapters 3 and 4, it is best to select the sensors by considering the individual terms of the performance metric. For example, the sensors ranked 2nd for the engine feed operation mode, sensors S15 and S16, have a lower detection term (0.0663), and criticality term (0.5714) than the sensors ranked 3rd, sensors S22 and S24, which have a detection term of 0.1192, and a criticality term of 0.7143. However, as the diagnostic term is higher for sensors S15 and S16 (0.8754), than for sensors S22 and S24 (0.5859), they are ranked higher. However, the sensors S15 and S16 are unlikely to be selected by an analyst due to the low detection term. Also, as discussed in Chapters 3 and 4, it is generally not beneficial to select two sensors in close proximity to each other, as this typically does not increase the performance metric by much.

Table 5.17 The sensors grouped by sections of the system

Group	Included sensors				Not included sensors		
1	S1	S1a	S4		S2	S3	S5
2	S10	S12	S12a		S8	S9	S11
3	S15	S15a	S23		S17	S22	S28
4	S16	S16a	S25		S20	S24	S29
5					S6	S7	S13
6	S14	S18	S19	S21			
7	S26						
8	S27						

If the performance metric of the best combination of sensors for each number of sensors is compared, it is observed that the increase in performance diminishes as the number of sensors is increased. This is observed in both operation modes, and is presented in the last column of Tables 5.18 and 5.19, respectively. This was also observed in section 3.4.1.1, section 4.4.3, and section 5.3.2.2.

In the next section, the fault diagnostics process is applied to the system using the selected sensor for each operation mode.

Table 5.18 Best performance metric for the engine feed operation mode for each number of sensors for the BBN

Number	Sensors	$I_{\{s\}}$	% diff.
1	S23	0.5601	0
2	S23 S25	0.7122	27.16
3	S1 S23 S25	0.7746	8.76
4	S1 S12 S23 S25	0.8377	8.15
5	S1 S12 S23 S25 S26	0.8690	3.74
6	S1 S12 S23 S25 S26 S27	0.8998	3.54
7	S1 S12 S15a S23 S25 S26 S27	0.9304	3.40
8	S1 S12 S15a S16a S23 S25 S26 S27	0.9609	3.28
9	S1 S12 S14 S15a S16a S23 S25 S26 S27	0.9674	0.68
33	All sensors	0.9688	0.14

Table 5.19 Best performance metric for the fuel transfer operation mode for each number of sensors for the BBN

Number	Sensors	$I_{\{s\}}$	% diff.
1	S23	0.5053	0
2	S4 S23	0.6919	36.93
3	S4 S23 S25	0.7830	13.17
4	S4 S10 S23 S25	0.8216	4.93
5	S1a S4 S10 S23 S25	0.8458	2.95
6	S1a S4 S10 S23 S25 S26	0.8695	2.80
7	S1a S4 S10 S12a S23 S25 S26	0.8928	2.68
8	S1a S4 S10 S12a S23 S25 S26 S27	0.9160	2.60
9	S1a S4 S10 S12a S15a S23 S25 S26 S27	0.9388	2.49
33	All sensors	0.9751	3.87

5.4.3. Fault diagnosis

The selected sensors for fault diagnostics are the first combination of nine sensors from Table 5.15 for the engine feed operation mode, and Table 5.16 for the fuel transfer operation mode. Therefore, the combinations of sensors selected for the engine feed operation mode is (S1, S12, S14, S15a, S16a, S23, S25, S26, S27) and the combination of sensors selected for the fuel transfer operation mode is (S1a, S4, S10, S12a, S15a, S23, S25, S26, S27). In order to determine the effectiveness of the selected sensors, they are used to diagnose failures in the system using the diagnostic method, as applied in section 4.5.

5.4.3.1. Fault Diagnosis Results

Each of the combinations of component failures used to calculate the performance metric are used to test the diagnostic process, i.e. 1568 per operation mode. Due to the hidden failures in the system, only approximately 39% of the combinations of component failures for the engine feed operation mode can be detected, and only approximately 54% of the combinations of component failures for the fuel transfer operation mode can be detected. However, as the detection term for the combination of sensors for the fuel transfer operation mode is less than 1, only approximately 49.65% of the component failures can be detected.

The results of the diagnostic process for the selected combinations of sensors are grouped together into cases which consist of combinations of component failures that have similar fault diagnostic results. There are 19 cases for the engine feed operation mode, and 17 cases for the fuel transfer operation mode. The cases are presented in Table 5.20 for the engine feed operation mode, and Table 5.21 for the fuel transfer operation mode, respectively. Note, the notation in Tables 5.20 and 5.21 is the same as in Tables 4.15, 4.16, 5.11, and 5.12.

The first case in Table 5.20 consists of component failures where one component has failed, and it has been diagnosed correctly with 100% confidence. As the component failures in this case, (and cases two and three), consist of only one component failure, they are significantly more likely to occur than the other combinations of component failures. This case consists of component failures for the booster pumps, transfer pumps, and the low and high pressure cocks.

The second case in Table 5.20 consists of component failures where one component has failed, and it has been diagnosed correctly with approximately 99% confidence. The component failures for this case consist of failures for the reserve transfer pumps. The reason the confidence is less than 100%, is because there are other combinations of component failures that can produce the same symptoms, but they are less likely to occur. An example combination of component failures for this case is TPRB (On) and NVR (2 way).

The third case in Table 5.20 consists of component failures where one component has failed, but there are two possible single component failures that can produce the same symptoms. This results in a probability of correct diagnosis of approximately 50% for each case. The probability that one component has failed in each case is slightly above 50% because the combination of both of the components failing produces the same set of symptoms, making each component more likely to be failed than not if this set of symptoms is observed. This is observed in case fourteen. The components for this case include the left and right dump valves.

Cases four, five and six in Table 5.20 consist of combinations of two component failures, only one of which is diagnosed. The cases consist of combinations of the failures in cases one, two, and three, respectively, along with a hidden failure, which will not be diagnosed.

Case seven in Table 5.20 consists of combinations of two component failures which are diagnosed correctly with 100% confidence. The components in this case include the low and high pressure cocks, the transfer pumps, the booster pumps, and the left and right dump valves.

The eighth case in Table 5.20 consists of combinations of two component failures, both of which are diagnosed correctly, the first with 100% confidence, and the second with approximately 99% confidence. This means that there are other combinations of component failures that produce the same set of sensor readings, but are much less likely to occur. The components included in this case are the booster pumps, the transfer pumps, the cross-feed valve, and the low and high pressure cocks.

Like the eighth case, cases nine and ten in Table 5.20 consist of combinations of two component failures, both of which are diagnosed correctly, but in case nine, the second component is diagnosed correctly with approximately 60% confidence, and in case ten, the second component is diagnosed correctly with approximately 50% confidence. Also, cases eleven, twelve, and thirteen are all combinations of two component failures, and both of the failures are diagnosed correctly. The difference in each of the cases, is the probability of the diagnosis being correct. In case twelve, where "diagnosed failure 2", and "diagnosed failure 3" have approximately 50% probability of being correct, in each combination, only one of these two failures has occurred.

The fourteenth case in Table 5.20 is a combination of two component failures where both are diagnosed correctly. This case was referred to in case three. The diagnostics process outputs that only one of the components has failed, but both of the components have actually failed. In order for system behaviour to return to normal, both of the component failures will need to be repaired.

The fifteenth case in Table 5.20 are combinations of two component failures, both of which are diagnosed, but the second component failure will not be diagnosed until after the first component has been repaired or replaced. The components included in this case are the transfer pumps, the low and high pressure cocks, and the booster pumps.

The sixteenth and seventeenth cases in Table 5.20 are combinations of two component failures, one of which is diagnosed correctly initially. However, in each combination of component failures, the second component failure is diagnosed incorrectly. When additional evidence of the components state is introduced, the correct component will be diagnosed in both of the cases.

The penultimate case in Table 5.20 are combinations of two component failures, but it is initially diagnosed incorrectly as one component failure. The diagnosed component has not actually failed, and when this evidence is introduced, the correct two component failures will be diagnosed. This was diagnosed incorrectly initially because the same set of symptoms are produced by the individual component failure, and the combination of two component failures, and the individual component failure is more likely to occur than the combination of two component failures.

The final case in Table 5.20 are combinations of two component failures, one of which is diagnosed incorrectly. The incorrectly diagnosed component is in its other failure mode, i.e. failed closed. However, this component failure is normally a hidden failure, and the symptoms produced are the same as in cases three and six.

The first three cases of Table 5.21 are combinations of one component failure, which is diagnosed correctly. In the first case, with 100% confidence, in the second case, greater than 99% confidence, and in the third case, with 50% confidence. In the third case, the failed component is either the “diagnosed failure 1”, or the “diagnosed failure 2”, with confidence of exactly 50% for both of them. This is because for these sets of sensors, the combination of both of the components failed produces a different set of sensor readings, and therefore, it is one of the components failed, and not both. The components in case one include booster pumps, transfer pumps, one directional valves, the transfer valves, and the low and high pressure cocks. The components in case two are the left forward fuselage tank booster pump, and the transfer pumps. Note, the reason it is only the left forward fuselage tank booster pump, and not the corresponding pump failure on the rear fuselage tank, is because only sensor S15a is used in the selection of sensors. The corresponding failure would be detected for the rear fuselage tank, if sensor S16a was included instead or in addition. The components used in case three, include the four refuel valves.

The fourth, fifth, and sixth cases of Table 5.21 are combinations of two component failures, one of which is diagnosed. The diagnosed component in each of the cases is the same as the component failures in cases one, two, and three, respectively, with the second component failure being one of the hidden failures.

The seventh, eighth, ninth, tenth, and eleventh cases of Table 5.21 are combinations of two component failures, both of which are diagnosed. Each of the cases have different probabilities of each component failure being correct. Note, in cases nine and eleven, the “diagnosed failure 1” is correct, and one of the “diagnosed failure 2” or “diagnosed failure 3” is correct.

The twelfth case of Table 5.21 consists of combinations of two component failures. However, the fault diagnostic process initially outputs that only one component has failed, but when the first component has been repaired or replaced, the second component failure will then be diagnosed correctly.

The thirteenth case of Table 5.21 consists of combinations of two component failures, but the fault diagnostic process outputs one component failure, which is not one of the correct component failures. When evidence that this component has not failed has been introduced, the correct component failures will be diagnosed. Note, the second component failure is either the “diagnosed failure 3” or “diagnosed failure 4”.

The fourteenth case of Table 5.21, like the thirteenth case, is a combination of two component failures, of which the first component failure is diagnosed correctly. However, the second component failure is not diagnosed correctly. When evidence that the second component is in its working state is introduced, the correct second component failure is diagnosed.

The fifteenth case of Table 5.21 consists of combinations of two component failures, one of which is diagnosed correctly. The second component failure is incorrect, the component is actually in its other failure mode, but as this component failure is normally hidden, it would not normally be observed. The resultant symptoms observed by the sensors are the same as in cases three and six.

The sixteenth and seventeenth cases of Table 5.21 expose a problem with the C++ script written to output the most likely failure which had not been observed before in either of the fault diagnostic methodologies. In both of these cases, the second component failure (in case sixteen) and the two component failures (in case seventeen) are not output by the fault diagnostic process. This is because the probability of the component being in another (working) state is slightly higher. However, as the probability of the component being in the failure mode is in excess of 45%, it is fairly likely that the component has failed, and would therefore be taken to the aircraft when it is to be repaired. Therefore, in future applications of either of the fault diagnostic techniques, instead of outputting the component’s most likely state, the components that have the highest probability of being in the failed state could be output. This is particularly important in case seventeen, as despite the sensors detecting that there is a component failure, the fault diagnostic process did not output any failed components, they had to be obtained manually by looking at the component state probabilities.

Table 5.20 Diagnostics of component failures for the engine feed operation mode using the BBN

Case	Number Diagnosed	Number Represented	Diagnosed failure 1	Probability	Diagnosed failure 2	Probability	Diagnosed failure 3	Probability	Diagnosed failure 4	Probability
1	1 of 1	2	BPFR (On)	100%						
		2	TPFF (On)	100%						
		2	TPLT (On)	100%						
		2	BPFL (Off)	100%						
		2	LLP (Cl)	100%						
		2	LHP (Cl)	100%						
2	1 of 1	2	TPLB (On)	99.9003%						
3	1 of 1	2	LDV (Op)	50.0250%	RDV (Op)	50.0250%				
4	1 of 2	76	BPFR (On)	100%						
		76	TPFF (On)	100%						
		74	TPLT (On)	100%						
		76	BPFL (Off)	100%						
		76	LLP (Cl)	100%						
		76	LHP (Cl)	100%						
5	1 of 2	76	TPLB (On)	99.9003%						
6	1of 2	72	LDV (Op)	50.0250%	RDV (Op)	50.0250%				
7	2 of 2	4	LLP (Cl)	100%	TPFF (On)	100%				
		4	LHP (Cl)	100%	TPFF (On)	100%				

Case	Number Diagnosed	Number Represented	Diagnosed failure 1	Probability	Diagnosed failure 2	Probability	Diagnosed failure 3	Probability	Diagnosed failure 4	Probability
		4	LLP (Cl)	100%	TPLT (On)	100%				
		4	LHP (Cl)	100%	TPLT (On)	100%				
		1	LLP (Cl)	100%	RLP (Cl)	100%				
		2	LLP (Cl)	100%	RHP (Cl)	100%				
		1	LHP (Cl)	100%	RHP (Cl)	100%				
		2	LDV (Op)	100%	RPV (Op)	100%				
		2	LDV (Op)	100%	DV (Op)	100%				
		2	TIV (Op)	100%	TPFF (On)	100%				
		2	CV (Op)	100%	BPFR (On)	100%				
		1	TPFF (On)	100%	TPRF (On)	100%				
		4	TPFF (On)	100%	TPLT (On)	100%				
		1	TPLT (On)	100%	TPRT (On)	100%				
		2	TPFF (On)	100%	BPFL (Off)	100%				
		4	TPLT (On)	100%	BPFL (Off)	100%				
		4	BPFR (On)	100%	TPFF (On)	100%				
		4	BPFR (On)	100%	TPLT (On)	100%				
		1	BPFL (Off)	100%	BPRL (Off)	100%				
		2	BPFL (Off)	100%	BPRR (On)	100%				

Case	Number Diagnosed	Number Represented	Diagnosed failure 1	Probability	Diagnosed failure 2	Probability	Diagnosed failure 3	Probability	Diagnosed failure 4	Probability
8	2 of 2	4	BPFL (Off)	100%	TPLB (On)	99.9003%				
		4	BPFR (On)	100%	TPLB (On)	99.9003%				
		4	TPFF (On)	100%	TPLB (On)	99.9003%				
		4	LLP (Cl)	100%	TPLB (On)	99.9003%				
		4	LHP (Cl)	100%	TPLB (On)	99.9003%				
		2	LLP (Cl)	100%	CV (Cl)	99.9874%				
		2	LHP (Cl)	100%	CV (Cl)	99.9874%				
9	2 of 2	2	TPLT (On)	100%	NVL (2 way)	61.6816%				
10	2of 2	4	LLP (Cl)	100%	BPFL (Off)	50%	BPFR (On)	50.2513%		
		4	LHP (Cl)	100%	BPFL (Off)	50%	BPFR (On)	50.2513%		
		4	RLP (Cl)	100%	BPFL (Off)	49.9747%	BPFR (On)	50.2764%		
		4	RHP (Cl)	100%	BPFL (Off)	49.9747%	BPFR (On)	50.2764%		
		4	BPFR (On)	100%	LDV (Op)	50%	RDV (Op)	50%		
		4	TPFF (On)	100%	LDV (Op)	50.0250%	RDV (Op)	50.0250%		
		4	TPLT (On)	100%	LDV (Op)	50.0250%	RDV (Op)	50.0250%		
		4	LLP (Cl)	100%	LDV (Op)	50.0250%	RDV (Op)	50.0250%		
		4	LHP (Cl)	100%	LDV (Op)	50.0250%	RDV (Op)	50.0250%		
11	2 of 2	2	BPFL (Off)	99.9995%	TPRF (On)	99.9995%				

Case	Number Diagnosed	Number Represented	Diagnosed failure 1	Probability	Diagnosed failure 2	Probability	Diagnosed failure 3	Probability	Diagnosed failure 4	Probability
		2	BPFL (Off)	99.9975%	BPFR (Off)	99.9975%				
		1	BPFR (On)	99.9007%	BPRR (On)	99.9007%				
12	2 of 2	4	BPFL (Off)	99.9499%	LDV (Op)	50.05%	RDV (Op)	50.0001%		
		4	TPLB (On)	99.9003%	LDV (Op)	50.0250%	RDV (Op)	50.0250%		
13	2 of 2	1	TPLB (On)	61.9627%	TPRB (On)	61.9627%				
14	2 of 2	1	LDV (Op)	50.0250%	RDV (Op)	50.0250%				
15	2 of 2 (one delayed)	2	BPFL (Off)	100%	BPFR (On)	100%				
		2	LLP (Cl)	100%	LHP (Cl)	100%				
		2	TPLT (On)	100%	TPLB (On)	99.9003%				
16	2 of 2 (one incorrect)	2	TPLT (On)	100%	NVL (2 way)	61.6816%	TPRB (On)	99.9003%		
17	2 of 2 (one incorrect)	2	TPLB (On)	61.9627%	TPRB (On)	61.9627%	NVL (2 way)	99.9400%		
18	2 of 2 (one incorrect)	2	TPLB (On)	99.9003%	TPLT (On)	100%	TVRF (Op)	100%		
19	1 of 2 (one incorrect)	2	LDV (Op)	50.0250%	RDV (Op)	50.0250%				

Table 5.21 Diagnostics of component failures for the fuel transfer operation mode using the BBN

Case	Number Diagnosed	Number Represented	Diagnosed failure 1	Probability	Diagnosed failure 2	Probability	Diagnosed failure 3	Probability	Diagnosed failure 4	Probability
1	1 of 1	2	BPFR (On)	100%						
		2	TPFF (On)	100%						
		2	TPLB (On)	100%						
		2	NVL (2 way)	100%						
		2	TVFF (Cl)	100%						
		2	LLP (Cl)	100%						
		2	LHP (Cl)	100%						
2	1 of 1	1	BPFL (Off)	99.9999%						
		2	TPLT (Off)	99.7986%						
3	1 of 1	2	RVLW (Op)	50%	RVRF (Op)	50%				
		2	RVRW (Op)	50%	RVFF (Op)	50%				
4	1 of 2	65	BPFR (On)	100%						
		66	TPFF (On)	100%						
		68	TPLB (On)	100%						
		66	NVL (2 way)	100%						
		68	TVFF (Cl)	100%						
		66	LLP (Cl)	100%						
		66	LHP (Cl)	100%						
		66	TPLT (Off)	99.7986%						

Case	Number Diagnosed	Number Represented	Diagnosed failure 1	Probability	Diagnosed failure 2	Probability	Diagnosed failure 3	Probability	Diagnosed failure 4	Probability
5	1 of 2	33	BPFL (Off)	99.9999%						
6	1 of 2	66	RVLW (Op)	50%	RVRF (Op)	50%				
		66	RVRW (Op)	50%	RVFF (Op)	50%				
7	2 of 2	2	BPFR (On)	100%	TPFF (On)	100%				
		2	BPFR (On)	100%	TPRF (On)	100%				
		2	BPFR (On)	100%	TPLB (On)	100%				
		2	BPFR (On)	100%	TPRB (On)	100%				
		2	BPFR (On)	100%	NVL (2 way)	100%				
		2	BPFR (On)	100%	NVR (2 way)	100%				
		2	BPFR (On)	100%	TVRF (Cl)	100%				
		2	BPFR (On)	100%	TVFF (Cl)	100%				
		2	TPFF (On)	100%	NVL (2 way)	100%				
		2	TPFF (On)	100%	NVR (2 way)	100%				
		2	TPFF (On)	100%	TVRF (Cl)	100%				
		2	TPFF (On)	100%	TVFF (Cl)	100%				
		4	TPFF (On)	100%	LLP (Cl)	100%				
		4	TPFF (On)	100%	LHP (Cl)	100%				
		1	TPRF (On)	100%	TPLB (On)	100%				
		1	TPRF (On)	100%	TPRB (On)	100%				

Case	Number Diagnosed	Number Represented	Diagnosed failure 1	Probability	Diagnosed failure 2	Probability	Diagnosed failure 3	Probability	Diagnosed failure 4	Probability
		2	TPLT (Off)	100%	TPLB (Off)	100%				
		1	TPLB (On)	100%	TPRB (On)	100%				
		2	TPLB (On)	100%	NVL (2 way)	100%				
		2	TPLB (On)	100%	NVR (2 way)	100%				
		4	TPLB (On)	100%	LLP (Cl)	100%				
		4	TPLB (On)	100%	LHP (Cl)	100%				
		2	RVLW (Op)	100%	RVRF (Op)	100%				
		1	TVRF (Cl)	100%	TVFF (Cl)	100%				
		2	TVRF (Cl)	100%	NVL (2 way)	100%				
		4	TVRF (Cl)	100%	LLP (Cl)	100%				
		4	TVRF (Cl)	100%	LHP (Cl)	100%				
		4	NVL (2 way)	100%	LLP (Cl)	100%				
		4	NVL (2 way)	100%	LHP (Cl)	100%				
		1	LLP (Cl)	100%	RLP (Cl)	100%				
		2	LLP (Cl)	100%	RHP (Cl)	100%				
		1	LHP (Cl)	100%	RHP (Cl)	100%				
		2	RPV (Op)	100%	LDV (Op)	100%				
		2	DV (Op)	100%	LDV (Op)	100%				

Case	Number Diagnosed	Number Represented	Diagnosed failure 1	Probability	Diagnosed failure 2	Probability	Diagnosed failure 3	Probability	Diagnosed failure 4	Probability
8	2 of 2	1	BPRR (On)	100%	BPFL (Off)	99.9999%				
		1	TPFF (On)	100%	BPFL (Off)	99.9999%				
		1	TPLB (On)	100%	BPFL (Off)	99.9999%				
		1	TPRB (On)	100%	BPFL (Off)	99.9999%				
		1	NVL (2 way)	100%	BPFL (Off)	99.9999%				
		1	NVR (2 way)	100%	BPFL (Off)	99.9999%				
		1	TVRF (Cl)	100%	BPFL (Off)	99.9999%				
		1	TVFF (Cl)	100%	BPFL (Off)	99.9999%				
		1	TPRF (On)	100%	TIV (Op)	99.9999%				
		1	TPLB (On)	100%	TPFF (On)	99.9999%				
		1	TPRB (On)	100%	TPFF (On)	99.9999%				
		2	NVL (2 way)	100%	TPLT (Off)	99.9999%				
		1	TPRF (On)	100%	TPFF (On)	99.9975%				
		1	BPRR (On)	100%	CV (Op)	99.9004%				
		2	NVR (2 way)	100%	TPLT (Off)	99.8002%				
		2	BPFR (On)	100%	TPLT (Off)	99.7986%				
		2	BPFR (On)	100%	TPRT (Off)	99.7986%				
		2	TPFF (On)	100%	TPLT (Off)	99.7986%				
		2	TPFF (On)	100%	TPRT (Off)	99.7986%				

Case	Number Diagnosed	Number Represented	Diagnosed failure 1	Probability	Diagnosed failure 2	Probability	Diagnosed failure 3	Probability	Diagnosed failure 4	Probability
		2	TVFF (Cl)	100%	TPLT (Off)	99.7986%				
		4	LLP (Cl)	100%	TPLT (Off)	99.7986%				
		4	LHP (Cl)	100%	TPLT (Off)	99.7986%				
		1	LLP (Cl)	100%	CV (Cl)	99.7904%				
		1	LHP (Cl)	100%	CV (Cl)	99.7904%				
		1	RHP (Cl)	100%	CV (Cl)	99.7893%				
		2	TVFF (Cl)	100%	TPLB (On)	99.2142%				
9	2 of 2	2	RLP (Cl)	100%	BPFL (Off)	49.9749%	BPFR (On)	50.2762%		
		2	RHP (Cl)	100%	BPFL (Off)	49.9749%	BPFR (On)	50.2762%		
		2	LLP (Cl)	100%	BPFL (Off)	49.9999%	BPFR (On)	50.2513%		
		2	LHP (Cl)	100%	BPFL (Off)	49.9999%	BPFR (On)	50.2513%		
		4	NVL (2 way)	100%	RVLW (Op)	50.0001%	RVRF (Op)	50.0001%		
		4	BPFR (On)	100%	RVLW (Op)	50%	RVRF (Op)	50%		
		4	BPFR (On)	100%	RVRW (Op)	50%	RVFF (Op)	50%		
		4	TPFF (On)	100%	RVLW (Op)	50%	RVRF (Op)	50%		
		4	TPFF (On)	100%	RVRW (Op)	50%	RVFF (Op)	50%		
		4	TPLT (Off)	100%	RVLW (Op)	50%	RVRF (Op)	50%		
		4	TPLB (On)	100%	RVRW (Op)	50%	RVFF (Op)	50%		

Case	Number Diagnosed	Number Represented	Diagnosed failure 1	Probability	Diagnosed failure 2	Probability	Diagnosed failure 3	Probability	Diagnosed failure 4	Probability
		4	NVR (2 way)	100%	RVLW (Op)	50%	RVRF (Op)	50%		
		8	LLP (Cl)	100%	RVLW (Op)	50%	RVRF (Op)	50%		
		8	LHP (Cl)	100%	RVLW (Op)	50%	RVRF (Op)	50%		
10	2 of 2	1	BPFL (Off)	99.9999%	TPLT (Off)	99.7986%				
		1	BPFL (Off)	99.9999%	TPRT (Off)	99.7986%				
		1	BPFL (Off)	99.9994%	TPRF (On)	99.9995%				
		2	BPFL (Off)	99.9975%	BPFR (Off)	99.9975%				
		1	RLP (Cl)	99.9750%	CV (Cl)	99.7644%				
		1	TPLT (Off)	99.7986%	TPRT (Off)	99.7986%				
		2	TPLT (Off)	99.0042%	TPRB (On)	99.2064%				
		1	TIV (Op)	97.5562%	TPFF (On)	97.5661%				
		1	BPFR (On)	99.9171%	BPRR (On)	83.3338%				
11	2 of 2	2	BPFL (Off)	99.9999%	RVLW (Op)	50%	RVRF (Op)	50%		
		2	BPFL (Off)	99.9999%	RVRW (Op)	50%	RVFF (Op)	50%		
		4	TPLT (Off)	99.8002%	RVRW (Op)	50%	RVFF (Op)	50%		
12	2 of 2 (one delayed)	1	LLP (Cl)	100%	BPRR (On)	100%				
		1	LHP (Cl)	100%	BPRR (On)	100%				
		1	RLP (Cl)	100%	BPRR (On)	100%				
		1	RHP (Cl)	100%	BPRR (On)	100%				

Case	Number Diagnosed	Number Represented	Diagnosed failure 1	Probability	Diagnosed failure 2	Probability	Diagnosed failure 3	Probability	Diagnosed failure 4	Probability
		2	TVRF (Cl)	100%	TPLB (On)	100%				
		1	TVRF (Cl)	100%	NVL (2 way)	100%				
		1	TVFF (Cl)	100%	NVL (2 way)	100%				
		2	LLP (Cl)	100%	LHP (Cl)	100%				
		2	TVRF (Cl)	100%	TPLT (Off)	99.7986%				
		1	BPFL (On)	99.9999%	BPFR (On)	100%				
		2	TPLT (Off)	99.7986%	TPLB (On)	100%				
		4	TVRF (Cl)	100%	RVLW (Op)	50%	RVRF (Op)	50%		
13	2 of 2 (incorrect)	4	TPLT (Off)	99.7986%	TPLB (On)	100%	RVLW (Op)	49.59%	RVRF (Op)	49.59%
14	2 of 2 (one incorrect)	1	BPFR (On)	99.9171%	BPRR (On)	83.3338%	CV (Op)	99.90%		
15	1 of 2 (one incorrect)	4	RVLW (Op)	50%	RVRF (Op)	50%				
16	2 of 2	4	TVFF (Cl)	100%	RVLW (Op)	49.6078%				
17	2 of 2	1	RVLW (Op)	45.3756%	RVRW (Op)	45.3756%				
		1	RVLW (Op)	45.3756%	RVFF (Op)	45.3756%				
		1	RVRW (Op)	45.3756%	RVRF (Op)	45.3756%				
		1	RVRF (Op)	45.3756%	RVFF (Op)	45.3756%				

In the next section, a discussion about how successful the BBN based fault diagnostic technique is on this system, is presented.

5.4.3.2. Discussion

The BBN based fault diagnostic process correctly diagnoses all the combinations of component failures that are detected. For the engine feed operation mode, all the component failures that can be detected, are detected, and can therefore be diagnosed. For the fuel transfer operation mode, the detection term is less than one, and therefore not all the failures that can be detected by the selected combination of sensors. This means that not all the failures are diagnosed, i.e. only the detected failures. For both operation modes, if a combination of sensors with a higher performance metric was selected, the diagnostic process could be improved, and for the fuel transfer operation mode, more component failures could be detected.

In some cases, additional evidence is required in order to correctly diagnose the component failures. In each case, no more than four components need to be inspected in order for the correct component failures to be determined. The cases in which this occurs are cases sixteen, seventeen and eighteen for the engine feed operation mode, and cases thirteen and fourteen for the fuel transfer operation mode.

There are a large number of hidden failures in each operation mode, 808/1568 for the engine feed operation mode and 622/1568 for the fuel transfer operation mode. Note, for a combination of sensors with a detection term of 1 for the fuel transfer operation mode, there are 524/1568 hidden failures. The hidden failures are components failing in the mode they are supposed to be in, or components failing in sections of the system that are not being used. There is also a large number of combinations of component failures where only one of the failures is diagnosed.

For both operation modes, there are cases where initially only one component failure is diagnosed, but the second component failure is diagnosed after the first component has been repaired or replaced. This would increase the repair time of the system, but it is unavoidable, unless additional components are taken to the system, increasing the transportation costs, potentially unnecessarily for a large number of component failures.

5.4.4. Summary

The BBN based methodology has been applied to the aircraft system and the results have been presented in this section of the chapter. This was completed in order to compare the results of the BBN based methodology with the results produced by the simulation based methodology presented in section 5.3. The comparison of the two methodologies is presented in section 5.5.

5.5. Comparison of the methodologies

In this section, the simulation based methodology and the BBN based methodology are compared. The comparison of the methodologies is split into four sections: the first section is the modelling of the system, the second is the selection of sensors, the third is the diagnosis of component failures, and the fourth provides a brief summary.

5.5.1. Comparison of the models

Both models represent the system well as the sensors can be used to determine the flow of fuel through the sections of the system. In both of the models, evidence about the component states can be introduced to the model, and the resultant sensor readings can be determined. Where the two methodologies differ, is the modelling accuracy of the sensor readings. In the BBN model of the system sensor readings are grouped into ranges of flow values in order to prevent the model from getting too large, but in the simulation model each sensor reading can be calculated numerically without the need for a state to be created for it. This enables sensor readings to be determined (and not have to be grouped into ranges), and therefore, a more accurate modelling process can be achieved. For example, if one pump is supplying 1 unit of fuel, in the BBN model the same sensor reading will be observed if there are two or three valves open, but in the simulation method, two different values will be observed, i.e. half a unit, and a third of a unit.

Another benefit of the simulation method is that for a given combination of component states, the sensor readings can be calculated significantly quicker than the BBN method, a fraction of a second instead of approximately 35 seconds. This is particularly beneficial for larger systems where there are a large number of combinations of component failures to be considered.

5.5.2. Comparison of the selection of sensors

In both cases, the sensor selection process is the same, i.e. calculating the performance metric for all combinations of sensors using the same equations. However, the two modelling methods result in slightly different performance metrics in most cases as the sensor readings are modelled differently. If the individual values of the performance metrics from Tables 5.4 and 5.13, and Tables 5.5 and 5.14 respectively, are compared, it is observed that the detection and criticality terms are identical in all cases, but the diagnostic terms are different: the diagnostic term is slightly higher for the simulation method in most cases. This is because of the sensor readings being grouped into ranges for the BBN methodology, as it means that some of the combinations of component failures produce the same combination of sensor readings for the BBN methodology, but produce different combinations of sensor readings for the simulation methodology. This is the same as discussed in the previous section but another example of this is in the fuel transfer operation mode, the component failure NVL (2 way) produces the sensor reading "-ve" for the BBN methodology, and "-1" for the simulation methodology, but the combination of component failures NVL (2 way) and TVRF (Cl) produces the sensor reading "-ve" for the BBN methodology, and "-2" for the simulation methodology, i.e. different for the simulation method but the same for the BBN methodology. Note, there are some sensors, such as sensor S1, which have the same diagnostic term for both methodologies. These are sensors where the sensor readings have not been grouped into ranges because they can only be one of three values, i.e. "E", "2", and "N".

The same is the case for combinations of 9 sensors for the engine feed operation mode, with the combinations of sensors in Table 5.15 being a subset of the combinations of sensors in Table 5.6. As with the individual sensors, the diagnostic term obtained by the simulation method is higher than the diagnostic term obtained by the BBN method. One thing that can be observed for the combinations of sensors for the engine feed operation mode is that for the simulation method the combinations S15a and S16, S15 and S16a, or S15a and S16a can be included, but in the BBN method, only the combination S15a and S16a can be included. The reason for this is because of three combinations of component failures, BPFR failed on and BPRR failed on, BPFR failed on and CV failed open, and BPRR failed on and CV failed open. For sensors S23 and S25 in the simulation method, the failure of the two pumps will result in the sensor reading of "2" for each of the sensors, but the other two combinations of component failures produce the sensor reading "1.5" for each of the sensors. Therefore, in order to distinguish between the other two combinations of component failures, at least one of the sensors, S15a and S16a, needs to be included. This is so that which of the two reserve booster pumps that has failed can be determined. However, for the BBN methodology, all three combinations of component failures result in the same sensor readings for sensors S23 and S25, i.e. ">1", and it means that in order to determine which of the three combinations of failures has occurred, both of the sensors next to the two reserve booster pumps need to be included, i.e. S15a and S16a. The results for the fuel transfer operation mode are not directly comparable as the combination of sensors for the fuel transfer operation mode includes fuel tank level sensors for the simulation method, and these sensors are not included in the BBN. However, it is worth noting that there are four different sensors in each of the selections of sensors, with only S1a, S12a, S26, S27, and either S15a or S16a (depending on which selection is made in Table 5.16) being selected in both methods. It is also worth noting that both the detection and diagnostic terms are higher for the simulation method than for the BBN method.

Another benefit of the simulation method is the ability to include the fuel tank level sensors. It is possible to include the level sensors in the BBN, but as discussed earlier, this would require not grouping the sensors readings into ranges, making the size of the conditional probability tables in the network larger. The inclusion of the fuel tank level sensors in the simulation method is particularly important for the fuel transfer operation mode, as some of the level sensors are included in the best combinations of sensors, i.e. enabling a higher maximum performance metric to be obtained.

5.5.3. Comparison of the fault diagnostics process

Both methodologies diagnose all combinations of component failures that are detected. However, both of the methods output the probability of the correct diagnosis differently. This is because the BBN method can consider every possible combination of component states, but the simulation method can only consider the component failures stored in the library. Therefore, in the BBN methodology, the fault diagnostic process outputs the probability of the components states, i.e. the probability that each of the components have failed, but in the simulation methodology, as it can only choose from the failures in the library, it outputs the probability of the most likely component failure divided by the probability of all component failures that can produce the observed failures. This means that the simulation methodology may appear to diagnose the component failures with a lower level of confidence. For example, the first failure in Table 5.11, is diagnosed with 91.8554% confidence, and the same failure in Table 5.20, is diagnosed with 100% confidence. However, if the probability that the component has failed output by the BBN, is multiplied by the probability of all other components being in their most likely state, then very similar values, (but not exactly the same), will be produced. The difference between these values is dependent on whether the combinations of sensor readings produced by the BBN method contain one of the sensor readings that is a range of values. Also, the fact the BBN can consider combinations of three (and more) component failures will also affect the value for the BBN if combinations of three (and more) component failures also produce the same observed symptoms.

One disadvantage of the simulation method, is that a library of observed sensor readings needs to be created. This means that component failures that are not in the library, may not be diagnosed correctly, but if the library is not exhaustive enough, then this will not be a problem. As the determination of the sensor readings using the simulation method is significantly faster than for the BBN methodology, (approximately 1 – 2 seconds instead of 15 – 16 hours), a large library can be constructed in a reasonable amount of time, reducing the likelihood that a failure will be observed that is not in the library.

5.5.4. Summary

There are a number of benefits of the simulation based methodology detailed in this section. Examples include more accurate sensor reading modelling, faster sensor reading determination, and better fault diagnosis, due to the higher diagnostic term. The more accurate sensor reading modelling is due to having to group the sensor readings into ranges for the BBN due to the time taken to construct the network, and the size of the conditional probability tables. As a result of the sensor reading being determined significantly faster by the C++ script, this method should enable modelling of larger systems, and is therefore, the methodology applied on the system presented in Chapter 6.

5.6. Summary

In this chapter, an alternative, simulation based methodology for system modelling and fault diagnostics is presented. This method is demonstrated by applying it to the aircraft fuel system presented in Chapter 4, with a few minor changes detailed in section 5.2. In this chapter, combinations of one and two component failures are considered for each of the 28 components for both operation modes. Like in Chapter 4, there are a large number of hidden failures, with approximately 39% of failures in the engine feed operation mode, and 54% of failures in the fuel transfer operation mode, being detectable by at least one of the 37 potential sensors that could be introduced to the system. The performance metric is calculated for each combination of nine (and fewer) sensors for both operation modes. The limit of nine sensors was selected because a combination of nine sensors can detect all of the component failures for the engine feed operation mode. However, twelve sensors would be required to detect all of the component failures for the fuel transfer operation mode. Using the selected combinations of sensors, combinations of one and two component failures were diagnosed using the proposed fault diagnostic process.

In order to verify that the proposed methodology works as desired, the BBN based methodology presented in Chapters 3 and 4 is applied to the same system. However, as the sensor readings are grouped into ranges, as discussed in section 5.4.1, there are only 33 possible sensor locations, (i.e. no level sensors are considered). Like in the application of the simulation based methodology, the performance metric was calculated for all combinations of nine (and fewer) sensors for both operation modes. The best combinations of sensors for each operation mode was selected, and used to diagnose all combinations of one and two component failures.

The chapter concludes by presenting a comparison of the two methodologies, in which it is concluded that the proposed simulation based methodology is the more suitable solution.

In the next chapter, the system modelling and fault diagnostics methodology proposed in this chapter is applied to a phased mission for a system, enabling the introduction of time dependence into the sensor selection and fault diagnostic processes.

Chapter 6 - Extension of the sensor selection and fault diagnostics methodology to phased mission systems

6.1. Introduction

In this chapter, the methodology for sensor selection proposed in Chapter 3, and the fault diagnostic process proposed in Chapter 5 are extended to a phased mission system, i.e. a system where the operation mode changes over time. In order to do this, the sensor performance metric considers the amount of time between component failure occurrence and its detection, the amount of time between failure detection and its diagnosis, and the amount of time between component failure occurrence and the time when the failure causes system failure. Therefore, the sensors that can quickly detect faults and diagnose failures are favoured over sensors that take longer to detect faults and diagnose failures. This is because it may be possible to prevent system failure by quickly detecting faults and diagnosing failures. Also, the component failures that occur earlier in the phased mission may have more effect on the performance of the system than the component failures that occur towards the end of the mission, as they will affect system performance for longer, and may therefore result in a higher probability of system failure, i.e. mission failure. However, if the failure occurs later on in the mission, it may still cause system failure, and therefore, still has to be considered in the sensor selection process. Note, system failure and mission failure are used in this chapter interchangeably as if the system fails, the mission will also fail. In addition, as the system considered in this chapter is significantly larger than the systems considered in the previous chapters, i.e. Chapters 3, 4, and 5 of this thesis, the number of possible sensors, and therefore, the number of possible combinations of sensors, is also significantly larger. As a result, an optimisation process, based on a GA method, is proposed in order to determine the best sensor combination for the system, as it would not be feasible to calculate the performance metric for each combination of sensors exhaustively.

This chapter begins by presenting the system which the methodology is applied to. The chapter continues by outlining the details of the example phased mission and the component failures considered. Next introduction of time dependence to the sensor performance metric is presented, followed by the details of the optimisation process. After this the proposed methodology is applied to the example phased mission system, and the results of the process of the modelling of the system, the sensor selection, and the fault diagnostics are presented. This chapter concludes with a summary of the work presented in the chapter.

6.2. Phased mission system description

The system presented in this chapter is the fuel system of the Airbus A380-800. It is the world's largest passenger aircraft and is powered by four engines which are manufactured by either Rolls Royce or Engine Alliance. It is capable of transporting more than 800 passengers a distance of up to 8,500 nautical miles, i.e. capable of flying from Hong Kong to New York directly, a flight duration of more than 15 hours. The aircraft has a maximum take-off weight of 575000 kg and a maximum landing weight of 394000 kg, and the aircraft has a maximum fuel capacity of approximately 325,000 litres (l), which corresponds to approximately 255000 kg.

The fuel is stored in eleven fuel tanks of the aircraft: five in each wing and one in the tail of the aircraft. In addition to the fuel tanks, there are vent and surge tanks in each wing and in the tail, which are used to help to reduce the production of air pockets in the fuel tanks during the refuel process. A labelled illustration of the tank layout in the aircraft is given in Figure 6.1, which is taken from Langton et al. (2009). The tanks are not of uniform volume, with the volumes of each of the tanks given in Table 6.1, where the density of the fuel is 0.785 kg/l. The volumes of the tanks and the fuel density are taken from Airbus (2006).

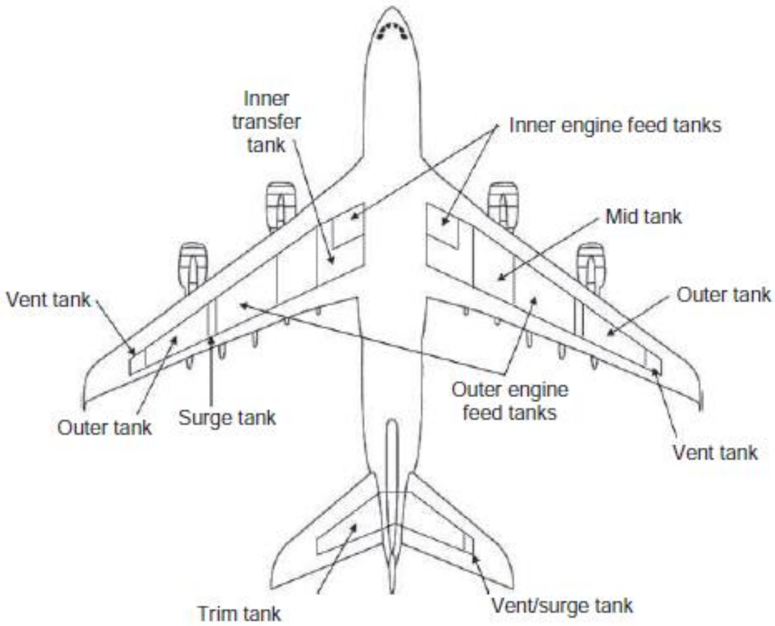


Figure 6.1 Illustration of aircraft fuel tank layout from Langton et al. (2009)

Table 6.1 Fuel tank volumes for the Airbus A380-800, (Airbus, 2006)

	Outer tanks	Outer engine feed tanks	Mid tanks	Inner transfer tanks	Inner engine feed tank	Trim tank	Total
Volume (l)	10520	27960	36460	46140	29340	23700	324540
Weight (kg)	8260	21950	28620	36220	23030	18600	254760

In this system, there is a significantly larger number of components than in the fuel system, analysed in Chapters 4 and 5; there are 66 components: 21 pumps and 45 valves. The full schematic, adapted from Langton et al. (2009), is given in Figure 6.2. Note, that the greyed out sections of the system are not considered in this thesis. The central section that is greyed out is the section that supplies fuel to the auxiliary power unit (APU), which is used to supply power to the on-board equipment, and is therefore, not directly related to the fuel supply to the engines. The other two greyed out sections on the edge of each wing represent heat exchangers, which are used to reduce the temperature of any fuel that is supplied to the engines which is not consumed so that it can be returned to the tanks. In this thesis, it is assumed that all fuel supplied to the engine will be consumed by the engine if the fuel can reach the engine, and the pipe is assumed to end where it changes from black to grey in the diagram. Therefore, the number of components that are considered is 62: 20 pumps and 42 valves.

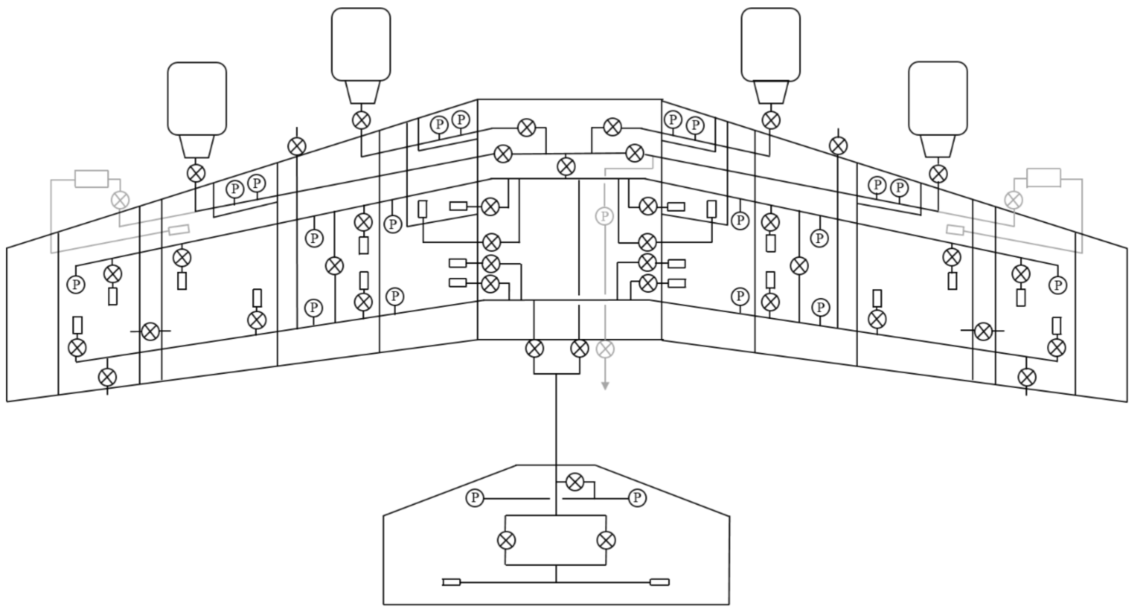


Figure 6.2 Schematic of Airbus A380-800 fuel system, adapted from Langton et al. (2009)

There are two considered phases of operation in this chapter: engine feed, and fuel transfer. Within these operation modes there are some sub-phases, for example, within the fuel transfer operation mode, there are many different sub-phases, as the fuel is passed from one tank to another. The fuel supplied to the engines is from the engine feed tanks, and therefore, each of the other tanks transfer fuel to the engine feed tanks, defined by a specific sub-phase and in a specific order to minimise the stress on the wings from the weight of the fuel, which could cause wing curvature. The order that the transferring of fuel is completed is presented in section 6.2.1, i.e. the description of the phased mission. In the engine feed operation mode, fuel can be supplied to the engines at different rates, as more fuel is required for take-off than cruise. Schematics for the engine feed and the fuel transfer operation modes are presented in Figures 6.3 and 6.4, respectively.

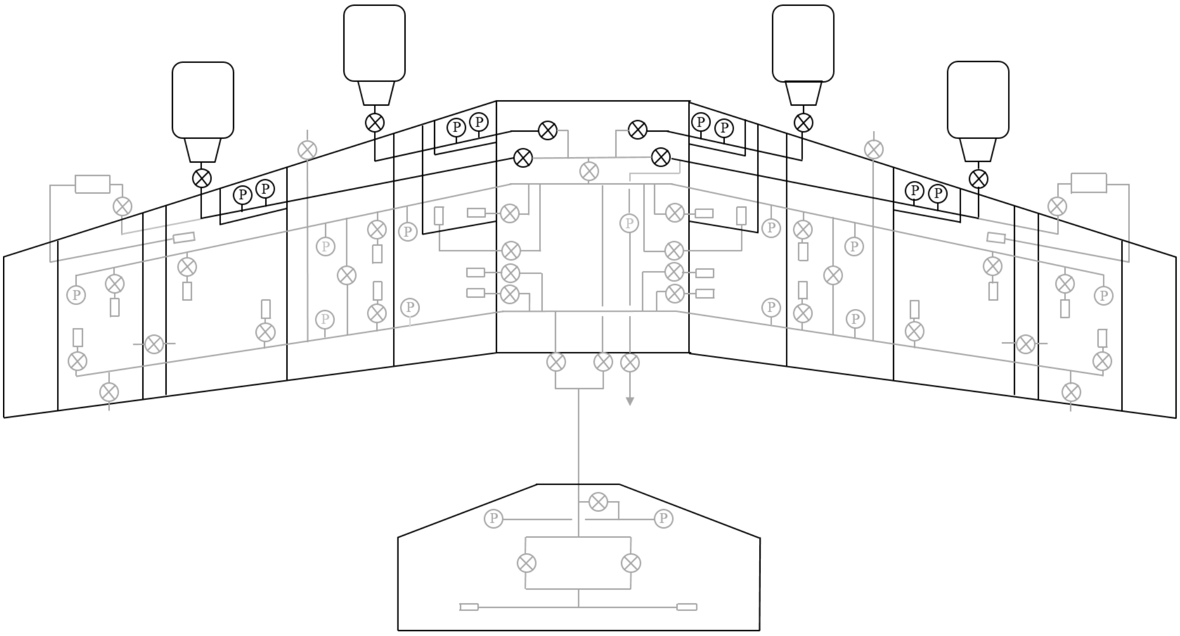


Figure 6.3 Schematic of Airbus A380-800 fuel system in the engine feed operation mode

In the two schematics, the greyed out sections are the sections of the system that are not used during the respective operation modes in normal operating conditions, i.e. with no component failures occurring. In the fuel transfer operation mode, it is assumed that the supply of fuel to the engine is the same as during the engine feed operation mode, in the same manner as that presented in Chapter 5, so that a supply of fuel to the engines is maintained. The engine feed process is not shown in Figure 6.4 in order to specifically demonstrate which components are used for the transfer of fuel between the tanks only. As with the previous system in Chapter 5, it is also assumed that there are primary and secondary pumps for supplying fuel to the engine, and there are also reserve valves for the fuel to pass into the inner engine feed tanks from the other tanks in the system during the fuel transfer phase. In contrast to the system modelled in Chapter 5, the secondary components do not automatically switch on/open when the primary components fail. This is because in order for the secondary components to be activated, a failure of the primary component must be detected and diagnosed. Therefore, this would require some form of manual or automatic command to activate the secondary component. This has not been considered, only the effect of the component failures on the system if no action is taken.

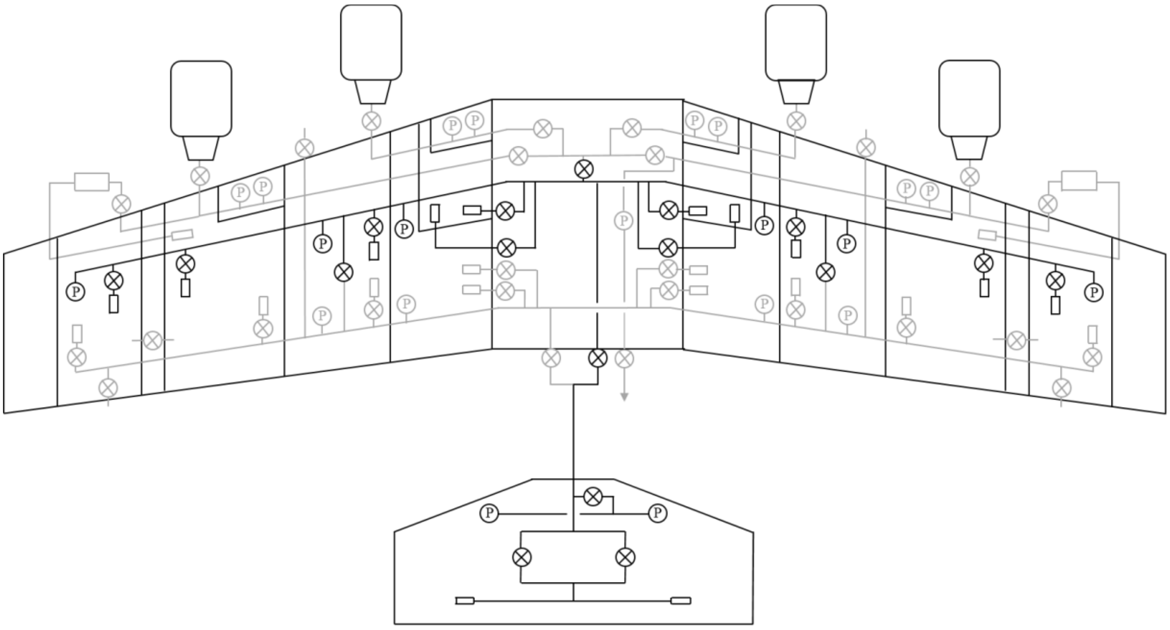


Figure 6.4 Schematic of Airbus A380-800 fuel system in the fuel transfer operation mode

In Figures 6.5 – 6.8 and Figures 6.9 – 6.12 the system is split into smaller sections in order to be able to label the components and the flow sensor locations more clearly. In the same format as in Chapters 4 and 5, the blue numbers are used to represent the components and the red numbers are used to represent the sensor locations. In addition to the flow sensors labelled in the figures, there is also a fuel level sensor in each of the tanks, labelled on Figures 6.9, 6.10 and 6.12. As before, the inclusion of sensors on the system does not affect the flow (or level) of fuel in the system. The full list of component numbers, their names and their descriptions is presented in Table 6.2. Note, that components numbers 2, 4, 6, 8, 46, 48, 50 and 52 are secondary components. Also note, all valves are two directional.

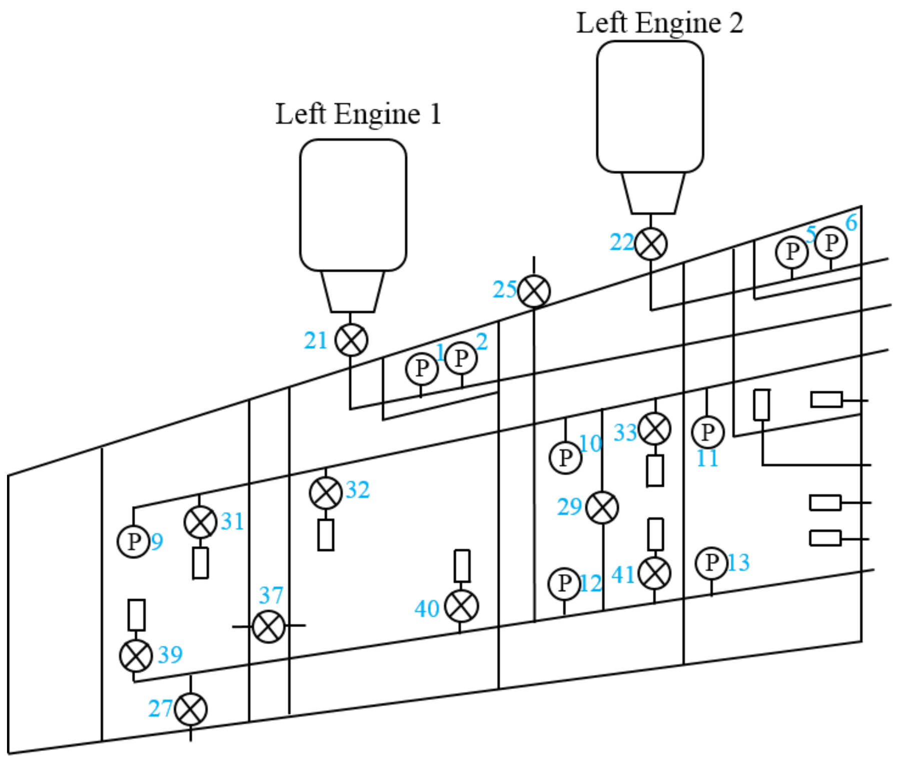


Figure 6.5 Left wing of Airbus A380-800 with components labelled

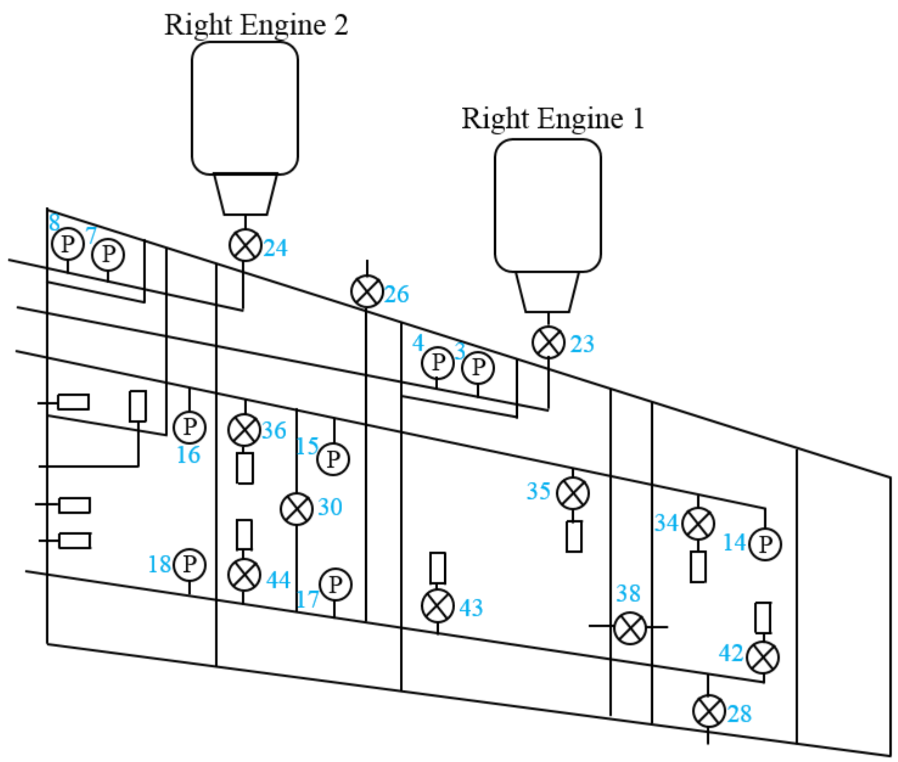


Figure 6.6 Right wing of Airbus A380-800 with components labelled

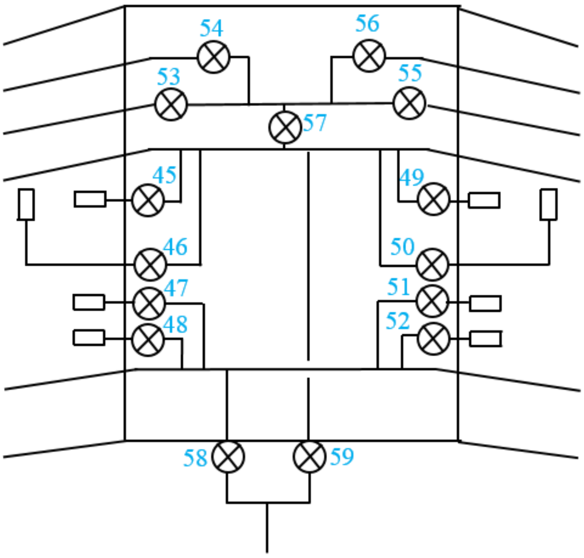


Figure 6.7 Centre of the Airbus A380-800 with components labelled

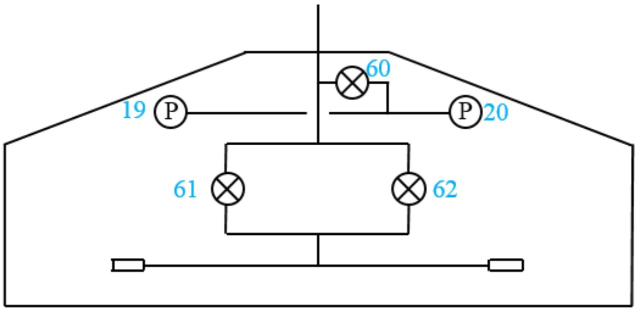


Figure 6.8 Trim tank of the Airbus A380-800 with components labelled

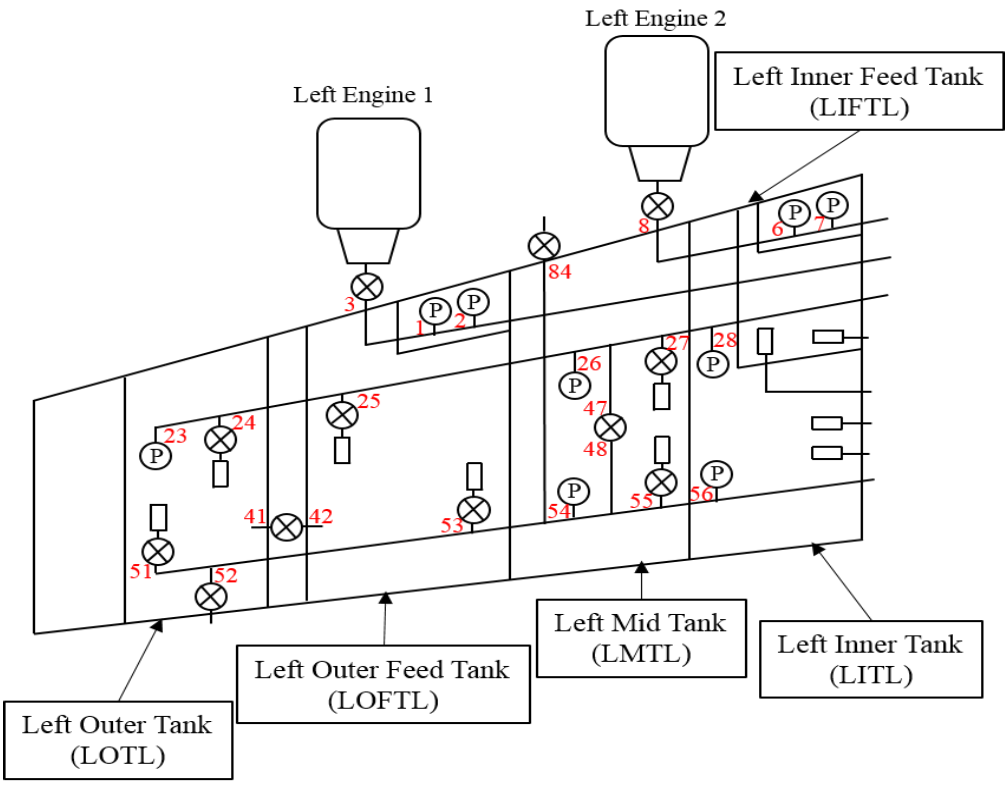


Figure 6.9 Left wing of Airbus A380-800 with sensor locations labelled

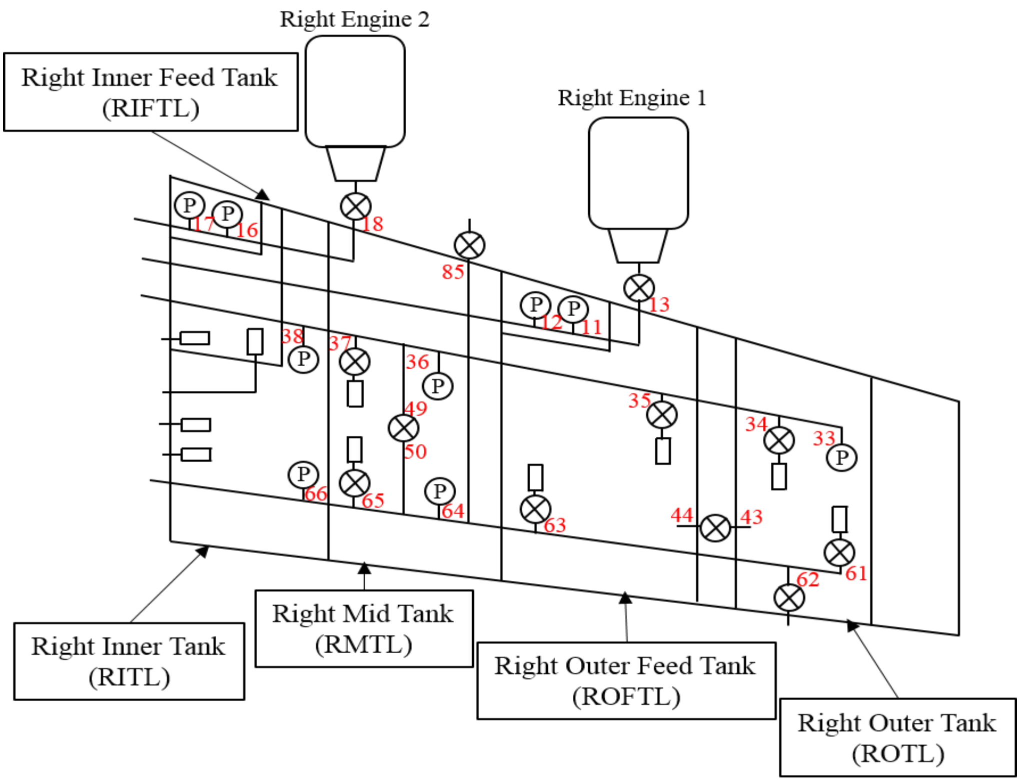


Figure 6.10 Right wing of Airbus A380-800 with sensor locations labelled

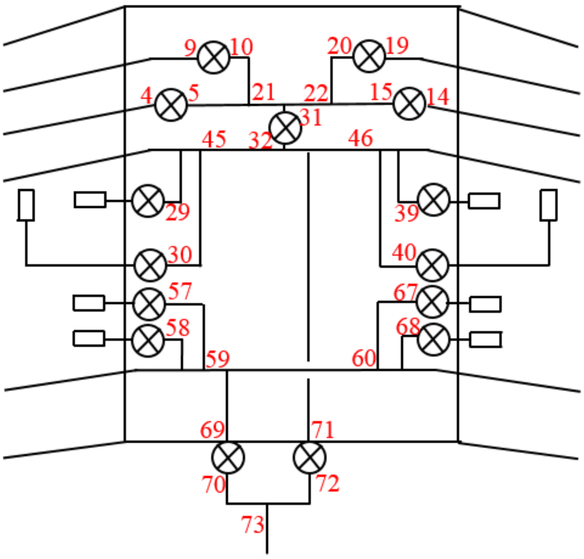


Figure 6.11 Centre of Airbus A380-800 with sensor locations labelled

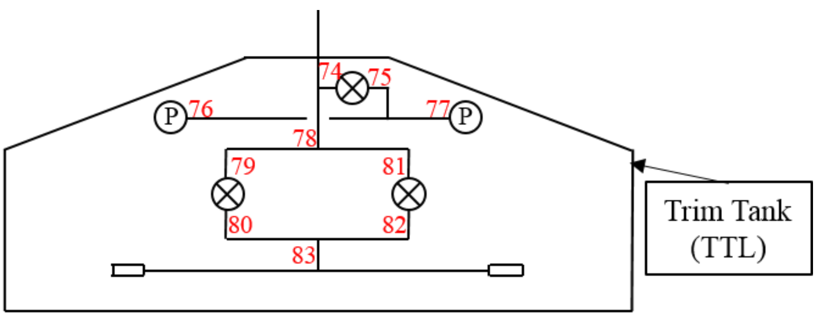
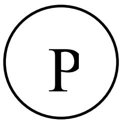
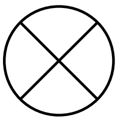


Figure 6.12 Trim tank of Airbus A380-800 with sensor locations labelled

Table 6.2 Description of components in the system

Type	Symbol	Number	Name	Description
Pump		1	L1P1	Left engine 1 Pump 1
		2	L1P2	Left engine 1 Pump 2
		3	R1P1	Right engine 1 Pump 1
		4	R1P2	Right engine 1 Pump 2
		5	L2P1	Left engine 2 Pump 1
		6	L2P2	Left engine 2 Pump 2
		7	R2P1	Right engine 2 Pump 1
		8	R2P2	Right engine 2 Pump 2
		9	LOTP	Left Outer tank Transfer Pump
		10	LMTP	Left Mid tank Transfer Pump
		11	LITP	Left Inner tank Transfer Pump
		12	LMDP	Left Mid tank Dump Pump
		13	LIDP	Left Inner tank Dump Pump
		14	ROTP	Right Outer tank Transfer Pump
		15	RMTP	Right Mid tank Transfer Pump
		16	RITP	Right Inner tank Transfer Pump
		17	RMDP	Right Mid tank Dump Pump
		18	RIDP	Right Inner tank Dump Pump
		19	LTP	Left Trim tank Pump
		20	RTP	Right Trim tank Pump
Valves		21	LEV1	Left Engine 1 Valve
		22	LEV2	Left Engine 2 Valve
		23	REV1	Right Engine 1 Valve
		24	REV2	Right Engine 2 Valve
		25	LRV	Left Refuel Valve
		26	RRV	Right Refuel Valve
		27	LDV	Left Dump Valve
		28	RDV	Right Dump Valve
		29	LFVP	Left Fuel Valve Path
		30	RFVP	Right Fuel Valve Path
		31	LOTV	Left Outer tank Transfer Valve
		32	LOETV	Left Outer Engine feed tank Transfer Valve
		33	LMTV	Left Mid tank Transfer Valve
		34	ROTV	Right Outer tank Transfer Valve

35	ROETV	Right Outer Engine feed tank Transfer Valve
36	RMTV	Right Mid tank Transfer Valve
37	LSV	Left Surge Valve
38	RSV	Right Surge Valve
39	LODV	Left Outer tank Dump Valve
40	LOEDV	Left Outer Engine feed tank Dump Valve
41	LMDV	Left Mid tank Dump Valve
42	RODV	Right Outer tank Dump Valve
43	ROEDV	Right Outer Engine feed tank Dump Valve
44	RMDV	Right Mid tank Dump Valve
45	LIEV1	Left Inner Engine Feed Valve 1
46	LIEV2	Left Inner Engine Feed Valve 2
47	LITV1	Left Inner Transfer Valve 1
48	LITV2	Left Inner Transfer Valve 2
49	RIEV1	Right Inner Engine Valve 1
50	RIEV2	Right Inner Engine Valve 2
51	RITV1	Right Inner Transfer Valve 1
52	RITV2	Right Inner Transfer Valve 2
53	LCV1	Left Cross feed Valve 1
54	LCV2	Left Cross feed Valve 2
55	RCV1	Right Cross feed Valve 1
56	RCV2	Right Cross feed Valve 2
57	CCV	Centre Cross feed Valve
58	DTV	Dump Trim tank Valve
59	FTTV	Fuel Transfer Trim tank Valve
60	TTDV	Trim tank Transfer and Dump Valve
61	LTTV	Left Trim Tank Valve
62	RTTV	Right Trim Tank Valve

In the next section, details of the example phased mission are presented, and the component failures and the considered times of occurrence in the mission are given.

6.2.1. Details of the phased mission

The fuel is transferred to the feed tanks from the other tanks in a specific order, as detailed in Airbus (2006). This document also details the quantity of fuel supplied to each engine during the cruise phase of the mission, at a rate of approximately 1.1 kg/s per engine. For simplicity, the rate modelled in this thesis is 1 kg/s.

As Airbus (2006) does not state the maximum flow rates of the pumps, the supply of fuel to the engines during the take-off phase can be assumed by considering the approximate maximum fuel jettison rate, stated in the document as 150000 kg/h. 12 of the 20 pumps are used to eject fuel from the system, and the remaining 8 pumps in the engine feed tanks are not used for this purpose. Note, although not explicitly stated in the document, it is assumed that this is to ensure that the supply of fuel to the engines is not lost, as it is possible that the fuel can be moved to eject it from the feed tanks if desired. The maximum jettison rate corresponds to approximately 4 kg/s for each of the 12 pumps, because some of the pumps will not be able to eject fuel for the whole hour (flow rate is quoted in units of kg per hour), as the maximum volume of the fuel in the tanks is less than this. For example, in an hour, each pump is capable of ejecting 14400 kg, but the maximum capacity of the outer tanks is 8260 kg, i.e. less than that. It is reasonable to assume that the fuel will be jettisoned from the system at the maximum possible rate, i.e. the maximum output from the pumps. It is therefore, reasonable to assume that the maximum supply of fuel to the engine by each pump will be the same rate, i.e. 4 kg/s. This rate, is therefore assumed to be the rate at which the fuel is supplied to the engines during take-off.

Like the rate of supply of fuel to the engines during take-off, the fuel transfer rate between tanks is also not stated in Airbus (2006). It is assumed to be at a rate greater than the rate of flow of fuel during the cruise phase in order to replenish the tanks faster than they are being depleted, but at a rate lower than the maximum supply rate, as this would most likely put higher strain on the pumps. Therefore, the fuel transfer rate is assumed to be 3 kg/s per pump.

It is stated in Airbus (2006) that in order to prevent wing bending, the aircraft takes off with very little fuel in the outer tanks. Therefore, immediately after take-off and climb, fuel is transferred from the inner tanks to the outer tanks until they are full. When the engine feed tanks are depleted to approximately 30%, (7000 kg), they are replenished by transferring fuel to the feed tanks from the inner tanks. When the inner tanks are nearly empty (it is assumed that the tanks are not run dry), the transferring of fuel is paused until the engine feed tanks are depleted to approximately 30% again. This process is then repeated, transferring the fuel from the mid tanks to the feed tanks, and then from the trim tanks to the feed tanks, and finally from the outer tanks to the feed tanks. The fuel in the feed tanks is then depleted through descent and landing of the aircraft. Note, typically there are a few hours' worth of additional fuel carried on board, in case of delays during landing, (14,400kg is consumed per hour during the cruise phase, but less than this would be required to remain airborne in proximity to the place of landing).

An example mission is detailed in Tables 6.3 and 6.4, with the duration and description of phases given in Table 6.3, and the quantity of fuel in each of the tanks at the end of each phase given in Table 6.4, assuming that the mission is completed as expected, i.e. no failure has occurred. Note that the initial quantities of fuel are given in the row for phase 0, and the times in Table 6.3 are given in minutes, as this is the time step used in this study. The total mission time is 720 minutes, (12 hours), well within the capability of the aircraft, hence the tanks in the aircraft are not full, i.e. 40000 kg under max fuel capacity. Note, the third column of Table 6.3, failure time, is discussed in the following section. For simplicity, take-off and climb are combined into one phase, and cruise, descent and landing at the end of the mission, are also combined into one phase. Note that in these operation phases, no fuel transfer is undertaken, only engine feed. Also note, all four engine feed tanks are assumed to start with the same quantity of fuel in them, despite having slightly different capacities, and are therefore grouped into one column, i.e. the quantity of fuel presented in the third column of Table 6.4 is in each of the four feed tanks, for example, 19000kg in each of the four tanks, 76000kg total, at the start of the mission.

Table 6.3 Timings of the phased mission

Phase number	Starting time (minutes)	Failure time (minutes)	Ending time (minutes)	Phase description
0	0	0	0	Initial quantities
1	0	13	25	Take-off and climb
2	25	45	65	Transfer of fuel from the inner to outer tanks
3	65	95	125	Cruise
4	125	195	265	Transfer of fuel from the inner to feed tanks
5	265	300	335	Cruise
6	335	405	475	Transfer of fuel from the mid to feed tanks
7	475	510	545	Cruise
8	545	565	585	Transfer of fuel from the trim to feed tanks
9	585	595	605	Cruise
10	605	625	645	Transfer of fuel from the outer to feed tanks
11	645	683	720	Cruise, descent and landing

Table 6.4 Fuel quantities for each phase of the mission

Phase Number	Outer tank quantities (kg)	Feed tank quantities (kg)	Mid tank quantities (kg)	Inner tank quantities (kg)	Trim tank quantity (kg)	Total quantity (kg)
0	600	19000	27000	34300	15400	215200
1	600	13000	27000	34300	15400	191200
2	8000	10600	27000	27100	15400	181600
3	8000	7000	27000	27100	15400	167200
4	8000	11200	27000	1900	15400	133600
5	8000	7000	27000	1900	15400	116800
6	8000	11200	1800	1900	15400	83200
7	8000	7000	1800	1900	15400	66400
8	8000	8200	1800	1900	1000	56800
9	8000	7000	1800	1900	1000	52000
10	600	8200	1800	1900	1000	42400
11	600	3700	1800	1900	1000	24400

6.2.2. Failure modelling

As in the previous chapters, there are a number of different component failures and modes that have been considered. In addition, as system operation is not considered at a single point in time in this case, the component failures can occur at various times during the mission. The times at which failure occurrence can occur are in the middle of each of the operation phases, i.e. there are 11 considered failure times. However, only one component failure per mission, i.e. no combinations of two or more component failures, are considered due to the large number of possible combinations, which is the result of the inclusion of multiple component failure modes and the time dimension. Also, due to a low probability of component failure occurrence, the probability that a second component failure occurs before the effects of the first failure are observed and addressed is low. In total, there are 2926 cases of failures considered, which includes failure of each of the components in each of their failure modes, and at each time of failure occurrence in the mission. For example, in order to analyse the effect that the time at which a failure occurs has on the ability of the sensors to detect the failure, multiple time instances for failures are considered, one in the middle time step of each phase, as described in the third column of Table 6.3.

Each of the components have multiple failure modes. For example, the pumps can fail in 7 different states. First of all, they can fail in the on failure modes in the three supply states detailed above, i.e. supplying 4 kg/s (take-off), 3 kg/s (transfer) and 1 kg/s (cruise). In addition, they can supply half of these values, i.e. supplying 2 kg/s, 1.5 kg/s and 0.5 kg/s, in order to represent degraded performance, with the supply of reduced amounts of fuel. The final failure mode of the pump is the off state, i.e. no movement of fuel, 0 kg/s. The valves have 3 different failure modes: failed open, failed half open (the radius of the opening is half that of a fully open valve), and failed closed. The valves failed open does not restrict the flow in anyway, whereas the valves failing closed stops the flow completely. If a valve is partially failed, it can result in a restriction on the quantity of fuel passing through it. There are two different situations, a partially open valve and all other valves closed, and a partially open valve and (at least) one other fully open valve in parallel. The first situation will result in no restriction on the quantity of fuel passing through the valve as the quantity of fuel going through the valve has to equal the quantity of fuel supplied to it. This is the case for the valves in the centre of the Airbus A380-800 system, i.e. valves that are in series with other valves in the system. These valves include components 29, 30, 37, 38, and 53 – 60. In reality, this would change the quantity of fuel passing through the valves by a small amount due to the added resistance of the smaller path, but as the pumps are assumed to be constant fuel output, this is not considered. The second situation, i.e. valves in parallel, results in a reduction in the amount of fuel passing through the partially open valve. If a junction is considered, one pipe splitting into two, each with a valve positioned in it, then if both valves were fully open, the flow of fuel would split evenly. However, if one of the valves was only half open, then 80% of the fuel will pass through the fully open valve, and 20% will pass through the half open valve. This is because the area of the valve is proportional to the square of the radius of the valve, and therefore, the area of a partially closed valve is equal to a quarter of the fully open valve. Pipe and tank failures, such as leaks and ruptures, are not considered in this thesis.

There are a number of component failures that can cause the system to fail. However, when the time dimension is considered, some component failures may be critical if they occur during one part of the mission, but they might not be critical if they occur during another part of the mission. For example, if the pump LITP (component 11) fails off in the first phase (take-off and climb) of the mission, it will be critical to the completion of the mission, as there will not be enough available fuel to feed the engines to be able to complete the mission, since without this pump the fuel will remain in the left inner tank and there will not be enough fuel available to complete the mission. However, if LITP fails off in the seventh phase of the mission, it will not be critical to the completion of the mission, as this pump is not used during the later phases. Therefore, the events in this chapter are defined to be critical to the system, but not component failures. Note an event is defined as a component failure occurring at a specific time. Critical events, i.e. events that cause system failure, are defined as events that result in the supply of fuel to the engines being below 75% of the amount that is normally supplied in the considered phase of the mission, i.e. events in which a supply of less than 12 kg/s between the four engines in the take-off phase, or events in which a supply of less than 3 kg/s between the four engines throughout the rest of the mission, are described to be critical. Another critical event for the system is an event that results in the weight of fuel in one wing being significantly heavier than in the other, because the centre of gravity will cause the aircraft to be imbalanced and potentially prevent it from being able to remain airborne. For demonstration purposes, the threshold is set to be one wing 20% heavier than the other. The final critical event for the system is events that result in the weight of fuel in the tanks at the end of the mission being above the maximum landing weight. This threshold is set at 30000 kg in this thesis, which corresponds to a take-off weight of approximately 570000 kg, approximately 5000 kg below the maximum take-off weight.

As the minimal cut sets for system failure are time-dependent, there are different minimal cut sets for each of the 720 time steps, which results in a large number of minimal cut sets. Instead of building a fault tree and obtaining the minimal cut sets, the C++ script used to model the system uses a series of if-then-else statements to determine if the criticality criteria are satisfied in order to determine whether system failure occurs. At each time step the supply of fuel to the engines is determined, and if it is lower than 75% of the amount of fuel that should be supplied at the same time step, then the mission is marked as critical. Also, at each time step, the total mass of the fuel in each wing is compared, and if one is 20% greater than the other the mission is marked as critical. Finally, if the weight of the system is greater than the maximum landing weight (i.e. more than 30000 kg of fuel remaining) at the end of the mission, the mission is marked as critical.

6.2.3. Summary of assumptions

In this section a summary of all the assumptions for the Airbus A380-800 system is presented. The assumptions are grouped into three sections, system operation and modelling, failures, and sensors.

System operation and modelling assumptions

- The greyed out sections of Figure 6.2 are not considered, i.e. the supply of fuel to the APU, and no heat exchangers, since all the fuel supplied to the engines is consumed and none is returned to the tanks.
- The fuel jettison and refuel operation modes are not considered.
- There is no resistance on the flow of fuel in the system, i.e. by pipes or valves, etc.
- When the line meets a junction, the fuel will split evenly along all the clear lines, i.e. the lines that do not have blocked valves in them.
- The mission length is 12 hours and the modelling time step is 1 minute.
- When the level of fuel in the engine feed tanks is reduced to approximately 30% of their capacity, they will be replenished by transferring the fuel from other tanks in the system. The order of the tanks that the fuel is transferred from is detailed in Airbus (2006) and in section 6.2.1.

Failure assumptions

- The pumps can move fuel around the system at 7 different rates: take-off rate (4 kg/s), degraded take-off rate (2 kg/s), fuel transfer rate (3 kg/s), degraded fuel transfer rate (1.5 kg/s), cruise rate (1 kg/s), degraded cruise rate (0.5 kg/s), and no movement of fuel (0 kg/s).
- The valves in the system can be fully open, partially open, or closed. Partially open valves in parallel allow 25% of the fuel that would normally pass through the valve, and valves in series do not restrict the flow, as detailed in the previous section.
- Only one component failure is considered per mission, i.e. no combinations of two component failures are considered, as was the case in Chapters 3, 4, and 5.
- The component failures are assumed to occur in the middle of each phase of the mission and the effects of the failure have stabilised by the next time step, i.e. within 1 minute.
- Once a component has failed, it stays in the same state for the rest of the mission, where possible. For example, a valve will stay open for the rest of the mission if it has failed open, and a pump will continue to output fuel (if there is fuel in the tank) for the rest of the mission if it has failed on.

- There are a number of reserve pumps and reserve valves in the system which would not normally be used, but failures of these components, such as pumps failing on and valves failing open, are considered in this chapter.
- The system is deemed to be critical if one wing is 20% heavier than the other, the supply of fuel to the four engines is less than 75% of the amount supplied under normal operating conditions, or the weight of the aircraft is higher than the maximum landing weight of 394000 kg, corresponding to 30000 kg of fuel left at the end of the mission.

<u>Sensor assumptions</u>

- There are two types of sensors: flow sensors and level sensors.
- The flow sensors can distinguish between the fuel line being empty (and therefore no flow of fuel) and the line being full (but no flow of fuel).
- The sensors are perfectly reliable, the flow sensors always measure the flow of fuel through them correctly, the level sensors always measure the fuel level in the tanks correctly, and the sensors are assumed not to fail.
- Flow sensors and level sensors are assumed to have the same cost.

6.3. Introduction of time dependence to the sensor performance metric

In order to apply the performance metric to a time-dependent system, the performance metric is adapted to consider the time when the component failures occur in the mission. The probability of component failure occurrence depends on time. First of all, the probability of each component failure is calculated by considering the reliability of the components, as detailed in Andrews & Moss (2002), where the probability of a component not failing at time T is equal to the reliability of the component, $R(T)$, as presented in Equation (6.1). Note, the exact details of the failure rate distribution is not important in this methodology, any failure distribution could be used with this method, a negative exponential distribution is used in this example.

$$R(T) = e^{-\lambda T} \tag{6.1}$$

where, λ is the failure rate, which is equal to $1/MTTF$, where $MTTF$ is the mean time to failure of the component. It is assumed that the value of λ is 0.000001 per time step for the pumps and 0.000005 per time step for the valves, which corresponds to values of $MTTF$ of approximately 694 days, and 139 days of continuous use, respectively. If the aircraft is used for approximately 16 hours a day, this corresponds to approximately 3 years for the pumps, and 7 months for the valves. Note, the reliability of the component $R(T)$ is equal to $1 - F(T)$, where $F(T)$ is the unreliability of the component and has a probability density function of $f(t) = \lambda e^{-\lambda t}$. Using this probability density function the probability that the component fails between two time steps, t and $t + 1$, can be calculated. It is the probability density function integrated over limits of t and $t + 1$ multiplied by the probability of the failure not occurring before time t. Therefore the probability that a component will fail in the time step is given in Equation (6.2).

$$
\begin{aligned}
F(t, t+1)R(0,t) &= \left(\int_{t}^{t+1} f(t')dt'\right) \times \left(1 - \int_{0}^{t} f(t')dt'\right) \\
&= \left(e^{-\lambda t} - e^{-\lambda(t+1)}\right)\left(1 + e^{-\lambda t} - 1\right) = e^{-2\lambda t} - e^{-2\lambda t - \lambda} \\
&= e^{-2\lambda t} - e^{-2\lambda t}e^{-\lambda} = e^{-2\lambda t}\left(1 - e^{-\lambda}\right)
\end{aligned}
\tag{6.2}
$$

The probability of each event, P_e, can be calculated by multiplying $F(t, t + 1)$ for the component that fails, by $R(T)$ for all other components. Note, this probability will be small because it is only considering the event where the component fails in that specific time step, but as all the events considered are when a component fails in one time step, all of the probability of events will be small, resulting in the correct ratio between the probability of all considered events. Therefore, the probability of all considered failures will be equal to the sum of P_e for all considered events.

Now that the probability of each of the component failures has been presented, the time dependence in each of the terms of the time-dependent performance metric can be developed.

6.3.1. Detection term

The detection term of the time-dependent performance metric introduces a factor to the detection term presented in Equation (3.1) (re-stated below) which considers the time of the failure, and the time of detection. The mission timeline is represented in the form shown in Figure 6.13.

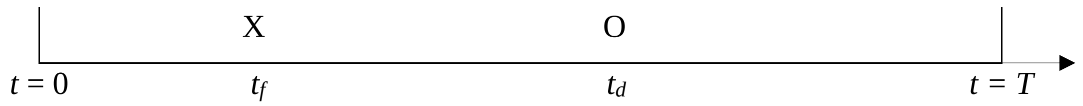


Figure 6.13 Representation of the timeline for the detection term

In this representation, the left and right vertical lines represent the start, $t = 0$, and end $t = T$, of the mission, respectively, with time increasing from left to right. The "X" in the diagram is used to represent the time of the component failure occurrence, $t = t_f$, (i.e. in the middle of a phase) and "O" represents the time when the sensor can detect the component failure, $t = t_d$. Note, the time of "X" and "O" can be identical, i.e. as soon as the failure occurs it can be detected, i.e. $t_f = t_d$. Also note, that the time of "X" and "O" can be in different phases of the mission. If the sensor cannot detect the failure, then as before, the probability of this failure event is not included in the detection term. However, if the component failure can be detected, then the detection term, presented in Equation (3.1), is multiplied by two factors. The proposed formula for the detection term is presented in Equation (6.3), where P_{md} has the same definition as stated in section 3.2.1, i.e. the sum of probabilities of the considered failures' occurrence that can be detected by at least one sensor out of all the possible sensors on the system. It is worth noting that the sum of P_e for all component failures that are detected ($N_d\{s\}$) by the sensor group is equal to P_d as defined in section 3.2.1. Note, ($N_d\{s\}$) is the number of events e detected by sensor s.

$$DE_{\{s\}} = \frac{P_d}{P_{md}} \tag{3.1}$$

$$DE_{\{s\}} = \frac{1}{P_{md}} \sum_{e=1}^{Nd\{s\}} P_e \left(1 - \frac{\left(t_{d,e} - t_{f,e}\right)}{T}\right)\left(1 - \frac{\left(t_{d,e} - t_{f,e}\right)}{\left(T - t_{f,e}\right)}\right) \tag{6.3}$$

The two additional factors take account of the cases when the component failure is not detected immediately, $\left(t_d > t_f\right)$, as the delay in detecting the failure will delay the appropriate action being taken to prevent system failure, (if it is possible to prevent), and the value of the detection term is smaller than in the situation when $t_d = t_f$. For both of the factors, the longer the time between the component failure and its detection, the smaller the factor is, resulting in a smaller detection term, since it is usually beneficial to be able to detect component failures as soon as possible. The first factor considers the delay of detection, i.e. the amount of time between component failure and its detection, in relation to the overall duration of the mission.

The smaller the delay, the higher the factor; also for a longer mission the same delay influences the factor less than for a shorter mission. This factor does not consider when in the mission the failure occurs, only how long it takes to detect it, for example, it takes 5 minutes to detect failure occurrence. The second factor, however, considers the delay of detection in relation to its time of occurrence, i.e. remaining time of the mission. This factor does not consider how long the system has operated for before the component failure, it only considers how long it takes the sensor to detect the component failure in relation to the remaining mission time, i.e. how long the failure stays in the system, before and after the detection if no remediation actions are taken. The smaller the delay, the higher the factor; also the earlier in the mission the delay occurs or the longer the mission, the higher the factor. In other words, the first factor considers the percentage of mission time that the failure is not detected for, and the second factor considers the percentage of the remaining mission time after the failure, that the failure is not detected for.

6.3.2. Diagnostic term

The diagnostic term of the time-dependent performance metric considers when after the completion of fault detection the best diagnostic capability can be obtained, i.e. the time step when the diagnostic term is at its maximum value due to the change of the sensor readings for each component failure. However, in some cases there may be a large delay between when the failure is detected and the highest diagnostic capability is obtained, but a relatively high diagnostic term is achieved comparatively soon after the failure being detected. Consider the simple example presented in Figure 6.14.

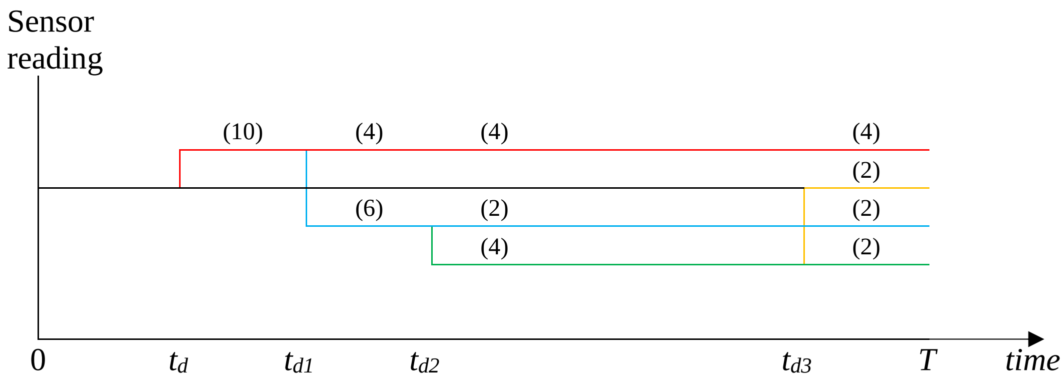


Figure 6.14 Representation of the timeline of the mission for the diagnostic term

The black line in the middle of the figure represents the sensor reading produced under normal operating conditions, i.e. when no failures occur. For simplicity, it is assumed to be the same sensor reading throughout the whole mission. At time t_d the sensor could detect a fault, when a different sensor reading is produced, as represented by the red line. There may be a number of different component failures that are detected at this point of the mission, and produce the same sensor reading, for example, 10. At time t_{d1}, for some of the component failures, the sensor reading will deviate again, and depending on the sensor reading observed at this time, the number of potential component failures that could have occurred is reduced, i.e. if one sensor reading is produced (red line), one of four component failures could have occurred, but if the other sensor reading is produced (blue line), one of six component failures could have occurred. Likewise, at time t_{d2}, depending on the sensor reading, the failed component could be one of 4 (red line), 2 (blue line), or 4 (green line), different component failures, respectively. Also, at time t_{d3}, depending on the sensor reading, the failed component could be one of 2 (yellow line), 4 (red line), 2 (blue line), or 2 (green line) different component failures, respectively. Note, at time t_{d3}, the sensor reading represented by the yellow line returns to the same value as the sensor reading observed if no failures have occurred. However, this does not mean that the two component failures represented by the yellow line can no longer be diagnosed as the sensor readings observed for the rest of the mission are considered, i.e. as soon as a failure has been detected, it cannot be undetected.

If these 10 component failures are the only component failures considered, and if time taken to carry out the best diagnostics is not considered, $DI_{td3} > DI_{td2} > DI_{td1} > DI_{td}$, where DI is the diagnostic term, as presented in section 3.2.2 and re-stated below. However, if the time between t_d and t_{d3} is significantly longer than the time between t_d and t_{d2}, then it might be useful to have a lower diagnostic capability, but in a significantly shorter time. Therefore, the factor used for DI evaluation, presented in Equation (6.4), considers the diagnostic term for each time step between the time of detection t_d and the end of the mission T, until the best value is achieved. Note that T_{step} can have any value between t_d and T and is in one minute increments as presented in section 6.2.1.

$$DI_{\{s\}} = \frac{\sum_{i=1}^{nrs} P_{mli}}{\sum_{i=1}^{nrs} P_{sri}} \tag{3.2}$$

$$Factor(T_{step}) = \left(1 - \frac{(T_{step} - t_d)}{T}\right)\left(1 - \frac{(T_{step} - t_d)}{(T - t_d)}\right) \tag{6.4}$$

As with the factor of the time-dependent detection term in section 6.3.1, this factor considers the amount of time it takes to achieve the diagnostic term in comparison to the overall duration of the mission, and in comparison to the remaining mission time after the detection has occurred. To begin with this factor is calculated for each time step, T_{step} and it is multiplied by the intermediate values of the diagnostic term for that considered deviated sensor reading, resulting in $Value(T_{step})$, as calculated in Equation (6.5). Note, in this expression, only the combinations of component failures that produce the considered sensor reading at time t_d are considered, i.e. not all of the possible sensor readings. For example, in Figure 6.14 $x_{max}(t_d) = 1$, as there is only one deviated sensor reading (red); $x_{max}(t_{d1}) = 2$ (red and blue), $x_{max}(t_{d2}) = 3$ (red, blue and green), and $x_{max}(t_{d3}) = 4$ (red, blue, green and yellow). Note, x_{max} is the number of possible deviated sensor readings. Therefore, the equation without the time dependency element, Equation (3.2), is updated, as there can be a number of P_{mlx} and P_{srx}.

$$Value(T_{step}) = \frac{\left(\sum_{x=1}^{x_{max}(T_{step})} P_{mlx}\right) \times Factor(T_{step})}{\sum_{x=1}^{x_{max}(T_{step})} P_{srx}} = \frac{N(T_{step}) \times Factor(T_{step})}{D(T_{step})} \tag{6.5}$$

For simplicity, $N(T_{step}) = \sum_{x=1}^{x_{max}(T_{step})} P_{mlx}$ and $D(T_{step}) = \sum_{x=1}^{x_{max}(T_{step})} P_{srx}$. The time step that results in the maximum value of the term $Value(T_{step})$, is denoted as $T_{stepmax}$, and it is used in the calculation of the time-dependent diagnostic term in Equation (6.6). As there can be multiple different deviations occurring at t_d (the number is $nrs(t_d)$) and any other point in time after, this process is repeated for all these different deviations. For example, in Figure 6.15, there are three different deviations (red line, blue line, and green line) from the normal operating conditions (black line) at time t_d, i.e. $nrs(t_d) = 3$.

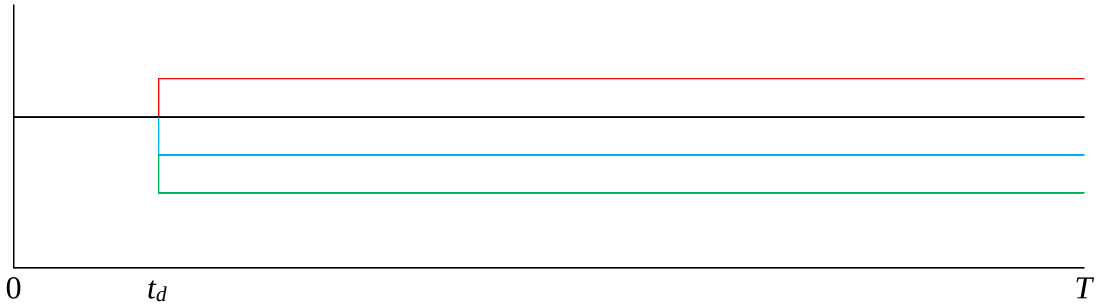


Figure 6.15 Representation of the timeline of the mission for the observed sensor readings at time t_d

This process is then repeated for all possible times of t_d, starting from the earliest detection time of a failure, t_{dmin}, until the end of the mission, T. The resulting diagnostic term is presented in Equation (6.6).

$$DI_{\{s\}} = \sum_{t=t_{dmin}}^{t=T} \frac{\sum_{i=1}^{nrs(t)} N(T_{stepmax})_i \times Factor(T_{stepmax})_i}{\sum_{i=1}^{nrs(t)} D(T_{stepmax})_i} \tag{6.6}$$

6.3.3. Criticality term

The criticality term of the time-dependent performance metric considers the duration between the failure occurrence and the failure causing system failure, i.e. one wing significantly heavier than the other, less than 75% of normal supply to the engines, or the weight of the aircraft being above the maximum landing weight at the end of the mission. Like with the detection term, the mission can be represented in a timeline in Figure 6.16, where “O” represents the time when the system becomes critical, t_c, where t_c can be any time between t_f (“X”), and the end of the mission, T, i.e. can become critical in a different phase of the mission.

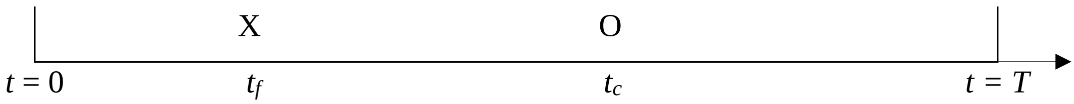


Figure 6.16 Representation of the timeline of the mission for criticality term

The criticality term of the performance metric presented in section 3.2.3, Equation (3.3) is restated for reference.

$$CR_{\{s\}} = \frac{Q_{sys} - Q_{sys}(q_s = 0)}{Q_{sys}} \tag{3.3}$$

The modification applied to the criticality term is applied to the two individual terms of the criticality term, Q_{sys}, and $Q_{sys}(q = 0)$. Therefore, the criticality term is in the same form as that expressed in Equation (3.3), but each of the individual terms are defined using Equations (6.7) and (6.8), respectively. In the criticality term presented in section 3.2.3, Q_{sys} is equal to the probability of system failure with no knowledge of any of the component states, i.e. the sum of the probability of occurrence of all component failures that would make the system critical. $Q_{sys}(q = 0)$ is defined in a similar way, i.e. the sum of probability of occurrence of all component failures that would make the system critical given that the non-deviated reading of sensor s occurs. If time dependency is considered, each probability of occurrence is multiplied by a factor, developed in a similar manner to the detection and diagnostic term. As before, this factor has two terms, the first term considers the percentage of time that the component has failed and the system is in a critical state in relation to the total mission time, and the second term considers the percentage of time that the system is in a critical state in relation to the remaining mission time after the component failure occurs. This factor will decrease the value of the criticality term for component failures that result in the system becoming critical later in the mission than the component failure. The sooner the system becomes critical after a failure occurs, the higher the factor, i.e. the failures that make the system critical quicker are more important than the failures that take a long time to make the system critical. The equations for the time-dependent expressions of Q_{sys} and $Q_{sys}(q = 0)$ are given in Equations (6.7) and (6.8), respectively. In Equation (6.7), the summation is over all critical events, $N_{c\{s\}}$, i.e. it is the same for all sensors, and in Equation (6.8), the summation is over all critical events that are not detected by the selected sensor, $N_{cnd\{s\}}$, i.e. different for each sensor. This is because Q_{sys} is the probability of system failure, and $Q_{sys}(q = 0)$ is the probability of system failure given that the non-deviated sensor reading of the sensor occurs.

$$Q_{sys} = \sum_{e=1}^{N_{c\{s\}}} P_e \left(1 - \frac{\left(t_{c,e} - t_{f,e}\right)}{T}\right)\left(1 - \frac{\left(t_{c,e} - t_{f,e}\right)}{\left(T - t_{f,e}\right)}\right) \tag{6.7}$$

$$Q_{sys}(q = 0) = \sum_{e=1}^{N_{cnd\{s\}}} P_e \left(1 - \frac{\left(t_{c,e} - t_{f,e}\right)}{T}\right)\left(1 - \frac{\left(t_{c,e} - t_{f,e}\right)}{\left(T - t_{f,e}\right)}\right) \tag{6.8}$$

However, in the case where the system is critical because the aircraft is over the maximum landing weight at the end of the mission, it is not clear at what time of the mission the system becomes critical, i.e. it is above the maximum landing weight from the start of the mission as the weight of the aircraft cannot increase mid-flight. Therefore, if the system is critical at the end of the mission only because it is above the maximum landing weight, then there is no time dependence included for this failure, i.e. the value that is summed for Q_{sys} (and $Q_{sys}(q = 0)$ if the sensor does not detect the component failure) is P_e, the probability of the event under consideration, i.e. with no time-dependent factor included.

The full criticality term is stated in Equation (6.9), note it is in the same format as Equation (3.3).

$$CR_{\{s\}} = \frac{Q_{sys} - Q_{sys}(q_s = 0)}{Q_{sys}} \tag{6.9}$$

6.3.4. Example

In order to demonstrate how each of the terms of the time-dependent performance metric is affected by varying the time of the failure, an example system is presented. Note, in each of the terms, the full term is not calculated as this would require all combinations of component failures to be considered for the sensor. Instead, the relative contribution of each individual component failure to each of the terms is compared, i.e. the right hand side of the summations for the detection and criticality term, and $Value$ for the diagnostic term.

The example system in Figure 6.17 consists of two pumps in parallel, connected to a valve, and the fuel then passes out through a waste gate, as was the case in the system presented in Chapter 3. A sensor is positioned downstream of the valve, before the waste gate.

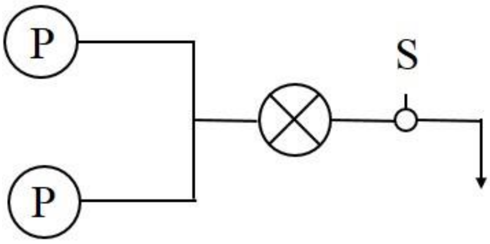


Figure 6.17 Example system for demonstration of the time-dependent performance metric

For this system, under normal operating conditions, both pumps supply equal amounts of fuel for the first 15 seconds of the mission, and then only the top pump supplies fuel for a further 5 seconds, i.e. the mission length is 20 seconds made up of two phases, a 15 second phase and a 5 second phase. Under normal operating conditions, the valve remains open throughout the whole mission. The sensor readings for the mission with no component failures are presented in Figure 6.18, i.e. for normal operating conditions. There are six different component failures presented here in order to demonstrate how the terms of the time-dependent performance metric are affected by different values for t_f, t_d, and t_c. Note, there may be a significantly larger number of component failures that could occur on the system as each component could fail at each time step and potentially in many different ways. The presented component failures descriptions, the values for t_f, t_d, t_c and the figure references are presented in Table 6.5. The system fails (i.e. the system is critical) if no fuel passes through the waste gate. Note, the system does not fail in cases B, C and E.

Table 6.5 Details of the considered missions

Case	Description	t_f	t_d	t_c	Figure
A	Valve fail closed	5	5	5	6.19
B	Bottom pump fail on	5	15	-	6.20
C	Bottom pump fail on	10	15	-	6.21
D	Top pump fail off	5	5	15	6.22
E	Bottom pump fail off	5	5	-	6.23
F	Top pump fail off	10	10	15	6.24

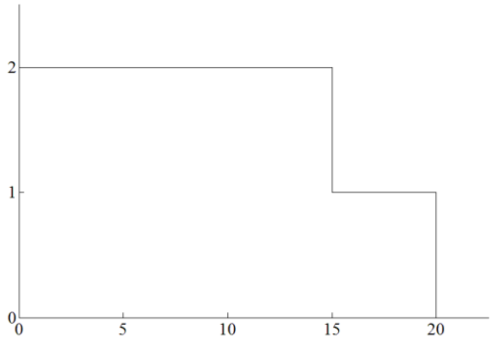


Figure 6.18 Sensor readings under normal operation conditions

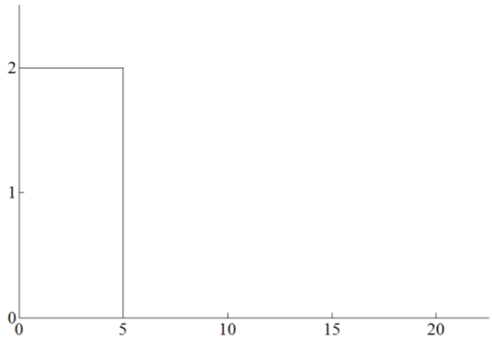


Figure 6.19 Sensor readings for case A

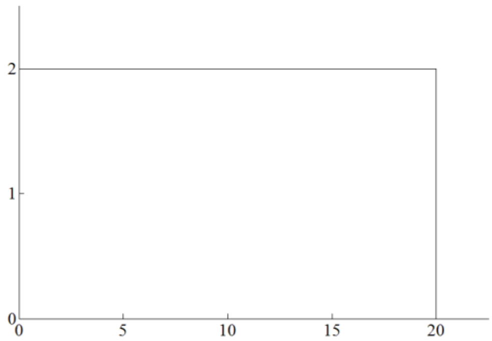


Figure 6.20 Sensor readings for case B

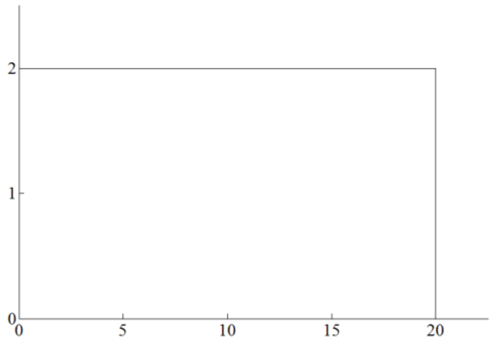


Figure 6.21 Sensor readings for case C

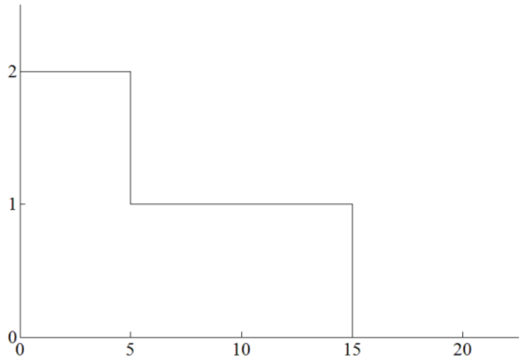


Figure 6.22 Sensor readings for case D

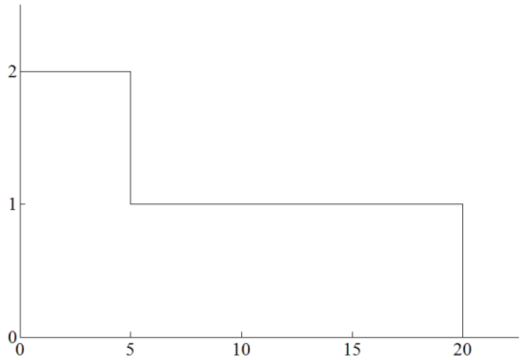


Figure 6.23 Sensor readings for case E

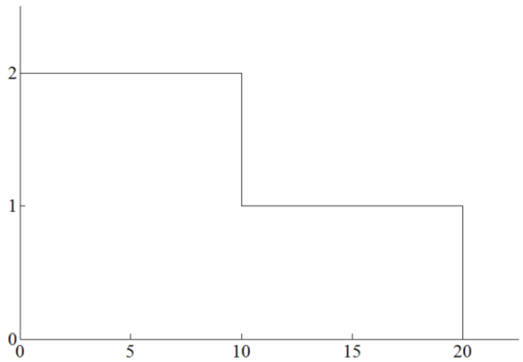


Figure 6.24 Sensor readings for case F

The time-dependent detection term is calculated for cases A, B, and C in Equations (6.10), (6.11), and (6.12), respectively, in order to demonstrate the effect of increasing the time between failure and detection, and changing the time of failure occurrence. Note, as stated before, the full detection term is not calculated as this would require all cases to be considered, instead only one term of the summation is presented for each of the three cases, the relative contribution to the detection term of each of the cases. Also note, that for simplicity P_e is assumed to be the same for each of cases, 0.01, i.e. the probability of that case occurring and none of the other cases occurring is 0.01.

$$Case\ A: 0.01\left(1-\left(\frac{5-5}{20}\right)\right)\left(1-\left(\frac{5-5}{20-5}\right)\right) = 0.01 \times 1 \times 1 = 0.01 \tag{6.10}$$

$$Case\ B: 0.01\left(1-\left(\frac{15-5}{20}\right)\right)\left(1-\left(\frac{15-5}{20-5}\right)\right) = 0.01 \times 0.5 \times 0.33 = 0.001667 \tag{6.11}$$

$$Case\ C: 0.01\left(1-\left(\frac{15-10}{20}\right)\right)\left(1-\left(\frac{15-10}{20-10}\right)\right) = 0.01 \times 0.75 \times 0.5 = 0.00375 \tag{6.12}$$

Firstly, if the second and third terms in each of the products are compared, it can be seen that the first of the two terms is largest for case A (1), and smallest for case B (0.5). The first term considers the time between failure occurrence and its detection, in relation to the duration of the mission. As the sensor detects the failure in case A immediately, the value of this term is at its maximum, i.e. equal to 1. As case B takes the longest for the failure to be detected after its occurrence, this value is the lowest of the three values. The same is observed for the second term, which considers the time between failure occurrence and its detection, in relation to the remaining time left in the mission. This results in case A being the most important for the detection term (0.01), case C being the second most important for the detection term (0.001667), and case B being the least important for the detection term (0.00375). This is as expected, as in case A the failure is detected immediately, in case C the failure is not detected for 5 seconds, and in case B the failure is not detected for 10 seconds, i.e. the longer the delay time, the smaller the value of the factor.

For the time-dependent diagnostic term, cases D and E are considered in order to demonstrate how the diagnosis of failures can improve over time. Both cases are detected 5 seconds into the mission, and they produce the same sensor reading up until 15 seconds into the mission, where the sensor reading changes in case D (changes to "0") but stays the same in case E. Therefore, if the sensor reading "1" is observed at 5 seconds into the mission, then it can be either case D or case E, but depending on what the sensor reading is at 15 seconds into the mission, it will either be case D (if the sensor reading is "0"), or case E (if the sensor reading is "1"). Therefore, using Equation (6.5), $Value(T_{step})$ is calculated at the two time points, 5 seconds (Equation (6.13)) and 15 seconds (Equation (6.14)) into the mission, in order to demonstrate how the time taken for diagnosis affects the diagnostic term. Note, the full diagnostic term is not calculated in this example as it would require all cases to be considered, instead only $Value(T_{step})$ is calculated. As before, all of the component failures are assumed to be equally likely, with a probability of occurrence of 0.01. Note, at 5 seconds into the mission, the probability of the sensor reading is equal to 0.02 as it can be produced by two events, i.e. case D and case E. Also note that as there are two sensor readings at 15 seconds into the mission, the first term is equal to 0.01 + 0.01 for the numerator and denominator, as there are two different sensor readings, (and therefore, two different most likely failures), i.e. they are summed over x from Equation (6.5).

$$Value(5) = \frac{0.01}{0.02} \times \left(1 - \frac{(5-5)}{20}\right)\left(1 - \frac{(5-5)}{(20-5)}\right) = 0.5 \times 1 \times 1 = 0.5 \tag{6.13}$$

$$Value(15) = \frac{0.01 + 0.01}{0.01 + 0.01} \times \left(1 - \frac{(15-5)}{20}\right)\left(1 - \frac{(15-5)}{(20-5)}\right) = 1 \times \frac{1}{2} \times \frac{1}{3} = 0.166667 \tag{6.14}$$

If $Value(5)$ and $Value(15)$ are compared, the $Value(5)$, i.e. 5 seconds into the mission is bigger, and as a result, it would be T_{step} equals 5 that would be used for the calculation of the diagnostic term. If the two last terms of the product to find $Value(5)$ and $Value(15)$ are considered, it can be seen that the penultimate and the last terms are significantly smaller in Equation (6.14) than in (6.13), which outweighs the difference in the first term of the two equations. As a result this makes $Value(5)$ larger than $Value(15)$, despite the better diagnostic ability of the sensors after 15 seconds.

For the time-dependent criticality term, cases A, D and F are considered. As stated before, the full criticality term is not calculated as this would require all cases to be considered, instead only one term of the summation is presented for each of the three cases, the relative contribution to the criticality term of each of the cases. Also as before, P_e is assumed to be 0.01 for all of the cases. This term is presented in Equations (6.15), (6.16), and (6.17) for the three cases respectively.

$$Case\ A: 0.01\left(1-\left(\frac{5-5}{20}\right)\right)\left(1-\left(\frac{5-5}{20-5}\right)\right)=0.01\times 1\times 1=0.01 \tag{6.15}$$

$$Case\ D: 0.01\left(1-\left(\frac{15-5}{20}\right)\right)\left(1-\left(\frac{15-5}{20-5}\right)\right)=0.01\times 0.5\times 0.33=0.001667 \tag{6.16}$$

$$Case\ F: 0.01\left(1-\left(\frac{15-10}{20}\right)\right)\left(1-\left(\frac{15-10}{20-10}\right)\right)=0.01\times 0.75\times 0.5=0.00375 \tag{6.17}$$

As the terms in each of the cases are the same as in Equations (6.10), (6.11), and (6.12), respectively, the same conclusions can be made as were made for the time-dependent detection term. As case A is critical immediately, this should be the most important case for the criticality term. In case D, the system is not critical until 10 seconds after the component failure has occurred, and therefore, it is the least important case for the criticality term. In case F, the system is critical 5 seconds after the occurrence of the component failure, and is therefore, the second most important. The importance of each of the cases is reflected in the values of each of the cases.

6.3.5. Discussion

In order to be able to apply the performance metric to a phased mission, the aspect of time dependence was introduced into the performance metric. The process was carried out in a similar way for each of the three terms, by introducing a factor that considered how long the failure affected the mission before the considered factor occurred, (detection, diagnosis, or becoming critical), in comparison to the length of the mission, and the remaining time of the mission from when the component failure occurred, (or was detected for the diagnostics term). For the detection and criticality terms, the computational requirements are higher than before, but not significantly more than for the time-independent performance metric, as a factor is multiplied by each term before the terms are summed for the time-dependent performance metric rather than just being summed for the time-independent performance metric. However, the diagnostic term is significantly more complicated than the other two terms, because the ability of the sensor to diagnose the component failures may improve as the mission progresses, and this had to be considered in the factor. (Note, the diagnostic ability cannot get worse as time progresses as the previous sensor readings can also be considered in the analysis). Therefore, the factor had to be calculated for a number of time steps and it had to be multiplied by P_{mli} and divided by P_{sri} for each of the remaining time steps in the mission. The maximum value of this calculation then had to be determined, and the corresponding factor, the corresponding value of P_{mli}, and the corresponding value of P_{sri} had to be substituted into the diagnostic term formula in order to calculate it. Finally, the values are summed over all considered component failures, which is the only step that is required for the time-independent diagnostic term. This makes the diagnostic term significantly more computationally intensive than the time-independent version, as a $Value(T_{step})$ needs to be calculated for every T_{step} between t_d and the end of the mission. This exacerbates the problem of the additional computation time required because of the large number of combinations of sensors, therefore applying an optimisation process, as discussed at the start of this chapter, to the sensor selection process is imperative because of the large number of sensor combinations. The optimisation process is presented in the next section of this chapter. Note, in order to make the calculation of the diagnostic term more efficient, the maximum value of $x_{max}(t)$ can be determined by considering the final time step $x_{max}(T)$, and then the calculation of $Value(T_{step})$ can be halted when $x_{max}(T_{step}) = x_{max}(T)$.

6.4. Sensor selection optimisation using GA

As there are a large number of sensors on this system, it is not feasible to exhaustively calculate the performance metric for all combinations of sensors (in excess of 61 million combinations of 5 sensors, and in excess of 1.1×10^{13} combinations of 10 sensors), therefore an optimisation process is needed. The optimisation process chosen in this thesis uses a Genetic Algorithm, which was presented in section 2.3.2 of this thesis, i.e. following the format presented in Figure 2.7.

In order to apply a genetic algorithm, the population and a fitness function needs to be defined. As genetic algorithms are typically completed using a population of binary strings, the available sensors are represented in this form. To do this, binary strings the length of the number of available sensors are created, in which the digit “1” represents the corresponding sensor being selected, and the digit “0” represents the corresponding sensor not being selected. For example, for ten possible sensors, the binary string 1001100011 would represent the sensor combination, sensor S1, S4, S5, S9 and S10. There is a constraint placed on the number of sensors on the system, which results in a penalty being applied to the value of the fitness if the constraint is broken. The penalty factor is equal to the square of the number of sensors in the combination, and the fitness is divided by it.

When the population is generated, the fitness function is calculated, and therefore it also needs to be defined. The obvious choice for the fitness function is the performance metric, however, as the calculation of the time-dependent diagnostic term takes significantly longer than the calculation of the other two terms, (i.e. several minutes for combinations of sensors with high performance metrics, in comparison to a couple of seconds for the other two terms), a modified fitness function, and resultant GA process is proposed. This modified GA process is referred to as a two-level GA.

For the two-level GA process, two fitness functions are proposed, the first of which is a simplified version of the performance metric, the average of the time-dependent detection and criticality terms of the performance metric. This is because these two terms can be calculated quickly, enabling more generations and members of the populations to be considered. The second fitness function is the full time-dependent performance metric. The two-level GA process applies the algorithm as presented in section 2.3.2.1, multiple times on different randomly generated populations (A1, A2, A3…), using the simplified performance metric as the fitness function. When the GA has converged, the best member of the final generation of each population (A1, A2, A3…), i.e. the one with the highest fitness function, is stored as a member in a new population, population (B). This is repeated until population (B) is populated, i.e. instead of one randomly generated population (A), there are multiple randomly generated populations (A1, A2, A3….). As the best combination of sensors for each application of the GA is selected, this should result in population (B) having a large number of different solutions, all with relatively high fitness values. The GA using the full time-dependent performance metric as the fitness function can then be applied to population (B). As population (B) should all have relatively high fitness values, fewer members in the population, and fewer generations will need to be calculated. This should enable a solution with a high performance metric to be obtained without calculating the full performance metric as many times, making the application of the GA significantly faster. A flowchart detailing the steps in the proposed genetic algorithm is presented in Figure 6.25. Note, in the flow chart, “genetic operators” refers to selection, crossover, elitism and mutation.

In the next section, the methodology is applied to the system presented in section 6.2.

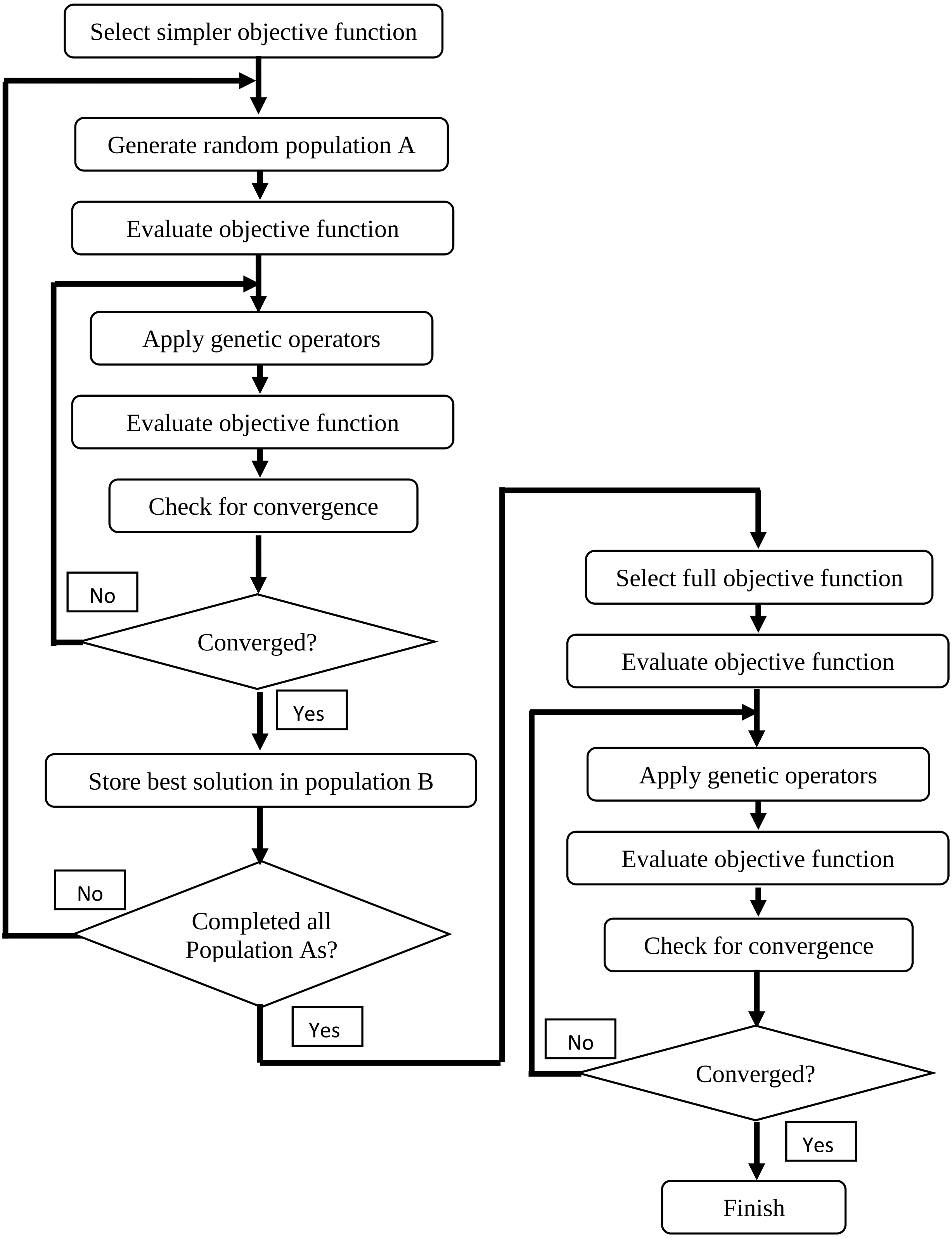


Figure 6.25 Flowchart for the proposed genetic algorithm

6.5. Application of the methodology

The proposed time-dependent sensor selection methodology is applied to the system presented in section 6.2. As stated in section 6.2.1, only individual component failures are considered, but they are considered at each of the eleven failure times presented in Table 6.3. This results in 2926 different missions considered, each mission with a different combination of failed component, failure mode of the component, and time of failure.

6.5.1. Modelling the system

The system was modelled using the methodology presented in section 5.1.1, i.e. using a series of if-then-else statements to determine the sensor readings at each time step of the mission. This model will enable the automatic calculation of the performance metric, and resultant sensor selection.

6.5.1.1. System model development

The first step in the system modelling methodology is normally to select the operation mode of the system, but as a phased mission is considered, the operation mode is different in different phases of the mission. Therefore, the operation mode is not selected at the start of the script. Instead, the first step in the script is to set the values of each of the fuel tanks and the fuel levels in each of the tanks at the start of the mission. In addition to this, the fuel supply rates for each of the states of the pumps is included, and the effect of each of the valves states on the flow of fuel is also added.

Next, each of the components and their mean-time-to-failures are included in the script, before including the time of mission phase changes, and the total length of the mission. The considered component failure times are also included.

The component states for each of the mission phases can then be read in from the input file and stored in vectors, which are then used to calculate each of the sensor readings at all of the time steps in the mission. Calculating the sensor reading is completed in the same way as presented in Figure 5.1, but as the fuel level changes throughout the mission, the quantity of fuel in the tanks needs to be considered in order to determine whether there is a supply of fuel in the system, or if there is an exit in the system for the fuel to pass through. For example, if a pump is on, it will only supply fuel to the system if there is fuel in the tank that the pump is located in, or if a valve is open, it will not allow fuel into the tank if the tank is full. Note, as the mission is modelled in time steps, there is either fuel flowing through for the whole time step, or none of the time step, i.e. there can be a small amount of fuel in the tank, but if the quantity is less than the amount of fuel supplied by the pump through the entire time step, no fuel will be supplied by the pump. In order to do this, the quantity of fuel in each of the tanks also needs to be updated at each time step.

By considering the component states in each phase of the mission, the probability of the mission can be calculated so it can be used in the calculation of the performance metric and during the fault diagnostic process. Finally, again using the component states in each phase of the mission, the criticality of the system can be determined.

6.5.1.2. Discussion

The model calculates the sensor readings for all of the time steps, of all of the missions in less than a minute, which is a negligible time in comparison to the time taken to calculate the performance metric. Therefore, the time taken to determine the sensor readings for all 96 different sensors, 720 time steps, and 2926 different missions considered by the model is not a limiting factor.

In the previous chapters, the sensor readings output by the model were verified by comparing to those output by other models, or by manually determining the sensor readings. For example, in Chapter 3, the sensor readings were determined manually, in Chapter 4, the sensor readings were determined manually and they were compared to the sensor readings produced by the alternative BBN presented in Figure 4.10, and in chapter 5, the output of the simulation model was compared to the outputs of the BBN developed in section 5.4. However, as this system is significantly larger than previous systems, it is impractical to manually determine the sensor readings, or to develop a BBN of the system, in order to verify that the model is outputting the correct sensor readings. Therefore, a series of consistency checks are included in the simulation to determine whether there are any errors in the script to calculate the sensor readings. For example, if a sensor in one section of the system measures that there is no fuel in that section of the system, but another sensor in the same section measures that there is, then there is a problem in the script that needs to be corrected. Other consistency checks include ensuring that the amount of fuel supplied by the pumps equals the amount of fuel exiting the system, checking that there is no fuel being supplied from empty tanks, and checking that there is no fuel passing through closed valves. In total, there are 233 consistency checks included in the script, and any errors that were found for any mission with a combination of two component failures occurring at all of the considered failure times in the mission, (approximately 4.2 million different missions) were corrected. Therefore, the model can be considered an accurate representation of the system.

In the next section, the model of the system is used to select the most suitable combination of sensors.

6.5.2. Sensor selection

The next step of the methodology is to select the sensors to be used for the diagnosis of component failures. In order to do this, the number of hidden failures needs to be determined. There are 2926 considered component failures, of which 778 are hidden, i.e. 2148 failures can be detected. This corresponds to a P_{md} of 0.004430, approximately 62% of the failures, where the sum of the probabilities of detected failures is divided by the sum of the probabilities of all considered failures. The hidden failures are presented in Table 6.6. Note, the details of the failures are presented in the form TO-1, where the text before the dash represents the description of the failure, and the text after the dash represents the phase of the mission in which the component fails. The text before the dash can be seven values for pumps, i.e. supplying the fuel at the rate supplied to the engines during take-off (TO), supplying the fuel at half of the rate supplied during take-off (TO/2), supplying the fuel at the rate that fuel is transferred between tanks (T), supplying the fuel at half of the rate that fuel is transferred between tanks (T/2), supplying the fuel at the rate it is supplied to the engines during the cruise phase (C), supplying the fuel at half of the rate it is supplied to the engines during the cruise phase (C/2), and supplying no fuel (0). For the valves, the possible values are the valve open (Op), the valve half open (Op/2), and the valve closed (Cl). For example, TO-1 represents the pump failure supplying the fuel at the rate supplied to the engines during take-off, in the first phase of the mission.

Table 6.6 Hidden component failure modes

Number of failures represented	Components	Failure details
40	L1P1, R1P1, L2P1, R2P1	C-2, C-3, C-4, C-5, C-6, C-7, C-8, C-9, C-10, C-11.
44	L1P2, R1P2, L2P2, R2P2	0-1, 0-2, 0-3, 0-4, 0-5, 0-6, 0-7, 0-8, 0-9, 0-10, 0-11.

14	LITP, RITP	0-5, 0-6, 0-7, 0-8, 0-9, 0-10, 0-11.
10	LMTP, RMTP	0-7, 0-8, 0-9, 0-10, 0-11.
6	LTP, RTP	0-9, 0-10, 0-11.
2	LOTP, ROTP	0-11.
44	LMDP, RMDP, LIDP, RIDP	0-1, 0-2, 0-3, 0-4, 0-5, 0-6, 0-7, 0-8, 0-9, 0-10, 0-11.
88	LEV1, LEV2, REV1, REV2	Op-1, Op-2, Op-3, Op-4, Op-5, Op-6, Op-7, Op-8, Op-9, Op-10, Op-11, Op/2-1, Op/2-2, Op/2-3, Op/2-4, Op/2-5, O/2-6, Op/2-7, Op/2-8, Op/2-9, Op/2-10, Op/2-11.
44	LCV1, LCV2, RCV1, RCV2	Cl-1, Cl-2, Cl-3, Cl-4, Cl-5, Cl-6, Cl-7, Cl-8, Cl-9, Cl-10, Cl-11.
13	CCV	Op-11, Op/2-11, Cl-1, Cl-2, Cl-3, Cl-4, Cl-5, Cl-6, Cl-7, Cl-8, Cl-9, Cl-10, Cl-11.
182	LRV, RRV, LODV, RODV, LDV, RDV, LOEDV, ROEDV, LMDV, RMDV, LITV1 RITV1, LITV2, RITV2	Op-11, Op/2-11, Cl-1, Cl-2, Cl-3, Cl-4, Cl-5, Cl-6, Cl-7, Cl-8, Cl-9, Cl-10, Cl-11.
22	LOTV, ROTV	Op-11, Op/2-11, Cl-3, Cl-4, Cl-5, Cl-6, Cl-7, Cl-8, Cl-9, Cl-10, Cl-11.
44	LOETV, ROETV, LIEV1, RIEV1	Op-3, Op-4, Op-5, Op-6, Op-7, Op-8, Op-9, Op-10, Op-11, Op/2-11, Cl-11.
78	LMTV, RMTV, LFVP, RFVP, LIEV2, RIEV2	Op-11, Op/2-11, Cl-1, Cl-2, Cl-3, Cl-4, Cl-5, Cl-6, Cl-7, Cl-8, Cl-9, Cl-10, Cl-11.
51	DTV, LTTV, RTTV	Op-9, Op-10, Op-11, Op/2-9, Op/2-10, Op/2-11, Cl-1, Cl-2, Cl-3, Cl-4, Cl-5, Cl-6, Cl-7, Cl-8, Cl-9, Cl-10, Cl-11.
5	FTTV	Op-11, Op/2-11, Cl-9, Cl-10, Cl-11.
25	TTDV	Op-1, Op-2, Op-3, Op-4, Op-5, Op-6, Op-7, Op-8, Op-9, Op-10, Op-11, Op/2-1, Op/2-2, Op/2-3, Op/2-4, Op/2-5, O/2-6, Op/2-7, Op/2-8, Op/2-9, Op/2-10, Op/2-11, Cl-9, Cl-10, Cl-11.
66	LSV, RSV	All failures hidden

The hidden failures in the system are components failing in failure modes they would be in during normal operating conditions, or components in sections of the system that are not normally used, or components failing in a later phase of the mission, after which the components are no longer used in the system. An example of the first case is LEV1 failing open, an example of the second case is any failure for LSV, and an example of the final case is LIEV1 failing open in the third phase of the mission, or later.

The maximum possible performance metric can be calculated by using all sensors on the system at once, i.e. all 96 sensors. The performance metric is 0.7960: with a detection term of 0.9219, a diagnostic term of 0.4661, and a criticality term of 1. Unlike for the systems discussed in the previous chapters, the maximum detection term is not equal to 1. This is because of the time-dependent factor in the detection term of the performance metric, i.e. some of the component failures are not detected at their time of occurrence. This is not the case for the criticality term, it is equal to 1, i.e. all of the critical component failures are detected at their time of occurrence. As in the previous chapters, the diagnostic term is also less than 1, this is because some of the component failures cannot be diagnosed exactly, i.e. more than one component failure produces the same symptoms for some of the component failures, and can therefore not be distinguished without further investigation.

6.5.2.1. Results

The performance metric was calculated exhaustively for all individual sensors, all combinations of two sensors and all combinations of three sensors. The sensor selection script to calculate the performance metric is similar to the sensor selection script used for the system presented in Chapters 4 and 5. There are two main modifications to the script, the first of which is comparing the sensor readings for each time step of the mission to the normal operating conditions case, instead of single sensor readings for each mission in the previous chapters. The second modification is the calculation of the performance metric uses the time-dependent version presented in section 6.3, instead of the time-independent version presented in section 3.2. The values of the performance metric and each of the terms for all of the individual sensors are presented in Table 6.7, and the top five ranked combinations of two and three sensors are presented in Table 6.8. Note, only one combination of sensors for each ranking is included in the table, but the number of combinations of sensors for each ranking is presented in the third column of Table 6.8.

Table 6.7 Ranking of individual sensors for the Airbus A380-800 fuel system

Rank	Sensor	$I_{\{s\}}$	$DE_{\{s\}}$	$DI_{\{s\}}$	$CR_{\{s\}}$
1	LOFTL	0.5147	0.5665	0.1795	0.7981
	ROFTL	0.5147	0.5665	0.1795	0.7981
2	S45	0.3718	0.3037	0.4440	0.3677
	S46	0.3718	0.3037	0.4440	0.3677
3	LIFTL	0.3582	0.3049	0.3411	0.4286
	RIFTL	0.3582	0.3049	0.3411	0.4286
4	LMTL	0.3410	0.0294	0.9639	0.0296
	RMTL	0.3410	0.0294	0.9639	0.0296
5	S25	0.3147	0.2856	0.2907	0.3677
	S35	0.3147	0.2856	0.2907	0.3677
6	S29	0.3138	0.2856	0.2882	0.3677
	S39	0.3138	0.2856	0.2882	0.3677
7	S06	0.2731	0.0359	0.6443	0.1390
	S16	0.2731	0.0359	0.6443	0.1390
8	S01	0.2701	0.1336	0.1489	0.5278
	S11	0.2701	0.1336	0.1489	0.5278
9	S03	0.2665	0.1394	0.1317	0.5283
	S13	0.2665	0.1394	0.1317	0.5283
10	S08	0.2504	0.0417	0.5700	0.1395
	S18	0.2504	0.0417	0.5700	0.1395
11	LITL	0.2500	0.0189	0.7128	0.0183
	RITL	0.2500	0.0189	0.7128	0.0183
12	S02	0.2497	0.1221	0.1194	0.5074
	S12	0.2497	0.1221	0.1194	0.5074
13	S07	0.2444	0.0245	0.5912	0.1174
	S17	0.2444	0.0245	0.5912	0.1174
14	LOTL	0.2430	0.0685	0.5992	0.0614
	ROTL	0.2430	0.0685	0.5992	0.0614
15	S04	0.2401	0.1163	0.0970	0.5070
	S14	0.2401	0.1163	0.0970	0.5070
16	S42	0.2274	0.0931	0.0859	0.5033

	S44	0.2274	0.0931	0.0859	0.5033
17	S09	0.2029	0.0187	0.4730	0.1170
	S19	0.2029	0.0187	0.4730	0.1170
18	S24	0.1658	0.1209	0.2790	0.0976
	S34	0.1658	0.1209	0.2790	0.0976
19	S41	0.1532	0.0050	0.4221	0.0324
	S43	0.1532	0.0050	0.4221	0.0324
20	S30	0.1350	0.0846	0.2279	0.0924
	S40	0.1350	0.0846	0.2279	0.0924
21	S27	0.1345	0.0846	0.2317	0.0871
	S37	0.1345	0.0846	0.2317	0.0871
22	S28	0.1205	0.0741	0.2103	0.0772
	S38	0.1205	0.0741	0.2103	0.0772
23	S70	0.1172	0.0203	0.3313	0.0001
24	S23	0.1149	0.0693	0.1953	0.0801
	S33	0.1149	0.0693	0.1953	0.0801
25	S26	0.1092	0.0696	0.1816	0.0763
	S36	0.1092	0.0696	0.1816	0.0763
26	S74	0.0968	0.0293	0.2610	0.0001
27	S79	0.0956	0.0259	0.2607	0.0001
	S81	0.0956	0.0259	0.2607	0.0001
28	S05	0.0930	0.1024	0.1767	0
	S10	0.0930	0.1024	0.1767	0
	S15	0.0930	0.1024	0.1767	0
	S20	0.0930	0.1024	0.1767	0
	S21	0.0930	0.1024	0.1767	0
	S22	0.0930	0.1024	0.1767	0
	S31	0.0930	0.1024	0.1767	0
29	S48	0.0843	0.0924	0.1111	0.0493
	S50	0.0843	0.0924	0.1111	0.0493
	S51	0.0843	0.0924	0.1111	0.0493
	S52	0.0843	0.0924	0.1111	0.0493
	S53	0.0843	0.0924	0.1111	0.0493

	S54	0.0843	0.0924	0.1111	0.0493
	S55	0.0843	0.0924	0.1111	0.0493
	S56	0.0843	0.0924	0.1111	0.0493
	S57	0.0843	0.0924	0.1111	0.0493
	S58	0.0843	0.0924	0.1111	0.0493
	S59	0.0843	0.0924	0.1111	0.0493
	S60	0.0843	0.0924	0.1111	0.0493
	S61	0.0843	0.0924	0.1111	0.0493
	S62	0.0843	0.0924	0.1111	0.0493
	S63	0.0843	0.0924	0.1111	0.0493
	S64	0.0843	0.0924	0.1111	0.0493
	S65	0.0843	0.0924	0.1111	0.0493
	S66	0.0843	0.0924	0.1111	0.0493
	S67	0.0843	0.0924	0.1111	0.0493
	S68	0.0843	0.0924	0.1111	0.0493
	S69	0.0843	0.0924	0.1111	0.0493
	S84	0.0843	0.0924	0.1111	0.0493
	S85	0.0843	0.0924	0.1111	0.0493
30	S71	0.0785	0.0839	0.0775	0.0741
31	S78	0.0753	0.0315	0.1943	0.0001
32	S72	0.0747	0.0405	0.1835	0.0001
	S73	0.0747	0.0405	0.1835	0.0001
33	S32	0.0725	0.0665	0.0770	0.0741
	S47	0.0725	0.0665	0.0770	0.0741
	S49	0.0725	0.0665	0.0770	0.0741
34	S75	0.0606	0.0319	0.1496	0.0001
35	S76	0.0593	0.0311	0.1466	0.0001
	S77	0.0593	0.0311	0.1466	0.0001
36	S80	0.0454	0.0112	0.1250	0
	S82	0.0454	0.0112	0.1250	0
37	TTL	0.0377	0.0236	0.0893	0.0001
38	S83	0.0246	0.0112	0.0625	0

Table 6.8 Performance metric for the top five rankings of combinations of two and three sensors for the Airbus A380-800 fuel system

Rank	Sensors	Number	$I_{\{s\}}$	$DE_{\{s\}}$	$DI_{\{s\}}$	$CR_{\{s\}}$
1	S45 LOFTL	4	0.6204	0.6322	0.3607	0.8682
2	LOFTL LIFTL	4	0.6143	0.6358	0.2925	0.9148
3	LOFTL ROFTL	1	0.5837	0.6020	0.2531	0.8961
4	S29 LOFTL	4	0.5790	0.6164	0.2523	0.8682
5	S06 LOFTL	6	0.5767	0.5942	0.2364	0.8995
1	S45 LOFTL RIFTL	4	0.6601	0.6658	0.3997	0.9148
2	S45 LOFTL ROFTL	2	0.6592	0.6654	0.3995	0.9127
3	LOFTL LIFTL RIFTL	2	0.6555	0.6725	0.3349	0.9593
4	LOFTL ROFTL LIFTL	2	0.6538	0.6712	0.3327	0.9573
5	S06 LOFTL RIFTL	4	0.6480	0.6635	0.3215	0.9589

The calculation of the performance metric for all combinations of three sensors took several weeks to complete, and as there are more than 20 times as many combinations of four sensors as there are three sensors, three sensors was deemed to be a sensible limit to the number of sensors to calculate the performance metric exhaustively. Therefore, the two-level genetic algorithm was used to calculate the sensor performance metric for all combinations of four and more sensors. In order to enable a comparison between the best result obtained by the two-level genetic algorithm and exhaustive calculation of the performance metric, the two-level genetic algorithm was also applied to combinations of three sensors. For the two-level genetic algorithm, 50 populations of 100 randomly generated members were considered for the first level. At the end of the 100th generation for each of the 50 populations, the best member of each of the populations was used to make up the population for the second level of the genetic algorithm. In the genetic algorithm, the selection rate was 0.2, the elitist rate was 0.1, and the mutation rate was 0.01, i.e. the best 20% of the population was exempt from crossover, the best 10% of the population were exempt from mutation, and 1% of the bits were flipped. Note, these rates were chosen so that the best solutions are preserved in each generation, and so that the populations do not converge too quickly, potentially resulting in a local maximum rather than a global maximum. The crossover in the algorithm was a single crossover point at a random location in the member. As stated in section 6.4, the fitness function for the first level of the genetic algorithm is the average of the detection and criticality terms, and the fitness function for the second level of the genetic algorithm is the performance metric, i.e. average of the terms.

Table 6.9 presents the best solutions for each number of sensors, (No. S.), for the first level of the genetic algorithm. The earliest generation, (Gen.), in which the best solution is achieved in any of the populations, i.e. out of 100, the number of populations in which this solution is obtained, (No. Pop), and the number of different combinations of sensors with this fitness value, (No. Comb.), both of which are out of 50.

Table 6.9 Best combinations of sensors at the end of the first level of the genetic algorithm using the simplified fitness function

No. S.	Sensors	Fit	$DE_{\{s\}}$	$CR_{\{s\}}$	Gen.	No. Pop.	No. Comb.
3	S21 LOFTL RIFTL	0.8265	0.7382	0.9148	2	50	25
4	S31 ROFTL LIFTL RIFTL	0.8671	0.7749	0.9593	10	35	13
5	S21 LOFTL ROFTL LIFTL RIFTL	0.9052	0.8104	1.0000	50	8	5
6	S10 S51 LOFTL ROFTL LIFTL RIFTL	0.9305	0.8609	1.0000	23	10	9
7	S03 S15 S18 S45 S46 S65 ROFTL LIFTL	0.9427	0.8854	1.0000	9	39	39
8	S08 S13 S21 S34 S60 S76 LOFTL RIFTL	0.9525	0.9049	1.0000	23	22	22
9	S15 S34 S58 S75 S81 LOFTL ROFTL LIFTL RIFTL	0.9610	0.9219	1.0000	37	23	23
10	S03 S08 S10 S24 S57 S65 S72 S76 ROFTL RIFTL	0.9610	0.9219	1.0000	13	46	46
12	S03 S13 S18 S22 S35 S38 S46 S72 S76 S85 ROFTL LIFTL	0.9610	0.9219	1.0000	8	50	50

The value of the fitness function for the combinations of sensors presented in Table 6.9 increases for all combinations of sensors, apart from for the combinations of 10 and 12 sensors, which have the same values as the combination of 9 sensors. If each of the individual terms in the table are studied, it can be observed that the detection term follows the same pattern as the fitness function, i.e. the value increases for all combinations of sensors up until combinations of 9 sensors, at which point, the detection term is the same value. However, the criticality term reaches its maximum value much earlier, with a combination of 5 achieving a criticality term of 1. Therefore, with regards to the criticality term there is no benefit in including more than 5 sensors.

When the outputs from the first level of the genetic algorithm are studied in more detail, it is observed that seven of the combinations of 10 sensors that achieve the maximum fitness function, are actually combinations of 9 sensors. This, along with the combinations of 9 and 10 sensors having the same fitness values, suggests that there is no benefit to considering more than 9 sensors on the system. However, when the diagnostic term is calculated, the best combination of 9 sensors observed for the population of sensors for the start of the second level of the genetic algorithm has a diagnostic term approximately 0.03 lower than the best combination of 10 sensors. Note, a similar fact is observed for the combinations of 12 sensors, i.e. one combination of sensors is actually a combination of 10 sensors, and six of the combinations of sensors are actually combinations of 11 sensors. Note, the combination of sensors for each number of sensors that achieved the best performance metric at the end of the first level of the genetic algorithm is presented in Table 6.10.

Table 6.10 Best combinations of sensors at the end of the first level of the genetic algorithm using the performance metric as the fitness function

No. S.	Sensors	$I_{\{s\}}$	$DE_{\{s\}}$	$DI_{\{s\}}$	$CR_{\{s\}}$
3	S21 LOFTL RIFTL	0.6438	0.7382	0.2785	0.9148
4	S31 ROFTL LIFTL RIFTL	0.6835	0.7749	0.3164	0.9593
5	S21 LOFTL ROFTL LIFTL RIFTL	0.7145	0.8104	0.3332	1.0000
6	S10 S51 LOFTL ROFTL LIFTL RIFTL	0.7296	0.8609	0.3279	1.0000
7	S06 S11 S21 S45 S59 LOFTL RIFTL	0.7588	0.8737	0.4032	0.9994
8	S06 S18 S22 S45 S52 S76 LOFTL ROFTL	0.7658	0.8991	0.3985	0.9997
9	S18 S21 S46 S62 S76 S81 LOFTL ROFTL LIFTL	0.7725	0.9219	0.3956	1.0000
10	S08 S18 S31 S45 S55 S70 S77 LOFTL ROFTL RITL	0.7735	0.9219	0.3987	1.0000
12	S03 S13 S18 S22 S35 S38 S46 S72 S76 S85 ROFTL LIFTL	0.7784	0.9219	0.4134	1.0000

In Table 6.11, the best combinations of each number of sensors at the end of the genetic algorithm are presented.

Table 6.11 Best combinations of sensors at the end of the second level of the genetic algorithm using the performance metric as the fitness function

No. S.	Sensors	$I_{\{s\}}$	$DE_{\{s\}}$	$DI_{\{s\}}$	$CR_{\{s\}}$	Generation
3	S46 LOFTL RIFTL	0.6601	0.6658	0.3997	0.9148	10
4	LOFTL ROFTL LIFTL RIFTL	0.6871	0.7080	0.3532	1.0000	33
5	S21 LOFTL ROFTL LIFTL RIFTL	0.7145	0.8104	0.3332	1.0000	0
6	S03 S06 S18 S20 S45 ROFTL	0.7387	0.8290	0.3873	0.9997	35
7	S06 S11 S21 S45 S59 LOFTL RIFTL	0.7588	0.8737	0.4032	0.9994	0
8	S06 S18 S22 S45 S52 S76 LOFTL ROFTL	0.7658	0.8991	0.3985	0.9997	0
9	S18 S21 S46 S62 S76 S81 LOFTL ROFTL LIFTL	0.7725	0.9219	0.3956	1.0000	0
10	S07 S13 S22 S45 S53 S74 S77 LOFTL LIFTL RIFTL	0.7750	0.9219	0.4031	1.0000	20
12	S01 S06 S07 S13 S20 S45 S57 S74 S77 LOFTL ROFTL RIFTL	0.7784	0.9219	0.4134	1.0000	0

Note, in the table, generation 0 refers to the initial population at the start of the second level of the genetic algorithm generated by the first level of the genetic algorithm, i.e. no improvement in the performance metric is observed throughout the second level of the genetic algorithm. This is observed for the combination of 5, 7, 8, 9 and 12 sensors in Table 6.11. There are a couple of potential reasons for this, the first is that the actual best solution is achieved during the first level of the genetic algorithm. This is unlikely to be the case as the diagnostic term is not considered in the first level of the fitness function. However, the best combination of sensors as determined by using the performance metric as the fitness function, is not the same combination of sensors obtained at the end of the first level of the genetic algorithm, using the simplified fitness function. Alternatively, the genetic operators may not be the best values, i.e. not allowing diverse enough combinations of sensors to be considered, and therefore, not resulting in the actual best combination of sensors being obtained. The effect of adjusting the genetic operators on the sensor combinations obtained by the GA could be studied in future work. Preliminary investigations into this are conducted in section 6.5.2.2.

The combinations of 9 and 10 sensors can both detect all of the failures, and the percentage difference to the maximum possible performance metric is 3.04% and 2.71%, respectively. As the performance metric for the combination of 9 sensors can be increased by more than 3%, it is considered to be worthwhile including the additional sensor on the system, i.e. using 10 sensors. However, it is not considered worthwhile to include an additional two sensors to achieve the small increase in performance metric for the combination of 12 sensors. Therefore, the combination of sensors used for fault diagnostics is the combination of 10 sensors presented in Table 6.11, i.e. (S07 S13 S22 S45 S53 S74 S77 LOFTL LIFTL RIFTL). The percentage difference between each number of sensors is presented in Table 6.12, and this demonstrates the diminishing returns of including additional sensors. The percentage difference to the maximum performance metric is also presented in the table.

Table 6.12 Difference in performance metric for each number of sensors

No. S.	Sensors	$I_{\{s\}}$	% diff.	% diff. to max
1	LOFTL	0.5147	0	54.65
2	S45 LOFTL	0.6204	20.54	28.30
3	S46 LOFTL RIFTL	0.6601	6.40	20.59
4	LOFTL ROFTL LIFTL RIFTL	0.6871	4.09	15.85
5	S21 LOFTL ROFTL LIFTL RIFTL	0.7145	3.99	11.41
6	S03 S06 S18 S20 S45 ROFTL	0.7387	3.39	7.76
7	S06 S11 S21 S45 S59 LOFTL RIFTL	0.7588	2.72	4.90
8	S06 S18 S22 S45 S52 S76 LOFTL ROFTL	0.7658	0.92	3.94
9	S18 S21 S46 S62 S76 S81 LOFTL ROFTL LIFTL	0.7725	0.87	3.04
10	S07 S13 S22 S45 S53 S74 S77 LOFTL LIFTL RIFTL	0.7750	0.32	2.71
12	S01 S06 S07 S13 S20 S45 S57 S74 S77 LOFTL ROFTL RIFTL	0.7784	0.44	2.26
96	All	0.7960	2.26	0

As the performance metric was calculated exhaustively for all combinations of 3 sensors, the combination of sensors achieved at each stage of the genetic algorithm can be compared to the best possible combination of three sensors. The performance metric for the combination of sensors achieved by the first level of the genetic algorithm is equal to the 20th highest ranked combination of three sensors, with 94 combinations of three sensors with a higher performance metric than this. However, at the end of the second level of the genetic algorithm the combination of three sensors obtained is one of the four joint best combination of three sensors. Whilst the best combination of sensors was obtained at the end of the second level of the genetic algorithm of this application, there is no guarantee that the best combination will be achieved in every application of the genetic algorithm, as the combination of sensors obtained is dependent on the crossover and mutation rates applied in the algorithm.

The genetic algorithm for combinations of three sensors was completed in approximately a seventh of the time taken to calculate the performance metric for all 142880 combinations of three sensors exhaustively. As the best combination of 3 sensors was obtained in the tenth generation of the second level of the genetic algorithm, the best combinations of three sensors was obtained in less than a tenth of the time (i.e. a couple of days instead of several weeks) to calculate the performance metric for all combinations of three sensors exhaustively. It is also worth noting that the reduction in time taken for combinations of three sensors is the smallest reduction that will be observed. This is because the exhaustive calculation of the performance metric takes exponentially longer as the number of sensors increases, but the time taken to apply the two-level genetic algorithm increases approximately linearly for each additional sensor, with the algorithm being applied to the combination of 10 sensors only taking approximately three times longer than the algorithm being applied to combinations of three sensors.

6.5.2.2. Discussion

There are a couple of things that are worth considering for future applications of the methodology, the first of which is changing the mutation rate in the two-level genetic algorithm and seeing how it affects the output of the algorithm. As the best members of each generation are preserved due to the elitism included in the algorithm, the best solution will never be lost, and adjusting the mutation rate may increase the chances of achieving the maximum performance metric for each number of sensors. A similar effect may be achieved by introducing multi-point crossover. Applying these modifications may remove the case observed for 5, 7, 8, 9 and 12 sensors, where no increase in the fitness function is achieved in the second level of the genetic algorithm. Preliminary investigations, (20 generations in the second level for 6 sensors), into increasing the mutation rate were completed. However, this led to an increased number of combinations of sensors breaking the constraint, and the resulting fitness value penalised. Therefore, increasing the mutation rate did not lead to an increased diversity of sensor combinations as many of the combinations could not be included. This could be investigated in future work.

As there is a constraint placed on the number of sensors for each application of the algorithm, some of the members of the population result in a number of sensors greater than that allowed by the constraint, and result in the fitness function value having a penalty factor applied, resulting in the combination of sensors being ignored. Therefore, that combination of sensors is unlikely to be selected as a member for crossover in the next generation. However, instead of making the fitness of the sensor combinations small, individual sensors could randomly be removed from the combination until the constraint is satisfied. This would result in more combinations of sensors being considered, potentially resulting in a better combination of sensors being determined. This may also mean that increasing the mutation rate may not be necessary, as currently, for a combination of 10 sensors there are 86 sensors not selected, and 10 sensors selected, so the probability of a new sensor being included is significantly higher than a sensor being removed by mutation. This would also increase the diversity of the population, potentially resulting in a better selection of sensors. As with modifying the mutation rate, preliminary investigations were completed on changing the application of the constraint. This resulted in the GA running faster than when the penalty function was included as the combinations of sensors that were breaking the constraint consisted of more sensors, and as the time taken to calculate the performance metric scales with the number of sensors, the constraint breaking combinations of sensors take longer to complete. Therefore, if there are no constraint breaking combinations of sensors, then the GA will run faster. There was no improvement observed in the selection of sensors, but only a limited number of generations (20 in the second level) were completed for one number of sensors (6 sensors), so there has not been enough investigation to conclude whether it would improve the selection of sensors or not. This could also be investigated in future work.

Another potential way that the sensor selection approach could be improved is to do a normal, single level genetic algorithm, i.e. using the performance metric as the fitness function for one population of 100 members for 100 generations. The two-level approach is proposed in this thesis in order to reduce the time taken to apply the genetic algorithm with the two-level approach taking approximately 25% of the time of the single-level genetic algorithm, but it may be affecting the selection of the sensors by not considering the effect of the diagnostic term until later in the algorithm. For example, the combination of three sensors in Table 6.10, the same combination as in Table 6.9, has a diagnostic term of 0.2785, but the combination of three sensors in Table 6.11 has a diagnostic term of 0.3997, significantly higher. However, only considering the detection and criticality terms in the first level of the genetic algorithm has less effect when more sensors are included on the system, as there are more different combinations of sensors that have high detection and criticality terms, and therefore, more variation in the diagnostic term observed. In contrast, all 50 combinations of three sensors from the end of the first level of the genetic algorithm have the same diagnostic terms. Therefore, using the two-level genetic algorithm may not have any negative effect on the selection of sensors.

Like in previous chapters, the combinations of sensors that are selected are distributed around the system, with flow sensors from different sections of the system, and level sensors in three of the four feed tanks. The only section of the system with two sensors in is the tail of the aircraft. Therefore, if the sensor combination was to be adapted, one of the sensors in the tail of the aircraft may not be included, and a sensor in a different location may be included, perhaps a level sensor in the fourth engine feed tank. However, if this was to be completed, no improvement may be found, and a large number of combinations may need to be tried in order to achieve a better combination of sensors, if it is possible at all.

In the next section, the effect of changing the component failure rates on the selection of sensors is studied.

6.5.2.3. The effect of changing the component failure rates on the sensor selection

In the same manner as in Section 3.4.1.3, the effect of changing the probability of the component failures on the selection of sensors is studied, so that the sensitivity of the sensor selection process on the component failure probabilities can be determined. In order to do this, different failure rates of each of the components are chosen, and the performance metric is calculated. In this subsection, the pumps are assumed to have a failure rate of 0.000005, and the valves are assumed to have a failure rate of 0.000001, i.e. the opposite of the failure rates presented in section 6.3. Note, these probabilities are only used in this subsection of the thesis, with the probability of component failures given in section 6.3 used in the rest of the chapter.

As the same component failures (just with different occurrence probabilities) are considered, the same number of component failures are detected, and cause the system to be critical. However, the value of P_{md} is different, with a value of 0.006934, which corresponds to approximately 84% of the failures that can be detected. In addition, the maximum performance metric is different, with a value of 0.8731: with a detection term of 0.9706, a diagnostic term of 0.6488, and a criticality term of 1. These values, including P_{md} are higher because of the increase in the probability of pump failure in comparison to valve failure. As pumps supply fuel to the system, a failure can be detected by more of the sensors, than to know exactly where the fuel is moving to, as this often requires a sensor on the path that fuel is flowing in.

As the work in this section is not used elsewhere, it is not necessary to calculate the performance metric for all numbers of sensors as before. For comparison, individual sensor performance metrics are calculated, and presented in Table 6.13.

Table 6.13 Ranking of individual sensors with the different component failure rates

Rank	Sensor	$I_{\{s\}}$	$DE_{\{s\}}$	$DI_{\{s\}}$	$CR_{\{s\}}$
1	LOFTL	0.4023	0.3970	0.2884	0.5215
	ROFTL	0.4023	0.3970	0.2884	0.5215
2	LIFTL	0.3851	0.3618	0.3159	0.4775
	RIFTL	0.3851	0.3618	0.3159	0.4775
3	S45	0.3677	0.3311	0.4536	0.3184
	S46	0.3677	0.3311	0.4536	0.3184
4	S06	0.3611	0.0694	0.8029	0.2111
	S16	0.3611	0.0694	0.8029	0.2111
5	S07	0.3582	0.0649	0.8068	0.2029
	S17	0.3582	0.0649	0.8068	0.2029
6	LMTL	0.3345	0.0410	0.9143	0.0482
	RMTL	0.3345	0.0410	0.9143	0.0482
7	S01	0.3171	0.0826	0.6108	0.2581
	S11	0.3171	0.0826	0.6108	0.2581
8	S02	0.3067	0.0781	0.5920	0.2500
	S12	0.3067	0.0781	0.5920	0.2500

9	S08	0.3023	0.0892	0.6052	0.2126
	S18	0.3023	0.0892	0.6052	0.2126
10	S25	0.3017	0.3268	0.2600	0.3184
	S35	0.3017	0.3268	0.2600	0.3184
11	S29	0.3012	0.3268	0.2584	0.3184
	S39	0.3012	0.3268	0.2584	0.3184
12	LITL	0.2904	0.0528	0.7678	0.0506
	RITL	0.2904	0.0528	0.7678	0.0506
13	LOTL	0.2726	0.0830	0.6154	0.1194
	ROTL	0.2726	0.0830	0.6154	0.1194
14	S03	0.2720	0.1024	0.4539	0.2595
	S13	0.2720	0.1024	0.4539	0.2595
15	S09	0.2628	0.0451	0.5418	0.2015
	S19	0.2628	0.0451	0.5418	0.2015
16	S41	0.2491	0.0159	0.6646	0.0667
	S43	0.2491	0.0159	0.6646	0.0667
17	S04	0.2380	0.0583	0.4071	0.2486
	S14	0.2380	0.0583	0.4071	0.2486
18	S28	0.2137	0.2215	0.2177	0.2020
	S38	0.2137	0.2215	0.2177	0.2020
19	S23	0.2071	0.2168	0.1907	0.2138
	S33	0.2071	0.2168	0.1907	0.2138
20	S26	0.2050	0.2179	0.1921	0.2049
	S36	0.2050	0.2179	0.1921	0.2049
21	S42	0.1986	0.0450	0.3135	0.2372
	S44	0.1986	0.0450	0.3135	0.2372
22	S24	0.1838	0.2184	0.1321	0.2010
	S34	0.1838	0.2184	0.1321	0.2010
23	S71	0.1624	0.2300	0.0591	0.1981
24	S30	0.1546	0.2098	0.0535	0.2004
	S40	0.1546	0.2098	0.0535	0.2004
25	S27	0.1544	0.2098	0.0536	0.1997
	S37	0.1544	0.2098	0.0536	0.1997

26	S32	0.1495	0.2074	0.0430	0.1981
	S47	0.1495	0.2074	0.0430	0.1981
	S49	0.1495	0.2074	0.0430	0.1981
27	S76	0.0857	0.0875	0.1696	0.00001
	S77	0.0857	0.0875	0.1696	0.00001
28	S75	0.0842	0.0905	0.1621	0.00001
29	S48	0.0761	0.1779	0.0443	0.0060
	S50	0.0761	0.1779	0.0443	0.0060
	S51	0.0761	0.1779	0.0443	0.0060
	S52	0.0761	0.1779	0.0443	0.0060
	S53	0.0761	0.1779	0.0443	0.0060
	S54	0.0761	0.1779	0.0443	0.0060
	S55	0.0761	0.1779	0.0443	0.0060
	S56	0.0761	0.1779	0.0443	0.0060
	S57	0.0761	0.1779	0.0443	0.0060
	S58	0.0761	0.1779	0.0443	0.0060
	S59	0.0761	0.1779	0.0443	0.0060
	S60	0.0761	0.1779	0.0443	0.0060
	S61	0.0761	0.1779	0.0443	0.0060
	S62	0.0761	0.1779	0.0443	0.0060
	S63	0.0761	0.1779	0.0443	0.0060
	S64	0.0761	0.1779	0.0443	0.0060
	S65	0.0761	0.1779	0.0443	0.0060
	S66	0.0761	0.1779	0.0443	0.0060
	S67	0.0761	0.1779	0.0443	0.0060
	S68	0.0761	0.1779	0.0443	0.0060
	S69	0.0761	0.1779	0.0443	0.0060
	S84	0.0761	0.1779	0.0443	0.0060
	S85	0.0761	0.1779	0.0443	0.0060
30	S05	0.0635	0.0139	0.1767	0
	S10	0.0635	0.0139	0.1767	0
	S15	0.0635	0.0139	0.1767	0
	S20	0.0635	0.0139	0.1767	0

	S21	0.0635	0.0139	0.1767	0
	S22	0.0635	0.0139	0.1767	0
	S31	0.0635	0.0139	0.1767	0
31	S74	0.0552	0.0260	0.1395	0.00001
32	S72	0.0530	0.0276	0.1314	0.00001
	S73	0.0530	0.0276	0.1314	0.00001
33	S70	0.0525	0.0045	0.1530	0.000007
34	S79	0.0515	0.0053	0.1491	0.000007
	S81	0.0515	0.0053	0.1491	0.000007
35	TTL	0.0476	0.0253	0.1174	0.00001
36	S78	0.0456	0.0060	0.1307	0.000007
37	S80	0.0422	0.0015	0.1250	0
	S82	0.0422	0.0015	0.1250	0
38	S83	0.0213	0.0015	0.0625	0

Whilst there is a change in the ranking due to the different performance metric observed by comparing Tables 6.7 and 6.13, the ranking is broadly similar, with an average absolute change in ranking of approximately 3.6. Generally, the higher ranked sensors are ranked higher in both cases, and the lower ranked sensors are ranked towards the bottom in both cases. There are some exceptions, with the biggest change being for sensor 70, which is ranked 23rd in Table 6.7, but ranked 33rd in Table 6.13, a difference of 10. However, the highest three ranked sensors, are the highest three ranked sensors in both of the tables, i.e. no change in rank, but the second and third ranked sensors are swapped. This suggests that the better selection of sensors is not affected too much by having different failure probabilities. However, without trying a large number of different component failure probabilities, it is not possible to say whether this would be true for a range of probabilities of component failures. Instead of calculating the performance metric for all numbers of sensors with the new probabilities, it was calculated using the two-level genetic algorithm for 10 sensors, as this is the number of sensors selected for use in the diagnostics process. The best combination of 10 sensors was achieved in the 34th generation, and the combination is (S01 S11 S18 S46 S63 S70 S75 LOFTL ROFTL LIFTL), which has a performance metric of 0.8281, consisting of a detection term of 0.9567, a diagnostic term of 0.5277, and a criticality term of 1. This combination of sensors is similar to the combination of sensors obtained using the previous failure rates. The sensors are distributed around the system as before, with sensors in different sections. However, the sensor combinations are different, but the location of the sensors on the system is similar, including three feed tank level sensors.

In the next section of this chapter, the combination of the 10 selected sensors using the previous component failure rates, (S07 S13 S22 S45 S53 S74 S77 LOFTL LIFTL RIFTL), is used to diagnose component failures in the system.

6.5.3. Fault diagnostics

The selected sensors are used to detect faults and diagnose failures. To do this, each of the sensor readings corresponding to the component failures used for the sensor selection process are introduced to the model, and diagnosis of the failures is attempted. To be able to diagnose the component failures, the C++ script used in Chapter 5 was modified to enable the code to compare the sensor readings for all time steps to the reference sensor readings, and not just individual sets of sensor readings, as in the Chapter 5. Another modification enables the code to output the diagnostic results when they change as time progresses through the mission. For this to be applied, all the possible failures are stored at each time step and at the following time steps, only the possible failures from the previous time step were checked, and not all failures in other possible time steps are considered.

6.5.3.1. Fault diagnostic results

The components are grouped into six groups; engine feed (EF) pumps, fuel transfer (FT) pumps, dump (D) pumps, engine feed (EF) valves, cross-feed (CF) valves, and dump and refuel (DR) valves. Table 6.14 presents a summary of the results of the diagnostics process, where some of the component failures are grouped together for brevity with the full diagnostic results presented in Appendix I. The probabilities given in Table 6.14 and Tables I.1 – I.6 are the probabilities that each component is in the failure mode. This probability is equal to the probability of each failure occurrence divided by the probability of all component failures that produce the observed symptoms, respectively, i.e. P_{mli}/P_{sri}. For example, if the probability in the tables is 50%, then there is a 50% likelihood that the component has failed. In the tables, "a% - b%" refers to a confidence of diagnosis of "a%" initially, but at a later time in the mission, a confidence of diagnosis of "b%" is achieved, where "b" > "a". Some of the component failures are not detected as soon as they occur, therefore, "a%d" refers to a confidence of diagnosis of "a%" but the failure is not detected at the time of occurrence, i.e. there is a delayed detection, $t_d \neq t_f$. Note, details of the length of the delay in detection are not presented due to the number of different variations observed. This is also the case when the confidence of diagnosis changes from "a% - b%", as discussed before. Also note, "0%" diagnosis confidence is used to represent hidden failures.

Table 6.14 Summary of diagnostic results of component failures

Probability	EF pumps	FT pumps	D pumps	EF valves	DR valves	CF valves
100%	262	45	-	22	52	-
50%	240	15	-	-	16	-
a% - 100%	4	197	-	-	36	-
a% - 50%	-	40	-	-	2	10
a% - b% - 100%	-	124	-	-	3	-
a% - b% - 50%	-	20	-	-	-	-
a% - b% - c% - 100%	-	21	-	-	1	-
50% < a% < 100%	-	-	-	22	-	-
0% < a% < 50%	-	72	264	-	48	48
a% - <50%	-	-	-	-	116	40
100%d	4	6	-	-	55	-
50%d	-	-	-	-	14	10
a% - < 100%d	-	2	-	-	33	-
0% < a% < 50%d	-	42	-	-	216	-
a% - < 50%d	-	-	-	-	24	-
16.66%	22	-	-	-	-	-
0%	84	32	44	88	473	57
TOTAL	616	616	308	132	1089	165

6.5.3.2. Discussion

The fault diagnostic process successfully diagnoses 2126 of the 2148 component failures that can be detected. Of these failures, 889 failures are diagnosed correctly with 100% confidence before the end of the mission. The other failures that are detected and diagnosed successfully can be grouped into three cases. The first case is when the observed sensor readings can be produced by a number of different component failures occurring at the same time in the mission. The component failures in this case each have the same probability of occurrence, and therefore, it is not possible to determine exactly which component failure has occurred without potentially having to inspect multiple components. The second case is when the observed sensor readings can be produced by a number of different component failures, however, the failures are either the same component failing in different phases of the mission, or the same component failing in a number of modes. This will mean that the actual failed component will be determined, but the failure mode will not be determined until the component is physically inspected. Also, if the component failure is known, but the time of the failure is not known, then this should not be a problem as the determination of the failure is more important than the determination of the exact time of failure occurrence, the failure is still detected at the same time. The final case is where the observed symptoms can be produced by a number of different component failures, some of which are more likely to occur than others. In this case, if the more likely failure has occurred, then the failure is diagnosed correctly. For example, LEV1 failing closed and L1P1 failing off both produce the same symptoms for the selected combination of sensors. However, both of the failures have different probabilities of occurrence, resulting in a probability of LEV1 being failed closed of 83.34%, and a probability of L1P1 being failed off of 16.66%. Therefore, if these symptoms are observed, if LEV1 has failed closed, it will be diagnosed correctly, but if L1P1 has failed off, the failure will not be diagnosed correctly initially. However, when the valve has been inspected and found to be working, the correct component failure will be diagnosed. Note, there are other groups of component failures that are initially diagnosed incorrectly, but are diagnosed correctly at a later time in the mission. For example, in the case where LITP fails supplying the fuel at the rate supplied during the cruise phase occurring in the second phase of the mission, the probability of it being diagnosed correctly is initially 12.49%, and the probability of another component failure (LMTV failing open) is higher (62.56%). However, at a later time in the mission, the probability of LITP failing supplying the rate of fuel supplied during the cruise phase, is 100%, and is therefore diagnosed correctly.

6.6. Summary

In this chapter, the methodology is applied to the Airbus A380-800 fuel system. The model of the system is constructed using a C++ script. The script is able to calculate the sensor readings of all 96 sensors at all 720 time steps of all 2926 missions in less than a minute. This is a negligible time in comparison to the rest of the application of the methodology. This was not the case for Bayesian Belief Network approach used in Chapter 4 (and in section 5.4), despite the system in this chapter being significantly larger. Therefore, the modelling approach used in this chapter and proposed in Chapter 5, is a more suitable modelling technique for large systems. In this chapter, consistency checks were introduced into the C++ script in order to ensure that there were no errors in the script, which may cause it to output combinations of sensor readings that are not possible. This was a useful addition in order to ensure that the model is accurate, without having to manually verify the sensor readings.

In addition to distinguishing between sensors that can detect and diagnose a large percentage of component failures, the time-dependent sensor performance metric considers the time taken for the sensor to detect a failure after its occurrence, how the ease of diagnosis improves as time passes after the detection of the failure, and the time between component failure occurrence and system failure, (if system failure occurs). The two-level genetic algorithm efficiently determines good combinations of sensors for each number of sensors in a significantly shorter time than determining them exhaustively. As it is not feasible to exhaustively calculate the performance metric for large numbers of sensors, it is not possible to determine definitively whether the best combination of sensors has been obtained. In section 6.5.2.2 there are a number of potential improvements to the two-level genetic algorithm suggested. These include modifying the mutation rate and the number of crossover points, in order to consider a more diverse population. Additionally, the application of constraints in the script can be changed such that the number of sensors is reduced to within the constraint and, therefore, the fitness function will not need a penalty factor to be included.

The fault diagnostic process correctly diagnoses 2126 of the 2148 component failures that can be detected using the selected combination of 10 sensors. The component failures that cannot be diagnosed correctly are cases where there are two different component failures that produce the same set of symptoms for the combination of selected sensors. In these 22 cases, the other component failure that produces the same symptoms is more likely to have occurred than the component that has actually failed, resulting in incorrect diagnosis. All of the other component failures can be diagnosed correctly, however some of the component failures are not diagnosed correctly until a later time in the mission. For some of the other component failures, the failed component is known, but the time of failure occurrence is not known, and some of the other component failures are where there are multiple different components and component states that are equally likely to have occurred that produce the same symptoms. In the last case, the failed component and its failure mode can be determined, but a number of components may need to be inspected beforehand.

Chapter 7 - Conclusions and future work

7.1. Introduction

In this thesis, a performance metric based sensor selection method has been developed which uses models of the system to automatically calculate the performance metric for all combinations of sensors in order to determine the most suitable combination. The aim of the research presented in this thesis is to propose a method for selecting sensors which are able to detect and diagnose as many different component failures as possible, whilst only using a minimal number of sensors on the system. The proposed sensor selection approach enables the most suitable combination of sensors to be chosen by considering the probability of the failures that the sensors detect, the ease of diagnosis of the failures, and the effect that the component failures have on the probability of system failure. In addition, time dependence was included into the performance metric in order to consider the occurrence time of the component failures and how this affects the system. This chapter summarises the outcomes of this research, and highlights work that could be carried out in the future.

7.2. Summary

The thesis began by presenting a review of the literature relevant to the work presented in the thesis. A number of different sensor selection methods are presented, with a number of different performance metric methodologies discussed, highlighting the individual terms of each of the metrics. This led to the proposal of a novel performance metric, consisting of three terms, in Chapter 3. The literature review continues by outlining a number of fault diagnostic techniques, focussing on Bayesian Belief Networks. This method was used to model the system in Chapters 3 and 4 and used to diagnose component failures on the system. The final section of the literature review presents an overview of optimisation techniques, primarily genetic algorithms, for use on larger systems where it is impossible to exhaustively calculate the performance metric for all combinations of sensors, as demonstrated in Chapter 6.

Chapter 3 of the thesis introduced the methodology for sensor selection and fault diagnostics. Each of the three terms of the newly proposed performance metric were developed individually, with the proposed performance metric being an average of the three terms. However, a discussion on the suitability of using the average of three terms was presented, suggesting that the relative importance of each of the terms could be tuned for each application specifically. This is a novel factor which is not presented in any of the reference literature discussed in Chapter 2. The presented fault diagnostic approach entailed developing a BBN model of the system, and introducing observed sensor readings to the model as evidence. The BBN automatically updates the probability of each of the components states, enabling the determination of which components are most likely to have failed. In order to demonstrate the proposed methodology an example system is presented and the methodology is applied to it. The flow of fuel throughout the system is modelled well, and the best combination of sensors is determined, and is used to diagnose component failures. Conclusions from this chapter state that it is good to select the sensors based on the proposed performance metric and the individual terms of the performance metric in order to ensure the sensor combination is suitable for all factors. In addition, it was suggested that the model should be constructed before applying the sensor selection process, as it can be used to aid the calculation of the performance metric.

Chapter 4 of the thesis extended the methodology presented in Chapter 3 by applying it to a simplified version of the aircraft fuel system, introduced by Moir & Seabridge (2011). Automation is introduced into the methodology by constructing the BBN at the start of the methodology rather than after the selection of the sensors, as in Chapter 3. This enables the sensor readings to be determined automatically and the performance metric of each of the sensors to be calculated using the BBN and a C++ script. The chosen combinations of sensors are then used to diagnose component failures in the system, and the process is successfully completed with all of the component failures diagnosed successfully with no more than two components that had not failed being inspected. Conclusions from this chapter include that whilst the BBN methodology models the system well, the size of the network can become excessively large for larger systems. In addition, in order to prevent the size of the network becoming excessively large, some of the sensor readings are grouped into ranges, which reduces the accuracy of the modelling of the system, and is therefore, not desirable.

In Chapter 5 an alternative modelling technique is presented in order to be able to model larger systems. This novel modelling technique uses a series of if-then-else statements in a C++ script in order to determine the sensor readings for each combination of component states. The modelling technique can be thought of as an evolution of BBNs, constructing the model using the same thought process used to complete the conditional probability tables of the BBNs. In addition, as the previous fault diagnostic technique required a BBN of the system, a new alternative fault diagnostic method is also proposed. This fault diagnostic method involves building a library of sensor readings for each combination of component failures that is used to calculate the performance metric. When the library is completed, observed sensor readings can be compared to the library and the component failures can be diagnosed. In order to ensure that the alternative modelling technique and fault diagnostic method is as good as the methodology used in Chapters 3 and 4, the two methodologies are applied to the un-simplified version of the fuel system introduced by Moir & Seabridge (2011) and the results of the sensor selection and fault diagnostics are compared. Conclusions from this chapter include that the system model constructed using the newly proposed C++ system modelling technique is able to determine the sensor readings for all combinations of component failures significantly faster than the BBN model of the system. In addition, the C++ model was also able to calculate exact sensor readings and not have to group sensor readings into ranges, as was the case for the BBN model. This enabled the C++ model to consider fuel tank level sensors, which the BBN model was unable to do due to needing to group the sensor readings into ranges, therefore decreasing the accuracy of the BBN model. Also, the same component failures can be diagnosed using the C++ model and the BBN model, but one drawback of the diagnostic technique for the C++ model is that it cannot diagnose component failures that were not stored in the library, which should not be observed if the library is extensive enough. However, potential solutions to this problem were suggested, such as outputting potential combinations of component failures that match some of the observed sensor readings. This could potentially mean that the component failures may be able to be determined.

In Chapter 6, time dependence was introduced to the proposed performance metric, i.e. considering the effect of component failures occurring at various times in a mission. In order to do this, a phased mission was considered for the Airbus A380-800 fuel system which included phases such as take-off, cruise and fuel transfer. This enabled component failures to be inserted into the mission at a number of different times, and the time taken to detect and diagnose the component failures considered when selecting the sensors. As in Chapter 5, the system was modelled using a series of if-then-else statements in a C++ script in order to calculate the sensor readings. The sensor readings for all sensors for a large number of missions, each with a large number of time steps were calculated quickly, significantly quicker than would be possible if completed using the BBN method. The sensor performance metric was calculated exhaustively for all combinations of sensors up to combinations of 3 sensors, and a novel, newly proposed two-level genetic algorithm was used to calculate the performance metric and determine suitable combinations of sensors up to combinations of 12 sensors. The two-level genetic algorithm completed a large number of genetic algorithms on different populations of combinations of sensors using a simplified version of the performance metric, before applying another genetic algorithm with the full performance metric on a population consisting of the best combinations of sensors from each of the populations in the first part of the proposed two-level genetic algorithm. All bar 22 of the considered component failures could be diagnosed correctly. The reason that the 22 component failures were not diagnosed correctly is because there are other component failures that produce the same sensor readings but are more likely to occur. However, when the components with a higher failure rate are inspected and found to not have failed, the correct component failures will be diagnosed.

7.3. Conclusions

There are a number of conclusions that can be made from the work presented in this thesis. The conclusions are separated into four sections: sensor selection, system modelling, fault diagnostics and optimisation using Genetic Algorithm. The key points from each of these categories are presented in this section, with the novelty in each of the sections of the conclusions highlighted.

<u>Sensor Selection</u>

- The novel performance metric based sensor selection approach enables the determination of the most suitable combinations of sensors for a given system by considering the percentage of component failures that can be detected, the ease of diagnosis of component failures, and the effect the detected failures have on the failure of the system.
- As the C++ sensor selection script outputs each of the individual terms of the performance metric, the optimum combination of sensors can be selected based on the individual terms of the performance metric according to the requirements of the specific system. This allows flexibility in the selection of sensors, making it suitable for a large number of systems. This is a novel feature not observed in the literature presented in the literature review.
- Time dependence was introduced into the performance metric in order to consider the effect of the failures occurring at different times in the mission. This is particularly useful for real systems where the operation mode changes throughout the mission.

System modelling

- The newly proposed system modelling technique using if-then-else statements in a C++ script enables the sensor readings for all sensors to be determined quickly, something that was not possible when using the BBN system modelling technique. This enables larger systems to be considered than would ordinarily be possible.
- The construction of the model in the C++ script took a significant amount of time, but it took less time than constructing the equivalent BBN of the system due to being able to copy and paste sections of the script. The time taken to construct the model using the C++ script could be further reduced by incorporating more modularisation into the code, potentially enabling even larger systems to be considered.
- The proposed novel modelling technique using a C++ script also enabled more accurate modelling of the system to be completed, enabling fuel tank level sensors to be included. The fuel tank level sensors were ranked highly for the example aircraft fuel system presented in Chapter 5, and the Airbus A380-800 fuel system presented in Chapter 6.

Fault diagnostics

- The proposed fault diagnostic technique can successfully diagnose all of the considered component failures, with a few exceptions where the observed symptoms can be produced by a number of different component failures, and the failure present is a failure with a lower failure probability than the other components. However, this would be the case with any probabilistic fault diagnostic technique, and is not a specific problem with this method.
- The library-based fault diagnostic technique has a potential drawback in comparison to the BBN-based diagnostic technique. If the observed symptoms have not been previously observed, i.e. the combination of component failures has not been seen before, then the diagnostic process will not be able to easily diagnose the component failure. However, if an extensive library is built, this situation should not occur. Also, as discussed in Chapter 5, indications of possible component failures can be determined which may help in the manual determination of the component failures.

Genetic Algorithm

- The novel two-level Genetic Algorithm was successfully applied to the sensor selection methodology. The newly proposed two-level Genetic Algorithm determined suitable combinations of sensors faster than a single-level Genetic Algorithm, and significantly faster than determining suitable combinations of sensors exhaustively.
- There is no evidence to suggest that completing a two-level Genetic Algorithm has a negative effect on the determination of suitable combinations of sensors when compared to a basic single-level Genetic Algorithm, but this cannot be confirmed without further investigation.

7.4. Future work

This section outlines potential future work that could be completed to extend the research presented in this thesis. As in the conclusion section, the future work is separated into four sections: sensor selection, system modelling, fault diagnostics and optimisation using Genetic Algorithm.

Sensor selection

- The time taken to calculate the time-dependent performance metric, specifically the diagnostic term, is significantly longer than when no time dependence is considered. Therefore, the time-dependent performance metric could be modified in the future in order to be able to calculate the performance metric faster, enabling more combinations of sensors to be considered.
- The C++ script could also be modified so that it does not penalise sensors that have multiples of the same component failure (just occurring at different times) producing the same sensor reading, such as the failures presented in group 32 of Table I.2 in Appendix I.
- The number of terms in the performance metric could also be extended, including factors such as the size and weight of the sensors, the cost of the sensors, the availability of the sensors, and the reliability of the sensors. This would make the method more suitable for real world applications, enabling multiple different types of sensors to be considered.

- The time of the component failure occurrences could be considered more dynamically, i.e. the time of occurrence in relation to the end of the phase changing, and the effect of this on the selections of the sensors.
- The time dependent performance metric could be extended to consider missions where multiple component failures occur, potentially changing the detection of failures, and how the method accounts for the detection of the second failure.
- The criticality term of the performance metric could also be adapted such that it considers the probability of the system becoming critical should another component fail.

System modelling

- Whilst the construction of the model in the C++ script took a significant amount of time, it took less time than constructing the equivalent BBN of the system. There are also sections of the script that can be re-used to construct other models, and when constructing models, copy and pasting of sections of script can be used. However, it may be possible to further increase the number of sections of code that can be used to determine multiple sensor readings, perhaps making the production of the model more efficient, and therefore, faster. This could potentially be achieved by a more extensive use of modularisation.
- Accurate flow of fuel modelling could also be developed, enabling a number of assumptions on how the flow propagates through the system to be removed. This would enable a more accurate simulation of the system, with the effects of component failures seen dynamically, rather than after the sensor readings had steadied. This would remove the requirement to consider longer time steps, such as the minute time step used in Chapter 6, and could be fractions of a second instead.
- The modelling of various other different types of systems could be considered, in order to determine the suitability of the proposed sensor selection, system modelling, and fault diagnostic methodology for other systems. There is no obvious reason why the methodology would not be suitable for a wide variety of different systems, but this needs to be investigated if the methodology is to be applied to other types of systems.
- The effect of redundant components in the system could be studied further, for example, the amount of time after failure occurrence that a secondary component

would be activated, and whether this would prevent the system from failing, and whether this would influence the selection of sensors.

- The effect of the environment the aircraft is in on the flow of fuel could also be studied, i.e. if the aircraft has a tail-wind, less power, and therefore less fuel, would be required to fly the aircraft. This may need to be accounted for in the modelling of the system, as it may suggest that a component failure has occurred when no components have failed.

Fault diagnostics

- Work could be completed on determining the accuracy of diagnosing component failures which are not included in the library. Whilst some suggestions were presented in Chapter 5, little investigation was completed on whether combinations of component failures that were not in the library could be diagnosed correctly.
- The fault diagnostic technique could be extended to be able to deal with the same component failure occurring at multiple different times in the mission better. This is of particular importance in real systems where each of the phases of the mission can take a long time, resulting in a large number of failure occurrence times, especially if the systems are modelled in time steps that are fractions of a second long.
- Further work could be completed on the fault diagnostic technique in order to determine how to diagnose component failures where multiple component failures have occurred but at different times, where the occurrence of the second component failure may mask the symptoms of the first component failure and confuse the fault diagnostic results.

Genetic Algorithm

- Future work on the Genetic Algorithm could include studying the effect of changing the mutation rate and the other genetic operators on the selection of sensors.
- In addition, the method could be extended by removing the penalty function when the constraint is broken, and instead, randomly removing one of the sensors from the combinations of sensors until the constraint is no longer broken, as suggested in Chapter 6. This prevents the random mutation from including more sensors than

are removed from the combinations of sensors, and as a result, not breaking the constraint. For example, for a combination of 10 sensors when there are 100 available sensors, 90 sensors can be included but only 10 sensors can be removed, therefore, making it significantly more likely that a sensor will be included than removed, and increasing the probability of breaking the constraint.

- Finally, further investigation could be undertaken on the effect of considering a two-level genetic algorithm, and whether this negatively affects the selection of the sensor combinations.

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Appendix A

Table A.1 Ranking for combinations of two sensors

Rank	Sensor	$I_{\{s\}}$	$DE_{\{s\}}$	$DI_{\{s\}}$	$CR_{\{s\}}$
1	S1 S7	0.8684	0.9870	0.6513	0.9754
	S1 S8	0.8684	0.9870	0.6513	0.9754
	S1 S9	0.8684	0.9870	0.6513	0.9754
	S1 S10	0.8684	0.9870	0.6513	0.9754
	S3 S7	0.8684	0.9870	0.6513	0.9754
	S3 S8	0.8684	0.9870	0.6513	0.9754
	S3 S9	0.8684	0.9870	0.6513	0.9754
	S3 S10	0.8684	0.9870	0.6513	0.9754
2	S2 S7	0.8663	0.9870	0.6447	0.9754
	S2 S8	0.8663	0.9870	0.6447	0.9754
	S2 S9	0.8663	0.9870	0.6447	0.9754
	S2 S10	0.8663	0.9870	0.6447	0.9754
	S4 S7	0.8663	0.9870	0.6447	0.9754
	S4 S8	0.8663	0.9870	0.6447	0.9754
	S4 S9	0.8663	0.9870	0.6447	0.9754
	S4 S10	0.8663	0.9870	0.6447	0.9754
3	S5 S7	0.8398	1.0000	0.5195	1.0000
	S5 S9	0.8398	1.0000	0.5195	1.0000
4	S5 S8	0.8377	1.0000	0.5130	1.0000
	S5 S10	0.8377	1.0000	0.5130	1.0000
	S6 S7	0.8377	1.0000	0.5130	1.0000
	S6 S8	0.8377	1.0000	0.5130	1.0000
	S6 S9	0.8377	1.0000	0.5130	1.0000
	S6 S10	0.8377	1.0000	0.5130	1.0000
	S7 S9	0.8377	1.0000	0.5130	1.0000
	S7 S10	0.8377	1.0000	0.5130	1.0000
	S7 S11	0.8377	1.0000	0.5130	1.0000

	S8 S9	0.8377	1.0000	0.5130	1.0000
	S9 S11	0.8377	1.0000	0.5130	1.0000
5	S8 S10	0.8355	1.0000	0.5065	1.0000
	S8 S11	0.8355	1.0000	0.5065	1.0000
	S10 S11	0.8355	1.0000	0.5065	1.0000
6	S7 S8	0.8084	0.9740	0.5133	0.9512
	S9 S10	0.8084	0.9740	0.5133	0.9512
7	S1 S3	0.7186	0.7532	0.5345	1.0000
	S1 S4	0.7143	0.7532	0.5172	1.0000
	S1 S5	0.7143	0.7532	0.5172	1.0000
	S1 S6	0.7143	0.7532	0.5172	1.0000
	S2 S3	0.7143	0.7532	0.5172	1.0000
	S3 S5	0.7143	0.7532	0.5172	1.0000
	S3 S6	0.7143	0.7532	0.5172	1.0000
8	S1 S11	0.7121	0.7532	0.5086	1.0000
	S2 S6	0.7121	0.7532	0.5086	1.0000
	S3 S11	0.7121	0.7532	0.5086	1.0000
	S4 S6	0.7121	0.7532	0.5086	1.0000
9	S2 S4	0.7100	0.7532	0.5000	1.0000
	S2 S5	0.7100	0.7532	0.5000	1.0000
	S2 S11	0.7100	0.7532	0.5000	1.0000
	S4 S5	0.7100	0.7532	0.5000	1.0000
	S4 S11	0.7100	0.7532	0.5000	1.0000
10	S5 S6	0.6710	0.7532	0.3448	1.0000
11	S5 S11	0.6688	0.7532	0.3362	1.0000
	S6 S11	0.6688	0.7532	0.3362	1.0000
12	S1 S2	0.3944	0.4740	0.3014	0.5665
	S3 S4	0.3944	0.4740	0.3014	0.5665

Table A.2 Ranking for combinations of three sensors

Rank	Sensor	$I_{\{s\}}$	$DE_{\{s\}}$	$DI_{\{s\}}$	$CR_{\{s\}}$
1	S1 S3 S7	0.8939	1.0000	0.6818	1.0000
	S1 S3 S9	0.8939	1.0000	0.6818	1.0000
2	S1 S3 S8	0.8918	1.0000	0.6753	1.0000
	S1 S3 S10	0.8918	1.0000	0.6753	1.0000
3	S1 S4 S7	0.8896	1.0000	0.6688	1.0000
	S1 S4 S9	0.8896	1.0000	0.6688	1.0000
	S1 S5 S7	0.8896	1.0000	0.6688	1.0000
	S1 S5 S9	0.8896	1.0000	0.6688	1.0000
	S2 S3 S7	0.8896	1.0000	0.6688	1.0000
	S2 S3 S9	0.8896	1.0000	0.6688	1.0000
	S3 S5 S7	0.8896	1.0000	0.6688	1.0000
	S3 S5 S9	0.8896	1.0000	0.6688	1.0000
4	S1 S4 S8	0.8874	1.0000	0.6623	1.0000
	S1 S4 S10	0.8874	1.0000	0.6623	1.0000
	S1 S5 S8	0.8874	1.0000	0.6623	1.0000
	S1 S5 S10	0.8874	1.0000	0.6623	1.0000
	S1 S6 S7	0.8874	1.0000	0.6623	1.0000
	S1 S6 S8	0.8874	1.0000	0.6623	1.0000
	S1 S6 S9	0.8874	1.0000	0.6623	1.0000
	S1 S6 S10	0.8874	1.0000	0.6623	1.0000
	S1 S7 S9	0.8874	1.0000	0.6623	1.0000
	S1 S7 S10	0.8874	1.0000	0.6623	1.0000
	S1 S7 S11	0.8874	1.0000	0.6623	1.0000
	S1 S8 S9	0.8874	1.0000	0.6623	1.0000
	S1 S9 S11	0.8874	1.0000	0.6623	1.0000
	S2 S3 S8	0.8874	1.0000	0.6623	1.0000
	S2 S3 S10	0.8874	1.0000	0.6623	1.0000
	S3 S5 S8	0.8874	1.0000	0.6623	1.0000
	S3 S5 S10	0.8874	1.0000	0.6623	1.0000
	S3 S6 S7	0.8874	1.0000	0.6623	1.0000
	S3 S6 S8	0.8874	1.0000	0.6623	1.0000
	S3 S6 S9	0.8874	1.0000	0.6623	1.0000
	S3 S6 S10	0.8874	1.0000	0.6623	1.0000

	S3 S7 S9	0.8874	1.0000	0.6623	1.0000
	S3 S7 S10	0.8874	1.0000	0.6623	1.0000
	S3 S7 S11	0.8874	1.0000	0.6623	1.0000
	S3 S8 S9	0.8874	1.0000	0.6623	1.0000
	S3 S9 S11	0.8874	1.0000	0.6623	1.0000
5	S1 S8 S10	0.8853	1.0000	0.6558	1.0000
	S1 S8 S11	0.8853	1.0000	0.6558	1.0000
	S1 S10 S11	0.8853	1.0000	0.6558	1.0000
	S2 S4 S7	0.8853	1.0000	0.6558	1.0000
	S2 S4 S9	0.8853	1.0000	0.6558	1.0000
	S2 S5 S7	0.8853	1.0000	0.6558	1.0000
	S2 S5 S9	0.8853	1.0000	0.6558	1.0000
	S2 S6 S7	0.8853	1.0000	0.6558	1.0000
	S2 S6 S8	0.8853	1.0000	0.6558	1.0000
	S2 S6 S9	0.8853	1.0000	0.6558	1.0000
	S2 S6 S10	0.8853	1.0000	0.6558	1.0000
	S2 S7 S9	0.8853	1.0000	0.6558	1.0000
	S2 S7 S10	0.8853	1.0000	0.6558	1.0000
	S2 S7 S11	0.8853	1.0000	0.6558	1.0000
	S2 S8 S9	0.8853	1.0000	0.6558	1.0000
	S2 S9 S11	0.8853	1.0000	0.6558	1.0000
	S3 S8 S10	0.8853	1.0000	0.6558	1.0000
	S3 S8 S11	0.8853	1.0000	0.6558	1.0000
	S3 S10 S11	0.8853	1.0000	0.6558	1.0000
	S4 S5 S7	0.8853	1.0000	0.6558	1.0000
	S4 S5 S9	0.8853	1.0000	0.6558	1.0000
	S4 S6 S7	0.8853	1.0000	0.6558	1.0000
	S4 S6 S8	0.8853	1.0000	0.6558	1.0000
	S4 S6 S9	0.8853	1.0000	0.6558	1.0000
	S4 S6 S10	0.8853	1.0000	0.6558	1.0000
	S4 S7 S9	0.8853	1.0000	0.6558	1.0000
	S4 S7 S10	0.8853	1.0000	0.6558	1.0000
	S4 S7 S11	0.8853	1.0000	0.6558	1.0000
	S4 S8 S9	0.8853	1.0000	0.6558	1.0000
	S4 S9 S11	0.8853	1.0000	0.6558	1.0000
6	S2 S4 S8	0.8831	1.0000	0.6494	1.0000

	S2 S4 S10	0.8831	1.0000	0.6494	1.0000
	S2 S5 S8	0.8831	1.0000	0.6494	1.0000
	S2 S5 S10	0.8831	1.0000	0.6494	1.0000
	S2 S8 S10	0.8831	1.0000	0.6494	1.0000
	S2 S8 S11	0.8831	1.0000	0.6494	1.0000
	S2 S10 S11	0.8831	1.0000	0.6494	1.0000
	S4 S5 S8	0.8831	1.0000	0.6494	1.0000
	S4 S5 S10	0.8831	1.0000	0.6494	1.0000
	S4 S8 S10	0.8831	1.0000	0.6494	1.0000
	S4 S8 S11	0.8831	1.0000	0.6494	1.0000
	S4 S10 S11	0.8831	1.0000	0.6494	1.0000
7	S1 S2 S7	0.8706	0.9870	0.6579	0.9754
	S1 S2 S8	0.8706	0.9870	0.6579	0.9754
	S1 S2 S9	0.8706	0.9870	0.6579	0.9754
	S1 S2 S10	0.8706	0.9870	0.6579	0.9754
	S3 S4 S7	0.8706	0.9870	0.6579	0.9754
	S3 S4 S8	0.8706	0.9870	0.6579	0.9754
	S3 S4 S9	0.8706	0.9870	0.6579	0.9754
	S3 S4 S10	0.8706	0.9870	0.6579	0.9754
8	S2 S7 S8	0.8684	0.9870	0.6513	0.9754
	S2 S9 S10	0.8684	0.9870	0.6513	0.9754
	S4 S7 S8	0.8684	0.9870	0.6513	0.9754
	S4 S9 S10	0.8684	0.9870	0.6513	0.9754
9	S1 S7 S8	0.8555	0.9870	0.6119	0.9754
	S1 S9 S10	0.8555	0.9870	0.6119	0.9754
	S3 S7 S8	0.8555	0.9870	0.6119	0.9754
	S3 S9 S10	0.8555	0.9870	0.6119	0.9754
10	S5 S6 S7	0.8398	1.0000	0.5195	1.0000
	S5 S6 S8	0.8398	1.0000	0.5195	1.0000
	S5 S6 S9	0.8398	1.0000	0.5195	1.0000
	S5 S6 S10	0.8398	1.0000	0.5195	1.0000
	S5 S7 S8	0.8398	1.0000	0.5195	1.0000
	S5 S7 S9	0.8398	1.0000	0.5195	1.0000
	S5 S7 S10	0.8398	1.0000	0.5195	1.0000
	S5 S7 S11	0.8398	1.0000	0.5195	1.0000
	S5 S8 S9	0.8398	1.0000	0.5195	1.0000

	S5 S9 S10	0.8398	1.0000	0.5195	1.0000
	S5 S9 S11	0.8398	1.0000	0.5195	1.0000
11	S5 S8 S10	0.8377	1.0000	0.5130	1.0000
	S5 S8 S11	0.8377	1.0000	0.5130	1.0000
	S5 S10 S11	0.8377	1.0000	0.5130	1.0000
	S6 S7 S8	0.8377	1.0000	0.5130	1.0000
	S6 S7 S9	0.8377	1.0000	0.5130	1.0000
	S6 S7 S10	0.8377	1.0000	0.5130	1.0000
	S6 S7 S11	0.8377	1.0000	0.5130	1.0000
	S6 S8 S9	0.8377	1.0000	0.5130	1.0000
	S6 S8 S10	0.8377	1.0000	0.5130	1.0000
	S6 S8 S11	0.8377	1.0000	0.5130	1.0000
	S6 S9 S10	0.8377	1.0000	0.5130	1.0000
	S6 S9 S11	0.8377	1.0000	0.5130	1.0000
	S6 S10 S11	0.8377	1.0000	0.5130	1.0000
	S7 S8 S9	0.8377	1.0000	0.5130	1.0000
	S7 S8 S10	0.8377	1.0000	0.5130	1.0000
	S7 S8 S11	0.8377	1.0000	0.5130	1.0000
	S7 S9 S10	0.8377	1.0000	0.5130	1.0000
	S7 S9 S11	0.8377	1.0000	0.5130	1.0000
	S7 S10 S11	0.8377	1.0000	0.5130	1.0000
	S8 S9 S10	0.8377	1.0000	0.5130	1.0000
	S8 S9 S11	0.8377	1.0000	0.5130	1.0000
	S9 S10 S11	0.8377	1.0000	0.5130	1.0000
12	S8 S10 S11	0.8355	1.0000	0.5065	1.0000
13	S2 S5 S6	0.7276	0.7532	0.5704	1.0000
	S4 S5 S6	0.7276	0.7532	0.5704	1.0000
14	S1 S2 S3	0.7208	0.7532	0.5431	1.0000
	S1 S3 S4	0.7208	0.7532	0.5431	1.0000
	S1 S3 S5	0.7208	0.7532	0.5431	1.0000
	S1 S3 S6	0.7208	0.7532	0.5431	1.0000
15	S1 S3 S11	0.7186	0.7532	0.5345	1.0000
16	S1 S2 S6	0.7165	0.7532	0.5259	1.0000
	S1 S4 S6	0.7165	0.7532	0.5259	1.0000
	S1 S5 S6	0.7165	0.7532	0.5259	1.0000

	S2 S3 S6	0.7165	0.7532	0.5259	1.0000
	S3 S4 S6	0.7165	0.7532	0.5259	1.0000
	S3 S5 S6	0.7165	0.7532	0.5259	1.0000
17	S1 S2 S4	0.7143	0.7532	0.5172	1.0000
	S1 S2 S5	0.7143	0.7532	0.5172	1.0000
	S1 S2 S11	0.7143	0.7532	0.5172	1.0000
	S1 S4 S5	0.7143	0.7532	0.5172	1.0000
	S1 S4 S11	0.7143	0.7532	0.5172	1.0000
	S1 S5 S11	0.7143	0.7532	0.5172	1.0000
	S1 S6 S11	0.7143	0.7532	0.5172	1.0000
	S2 S3 S4	0.7143	0.7532	0.5172	1.0000
	S2 S3 S5	0.7143	0.7532	0.5172	1.0000
	S2 S3 S11	0.7143	0.7532	0.5172	1.0000
	S3 S4 S5	0.7143	0.7532	0.5172	1.0000
	S3 S4 S11	0.7143	0.7532	0.5172	1.0000
	S3 S5 S11	0.7143	0.7532	0.5172	1.0000
	S3 S6 S11	0.7143	0.7532	0.5172	1.0000
18	S2 S4 S6	0.7121	0.7532	0.5086	1.0000
	S2 S6 S11	0.7121	0.7532	0.5086	1.0000
	S4 S6 S11	0.7121	0.7532	0.5086	1.0000
19	S2 S4 S5	0.7100	0.7532	0.5000	1.0000
	S2 S4 S11	0.7100	0.7532	0.5000	1.0000
	S2 S5 S11	0.7100	0.7532	0.5000	1.0000
	S4 S5 S11	0.7100	0.7532	0.5000	1.0000
20	S5 S6 S11	0.6710	0.7532	0.3448	1.0000

Table A.3 Ranking of combinations of two sensors with different component failure rates

Rank	Sensor	$I_{\{s\}}$	$DE_{\{s\}}$	$DI_{\{s\}}$	$CR_{\{s\}}$
1	S1 S7	0.9641	0.9959	0.9059	0.9944
	S1 S8	0.9641	0.9959	0.9059	0.9944
	S1 S9	0.9641	0.9959	0.9059	0.9944
	S1 S10	0.9641	0.9959	0.9059	0.9944
	S3 S7	0.9641	0.9959	0.9059	0.9944
	S3 S8	0.9641	0.9959	0.9059	0.9944
	S3 S9	0.9641	0.9959	0.9059	0.9944
	S3 S10	0.9641	0.9959	0.9059	0.9944
2	S2 S7	0.9629	0.9959	0.9022	0.9943
	S2 S8	0.9629	0.9959	0.9022	0.9943
	S2 S9	0.9629	0.9959	0.9022	0.9943
	S2 S10	0.9629	0.9959	0.9022	0.9943
	S4 S7	0.9629	0.9959	0.9022	0.9943
	S4 S8	0.9629	0.9959	0.9022	0.9943
	S4 S9	0.9629	0.9959	0.9022	0.9943
	S4 S10	0.9629	0.9959	0.9022	0.9943
3	S1 S3	0.9234	0.9321	0.8991	1.0000
4	S1 S5	0.9208	0.9321	0.8910	1.0000
	S3 S5	0.9208	0.9321	0.8910	1.0000
	S1 S4	0.9208	0.9321	0.8910	1.0000
	S2 S3	0.9208	0.9321	0.8910	1.0000
5	S1 S6	0.9197	0.9321	0.8873	1.0000
	S3 S6	0.9197	0.9321	0.8873	1.0000
6	S1 S11	0.9196	0.9321	0.8870	1.0000
	S3 S11	0.9196	0.9321	0.8870	1.0000
7	S2 S6	0.9184	0.9321	0.8833	1.0000
	S4 S6	0.9184	0.9321	0.8833	1.0000
8	S2 S5	0.9183	0.9321	0.8829	1.0000
	S2 S11	0.9183	0.9321	0.8829	1.0000
	S4 S5	0.9183	0.9321	0.8829	1.0000
	S4 S11	0.9183	0.9321	0.8829	1.0000

	S2 S4	0.9183	0.9321	0.8829	1.0000
9	S5 S7	0.8417	1.0000	0.5251	1.0000
	S5 S9	0.8417	1.0000	0.5251	1.0000
10	S5 S8	0.8416	1.0000	0.5247	1.0000
	S5 S10	0.8416	1.0000	0.5247	1.0000
11	S6 S7	0.8304	1.0000	0.4911	1.0000
	S6 S8	0.8304	1.0000	0.4911	1.0000
	S6 S9	0.8304	1.0000	0.4911	1.0000
	S6 S10	0.8304	1.0000	0.4911	1.0000
	S7 S9	0.8304	1.0000	0.4911	1.0000
	S7 S10	0.8304	1.0000	0.4911	1.0000
	S7 S11	0.8304	1.0000	0.4911	1.0000
	S8 S9	0.8304	1.0000	0.4911	1.0000
	S9 S11	0.8304	1.0000	0.4911	1.0000
12	S8 S10	0.8302	1.0000	0.4907	1.0000
	S8 S11	0.8302	1.0000	0.4907	1.0000
	S10 S11	0.8302	1.0000	0.4907	1.0000
13	S7 S8	0.8227	0.9918	0.4917	0.9886
	S9 S10	0.8227	0.9918	0.4917	0.9886
14	S5 S6	0.7939	0.9321	0.4823	1.0000
15	S5 S11	0.7938	0.9321	0.4820	1.0000
16	S6 S11	0.7825	0.9321	0.4459	1.0000
17	S1 S2	0.4749	0.5124	0.8252	0.4895
	S3 S4	0.4749	0.5124	0.8252	0.4895

Table A.4 Ranking of combinations of three sensors with different component failure rates

Rank	Sensor	$I_{\{s\}}$	$DE_{\{s\}}$	$DI_{\{s\}}$	$CR_{\{s\}}$
1	S1 S3 S7	0.9738	1.0000	0.9214	1.0000
	S1 S3 S9	0.9738	1.0000	0.9214	1.0000
2	S1 S3 S8	0.9737	1.0000	0.9211	1.0000
	S1 S3 S10	0.9737	1.0000	0.9211	1.0000
3	S1 S5 S7	0.9713	1.0000	0.9139	1.0000
	S1 S5 S9	0.9713	1.0000	0.9139	1.0000
	S3 S5 S7	0.9713	1.0000	0.9139	1.0000
	S3 S5 S9	0.9713	1.0000	0.9139	1.0000
4	S1 S5 S8	0.9712	1.0000	0.9135	1.0000
	S1 S5 S10	0.9712	1.0000	0.9135	1.0000
	S3 S5 S8	0.9712	1.0000	0.9135	1.0000
	S3 S5 S10	0.9712	1.0000	0.9135	1.0000
5	S1 S6 S7	0.9700	1.0000	0.9101	1.0000
	S1 S6 S8	0.9700	1.0000	0.9101	1.0000
	S1 S6 S9	0.9700	1.0000	0.9101	1.0000
	S1 S6 S10	0.9700	1.0000	0.9101	1.0000
	S1 S7 S9	0.9700	1.0000	0.9101	1.0000
	S1 S7 S10	0.9700	1.0000	0.9101	1.0000
	S1 S7 S11	0.9700	1.0000	0.9101	1.0000
	S1 S8 S9	0.9700	1.0000	0.9101	1.0000
	S1 S9 S11	0.9700	1.0000	0.9101	1.0000
	S3 S6 S7	0.9700	1.0000	0.9101	1.0000
	S3 S6 S8	0.9700	1.0000	0.9101	1.0000
	S3 S6 S9	0.9700	1.0000	0.9101	1.0000
	S3 S6 S10	0.9700	1.0000	0.9101	1.0000
	S3 S7 S9	0.9700	1.0000	0.9101	1.0000
	S3 S7 S10	0.9700	1.0000	0.9101	1.0000
	S3 S7 S11	0.9700	1.0000	0.9101	1.0000
	S3 S8 S9	0.9700	1.0000	0.9101	1.0000
	S3 S9 S11	0.9700	1.0000	0.9101	1.0000
6	S1 S8 S10	0.9699	1.0000	0.9097	1.0000
	S1 S8 S11	0.9699	1.0000	0.9097	1.0000
	S1 S10 S11	0.9699	1.0000	0.9097	1.0000

	S3 S8 S10	0.9699	1.0000	0.9097	1.0000
	S3 S8 S11	0.9699	1.0000	0.9097	1.0000
	S3 S10 S11	0.9699	1.0000	0.9097	1.0000
7	S1 S4 S7	0.9692	1.0000	0.9076	1.0000
	S1 S4 S9	0.9692	1.0000	0.9076	1.0000
	S2 S3 S7	0.9692	1.0000	0.9076	1.0000
	S2 S3 S9	0.9692	1.0000	0.9076	1.0000
8	S1 S4 S8	0.9691	1.0000	0.9072	1.0000
	S1 S4 S10	0.9691	1.0000	0.9072	1.0000
	S2 S3 S8	0.9691	1.0000	0.9072	1.0000
	S2 S3 S10	0.9691	1.0000	0.9072	1.0000
9	S2 S4 S7	0.9688	1.0000	0.9063	1.0000
	S2 S4 S9	0.9688	1.0000	0.9063	1.0000
	S2 S5 S7	0.9688	1.0000	0.9063	1.0000
	S2 S5 S9	0.9688	1.0000	0.9063	1.0000
	S2 S6 S7	0.9688	1.0000	0.9063	1.0000
	S2 S6 S8	0.9688	1.0000	0.9063	1.0000
	S2 S6 S9	0.9688	1.0000	0.9063	1.0000
	S2 S6 S10	0.9688	1.0000	0.9063	1.0000
	S2 S7 S9	0.9688	1.0000	0.9063	1.0000
	S2 S7 S10	0.9688	1.0000	0.9063	1.0000
	S2 S7 S11	0.9688	1.0000	0.9063	1.0000
	S2 S8 S9	0.9688	1.0000	0.9063	1.0000
	S2 S9 S11	0.9688	1.0000	0.9063	1.0000
	S4 S5 S7	0.9688	1.0000	0.9063	1.0000
	S4 S5 S9	0.9688	1.0000	0.9063	1.0000
	S4 S6 S7	0.9688	1.0000	0.9063	1.0000
	S4 S6 S8	0.9688	1.0000	0.9063	1.0000
	S4 S6 S9	0.9688	1.0000	0.9063	1.0000
	S4 S6 S10	0.9688	1.0000	0.9063	1.0000
	S4 S7 S9	0.9688	1.0000	0.9063	1.0000
	S4 S7 S10	0.9688	1.0000	0.9063	1.0000
	S4 S7 S11	0.9688	1.0000	0.9063	1.0000
	S4 S8 S9	0.9688	1.0000	0.9063	1.0000
	S4 S9 S11	0.9688	1.0000	0.9063	1.0000
10	S2 S4 S8	0.9687	1.0000	0.9060	1.0000

	S2 S4 S10	0.9687	1.0000	0.9060	1.0000
	S2 S5 S8	0.9687	1.0000	0.9060	1.0000
	S2 S5 S10	0.9687	1.0000	0.9060	1.0000
	S2 S8 S10	0.9687	1.0000	0.9060	1.0000
	S2 S8 S11	0.9687	1.0000	0.9060	1.0000
	S2 S10 S11	0.9687	1.0000	0.9060	1.0000
	S4 S5 S8	0.9687	1.0000	0.9060	1.0000
	S4 S5 S10	0.9687	1.0000	0.9060	1.0000
	S4 S8 S10	0.9687	1.0000	0.9060	1.0000
	S4 S8 S11	0.9687	1.0000	0.9060	1.0000
	S4 S10 S11	0.9687	1.0000	0.9060	1.0000
11	S1 S2 S7	0.9654	0.9959	0.9097	0.9943
	S1 S2 S9	0.9654	0.9959	0.9097	0.9943
	S3 S4 S7	0.9654	0.9959	0.9097	0.9943
	S3 S4 S9	0.9654	0.9959	0.9097	0.9943
12	S1 S2 S8	0.9654	0.9959	0.9097	0.9943
	S1 S2 S10	0.9654	0.9959	0.9097	0.9943
	S3 S4 S8	0.9654	0.9959	0.9097	0.9943
	S3 S4 S10	0.9654	0.9959	0.9097	0.9943
13	S1 S7 S8	0.9642	0.9959	0.9063	0.9943
	S1 S9 S10	0.9642	0.9959	0.9063	0.9943
	S3 S7 S8	0.9642	0.9959	0.9063	0.9943
	S3 S9 S10	0.9642	0.9959	0.9063	0.9943
14	S2 S7 S8	0.9630	0.9959	0.9025	0.9943
	S2 S9 S10	0.9630	0.9959	0.9025	0.9943
	S4 S7 S8	0.9630	0.9959	0.9025	0.9943
	S4 S9 S10	0.9630	0.9959	0.9025	0.9943
15	S2 S4 S6	0.9358	0.9321	0.9391	1.0000
16	S1 S2 S3	0.9236	0.9321	0.8999	1.0000
	S1 S3 S4	0.9236	0.9321	0.8999	1.0000
17	S1 S3 S5	0.9235	0.9321	0.8995	1.0000
	S1 S3 S6	0.9235	0.9321	0.8995	1.0000
18	S1 S3 S11	0.9234	0.9321	0.8991	1.0000
19	S1 S2 S6	0.9210	0.9321	0.8914	1.0000
	S1 S4 S6	0.9210	0.9321	0.8914	1.0000

	S1 S5 S6	0.9210	0.9321	0.8914	1.0000
	S2 S3 S6	0.9210	0.9321	0.8914	1.0000
	S3 S4 S6	0.9210	0.9321	0.8914	1.0000
	S3 S5 S6	0.9210	0.9321	0.8914	1.0000
20	S1 S2 S4	0.9208	0.9321	0.8910	1.0000
	S1 S2 S5	0.9208	0.9321	0.8910	1.0000
	S1 S2 S11	0.9208	0.9321	0.8910	1.0000
	S1 S4 S5	0.9208	0.9321	0.8910	1.0000
	S1 S4 S11	0.9208	0.9321	0.8910	1.0000
	S1 S5 S11	0.9208	0.9321	0.8910	1.0000
	S2 S3 S4	0.9208	0.9321	0.8910	1.0000
	S2 S3 S5	0.9208	0.9321	0.8910	1.0000
	S2 S3 S11	0.9208	0.9321	0.8910	1.0000
	S3 S4 S5	0.9208	0.9321	0.8910	1.0000
	S3 S4 S11	0.9208	0.9321	0.8910	1.0000
	S3 S5 S11	0.9208	0.9321	0.8910	1.0000
21	S1 S6 S11	0.9197	0.9321	0.8873	1.0000
	S3 S6 S11	0.9197	0.9321	0.8873	1.0000
22	S2 S5 S6	0.9184	0.9321	0.8833	1.0000
	S2 S6 S11	0.9184	0.9321	0.8833	1.0000
	S4 S5 S6	0.9184	0.9321	0.8833	1.0000
	S4 S6 S11	0.9184	0.9321	0.8833	1.0000
23	S2 S4 S5	0.9183	0.9321	0.8829	1.0000
	S2 S4 S11	0.9183	0.9321	0.8829	1.0000
	S2 S5 S11	0.9183	0.9321	0.8829	1.0000
	S4 S5 S11	0.9183	0.9321	0.8829	1.0000
24	S5 S6 S7	0.8417	1.0000	0.5251	1.0000
	S5 S6 S8	0.8417	1.0000	0.5251	1.0000
	S5 S6 S9	0.8417	1.0000	0.5251	1.0000
	S5 S6 S10	0.8417	1.0000	0.5251	1.0000
	S5 S7 S8	0.8417	1.0000	0.5251	1.0000
	S5 S7 S9	0.8417	1.0000	0.5251	1.0000
	S5 S7 S10	0.8417	1.0000	0.5251	1.0000
	S5 S7 S11	0.8417	1.0000	0.5251	1.0000
	S5 S8 S9	0.8417	1.0000	0.5251	1.0000

	S5 S9 S10	0.8417	1.0000	0.5251	1.0000
	S5 S9 S11	0.8417	1.0000	0.5251	1.0000
25	S5 S8 S10	0.8416	1.0000	0.5247	1.0000
	S5 S8 S11	0.8416	1.0000	0.5247	1.0000
	S5 S10 S11	0.8416	1.0000	0.5247	1.0000
26	S6 S7 S8	0.8344	1.0000	0.5033	1.0000
	S6 S7 S9	0.8344	1.0000	0.5033	1.0000
	S6 S7 S10	0.8344	1.0000	0.5033	1.0000
	S6 S7 S11	0.8344	1.0000	0.5033	1.0000
	S6 S8 S9	0.8344	1.0000	0.5033	1.0000
	S6 S8 S10	0.8344	1.0000	0.5033	1.0000
	S6 S8 S11	0.8344	1.0000	0.5033	1.0000
	S6 S9 S10	0.8344	1.0000	0.5033	1.0000
	S6 S9 S11	0.8344	1.0000	0.5033	1.0000
	S6 S10 S11	0.8344	1.0000	0.5033	1.0000
	S7 S8 S9	0.8344	1.0000	0.5033	1.0000
	S7 S8 S10	0.8344	1.0000	0.5033	1.0000
	S7 S8 S11	0.8344	1.0000	0.5033	1.0000
	S7 S9 S10	0.8344	1.0000	0.5033	1.0000
	S7 S9 S11	0.8344	1.0000	0.5033	1.0000
	S7 S10 S11	0.8344	1.0000	0.5033	1.0000
	S8 S9 S10	0.8344	1.0000	0.5033	1.0000
	S8 S9 S11	0.8344	1.0000	0.5033	1.0000
	S9 S10 S11	0.8344	1.0000	0.5033	1.0000
27	S8 S10 S11	0.8343	1.0000	0.5030	1.0000
28	S5 S6 S11	0.8048	0.9321	0.5175	1.0000

Appendix B

Table B.1 CPT for sensor S1

Supply 2	Supply							
Valve 1	Open							
Section 3	V4 Open, V5 Open				V4 Open, V5 Blocked			
Valve 3	Open		Blocked		Open		Blocked	
Pump 1	On	Off	On	Off	On	Off	On	Off
N	0	1	1	1	0	1	1	1
E	0	0	0	0	0	0	0	0
1	1	0	0	0	1	0	0	0
Supply 2	Supply							
Valve 1	Open							
Section 3	V4 Blocked, V5 Open				V4 Blocked, V5 Blocked			
Valve 3	Open		Blocked		Open		Blocked	
Pump 1	On	Off	On	Off	On	Off	On	Off
N	0	1	1	1	1	1	1	1
E	0	0	0	0	0	0	0	0
1	1	0	0	0	0	0	0	0
Supply 2	Supply							
Valve 1	Blocked							
Section 3	V4 Open, V5 Open				V4 Open, V5 Blocked			
Valve 3	Open		Blocked		Open		Blocked	
Pump 1	On	Off	On	Off	On	Off	On	Off
N	1	0	1	0	1	0	1	0
E	0	1	0	1	0	1	0	1
1	0	0	0	0	0	0	0	0
Supply 2	Supply							
Valve 1	Blocked							
Section 3	V4 Blocked, V5 Open				V4 Blocked, V5 Blocked			
Valve 3	Open		Blocked		Open		Blocked	
Pump 1	On	Off	On	Off	On	Off	On	Off
N	1	0	1	0	1	0	1	0

E	0	1	0	1	0	1	0	1
1	0	0	0	0	0	0	0	0
Supply 2	No Supply							
Valve 1	Open							
Section 3	V4 Open, V5 Open				V4 Open, V5 Blocked			
Valve 3	Open		Blocked		Open		Blocked	
Pump 1	On	Off	On	Off	On	Off	On	Off
N	0	0	1	0	0	0	1	0
E	0	1	0	1	0	1	0	1
1	1	0	0	0	1	0	0	0
Supply 2	No Supply							
Valve 1	Open							
Section 3	V4 Blocked, V5 Open				V4 Blocked, V5 Blocked			
Valve 3	Open		Blocked		Open		Blocked	
Pump 1	On	Off	On	Off	On	Off	On	Off
N	0	0	1	0	1	0	1	0
E	0	1	0	1	0	1	0	1
1	1	0	0	0	0	0	0	0
Supply 2	No Supply							
Valve 1	Blocked							
Section 3	V4 Open, V5 Open				V4 Open, V5 Blocked			
Valve 3	Open		Blocked		Open		Blocked	
Pump 1	On	Off	On	Off	On	Off	On	Off
N	1	0	1	0	1	0	1	0
E	0	1	0	1	0	1	0	1
1	0	0	0	0	0	0	0	0
Supply 2	No Supply							
Valve 1	Blocked							
Section 3	V4 Blocked, V5 Open				V4 Blocked, V5 Blocked			
Valve 3	Open		Blocked		Open		Blocked	
Pump 1	On	Off	On	Off	On	Off	On	Off
N	1	0	1	0	1	0	1	0
E	0	1	0	1	0	1	0	1
1	0	0	0	0	0	0	0	0

Table B.2 CPT for sensor S2

Section 3	V4 Open, V5 Open							
Valve 3	Open				Blocked			
Supply 2	Supply		No Supply		Supply		No Supply	
Supply 1	Sup	No Sup	Sup	No Sup	Sup	No Sup	Sup	No Sup
N	0	1	0	0	1	1	1	0
E	0	0	0	1	0	0	0	1
1	1	0	1	0	0	0	0	0
Section 3	V4 Open, V5 Blocked							
Valve 3	Open				Blocked			
Supply 2	Supply		No Supply		Supply		No Supply	
Supply 1	Sup	No Sup	Sup	No Sup	Sup	No Sup	Sup	No Sup
N	0	1	0	0	1	1	1	0
E	0	0	0	1	0	0	0	1
1	1	0	1	0	0	0	0	0
Section 3	V4 Blocked, V5 Open							
Valve 3	Open				Blocked			
Supply 2	Supply		No Supply		Supply		No Supply	
Supply 1	Sup	No Sup	Sup	No Sup	Sup	No Sup	Sup	No Sup
N	0	1	0	0	1	1	1	0
E	0	0	0	1	0	0	0	1
1	1	0	1	0	0	0	0	0
Section 3	V4 Blocked, V5 Blocked							
Valve 3	Open				Blocked			
Supply 2	Supply		No Supply		Supply		No Supply	
Supply 1	Sup	No Sup	Sup	No Sup	Sup	No Sup	Sup	No Sup
N	1	1	1	0	1	1	1	0
E	0	0	0	1	0	0	0	1
1	0	0	0	0	0	0	0	0

Table B.3 CPT for sensor S3

Supply 1	Supply							
Valve 2	Open							
Section 3	V4 Open, V5 Open				V4 open, V5 blocked			
Valve 3	Open		Blocked		Open		Blocked	
Pump 2	On	Off	On	Off	On	Off	On	Off
N	0	1	1	1	0	1	1	1
E	0	0	0	0	0	0	0	0
1	1	0	0	0	1	0	0	0
Supply 1	Supply							
Valve 2	Open							
Section 3	V4 Blocked, V5 Open				V4 blocked, V5 blocked			
Valve 3	Open		Blocked		Open		Blocked	
Pump 2	On	Off	On	Off	On	Off	On	Off
N	0	1	1	1	1	1	1	1
E	0	0	0	0	0	0	0	0
1	1	0	0	0	0	0	0	0
Supply 1	Supply							
Valve 2	Blocked							
Section 3	V4 Open, V5 Open				V4 open, V5 blocked			
Valve 3	Open		Blocked		Open		Blocked	
Pump 2	On	Off	On	Off	On	Off	On	Off
N	1	0	1	0	1	0	1	0
E	0	1	0	1	0	1	0	1
1	0	0	0	0	0	0	0	0
Supply 1	Supply							
Valve 2	Blocked							
Section 3	V4 Blocked, V5 Open				V4 blocked, V5 blocked			
Valve 3	Open		Blocked		Open		Blocked	
Pump 2	On	Off	On	Off	On	Off	On	Off
N	1	0	1	0	1	0	1	0
E	0	1	0	1	0	1	0	1
1	0	0	0	0	0	0	0	0

Supply 1	No Supply							
Valve 2	Open							
Section 3	V4 Open, V5 Open				V4 open, V5 blocked			
Valve 3	Open		Blocked		Open		Blocked	
Pump 2	On	Off	On	Off	On	Off	On	Off
N	0	0	1	0	0	0	1	0
E	0	1	0	1	0	1	0	1
1	1	0	0	0	1	0	0	0
Supply 1	No Supply							
Valve 2	Open							
Section 3	V4 Blocked, V5 Open				V4 blocked, V5 blocked			
Valve 3	Open		Blocked		Open		Blocked	
Pump 2	On	Off	On	Off	On	Off	On	Off
N	0	0	1	0	1	0	1	0
E	0	1	0	1	0	1	0	1
1	1	0	0	0	0	0	0	0
Supply 1	No Supply							
Valve 2	Blocked							
Section 3	V4 Open, V5 Open				V4 open, V5 blocked			
Valve 3	Open		Blocked		Open		Blocked	
Pump 2	On	Off	On	Off	On	Off	On	Off
N	1	0	1	0	1	0	1	0
E	0	1	0	1	0	1	0	1
1	0	0	0	0	0	0	0	0
Supply 1	No Supply							
Valve 2	Blocked							
Section 3	V4 Blocked, V5 Open				V4 blocked, V5 blocked			
Valve 3	Open		Blocked		Open		Blocked	
Pump 2	On	Off	On	Off	On	Off	On	Off
N	1	0	1	0	1	0	1	0
E	0	1	0	1	0	1	0	1
1	0	0	0	0	0	0	0	0

Table B.4 CPT for sensor S4

Section 3	V4 Open, V5 Open							
Valve 3	Open				Blocked			
Supply 1	Supply		No Supply		Supply		No Supply	
Supply 2	Sup	No Sup	Sup	No Sup	Sup	No Sup	Sup	No Sup
N	0	1	0	0	1	1	1	0
E	0	0	0	1	0	0	0	1
1	1	0	1	0	0	0	0	0
Section 3	V4 Open, V5 Blocked							
Valve 3	Open				Blocked			
Supply 1	Supply		No Supply		Supply		No Supply	
Supply 2	Sup	No Sup	Sup	No Sup	Sup	No Sup	Sup	No Sup
N	0	1	0	0	1	1	1	0
E	0	0	0	1	0	0	0	1
1	1	0	1	0	0	0	0	0
Section 3	V4 Blocked, V5 Open							
Valve 3	Open				Blocked			
Supply 1	Supply		No Supply		Supply		No Supply	
Supply 2	Sup	No Sup	Sup	No Sup	Sup	No Sup	Sup	No Sup
N	0	1	0	0	1	1	1	0
E	0	0	0	1	0	0	0	1
1	1	0	1	0	0	0	0	0
Section 3	V4 Blocked, V5 Blocked							
Valve 3	Open				Blocked			
Supply 1	Supply		No Supply		Supply		No Supply	
Supply 2	Sup	No Sup	Sup	No Sup	Sup	No Sup	Sup	No Sup
N	1	1	1	0	1	1	1	0
E	0	0	0	1	0	0	0	1
1	0	0	0	0	0	0	0	0

Table B.5 CPT for sensor S5

Section 3	V4 Open, V5 Open					
Valve 3	Open			Blocked		
Supply	FS	NS	PS	FS	NS	PS
N	0	0	0	1	0	1
E	0	1	0	0	1	0
1	0	0	1	0	0	0
2	1	0	0	0	0	0
Section 3	V4 Open, V5 Blocked					
Valve 3	Open			Blocked		
Supply	FS	NS	PS	FS	NS	PS
N	0	0	0	1	0	1
E	0	1	0	0	1	0
1	0	0	1	0	0	0
2	1	0	0	0	0	0
Section 3	V4 Blocked, V5 Open					
Valve 3	Open			Blocked		
Supply	FS	NS	PS	FS	NS	PS
N	0	0	0	1	0	1
E	0	1	0	0	1	0
1	0	0	1	0	0	0
2	1	0	0	0	0	0
Section 3	V4 Blocked, V5 Blocked					
Valve 3	Open			Blocked		
Supply	FS	NS	PS	FS	NS	PS
N	1	0	1	1	0	1
E	0	1	0	0	1	0
1	0	0	0	0	0	0
2	0	0	0	0	0	0

Table B.6 CPT for sensor S6

Section 3	V4 Open, V5 Open					
Valve 3	Open			Blocked		
Supply	FS	NS	PS	FS	NS	PS
N	0	0	0	0	0	0
E	0	1	0	1	1	1
1	0	0	1	0	0	0
2	1	0	0	0	0	0
Section 3	V4 Open, V5 Blocked					
Valve 3	Open			Blocked		
Supply	FS	NS	PS	FS	NS	PS
N	0	0	0	0	0	0
E	0	1	0	1	1	1
1	0	0	1	0	0	0
2	1	0	0	0	0	0
Section 3	V4 Blocked, V5 Open					
Valve 3	Open			Blocked		
Supply	FS	NS	PS	FS	NS	PS
N	0	0	0	0	0	0
E	0	1	0	1	1	1
1	0	0	1	0	0	0
2	1	0	0	0	0	0
Section 3	V4 Blocked, V5 Blocked					
Valve 3	Open			Blocked		
Supply	FS	NS	PS	FS	NS	PS
N	1	0	1	0	0	0
E	0	1	0	1	1	1
1	0	0	0	0	0	0
2	0	0	0	0	0	0

Table B.7 CPT for sensor S7

Section 3	V4 Open, V5 Open					
Valve 3	Open			Blocked		
Supply	FS	NS	PS	FS	NS	PS
N	0	0	0	0	0	0
E	0	1	0	1	1	1
0.5	0	0	1	0	0	0
1	1	0	0	0	0	0
2	0	0	0	0	0	0
Section 3	V4 Open, V5 Blocked					
Valve 3	Open			Blocked		
Supply	FS	NS	PS	FS	NS	PS
N	0	0	0	0	0	0
E	0	1	0	1	1	1
0.5	0	0	0	0	0	0
1	0	0	1	0	0	0
2	1	0	0	0	0	0
Section 3	V4 Blocked, V5 Open					
Valve 3	Open			Blocked		
Supply	FS	NS	PS	FS	NS	PS
N	1	0	1	0	0	0
E	0	1	0	1	1	1
0.5	0	0	0	0	0	0
1	0	0	0	0	0	0
2	0	0	0	0	0	0
Section 3	V4 Blocked, V5 Blocked					
Valve 3	Open			Blocked		
Supply	FS	NS	PS	FS	NS	PS
N	1	0	1	0	0	0
E	0	1	0	1	1	1
0.5	0	0	0	0	0	0
1	0	0	0	0	0	0
2	0	0	0	0	0	0

Table B.8 CPT for sensor S8

Section 3	V4 Open, V5 Open					
Valve 3	Open			Blocked		
Supply	FS	NS	PS	FS	NS	PS
N	0	0	0	0	0	0
E	0	1	0	1	1	1
0.5	0	0	1	0	0	0
1	1	0	0	0	0	0
2	0	0	0	0	0	0
Section 3	V4 Open, V5 Blocked					
Valve 3	Open			Blocked		
Supply	FS	NS	PS	FS	NS	PS
N	0	0	0	0	0	0
E	0	1	0	1	1	1
0.5	0	0	0	0	0	0
1	0	0	1	0	0	0
2	1	0	0	0	0	0
Section 3	V4 Blocked, V5 Open					
Valve 3	Open			Blocked		
Supply	FS	NS	PS	FS	NS	PS
N	1	0	1	0	0	0
E	0	1	0	1	1	1
0.5	0	0	0	0	0	0
1	0	0	0	0	0	0
2	0	0	0	0	0	0
Section 3	V4 Blocked, V5 Blocked					
Valve 3	Open			Blocked		
Supply	FS	NS	PS	FS	NS	PS
N	0	0	0	0	0	0
E	1	1	1	1	1	1
0.5	0	0	0	0	0	0
1	0	0	0	0	0	0
2	0	0	0	0	0	0

Table B.9 CPT for sensor S9

Section 3	V4 Open, V5 Open					
Valve 3	Open			Blocked		
Supply	FS	NS	PS	FS	NS	PS
N	0	0	0	0	0	0
E	0	1	0	1	1	1
0.5	0	0	1	0	0	0
1	1	0	0	0	0	0
2	0	0	0	0	0	0
Section 3	V4 Open, V5 Blocked					
Valve 3	Open			Blocked		
Supply	FS	NS	PS	FS	NS	PS
N	1	0	1	0	0	0
E	0	1	0	1	1	1
0.5	0	0	0	0	0	0
1	0	0	0	0	0	0
2	0	0	0	0	0	0
Section 3	V4 Blocked, V5 Open					
Valve 3	Open			Blocked		
Supply	FS	NS	PS	FS	NS	PS
N	0	0	0	0	0	0
E	0	1	0	1	1	1
0.5	0	0	0	0	0	0
1	0	0	1	0	0	0
2	1	0	0	0	0	0
Section 3	V4 Blocked, V5 Blocked					
Valve 3	Open			Blocked		
Supply	FS	NS	PS	FS	NS	PS
N	1	0	1	0	0	0
E	0	1	0	1	1	1
0.5	0	0	0	0	0	0
1	0	0	0	0	0	0
2	0	0	0	0	0	0

Table B.10 CPT for sensor S10

Section 3	V4 Open, V5 Open					
Valve 3	Open			Blocked		
Supply	FS	NS	PS	FS	NS	PS
N	0	0	0	0	0	0
E	0	1	0	1	1	1
0.5	0	0	1	0	0	0
1	1	0	0	0	0	0
2	0	0	0	0	0	0
Section 3	V4 Open, V5 Blocked					
Valve 3	Open			Blocked		
Supply	FS	NS	PS	FS	NS	PS
N	1	0	1	0	0	0
E	0	1	0	1	1	1
0.5	0	0	0	0	0	0
1	0	0	0	0	0	0
2	0	0	0	0	0	0
Section 3	V4 Blocked, V5 Open					
Valve 3	Open			Blocked		
Supply	FS	NS	PS	FS	NS	PS
N	0	0	0	0	0	0
E	0	1	0	1	1	1
0.5	0	0	0	0	0	0
1	0	0	1	0	0	0
2	1	0	0	0	0	0
Section 3	V4 Blocked, V5 Blocked					
Valve 3	Open			Blocked		
Supply	FS	NS	PS	FS	NS	PS
N	0	0	0	0	0	0
E	1	1	1	1	1	1
0.5	0	0	0	0	0	0
1	0	0	0	0	0	0
2	0	0	0	0	0	0

Appendix C

Table C.1 Diagnosis of component failures using sensors (S1 S3 S7), ranked 1st with a diagnostic term of 0.6818

Case	No.	Failure	DF1	Prob	DF2	Prob	DF3	Prob	Group
1	6	V4	V4	100%					1a
	7	V5	V5	100%					1a
	8	P1 P2	P1	100%	P2	100%			2a
	9	P1 V1	P1	100%	V1	100%			2a
	15	P2 V2	P2	100%	V2	100%			2a
	28	V4 V5	V4	100%	V5	100%			2a
2	5	V3	V3	95.84%					1b
	10	P1 V2	P1	100%	V2	95.47%			2b
	14	P2 V1	P2	100%	V1	95.47%			2b
3	1	P1	P1	50%	V1	50%			1c
	2	P2	P2	50%	V2	50%			1c
	3	V1	P1	50%	V1	50%			1c
	4	V2	P2	50%	V2	50%			1c
4	12	P1 V4	V4	100%	P1	50%	V1	50%	2c
	13	P1 V5	V5	100%	P1	50%	V1	50%	2c
	17	P2 V4	V4	100%	P2	50%	V2	50%	2c
	18	P2 V5	V5	100%	P2	50%	V2	50%	2c
	21	V1 V4	V4	100%	P1	50%	V1	50%	2c
	22	V1 V5	V5	100%	P1	50%	V1	50%	2c
	24	V2 V4	V4	100%	P2	50%	V2	50%	2c
	25	V2 V5	V5	100%	P2	50%	V2	50%	2c
5	26	V3 V4	V3	95.84%					3d
	27	V3 V5	V3	95.84%					3d
6	11	P1 V3	V3	95.84%					3e
	16	P2 V3	V3	95.84%					3e
	20	V1 V3	V3	95.84%					3e
	23	V2 V3	V3	95.84%					3e
7	19	V1 V2	V3	95.84%					4a

Table C.2 Diagnosis of component failures using sensors (S1 S3 S8), ranked 2nd with a diagnostic term of 0.6753

Case	No.	Failure	DF1	Prob	DF2	Prob	DF3	Prob	Group
1	6	V4	V4	100%					1a
	7	V5	V5	100%					1a
	8	P1 P2	P1	100%	P2	100%			2a
	9	P1 V1	P1	100%	V1	100%			2a
	15	P2 V2	P2	100%	V2	100%			2a
2	5	V3	V3	91.68%					1b
	10	P1 V2	P1	100%	V2	95.26%			2b
	14	P2 V1	P2	100%	V1	95.26%			2b
3	1	P1	P1	50%	V1	50%			1c
	2	P2	P2	50%	V2	50%			1c
	3	V1	P1	50%	V1	50%			1c
	4	V2	P2	50%	V2	50%			1c
4	12	P1 V4	V4	100%	P1	50%	V1	50%	2c
	13	P1 V5	V5	100%	P1	50%	V1	50%	2c
	17	P2 V4	V4	100%	P2	50%	V2	50%	2c
	18	P2 V5	V5	100%	P2	50%	V2	50%	2c
	21	V1 V4	V4	100%	P1	50%	V1	50%	2c
	22	V1 V5	V5	100%	P1	50%	V1	50%	2c
	24	V2 V4	V4	100%	P2	50%	V2	50%	2c
	25	V2 V5	V5	100%	P2	50%	V2	50%	2c
5	26	V3 V4	V3	91.68%					3d
	27	V3 V5	V3	91.68%					3d
6	11	P1 V3	V3	91.68%					3e
	16	P2 V3	V3	91.68%					3e
	20	V1 V3	V3	91.68%					3e
	23	V2 V3	V3	91.68%					3e
7	28	V4 V5	V3	91.68%					4b
8	19	V1 V2	V3	91.68%					4c

Table C.3 Diagnosis of component failures using sensors (S1 S4 S7), ranked 3rd with a diagnostic term of 0.6688

Case	No.	Failure	DF1	Prob	DF2	Prob	DF3	Prob	Group
1	5	V3	V3	100%					1a
	6	V4	V4	100%					1a
	7	V5	V5	100%					1a
	9	P1 V1	P1	100%	V1	100%			2a
	28	V4 V5	V4	100%	V5	100%			2a
2	1	P1	P1	50%	V1	50%			1c
	2	P2	P2	50%	V2	50%			1c
	3	V1	P1	50%	V1	50%			1c
	4	V2	P2	50%	V2	50%			1c
3	12	P1 V4	V4	100%	P1	50%	V1	50%	2c
	13	P1 V5	V5	100%	P1	50%	V1	50%	2c
	21	V1 V4	V4	100%	P1	50%	V1	50%	2c
	22	V1 V5	V5	100%	P1	50%	V1	50%	2c
	8	P1 P2	P1	100%	P2	51.28%	V2	51.28%	2c
	10	P1 V2	P1	100%	P2	51.28%	V2	51.28%	2c
	14	P2 V1	V1	100%	P2	51.28%	V2	51.28%	2c
	17	P2 V4	V4	100%	P2	51.28%	V2	51.28%	2c
	18	P2 V5	V5	100%	P2	51.28%	V2	51.28%	2c
	19	V1 V2	V1	100%	P2	51.28%	V2	51.28%	2c
	24	V2 V4	V4	100%	P2	51.28%	V2	51.28%	2c
	25	V2 V5	V5	100%	P2	51.28%	V2	51.28%	2c
4	15	P2 V2	P2	51.28%	V2	51.28%			2e
5	26	V3 V4	V3	100%					3d
	27	V3 V5	V3	100%					3d
6	11	P1 V3	V3	100%					3e
	16	P2 V3	V3	100%					3e
	20	V1 V3	V3	100%					3e
	23	V2 V3	V3	100%					3e

Table C.4 Diagnosis of component failures using sensors (S1 S4 S8), ranked 4th with a diagnostic term of 0.6623

Case	No.	Failure	DF1	Prob	DF2	Prob	DF3	Prob	Group
1	6	V4	V4	100%					1a
	7	V5	V5	100%					1a
	9	P1 V1	P1	100%	V1	100%			2a
2	5	V3	V3	95.47%					1b
3	1	P1	P1	50%	V1	50%			1c
	2	P2	P2	50%	V2	50%			1c
	3	V1	P1	50%	V1	50%			1c
	4	V2	P2	50%	V2	50%			1c
4	12	P1 V4	V4	100%	P1	50%	V1	50%	2c
	13	P1 V5	V5	100%	P1	50%	V1	50%	2c
	21	V1 V4	V4	100%	P1	50%	V1	50%	2c
	22	V1 V5	V5	100%	P1	50%	V1	50%	2c
	8	P1 P2	P1	100%	P2	51.28%	V2	51.28%	2c
	10	P1 V2	P1	100%	P2	51.28%	V2	51.28%	2c
	14	P2 V1	V1	100%	P2	51.28%	V2	51.28%	2c
	17	P2 V4	V4	100%	P2	51.28%	V2	51.28%	2c
	18	P2 V5	V5	100%	P2	51.28%	V2	51.28%	2c
	19	V1 V2	V1	100%	P2	51.28%	V2	51.28%	2c
	24	V2 V4	V4	100%	P2	51.28%	V2	51.28%	2c
	25	V2 V5	V5	100%	P2	51.28%	V2	51.28%	2c
5	15	P2 V2	P2	51.28%	V2	51.28%			2e
6	26	V3 V4	V3	95.47%					3d
	27	V3 V5	V3	95.47%					3d
7	11	P1 V3	V3	95.47%					3e
	16	V1 V3	V3	95.47%					3e
	20	P2 V3	V3	95.47%					3e
	23	V2 V3	V3	95.47%					3e
8	28	V4 V5	V3	95.47%					4a

Table C.5 Diagnosis of component failures using sensors (S1 S8 S10), ranked 5th with a diagnostic term of 0.6558

Case	No.	Failure	DF1	Prob	DF2	Prob	DF3	Prob	Group
1	6	V4	V4	100%					1a
	7	V5	V5	100%					1a
	9	P1 V1	P1	100%	V1	100%			2a
2	5	V3	V3	88.04%					1b
3	1	P1	P1	50%	V1	50%			1c
	3	V1	P1	50%	V1	50%			1c
	2	P2	P2	51.28%	V2	51.28%			1c
	4	V2	P2	51.28%	V2	51.28%			1c
4	12	P1 V4	V4	100%	P1	50%	V1	50%	2c
	13	P1 V5	V5	100%	P1	50%	V1	50%	2c
	21	V1 V4	V4	100%	P1	50%	V1	50%	2c
	22	V1 V5	V5	100%	P1	50%	V1	50%	2c
	8	P1 P2	P1	100%	P2	50.07%	V2	50.07%	2c
	10	P1 V2	P1	100%	P2	50.07%	V2	50.07%	2c
	17	P2 V4	V4	100%	P2	51.28%	V2	51.28%	2c
	18	P2 V5	V5	100%	P2	51.28%	V2	51.28%	2c
	24	V2 V4	V4	100%	P2	51.28%	V2	51.28%	2c
	25	V2 V5	V5	100%	P2	51.28%	V2	51.28%	2c
5	15	P2 V2	P2	51.28%	V2	51.28%			2e
6	26	V3 V4	V3	88.04%					3d
	27	V3 V5	V3	88.04%					3d
7	11	P1 V3	V3	88.04%					3e
	20	V1 V3	V3	88.04%					3e
	16	P2 V3	V3	88.04%					3e
	23	V2 V3	V3	88.04%					3e
8	28	V4 V5	V3	88.04%					4c
9	14	P2 V1	V3	88.04%					4d
	19	V1 V2	V3	88.04%					4d

Table C.6 Diagnosis of component failures using sensors (S2 S4 S8), ranked 6th with a diagnostic term of 0.6494

Case	No.	Failure	DF1	Prob	DF2	Prob	DF3	Prob	DF4	Prob	Group
1	6	V4	V4	100%							1a
	7	V5	V5	100%							1a
2	5	V3	V3	95.47%							1b
3	1	P1	P1	51.28%	V1	51.28%					1c
	2	P2	P2	51.28%	V2	51.28%					1c
	3	V1	P1	51.28%	V1	51.28%					1c
	4	V2	P2	51.28%	V2	51.28%					1c
4	12	P1 V4	V4	100%	P1	51.28%	V1	51.28%			2c
	13	P1 V5	V5	100%	P1	51.28%	V1	51.28%			2c
	17	P2 V4	V4	100%	P2	51.28%	V2	51.28%			2c
	18	P2 V5	V5	100%	P2	51.28%	V2	51.28%			2c
	21	V1 V4	V4	100%	P1	51.28%	V1	51.28%			2c
	22	V1 V5	V5	100%	P1	51.28%	V1	51.28%			2c
	24	V2 V4	V4	100%	P2	51.28%	V2	51.28%			2c
	25	V2 V5	V5	100%	P2	51.28%	V2	51.28%			2c
5	9	P1 V1	P1	51.28%	V1	51.28%					2e
	15	P2 V2	P2	51.28%	V2	51.28%					2e
	8	P1 P2	P1	51.28%	P2	51.28%	V1	51.28%	V2	51.28%	2f
	10	P1 V2	P1	51.28%	P2	51.28%	V1	51.28%	V2	51.28%	2f
	14	P2 V1	P1	51.28%	P2	51.28%	V1	51.28%	V2	51.28%	2f
	19	V1 V2	P1	51.28%	P2	51.28%	V1	51.28%	V2	51.28%	2f
6	26	V3 V4	V3	95.47%							3d
	27	V3 V5	V3	95.47%							3d
7	11	P1 V3	V3	95.47%							3e
	16	P2 V3	V3	95.47%							3e
	20	V1 V3	V3	95.47%							3e
	23	V2 V3	V3	95.47%							3e
8	28	V4 V5	V3	95.47%							4a

Table C.7 Diagnosis of component failures using sensors (S5 S6 S7), ranked 10th with a diagnostic term of 0.5195

Case	No.	Failure	DF1	Prob (%)	DF2	Prob (%)	DF3	Prob (%)	DF4	Prob (%)	DF5	Prob (%)	Group
1	6	V4	V4	100									1a
	7	V5	V5	100									1a
	28	V4 V5	V4	100	V5	100							2a
2	5	V3	V3	95.44									1b
3	1	P1	P1	25.64	V1	25.64	P2	25.64	V2	25.64			1d
	2	P2	P1	25.64	V1	25.64	P2	25.64	V2	25.64			1d
	3	V1	P1	25.64	V1	25.64	P2	25.64	V2	25.64			1d
	4	V2	P1	25.64	V1	25.64	P2	25.64	V2	25.64			1d
4	12	P1 V4	V4	100	P1	25.64	V1	25.64	P2	25.64	V2	25.64	2d
	13	P1 V5	V5	100	P1	25.64	V1	25.64	P2	25.64	V2	25.64	2d
	17	P2 V4	V4	100	P1	25.64	V1	25.64	P2	25.64	V2	25.64	2d
	18	P2 V5	V5	100	P1	25.64	V1	25.64	P2	25.64	V2	25.64	2d
	21	V1 V4	V4	100	P1	25.64	V1	25.64	P2	25.64	V2	25.64	2d
	22	V1 V5	V5	100	P1	25.64	V1	25.64	P2	25.64	V2	25.64	2d
	24	V2 V4	V4	100	P1	25.64	V1	25.64	P2	25.64	V2	25.64	2d
	25	V2 V5	V5	100	P1	25.64	V1	25.64	P2	25.64	V2	25.64	2d
5	8	P1 P2	P1	51.28	P2	51.28	V1	51.28	V2	51.28			2f
	10	P1 V2	P1	51.28	V1	51.28	P2	51.28	V2	51.28			2f
	14	P2 V1	P1	51.28	V1	51.28	P2	51.28	V2	51.28			2f
	19	V1 V2	P1	51.28	V1	51.28	P2	51.28	V2	51.28			2f
6	9	P1 V1	P1	25.64	V1	25.64	P2	25.64	V2	25.64			2g
	15	P2 V2	P1	25.64	V1	25.64	P2	25.64	V2	25.64			2g
7	26	V3 V4	V3	100									3a
	27	V3 V5	V3	100									3a
8	11	P1 V3	V3	100									3c
	16	P2 V3	V3	100									3c
	20	V1 V3	V3	100									3c
	23	V2 V3	V3	100									3c

Table C.8 Diagnosis of component failures using sensors (S5 S8 S10), ranked 11th with a diagnostic term of 0.5130

Case	No.	Failure	DF1	Prob (%)	DF2	Prob (%)	DF3	Prob (%)	DF4	Prob (%)	DF5	Prob (%)	Group
1	6	V4	V4	100									1a
	7	V5	V5	100									1a
2	5	V3	V3	95.47									1b
3	1	P1	P1	25.64	V1	25.64	P2	25.64	V2	25.64			1d
	2	P2	P1	25.64	V1	25.64	P2	25.64	V2	25.64			1d
	3	V1	P1	25.64	V1	25.64	P2	25.64	V2	25.64			1d
	4	V2	P1	25.64	V1	25.64	P2	25.64	V2	25.64			1d
4	12	P1 V4	V4	100	P1	25.64	V1	25.64	P2	25.64	V2	25.64	2d
	13	P1 V5	V5	100	P1	25.64	V1	25.64	P2	25.64	V2	25.64	2d
	17	P2 V4	V4	100	P1	25.64	V1	25.64	P2	25.64	V2	25.64	2d
	18	P2 V5	V5	100	P1	25.64	V1	25.64	P2	25.64	V2	25.64	2d
	21	V1 V4	V4	100	P1	25.64	V1	25.64	P2	25.64	V2	25.64	2d
	22	V1 V5	V5	100	P1	25.64	V1	25.64	P2	25.64	V2	25.64	2d
	24	V2 V4	V4	100	P1	25.64	V1	25.64	P2	25.64	V2	25.64	2d
	25	V2 V5	V5	100	P1	25.64	V1	25.64	P2	25.64	V2	25.64	2d
5	8	P1 P2	P1	51.28	P2	51.28	V1	51.28	V2	51.28			2f
	10	P1 V2	P1	51.28	P2	51.28	V1	51.28	V2	51.28			2f
	14	P2 V1	P1	51.28	P2	51.28	V1	51.28	V2	51.28			2f
	19	V1 V2	P1	51.28	V1	51.28	P2	51.28	V2	51.28			2f
6	9	P1 V1	P1	25.64	V1	25.64	P2	25.64	V2	25.64			2g
	15	P2 V2	P1	25.64	V1	25.64	P2	25.64	V2	25.64			2g
7	26	V3 V4	V3	100									3d
	27	V3 V5	V3	100									3d
8	11	P1 V3	V3	100									3f
	16	P2 V3	V3	100									3f
	20	V1 V3	V3	100									3f
	23	V2 V3	V3	100									3f
9	28	V4 V5	V3	95.47									4a

Table C.9 Diagnosis of component failures using sensors (S8 S10 S11), ranked 12th with a diagnostic term of 0.5065

Case	No.	Failure	DF1	Prob (%)	DF2	Prob (%)	DF3	Prob (%)	DF4	Prob (%)	DF5	Prob (%)	Group
1	6	V4	V4	100									1a
	7	V5	V5	100									1a
2	5	V3	V3	81.46									1b
3	1	P1	P1	25.64	V1	25.64	P2	25.64	V2	25.64			1d
	2	P2	P1	25.64	V1	25.64	P2	25.64	V2	25.64			1d
	3	V1	P1	25.64	V1	25.64	P2	25.64	V2	25.64			1d
	4	V2	P1	25.64	V1	25.64	P2	25.64	V2	25.64			1d
4	12	P1 V4	V4	100	P1	25.64	V1	25.64	P2	25.64	V2	25.64	2d
	13	P1 V5	V5	100	P1	25.64	V1	25.64	P2	25.64	V2	25.64	2d
	17	P2 V4	V4	100	P1	25.64	V1	25.64	P2	25.64	V2	25.64	2d
	18	P2 V5	V5	100	P1	25.64	V1	25.64	P2	25.64	V2	25.64	2d
	21	V1 V4	V4	100	P1	25.64	V1	25.64	P2	25.64	V2	25.64	2d
	22	V1 V5	V5	100	P1	25.64	V1	25.64	P2	25.64	V2	25.64	2d
	24	V2 V4	V4	100	P1	25.64	V1	25.64	P2	25.64	V2	25.64	2d
	25	V2 V5	V5	100	P1	25.64	V1	25.64	P2	25.64	V2	25.64	2d
5	9	P1 V1	P1	25.64	V1	25.64	P2	25.64	V2	25.64			2g
	15	P2 V2	P1	25.64	V1	25.64	P2	25.64	V2	25.64			2g
6	26	V3 V4	V3	81.46									3d
	27	V3 V5	V3	81.46									3d
7	11	P1 V3	V3	81.46									3f
	16	P2 V3	V3	81.46									3f
	20	V1 V3	V3	81.46									3f
	23	V2 V3	V3	81.46									3f
8	28	V4 V5	V3	81.46									4e
9	8	P1 P2	V3	81.46									4f
	10	P1 V2	V3	81.46									4f
	14	P2 V1	V3	81.46									4f
	19	V1 V2	V3	81.46									4f

Appendix D

Table D.1 Sensor readings for the individual component failures for the engine feed operation mode

Component failure	S01	S01a	S02	S03	S04	S05	S06	S07	S08	S09	S10
No fault	E	E	E	E	E	E	E	E	E	E	E
TPLT on	1	N	N	N	1	N	E	E	E	E	E
TPLT off	E	E	E	E	E	E	E	E	E	E	E
TPLB on	N	1	N	N	1	N	E	E	E	E	E
TPLB off	E	E	E	E	E	E	E	E	E	E	E
TPRT on	E	E	E	E	E	E	E	E	N	N	1
TPRT off	E	E	E	E	E	E	E	E	E	E	E
TPRB on	E	E	E	E	E	E	E	E	N	N	1
TPRB off	E	E	E	E	E	E	E	E	E	E	E
TPFF on	E	E	E	E	E	E	E	E	E	E	E
TPFF off	E	E	E	E	E	E	E	E	E	E	E
TPRF on	E	E	E	E	E	E	E	E	E	E	E
TPRF off	E	E	E	E	E	E	E	E	E	E	E
BPFL on	E	E	E	E	E	E	E	E	E	E	E
BPFL off	E	E	E	E	E	E	E	E	E	E	E
BPFR on	E	E	E	E	E	E	E	E	E	E	E
BPFR off	E	E	E	E	E	E	E	E	E	E	E
BPRL on	E	E	E	E	E	E	E	E	E	E	E
BPRL off	E	E	E	E	E	E	E	E	E	E	E
BPRR on	E	E	E	E	E	E	E	E	E	E	E
BPRR off	E	E	E	E	E	E	E	E	E	E	E
RVLW open	E	E	E	E	E	E	E	E	E	E	E
RVLW closed	E	E	E	E	E	E	E	E	E	E	E
RVRW open	E	E	E	E	E	E	E	E	E	E	E
RVRW closed	E	E	E	E	E	E	E	E	E	E	E
RVFF open	E	E	E	E	E	E	E	E	E	E	E
RVFF closed	E	E	E	E	E	E	E	E	E	E	E

RVRF open	E	E	E	E	E	E	E	E	E	E	E
RVRF closed	E	E	E	E	E	E	E	E	E	E	E
TVFF open	E	E	E	E	E	E	E	E	E	E	E
TVFF closed	E	E	E	E	E	E	E	E	E	E	E
TVRF open	E	E	E	E	E	E	E	E	E	E	E
TVRF closed	E	E	E	E	E	E	E	E	E	E	E
LDV open	E	E	E	E	E	E	E	E	E	E	E
LDV closed	E	E	E	E	E	E	E	E	E	E	E
RDV open	E	E	E	E	E	E	E	E	E	E	E
RDV closed	E	E	E	E	E	E	E	E	E	E	E
DV open	E	E	E	E	E	E	E	E	E	E	E
DV closed	E	E	E	E	E	E	E	E	E	E	E
CV open	E	E	E	E	E	E	E	E	E	E	E
CV closed	E	E	E	E	E	E	E	E	E	E	E
RPV open	E	E	E	E	E	E	E	E	E	E	E
RPV closed	E	E	E	E	E	E	E	E	E	E	E
LLP open	E	E	E	E	E	E	E	E	E	E	E
LLP closed	E	E	E	E	E	E	E	E	E	E	E
LHP open	E	E	E	E	E	E	E	E	E	E	E
LHP closed	E	E	E	E	E	E	E	E	E	E	E
RLP open	E	E	E	E	E	E	E	E	E	E	E
RLP closed	E	E	E	E	E	E	E	E	E	E	E
RHP open	E	E	E	E	E	E	E	E	E	E	E
RHP closed	E	E	E	E	E	E	E	E	E	E	E
TIV open	E	E	E	E	E	E	E	E	E	E	E
TIV closed	E	E	E	E	E	E	E	E	E	E	E
NVL 2 way	E	E	E	E	E	E	E	E	E	E	E
NVL closed	E	E	E	E	E	E	E	E	E	E	E
NVR 2 way	E	E	E	E	E	E	E	E	E	E	E
NVR closed	E	E	E	E	E	E	E	E	E	E	E

Continued…

Component failure	S11	S12	S12a	S13	S14	S15	S15a	S16	S16a	S17	S18

No fault	E	E	E	E	E	1	N	1	N	N	E
TPLT on	E	E	E	E	E	1	N	1	N	N	E
TPLT off	E	E	E	E	E	1	N	1	N	N	E
TPLB on	E	E	E	E	E	1	N	1	N	N	E
TPLB off	E	E	E	E	E	1	N	1	N	N	E
TPRT on	N	1	N	E	E	1	N	1	N	N	E
TPRT off	E	E	E	E	E	1	N	1	N	N	E
TPRB on	N	N	1	E	E	1	N	1	N	N	E
TPRB off	E	E	E	E	E	1	N	1	N	N	E
TPFF on	E	E	E	E	E	1	N	1	N	N	E
TPFF off	E	E	E	E	E	1	N	1	N	N	E
TPRF on	E	E	E	E	E	1	N	1	N	N	E
TPRF off	E	E	E	E	E	1	N	1	N	N	E
BPFL on	E	E	E	E	E	1	N	1	N	N	E
BPFL off	E	E	E	E	E	N	1	1	N	N	E
BPFR on	E	E	E	E	E	1	1	1	N	N	E
BPFR off	E	E	E	E	E	1	N	1	N	N	E
BPRL on	E	E	E	E	E	1	N	1	N	N	E
BPRL off	E	E	E	E	E	1	N	N	1	N	E
BPRR on	E	E	E	E	E	1	N	1	1	N	E
BPRR off	E	E	E	E	E	1	N	1	N	N	E
RVLW open	E	E	E	E	E	1	N	1	N	N	E
RVLW closed	E	E	E	E	E	1	N	1	N	N	E
RVRW open	E	E	E	E	E	1	N	1	N	N	E
RVRW closed	E	E	E	E	E	1	N	1	N	N	E
RVFF open	E	E	E	E	E	1	N	1	N	N	E
RVFF closed	E	E	E	E	E	1	N	1	N	N	E
RVRF open	E	E	E	E	E	1	N	1	E	E	E
RVRF closed	E	E	E	E	E	1	N	1	E	E	E
TVFF open	E	E	E	E	E	1	N	1	N	N	E
TVFF closed	E	E	E	E	E	1	N	1	N	N	E
TVRF open	E	E	E	E	E	1	N	1	N	N	E
TVRF closed	E	E	E	E	E	1	N	1	N	N	E

LDV open	E	E	E	E	N	1	N	1	N	N	N
LDV closed	E	E	E	E	E	1	N	1	N	N	E
RDV open	E	E	E	E	N	1	N	1	N	N	N
RDV closed	E	E	E	E	E	1	N	1	N	N	E
DV open	E	E	E	E	E	1	N	1	N	N	E
DV closed	E	E	E	E	E	1	N	1	N	N	E
CV open	E	E	E	E	E	1	N	1	N	N	E
CV closed	E	E	E	E	E	1	N	1	N	N	E
RPV open	E	E	E	E	E	1	N	1	N	N	E
RPV closed	E	E	E	E	E	1	N	1	N	N	E
LLP open	E	E	E	E	E	1	N	1	N	N	E
LLP closed	E	E	E	E	E	N	N	1	N	N	E
LHP open	E	E	E	E	E	1	N	1	N	N	E
LHP closed	E	E	E	E	E	N	N	1	N	N	E
RLP open	E	E	E	E	E	1	N	1	N	N	E
RLP closed	E	E	E	E	E	1	N	N	N	N	E
RHP open	E	E	E	E	E	1	N	1	N	N	E
RHP closed	E	E	E	E	E	1	N	N	N	N	E
TIV open	E	E	E	E	E	1	N	1	N	N	E
TIV closed	E	E	E	E	E	1	N	1	N	N	E
NVL 2 way	E	E	E	E	E	1	N	1	N	N	E
NVL closed	E	E	E	E	E	1	N	1	N	N	E
NVR 2 way	E	E	E	E	E	1	N	1	N	N	E
NVR closed	E	E	E	E	E	1	N	1	N	N	E

Continued…

Component failure	S19	S20	S21	S22	S23	S24	S25	S26	S27	S28	S29
No fault	E	N	E	1	1	1	1	E	E	N	N
TPLT on	E	N	E	1	1	1	1	E	E	N	N
TPLT off	E	N	E	1	1	1	1	E	E	N	N
TPLB on	E	N	E	1	1	1	1	E	E	N	N
TPLB off	E	N	E	1	1	1	1	E	E	N	N
TPRT on	E	N	E	1	1	1	1	E	E	N	N

TPRT off	E	N	E	1	1	1	1	E	E	N	N
TPRB on	E	N	E	1	1	1	1	E	E	N	N
TPRB off	E	N	E	1	1	1	1	E	E	N	N
TPFF on	E	N	E	1	1	1	1	1	1	N	N
TPFF off	E	N	E	1	1	1	1	E	E	N	N
TPRF on	E	N	E	1	1	1	1	-1	-1	N	N
TPRF off	E	N	E	1	1	1	1	E	E	N	N
BPFL on	E	N	E	1	1	1	1	E	E	N	N
BPFL off	E	N	E	1	1	1	1	E	E	N	N
BPFR on	E	N	E	2	2	1	1	E	E	N	N
BPFR off	E	N	E	1	1	1	1	E	E	N	N
BPRL on	E	N	E	1	1	1	1	E	E	N	N
BPRL off	E	N	E	1	1	1	1	E	E	N	N
BPRR on	E	N	E	1	1	2	2	E	E	N	N
BPRR off	E	N	E	1	1	1	1	E	E	N	N
RVLW open	E	N	E	1	1	1	1	E	E	N	N
RVLW closed	E	N	E	1	1	1	1	E	E	N	N
RVRW open	E	N	E	1	1	1	1	E	E	N	N
RVRW closed	E	N	E	1	1	1	1	E	E	N	N
RVFF open	E	N	E	1	1	1	1	E	E	N	N
RVFF closed	E	N	E	1	1	1	1	E	E	N	N
RVRF open	E	N	E	1	1	1	1	E	E	N	N
RVRF closed	E	N	E	1	1	1	1	E	E	N	N
TVFF open	E	N	E	1	1	1	1	E	E	N	N
TVFF closed	E	N	E	1	1	1	1	E	E	N	N
TVRF open	E	N	E	1	1	1	1	E	E	N	N
TVRF closed	E	N	E	1	1	1	1	E	E	N	N
LDV open	N	N	N	1	1	1	1	E	E	N	N
LDV closed	E	N	E	1	1	1	1	E	E	N	N
RDV open	N	N	N	1	1	1	1	E	E	N	N
RDV closed	E	N	E	1	1	1	1	E	E	N	N
DV open	E	N	E	1	1	1	1	E	E	N	N
DV closed	E	N	E	1	1	1	1	E	E	N	N

CV open	E	N	E	1	1	1	1	E	E	N	N
CV closed	E	N	E	1	1	1	1	E	E	N	N
RPV open	E	N	E	1	1	1	1	E	E	N	N
RPV closed	E	N	E	1	1	1	1	E	E	N	N
LLP open	E	N	E	1	1	1	1	E	E	N	N
LLP closed	E	N	E	N	E	1	1	E	E	N	N
LHP open	E	N	E	1	1	1	1	E	E	N	N
LHP closed	E	N	E	N	N	1	1	E	E	N	N
RLP open	E	N	E	1	1	1	1	E	E	N	N
RLP closed	E	N	E	1	1	N	E	E	E	N	N
RHP open	E	N	E	1	1	1	1	E	E	N	N
RHP closed	E	N	E	1	1	N	N	E	E	N	N
TIV open	E	N	E	1	1	1	1	E	E	N	N
TIV closed	E	N	E	1	1	1	1	E	E	N	N
NVL 2 way	E	N	E	1	1	1	1	E	E	N	N
NVL closed	E	N	E	1	1	1	1	E	E	N	N
NVR 2 way	E	N	E	1	1	1	1	E	E	N	N
NVR closed	E	N	E	1	1	1	1	E	E	N	N

Table D.2 Sensor readings for the individual component failures for the fuel transfer operation mode

Component failure	S01	S01a	S02	S03	S04	S05	S06	S07	S08	S09	S10
No fault	1	N	N	N	1	N	E	E	N	N	1
TPLT on	1	N	N	N	1	N	E	E	N	N	1
TPLT off	N	1	N	N	1	N	E	E	N	N	1
TPLB on	1	1	N	N	2	N	E	E	N	N	1
TPLB off	1	N	N	N	1	N	E	E	N	N	1
TPRT on	1	N	N	N	1	N	E	E	N	N	1
TPRT off	1	N	N	N	1	N	E	E	N	N	1
TPRB on	1	N	N	N	1	N	E	E	N	N	2
TPRB off	1	N	N	N	1	N	E	E	N	N	1
TPFF on	1	N	N	N	1	N	E	E	N	N	1
TPFF off	1	N	N	N	1	N	E	E	N	N	1
TPRF on	1	N	N	N	1	N	E	E	N	N	1
TPRF off	1	N	N	N	1	N	E	E	N	N	1
BPFL on	1	N	N	N	1	N	E	E	N	N	1
BPFL off	1	N	N	N	1	N	E	E	N	N	1
BPFR on	1	N	N	N	1	N	E	E	N	N	1
BPFR off	1	N	N	N	1	N	E	E	N	N	1
BPRL on	1	N	N	N	1	N	E	E	N	N	1
BPRL off	1	N	N	N	1	N	E	E	N	N	1
BPRR on	1	N	N	N	1	N	E	E	N	N	1
BPRR off	1	N	N	N	1	N	E	E	N	N	1
RVLW open	1	N	0.5	N	0.5	N	E	E	N	N	1
RVLW closed	1	N	N	N	1	N	E	E	N	N	1
RVRW open	1	N	N	N	1	N	E	E	N	N	0.5
RVRW closed	1	N	N	N	1	N	E	E	N	N	1
RVFF open	1	N	N	N	1	N	E	E	N	0.5	0.5
RVFF closed	1	N	N	N	1	N	E	E	N	N	1
RVRF open	1	N	N	0.5	0.5	N	E	E	N	N	1
RVRF closed	1	N	N	N	1	N	E	E	N	N	1
TVFF open	1	N	N	N	1	N	E	E	N	N	1

TVFF closed	1	N	N	N	1	N	E	E	N	N	N
TVRF open	1	N	N	N	1	N	E	E	N	N	1
TVRF closed	N	N	N	N	N	N	E	E	N	N	1
LDV open	1	N	N	N	1	N	E	E	N	N	1
LDV closed	1	N	N	N	1	N	E	E	N	N	1
RDV open	1	N	N	N	1	N	E	E	N	N	1
RDV closed	1	N	N	N	1	N	E	E	N	N	1
DV open	1	N	N	N	1	N	E	E	N	N	1
DV closed	1	N	N	N	1	N	E	E	N	N	1
CV open	1	N	N	N	1	N	E	E	N	N	1
CV closed	1	N	N	N	1	N	E	E	N	N	1
RPV open	1	N	N	N	1	N	E	E	N	N	1
RPV closed	1	N	N	N	1	N	E	E	N	N	1
LLP open	1	N	N	N	1	N	E	E	N	N	1
LLP closed	1	N	N	N	1	N	E	E	N	N	1
LHP open	1	N	N	N	1	N	E	E	N	N	1
LHP closed	1	N	N	N	1	N	E	E	N	N	1
RLP open	1	N	N	N	1	N	E	E	N	N	1
RLP closed	1	N	N	N	1	N	E	E	N	N	1
RHP open	1	N	N	N	1	N	E	E	N	N	1
RHP closed	1	N	N	N	1	N	E	E	N	N	1
TIV open	1	N	N	N	1	N	E	E	N	N	1
TIV closed	1	N	N	N	1	N	E	E	N	N	1
NVL 2 way	1	N	N	N	0.5	-0.5	-0.5	0.5	0.5	N	1.5
NVL closed	1	N	N	N	1	N	E	E	N	N	1
NVR 2 way	1	N	N	N	1.5	0.5	0.5	-0.5	-0.5	N	0.5
NVR closed	1	N	N	N	1	N	E	E	N	N	1

Continued…

Component failure	S11	S12	S12a	S13	S14	S15	S15a	S16	S16a	S17	S18
No fault	N	1	N	E	E	E	E	E	E	E	E
TPLT on	N	1	N	E	E	E	E	E	E	E	E
TPLT off	N	1	N	E	E	E	E	E	E	E	E

TPLB on	N	1	N	E	E	E	E	E	E	E	E
TPLB off	N	1	N	E	E	E	E	E	E	E	E
TPRT on	N	1	N	E	E	E	E	E	E	E	E
TPRT off	N	N	1	E	E	E	E	E	E	E	E
TPRB on	N	1	1	E	E	E	E	E	E	E	E
TPRB off	N	1	N	E	E	E	E	E	E	E	E
TPFF on	N	1	1	E	E	E	E	E	E	E	E
TPFF off	N	1	1	E	E	E	E	E	E	E	E
TPRF on	N	1	1	E	E	E	E	E	E	E	E
TPRF off	N	1	1	E	E	E	E	E	E	E	E
BPFL on	N	1	1	E	E	1	N	E	E	N	E
BPFL off	N	1	1	E	E	E	E	E	E	E	E
BPFR on	N	1	1	E	E	N	1	E	E	N	E
BPFR off	N	1	1	E	E	E	E	E	E	E	E
BPRL on	N	1	1	E	E	E	E	1	N	E	E
BPRL off	N	1	1	E	E	E	E	E	E	E	E
BPRR on	N	1	1	E	E	E	E	N	1	E	E
BPRR off	N	1	1	E	E	E	E	E	E	E	E
RVLW open	N	1	1	E	E	E	E	E	E	E	E
RVLW closed	N	1	1	E	E	E	E	E	E	E	E
RVRW open	0.5	1	1	E	E	E	E	E	E	E	E
RVRW closed	N	1	1	E	E	E	E	E	E	E	E
RVFF open	N	1	1	E	E	E	E	E	E	E	E
RVFF closed	N	1	1	E	E	E	E	E	E	E	E
RVRF open	N	1	1	E	E	E	E	E	E	E	E
RVRF closed	N	1	1	E	E	E	E	E	E	E	E
TVFF open	N	1	1	E	E	E	E	E	E	E	E
TVFF closed	N	N	N	E	E	E	E	E	E	E	E
TVRF open	N	1	1	E	E	E	E	E	E	E	E
TVRF closed	N	1	1	E	E	E	E	E	E	E	E
LDV open	N	1	1	E	E	E	E	E	E	E	E
LDV closed	N	1	1	E	E	E	E	E	E	E	E
RDV open	N	1	1	E	E	E	E	E	E	E	E

RDV closed	N	1	1	E	E	E	E	E	E	E	E
DV open	N	1	1	E	E	E	E	E	E	E	E
DV closed	N	1	1	E	E	E	E	E	E	E	E
CV open	N	1	1	E	E	E	E	E	E	E	E
CV closed	N	1	1	E	E	E	E	E	E	E	E
RPV open	N	1	1	E	E	E	E	E	E	E	E
RPV closed	N	1	1	E	E	E	E	E	E	E	E
LLP open	N	1	1	E	E	E	E	E	E	E	E
LLP closed	N	1	1	E	E	E	E	E	E	E	E
LHP open	N	1	1	E	E	E	E	E	E	E	E
LHP closed	N	1	1	E	E	E	E	E	E	E	E
RLP open	N	1	1	E	E	E	E	E	E	E	E
RLP closed	N	1	1	E	E	E	E	E	E	E	E
RHP open	N	1	1	E	E	E	E	E	E	E	E
RHP closed	N	1	1	E	E	E	E	E	E	E	E
TIV open	N	1	1	E	E	E	E	E	E	E	E
TIV closed	N	1	1	E	E	E	E	E	E	E	E
NVL 2 way	N	1	1	N	E	E	E	E	E	E	E
NVL closed	N	1	1	E	E	E	E	E	E	E	E
NVR 2 way	N	1	1	N	E	E	E	E	E	E	E
NVR closed	N	1	1	E	E	E	E	E	E	E	E

Continued…

Component failure	S19	S20	S21	S22	S23	S24	S25	S26	S27	S28	S29
No fault	E	E	E	E	E	E	E	E	E	E	E
TPLT on	E	E	E	E	E	E	E	E	E	E	E
TPLT off	E	E	E	E	E	E	E	E	E	E	E
TPLB on	E	E	E	E	E	E	E	E	E	E	E
TPLB off	E	E	E	E	E	E	E	E	E	E	E
TPRT on	E	E	E	E	E	E	E	E	E	E	E
TPRT off	E	E	E	E	E	E	E	E	E	E	E
TPRB on	E	E	E	E	E	E	E	E	E	E	E
TPRB off	E	E	E	E	E	E	E	E	E	E	E

TPFF on	E	E	E	E	E	E	E	1	1	E	E
TPFF off	E	E	E	E	E	E	E	E	E	E	E
TPRF on	E	E	E	E	E	E	E	-1	-1	E	E
TPRF off	E	E	E	E	E	E	E	E	E	E	E
BPFL on	E	E	E	1	1	E	E	E	E	N	E
BPFL off	E	E	E	E	E	E	E	E	E	E	E
BPFR on	E	E	E	1	1	E	E	E	E	N	E
BPFR off	E	E	E	E	E	E	E	E	E	E	E
BPRL on	E	N	E	E	E	1	1	E	E	E	N
BPRL off	E	E	E	E	E	E	E	E	E	E	E
BPRR on	E	N	E	E	E	1	1	E	E	E	N
BPRR off	E	E	E	E	E	E	E	E	E	E	E
RVLW open	E	E	E	E	E	E	E	E	E	E	E
RVLW closed	E	E	E	E	E	E	E	E	E	E	E
RVRW open	E	E	E	E	E	E	E	E	E	E	E
RVRW closed	E	E	E	E	E	E	E	E	E	E	E
RVFF open	E	E	E	E	E	E	E	E	E	E	E
RVFF closed	E	E	E	E	E	E	E	E	E	E	E
RVRF open	E	E	E	E	E	E	E	E	E	E	E
RVRF closed	E	E	E	E	E	E	E	E	E	E	E
TVFF open	E	E	E	E	E	E	E	E	E	E	E
TVFF closed	E	E	E	E	E	E	E	E	E	E	E
TVRF open	E	E	E	E	E	E	E	E	E	E	E
TVRF closed	E	E	E	E	E	E	E	E	E	E	E
LDV open	E	E	E	E	E	E	E	E	E	E	E
LDV closed	E	E	E	E	E	E	E	E	E	E	E
RDV open	E	E	E	E	E	E	E	E	E	E	E
RDV closed	E	E	E	E	E	E	E	E	E	E	E
DV open	E	E	E	E	E	E	E	E	E	E	E
DV closed	E	E	E	E	E	E	E	E	E	E	E
CV open	E	E	E	E	E	E	E	E	E	E	E
CV closed	E	E	E	E	E	E	E	E	E	E	E
RPV open	E	E	E	E	E	E	E	E	E	E	E

RPV closed	E	E	E	E	E	E	E	E	E	E	E
LLP open	E	E	E	E	E	E	E	E	E	E	E
LLP closed	E	E	E	E	E	E	E	E	E	E	E
LHP open	E	E	E	E	E	E	E	E	E	E	E
LHP closed	E	E	E	E	E	E	E	E	E	E	E
RLP open	E	E	E	E	E	E	E	E	E	E	E
RLP closed	E	E	E	E	E	E	E	E	E	E	E
RHP open	E	E	E	E	E	E	E	E	E	E	E
RHP closed	E	E	E	E	E	E	E	E	E	E	E
TIV open	E	E	E	E	E	E	E	E	E	E	E
TIV closed	E	E	E	E	E	E	E	E	E	E	E
NVL 2 way	E	E	E	E	E	E	E	E	E	E	E
NVL closed	E	E	E	E	E	E	E	E	E	E	E
NVR 2 way	E	E	E	E	E	E	E	E	E	E	E
NVR closed	E	E	E	E	E	E	E	E	E	E	E

Table D.3 Sensor readings for the individual component failures for the fuel jettison operation mode

Component failure	S01	S01a	S02	S03	S04	S05	S06	S07	S08	S09	S10
No fault	E	E	E	E	E	E	E	E	E	E	E
TPLT on	1	N	N	N	1	N	E	E	E	E	E
TPLT off	E	E	E	E	E	E	E	E	E	E	E
TPLB on	N	1	N	N	1	N	E	E	E	E	E
TPLB off	E	E	E	E	E	E	E	E	E	E	E
TPRT on	E	E	E	E	E	E	E	E	N	N	1
TPRT off	E	E	E	E	E	E	E	E	E	E	E
TPRB on	E	E	E	E	E	E	E	E	N	N	1
TPRB off	E	E	E	E	E	E	E	E	E	E	E
TPFF on	E	E	E	E	E	E	E	E	E	E	E
TPFF off	E	E	E	E	E	E	E	E	E	E	E
TPRF on	E	E	E	E	E	E	E	E	E	E	E
TPRF off	E	E	E	E	E	E	E	E	E	E	E
BPFL on	E	E	E	E	E	E	E	E	E	E	E
BPFL off	E	E	E	E	E	E	E	E	E	E	E
BPFR on	E	E	E	E	E	E	E	E	E	E	E
BPFR off	E	E	E	E	E	E	E	E	E	E	E
BPRL on	E	E	E	E	E	E	E	E	E	E	E
BPRL off	E	E	E	E	E	E	E	E	E	E	E
BPRR on	E	E	E	E	E	E	E	E	E	E	E
BPRR off	E	E	E	E	E	E	E	E	E	E	E
RVLW open	E	E	E	E	E	E	E	E	E	E	E
RVLW closed	E	E	E	E	E	E	E	E	E	E	E
RVRW open	E	E	E	E	E	E	E	E	E	E	E
RVRW closed	E	E	E	E	E	E	E	E	E	E	E
RVFF open	E	E	E	E	E	E	E	E	E	E	E
RVFF closed	E	E	E	E	E	E	E	E	E	E	E
RVRF open	E	E	E	E	E	E	E	E	E	E	E
RVRF closed	E	E	E	E	E	E	E	E	E	E	E
TVFF open	E	E	E	E	E	E	E	E	E	E	E

TVFF closed	E	E	E	E	E	E	E	E	E	E	E
TVRF open	E	E	E	E	E	E	E	E	E	E	E
TVRF closed	E	E	E	E	E	E	E	E	E	E	E
LDV open	E	E	E	E	E	E	E	E	E	E	E
LDV closed	E	E	E	E	E	E	E	E	E	E	E
RDV open	E	E	E	E	E	E	E	E	E	E	E
RDV closed	E	E	E	E	E	E	E	E	E	E	E
DV open	E	E	E	E	E	E	E	E	E	E	E
DV closed	E	E	E	E	E	E	E	E	E	E	E
CV open	E	E	E	E	E	E	E	E	E	E	E
CV closed	E	E	E	E	E	E	E	E	E	E	E
RPV open	N	N	N	N	0.8	0.8	0.8	0.8	N	N	0.8
RPV closed	E	E	E	E	E	E	E	E	E	E	E
LLP open	E	E	E	E	E	E	E	E	E	E	E
LLP closed	E	E	E	E	E	E	E	E	E	E	E
LHP open	E	E	E	E	E	E	E	E	E	E	E
LHP closed	E	E	E	E	E	E	E	E	E	E	E
RLP open	E	E	E	E	E	E	E	E	E	E	E
RLP closed	E	E	E	E	E	E	E	E	E	E	E
RHP open	E	E	E	E	E	E	E	E	E	E	E
RHP closed	E	E	E	E	E	E	E	E	E	E	E
TIV open	E	E	E	E	E	E	E	E	E	E	E
TIV closed	E	E	E	E	E	E	E	E	E	E	E
NVL 2 way	E	E	E	E	E	E	E	E	E	E	E
NVL closed	E	E	E	E	E	E	E	E	E	E	E
NVR 2 way	E	E	E	E	E	E	E	E	E	E	E
NVR closed	E	E	E	E	E	E	E	E	E	E	E

Continued…

Component failure	S11	S12	S12a	S13	S14	S15	S15a	S16	S16a	S17	S18
No fault	E	E	E	E	N	1	1	1	1	-0.66	-0.66
TPLT on	E	E	E	E	N	1	1	1	1	-0.66	-0.66
TPLT off	E	E	E	E	N	1	1	1	1	-0.66	-0.66

TPLB on	E	E	E	E	N	1	1	1	1	-0.66	-0.66
TPLB off	E	E	E	E	N	1	1	1	1	-0.66	-0.66
TPRT on	N	1	N	E	N	1	1	1	1	-0.66	-0.66
TPRT off	E	E	E	E	N	1	1	1	1	-0.66	-0.66
TPRB on	N	N	1	E	N	1	1	1	1	-0.66	-0.66
TPRB off	E	E	E	E	N	1	1	1	1	-0.66	-0.66
TPFF on	E	E	E	E	N	1	1	1	1	-0.66	-0.66
TPFF off	E	E	E	E	N	1	1	1	1	-0.66	-0.66
TPRF on	E	E	E	E	N	1	1	1	1	-0.66	-0.66
TPRF off	E	E	E	E	N	1	1	1	1	-0.66	-0.66
BPFL on	E	E	E	E	N	1	1	1	1	-0.66	-0.66
BPFL off	E	E	E	E	N	N	1	1	1	N	N
BPFR on	E	E	E	E	N	1	1	1	1	-0.66	-0.66
BPFR off	E	E	E	E	N	1	N	1	1	N	N
BPRL on	E	E	E	E	N	1	1	1	1	-0.66	-0.66
BPRL off	E	E	E	E	N	1	1	N	1	-1	-1
BPRR on	E	E	E	E	N	1	1	1	1	-0.66	-0.66
BPRR off	E	E	E	E	N	1	1	1	N	-1	-1
RVLW open	E	E	E	E	N	1	1	1	1	-0.66	-0.66
RVLW closed	E	E	E	E	N	1	1	1	1	-0.66	-0.66
RVRW open	E	E	E	E	N	1	1	1	1	-0.66	-0.66
RVRW closed	E	E	E	E	N	1	1	1	1	-0.66	-0.66
RVFF open	E	E	E	E	N	1	1	1	1	-0.66	-0.66
RVFF closed	E	E	E	E	N	1	1	1	1	-0.66	-0.66
RVRF open	E	E	E	E	N	1	1	1	1	-0.66	-0.66
RVRF closed	E	E	E	E	N	1	1	1	1	-0.66	-0.66
TVFF open	E	E	E	E	N	1	1	1	1	-0.66	-0.66
TVFF closed	E	E	E	E	N	1	1	1	1	-0.66	-0.66
TVRF open	E	E	E	E	N	1	1	1	1	-0.66	-0.66
TVRF closed	E	E	E	E	N	1	1	1	1	-0.66	-0.66
LDV open	E	E	E	E	N	1	1	1	1	-0.66	-0.66
LDV closed	E	E	E	E	N	1	1	1	1	N	N
RDV open	E	E	E	E	N	1	1	1	1	-0.66	-0.66

RDV closed	E	E	E	E	N	1	1	1	1	-0.66	-0.66
DV open	E	E	E	E	N	1	1	1	1	-0.66	-0.66
DV closed	E	E	E	E	N	1	1	1	1	N	N
CV open	E	E	E	E	N	1	1	1	1	-0.66	-0.66
CV closed	E	E	E	E	N	1	1	1	1	-0.66	-0.66
RPV open	N	N	N	-1.6	-1.6	1	1	1	1	-1.2	-1.2
RPV closed	E	E	E	E	N	1	1	1	1	-0.66	-0.66
LLP open	E	E	E	E	N	1	1	1	1	-0.66	-0.66
LLP closed	E	E	E	E	N	1	1	1	1	-2	-2
LHP open	E	E	E	E	N	1	1	1	1	-0.66	-0.66
LHP closed	E	E	E	E	N	1	1	1	1	-2	-2
RLP open	E	E	E	E	N	1	1	1	1	-0.66	-0.66
RLP closed	E	E	E	E	N	1	1	1	1	N	N
RHP open	E	E	E	E	N	1	1	1	1	-0.66	-0.66
RHP closed	E	E	E	E	N	1	1	1	1	N	N
TIV open	E	E	E	E	N	1	1	1	1	-0.66	-0.66
TIV closed	E	E	E	E	N	1	1	1	1	-0.66	-0.66
NVL 2 way	E	E	E	E	N	1	1	1	1	-0.66	-0.66
NVL closed	E	E	E	E	N	1	1	1	1	-0.66	-0.66
NVR 2 way	E	E	E	E	N	1	1	1	1	-0.66	-0.66
NVR closed	E	E	E	E	N	1	1	1	1	-0.66	-0.66

Continued…

Component failure	S19	S20	S21	S22	S23	S24	S25	S26	S27	S28	S29
No fault	-0.66	-0.66	-1.33	-1.33	-1.33	-1.33	-1.33	E	E	N	N
TPLT on	-0.66	-0.66	-1.33	-1.33	-1.33	-1.33	-1.33	E	E	N	N
TPLT off	-0.66	-0.66	-1.33	-1.33	-1.33	-1.33	-1.33	E	E	N	N
TPLB on	-0.66	-0.66	-1.33	-1.33	-1.33	-1.33	-1.33	E	E	N	N
TPLB off	-0.66	-0.66	-1.33	-1.33	-1.33	-1.33	-1.33	E	E	N	N
TPRT on	-0.66	-0.66	-1.33	-1.33	-1.33	-1.33	-1.33	E	E	N	N
TPRT off	-0.66	-0.66	-1.33	-1.33	-1.33	-1.33	-1.33	E	E	N	N
TPRB on	-0.66	-0.66	-1.33	-1.33	-1.33	-1.33	-1.33	E	E	N	N
TPRB off	-0.66	-0.66	-1.33	-1.33	-1.33	-1.33	-1.33	E	E	N	N

TPFF on	-0.66	-0.66	-1.33	-1.33	-1.33	-1.33	-1.33	1	1	N	N
TPFF off	-0.66	-0.66	-1.33	-1.33	-1.33	-1.33	-1.33	E	E	N	N
TPRF on	-0.66	-0.66	-1.33	-1.33	-1.33	-1.33	-1.33	-1	-1	N	N
TPRF off	-0.66	-0.66	-1.33	-1.33	-1.33	-1.33	-1.33	E	E	N	N
BPFL on	-0.66	-0.66	-1.33	-1.33	-1.33	-1.33	-1.33	E	E	N	N
BPFL off	-1	-1	-1	-1	-1	-1	-1	E	E	N	N
BPFR on	-0.66	-0.66	-1.33	-1.33	-1.33	-1.33	-1.33	E	E	N	N
BPFR off	-1	-1	-1	-1	-1	-1	-1	E	E	N	N
BPRL on	-0.66	-0.66	-1.33	-1.33	-1.33	-1.33	-1.33	E	E	N	N
BPRL off	N	N	-1	-1	-1	-1	-1	E	E	N	N
BPRR on	-0.66	-0.66	-1.33	-1.33	-1.33	-1.33	-1.33	E	E	N	N
BPRR off	N	N	-1	-1	-1	-1	-1	E	E	N	N
RVLW open	-0.66	-0.66	-1.33	-1.33	-1.33	-1.33	-1.33	E	E	N	N
RVLW closed	-0.66	-0.66	-1.33	-1.33	-1.33	-1.33	-1.33	E	E	N	N
RVRW open	-0.66	-0.66	-1.33	-1.33	-1.33	-1.33	-1.33	E	E	N	N
RVRW closed	-0.66	-0.66	-1.33	-1.33	-1.33	-1.33	-1.33	E	E	N	N
RVFF open	-0.66	-0.66	-1.33	-1.33	-1.33	-1.33	-1.33	E	E	N	N
RVFF closed	-0.66	-0.66	-1.33	-1.33	-1.33	-1.33	-1.33	E	E	N	N
RVRF open	-0.66	-0.66	-1.33	-1.33	-1.33	-1.33	-1.33	E	E	N	N
RVRF closed	-0.66	-0.66	-1.33	-1.33	-1.33	-1.33	-1.33	E	E	N	N
TVFF open	-0.66	-0.66	-1.33	-1.33	-1.33	-1.33	-1.33	E	E	N	N
TVFF closed	-0.66	-0.66	-1.33	-1.33	-1.33	-1.33	-1.33	E	E	N	N
TVRF open	-0.66	-0.66	-1.33	-1.33	-1.33	-1.33	-1.33	E	E	N	N
TVRF closed	-0.66	-0.66	-1.33	-1.33	-1.33	-1.33	-1.33	E	E	N	N
LDV open	-0.66	-0.66	-1.33	-1.33	-1.33	-1.33	-1.33	E	E	N	N
LDV closed	-0.66	-0.66	-1	-2	-2	-1	-1	E	E	N	N
RDV open	-0.66	-0.66	-1.33	-1.33	-1.33	-1.33	-1.33	E	E	N	N
RDV closed	N	N	-1	-1	-1	-2	-2	E	E	N	N
DV open	-0.66	-0.66	-1.33	-1.33	-1.33	-1.33	-1.33	E	E	N	N
DV closed	N	N	N	-2	-2	-2	-2	E	E	N	N
CV open	-0.66	-0.66	-1.33	-1.33	-1.33	-1.33	-1.33	E	E	N	N
CV closed	-0.66	-0.66	-1.33	-1.33	-1.33	-1.33	-1.33	E	E	N	N
RPV open	-1.2	-1.2	-0.8	-0.8	-0.8	-0.8	-0.8	E	E	N	N

RPV closed	-0.66	-0.66	-1.33	-1.33	-1.33	-1.33	-1.33	E	E	N	N
LLP open	-0.66	-0.66	-1.33	-1.33	-1.33	-1.33	-1.33	E	E	N	N
LLP closed	N	N	-2	N	E	-2	-2	E	E	N	N
LHP open	-0.66	-0.66	-1.33	-1.33	-1.33	-1.33	-1.33	E	E	N	N
LHP closed	N	N	-2	N	N	-2	-2	E	E	N	N
RLP open	-0.66	-0.66	-1.33	-1.33	-1.33	-1.33	-1.33	E	E	N	N
RLP closed	-2	-2	-2	-2	-2	N	E	E	E	N	N
RHP open	-0.66	-0.66	-1.33	-1.33	-1.33	-1.33	-1.33	E	E	N	N
RHP closed	-2	-2	-2	-2	-2	N	N	E	E	N	N
TIV open	-0.66	-0.66	-1.33	-1.33	-1.33	-1.33	-1.33	E	E	N	N
TIV closed	-0.66	-0.66	-1.33	-1.33	-1.33	-1.33	-1.33	E	E	N	N
NVL 2 way	-0.66	-0.66	-1.33	-1.33	-1.33	-1.33	-1.33	E	E	N	N
NVL closed	-0.66	-0.66	-1.33	-1.33	-1.33	-1.33	-1.33	E	E	N	N
NVR 2 way	-0.66	-0.66	-1.33	-1.33	-1.33	-1.33	-1.33	E	E	N	N
NVR closed	-0.66	-0.66	-1.33	-1.33	-1.33	-1.33	-1.33	E	E	N	N

Table D.4 Sensor readings for the individual component failures for the refuel operation mode

Component failure	S01	S01a	S02	S03	S04	S05	S06	S07	S08	S09	S10
No fault	N	N	1	1	N	2	2	2	2	1	N
TPLT on	1	N	1.5	1.5	N	2	2	2	2	1	N
TPLT off	N	N	1	1	N	2	2	2	2	1	N
TPLB on	N	1	1.5	1.5	N	2	2	2	2	1	N
TPLB off	N	N	1	1	N	2	2	2	2	1	N
TPRT on	N	N	1	1	N	2	2	2	2	1.5	N
TPRT off	N	N	1	1	N	2	2	2	2	1	N
TPRB on	N	N	1	1	N	2	2	2	2	1.5	N
TPRB off	N	N	1	1	N	2	2	2	2	1	N
TPFF on	N	N	1	1	N	2	2	2	2	1	N
TPFF off	N	N	1	1	N	2	2	2	2	1	N
TPRF on	N	N	1	1	N	2	2	2	2	1	N
TPRF off	N	N	1	1	N	2	2	2	2	1	N
BPFL on	N	N	1	1	N	2	2	2	2	1	N
BPFL off	N	N	1	1	N	2	2	2	2	1	N
BPFR on	N	N	1	1	N	2	2	2	2	1	N
BPFR off	N	N	1	1	N	2	2	2	2	1	N
BPRL on	N	N	1	1	N	2	2	2	2	1	N
BPRL off	N	N	1	1	N	2	2	2	2	1	N
BPRR on	N	N	1	1	N	2	2	2	2	1	N
BPRR off	N	N	1	1	N	2	2	2	2	1	N
RVLW open	N	N	1	1	N	2	2	2	2	1	N
RVLW closed	N	N	N	2	N	2	2	2	2	1	N
RVRW open	N	N	1	1	N	2	2	2	2	1	N
RVRW closed	N	N	1	1	N	2	2	2	2	N	N
RVFF open	N	N	1	1	N	2	2	2	2	1	N
RVFF closed	N	N	1	1	N	2	2	2	2	2	N
RVRF open	N	N	1	1	N	2	2	2	2	1	N
RVRF closed	N	N	2	N	N	2	2	2	2	1	N
TVFF open	N	N	1	1	N	2	2	2	2	0.66	0.66

TVFF closed	N	N	1	1	N	2	2	2	2	1	N
TVRF open	N	N	0.66	0.66	0.66	2	2	2	2	1	N
TVRF closed	N	N	1	1	N	2	2	2	2	1	N
LDV open	N	N	1	1	N	2	2	2	2	1	N
LDV closed	N	N	1	1	N	2	2	2	2	1	N
RDV open	N	N	1	1	N	2	2	2	2	1	N
RDV closed	N	N	1	1	N	2	2	2	2	1	N
DV open	N	N	1	1	N	2	2	2	2	1	N
DV closed	N	N	1	1	N	2	2	2	2	1	N
CV open	N	N	1	1	N	2	2	2	2	1	N
CV closed	N	N	1	1	N	2	2	2	2	1	N
RPV open	N	N	1	1	N	2	2	2	2	1	N
RPV closed	N	N	1	1	N	2	2	2	2	1	N
LLP open	N	N	1	1	N	2	2	2	2	1	N
LLP closed	N	N	1	1	N	2	2	2	2	1	N
LHP open	N	N	1	1	N	2	2	2	2	1	N
LHP closed	N	N	1	1	N	2	2	2	2	1	N
RLP open	N	N	1	1	N	2	2	2	2	1	N
RLP closed	N	N	1	1	N	2	2	2	2	1	N
RHP open	N	N	1	1	N	2	2	2	2	1	N
RHP closed	N	N	1	1	N	2	2	2	2	1	N
TIV open	N	N	1	1	N	2	2	2	2	1	N
TIV closed	N	N	1	1	N	2	2	2	2	1	N
NVL 2 way	N	N	1	1	N	2	2	2	2	1	N
NVL closed	E	E	E	E	E	E	N	4	4	2	N
NVR 2 way	N	N	1	1	N	2	2	2	2	1	N
NVR closed	N	N	2	2	N	4	4	N	E	E	E

Continued…

Component failure	S11	S12	S12a	S13	S14	S15	S15a	S16	S16a	S17	S18
No fault	1	N	N	N	E	E	E	E	E	E	E
TPLT on	1	N	N	N	E	E	E	E	E	E	E
TPLT off	1	N	N	N	E	E	E	E	E	E	E

TPLB on	1	N	N	N	E	E	E	E	E	E	E
TPLB off	1	N	N	N	E	E	E	E	E	E	E
TPRT on	1.5	1	N	N	E	E	E	E	E	E	E
TPRT off	1	N	N	N	E	E	E	E	E	E	E
TPRB on	1.5	N	1	N	E	E	E	E	E	E	E
TPRB off	1	N	N	N	E	E	E	E	E	E	E
TPFF on	1	N	N	N	E	E	E	E	E	E	E
TPFF off	1	N	N	N	E	E	E	E	E	E	E
TPRF on	1	N	N	N	E	E	E	E	E	E	E
TPRF off	1	N	N	N	E	E	E	E	E	E	E
BPFL on	1	N	N	N	E	1	N	E	E	N	E
BPFL off	1	N	N	N	E	E	E	E	E	E	E
BPFR on	1	N	N	N	E	N	1	E	E	N	E
BPFR off	1	N	N	N	E	E	E	E	E	E	E
BPRL on	1	N	N	N	E	E	E	1	N	E	E
BPRL off	1	N	N	N	E	E	E	E	E	E	E
BPRR on	1	N	N	N	E	E	E	N	1	E	E
BPRR off	1	N	N	N	E	E	E	E	E	E	E
RVLW open	1	N	N	N	E	E	E	E	E	E	E
RVLW closed	1	N	N	N	E	E	E	E	E	E	E
RVRW open	1	N	N	N	E	E	E	E	E	E	E
RVRW closed	N	N	N	N	E	E	E	E	E	E	E
RVFF open	1	N	N	N	E	E	E	E	E	E	E
RVFF closed	2	N	N	N	E	E	E	E	E	E	E
RVRF open	1	N	N	N	E	E	E	E	E	E	E
RVRF closed	1	N	N	N	E	E	E	E	E	E	E
TVFF open	0.66	N	N	N	E	E	E	E	E	E	E
TVFF closed	1	N	N	N	E	E	E	E	E	E	E
TVRF open	1	N	N	N	E	E	E	E	E	E	E
TVRF closed	1	N	N	N	E	E	E	E	E	E	E
LDV open	1	N	N	N	E	E	E	E	E	E	E
LDV closed	1	N	N	N	E	E	E	E	E	E	E
RDV open	1	N	N	N	E	E	E	E	E	E	E

RDV closed	1	N	N	N	E	E	E	E	E	E	E
DV open	1	N	N	N	E	E	E	E	E	E	E
DV closed	1	N	N	N	E	E	E	E	E	E	E
CV open	1	N	N	N	E	E	E	E	E	E	E
CV closed	1	N	N	N	E	E	E	E	E	E	E
RPV open	1	N	N	N	N	E	E	E	E	E	N
RPV closed	1	N	N	N	E	E	E	E	E	E	E
LLP open	1	N	N	N	E	E	E	E	E	E	E
LLP closed	1	N	N	N	E	E	E	E	E	E	E
LHP open	1	N	N	N	E	E	E	E	E	E	E
LHP closed	1	N	N	N	E	E	E	E	E	E	E
RLP open	1	N	N	N	E	E	E	E	E	E	E
RLP closed	1	N	N	N	E	E	E	E	E	E	E
RHP open	1	N	N	N	E	E	E	E	E	E	E
RHP closed	1	N	N	N	E	E	E	E	E	E	E
TIV open	1	N	N	N	E	E	E	E	E	E	E
TIV closed	1	N	N	N	E	E	E	E	E	E	E
NVL 2 way	1	N	N	N	E	E	E	E	E	E	E
NVL closed	2	N	N	N	E	E	E	E	E	E	E
NVR 2 way	1	N	N	N	E	E	E	E	E	E	E
NVR closed	E	E	E	N	E	E	E	E	E	E	E

Continued…

Component failure	S19	S20	S21	S22	S23	S24	S25	S26	S27	S28	S29
No fault	E	E	E	E	E	E	E	E	E	E	E
TPLT on	E	E	E	E	E	E	E	E	E	E	E
TPLT off	E	E	E	E	E	E	E	E	E	E	E
TPLB on	E	E	E	E	E	E	E	E	E	E	E
TPLB off	E	E	E	E	E	E	E	E	E	E	E
TPRT on	E	E	E	E	E	E	E	E	E	E	E
TPRT off	E	E	E	E	E	E	E	E	E	E	E
TPRB on	E	E	E	E	E	E	E	E	E	E	E
TPRB off	E	E	E	E	E	E	E	E	E	E	E

TPFF on	E	E	E	E	E	E	E	1	1	E	E
TPFF off	E	E	E	E	E	E	E	E	E	E	E
TPRF on	E	E	E	E	E	E	E	-1	-1	E	E
TPRF off	E	E	E	E	E	E	E	E	E	E	E
BPFL on	E	E	E	1	1	E	E	E	E	N	E
BPFL off	E	E	E	E	E	E	E	E	E	E	E
BPFR on	E	E	E	1	1	E	E	E	E	N	E
BPFR off	E	E	E	E	E	E	E	E	E	E	E
BPRL on	E	N	E	E	E	1	1	E	E	E	N
BPRL off	E	E	E	E	E	E	E	E	E	E	E
BPRR on	E	N	E	E	E	1	1	E	E	E	N
BPRR off	E	E	E	E	E	E	E	E	E	E	E
RVLW open	E	E	E	E	E	E	E	E	E	E	E
RVLW closed	E	E	E	E	E	E	E	E	E	E	E
RVRW open	E	E	E	E	E	E	E	E	E	E	E
RVRW closed	E	E	E	E	E	E	E	E	E	E	E
RVFF open	E	E	E	E	E	E	E	E	E	E	E
RVFF closed	E	E	E	E	E	E	E	E	E	E	E
RVRF open	E	E	E	E	E	E	E	E	E	E	E
RVRF closed	E	E	E	E	E	E	E	E	E	E	E
TVFF open	E	E	E	E	E	E	E	E	E	E	E
TVFF closed	E	E	E	E	E	E	E	E	E	E	E
TVRF open	E	E	E	E	E	E	E	E	E	E	E
TVRF closed	E	E	E	E	E	E	E	E	E	E	E
LDV open	E	E	E	E	E	E	E	E	E	E	E
LDV closed	E	E	E	E	E	E	E	E	E	E	E
RDV open	E	E	E	E	E	E	E	E	E	E	E
RDV closed	E	E	E	E	E	E	E	E	E	E	E
DV open	E	E	E	E	E	E	E	E	E	E	E
DV closed	E	E	E	E	E	E	E	E	E	E	E
CV open	E	E	E	E	E	E	E	E	E	E	E
CV closed	E	E	E	E	E	E	E	E	E	E	E
RPV open	N	E	N	E	E	E	E	E	E	E	E

RPV closed	E	E	E	E	E	E	E	E	E	E	E
LLP open	E	E	E	E	E	E	E	E	E	E	E
LLP closed	E	E	E	E	E	E	E	E	E	E	E
LHP open	E	E	E	E	E	E	E	E	E	E	E
LHP closed	E	E	E	E	E	E	E	E	E	E	E
RLP open	E	E	E	E	E	E	E	E	E	E	E
RLP closed	E	E	E	E	E	E	E	E	E	E	E
RHP open	E	E	E	E	E	E	E	E	E	E	E
RHP closed	E	E	E	E	E	E	E	E	E	E	E
TIV open	E	E	E	E	E	E	E	E	E	E	E
TIV closed	E	E	E	E	E	E	E	E	E	E	E
NVL 2 way	E	E	E	E	E	E	E	E	E	E	E
NVL closed	E	E	E	E	E	E	E	E	E	E	E
NVR 2 way	E	E	E	E	E	E	E	E	E	E	E
NVR closed	E	E	E	E	E	E	E	E	E	E	E

Appendix E

Table E.1 CPT for the components TPLT and TPRT

Operation mode	Engine Feed	Fuel Transfer
Working on	0	0.990
Failed on	0.005	0.005
Failed off	0.005	0.005
Working off	0.990	0

Table E.2 CPT for the components BPFL and BPRL

Operation mode	Engine Feed	Fuel Transfer
Working on	0.990	0
Failed on	0.005	0.005
Failed off	0.005	0.005
Working off	0	0.990

Table E.3 CPT for the components RVLW, RVRW, RVFF, RVRF, LDV, RDV, DV, RPV

Operation mode	Engine Feed	Fuel Transfer
Working open	0	0
Failed open	0.001	0.001
Failed closed	0.001	0.001
Working closed	0.998	0.998

Table E.4 CPT for the components TVFF, TVRF, LLP, LHP, RLP and RHP

Operation mode	Engine Feed	Fuel Transfer
Working open	0.998	0.998
Failed open	0.001	0.001
Failed closed	0.001	0.001
Working closed	0	0

Table E.5 CPT for the components NVL and NVR

Operation mode	Engine Feed	Fuel Transfer
Working (1 way)	0.991	0.991
Failed open (2 way)	0.008	0.008
Failed closed	0.001	0.001

Appendix F

In this appendix, the relationships between all the nodes in Figures 4.9 and 4.10 are presented. Note, nodes that end in a lower case "s" have the same description as the nodes with same name, they simplify the conditional probability tables for the determination of states for other nodes. For example, the pump, BPFL has an additional node, BPFLs. BPFL has four states, working on, failed on, failed off and working off, but for most other nodes, it does not matter whether the pump is working on or failed on, only that the pump is on. Therefore, BPFLs is added and only has two states, on and off. The nodes in the network presented in Figure 4.9 are presented in Figures F.1 – F.28, and the nodes in the network presented in Figure 4.10 are presented in Figures F.29 to F.33. Note, the relationships of the fault and criticality nodes are not presented for Figure 4.10 as they are the same as those for Figure 4.9, and can be found in Figures F.27 and F.28, respectively.

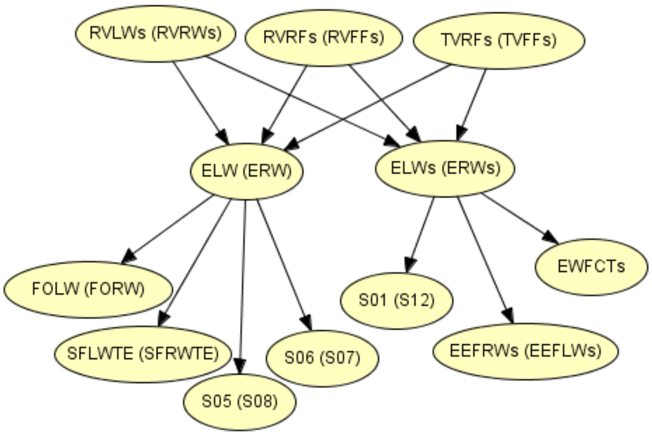

Figure F.1 Relationships of the nodes ELW and ERW (exit left/right wing)

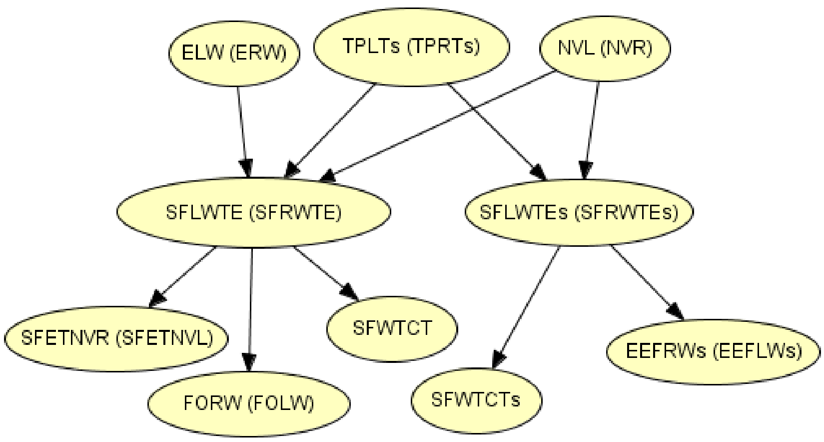

Figure F.2 Relationships of the nodes SFLWTE and SFRWTE (supply from left/right wing to elsewhere)

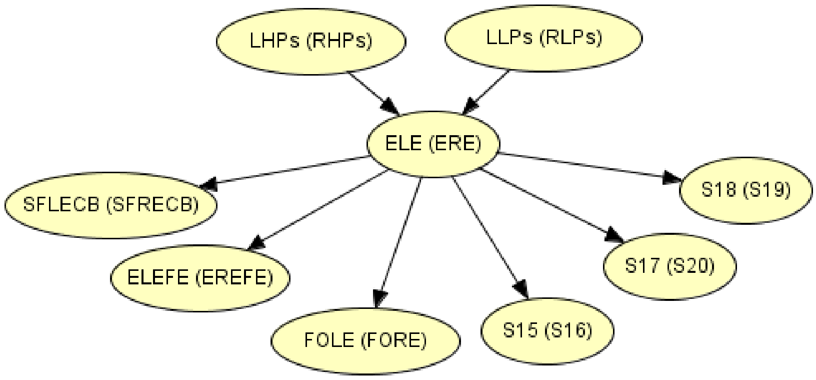

Figure F.3 Relationships of the nodes ELE and ERE (exit left/right engine)

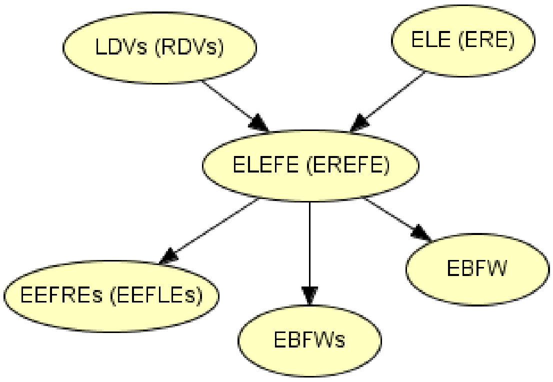

Figure F.4 Relationships of the nodes ELEFE and EREFE (exit left/right engine from elsewhere)

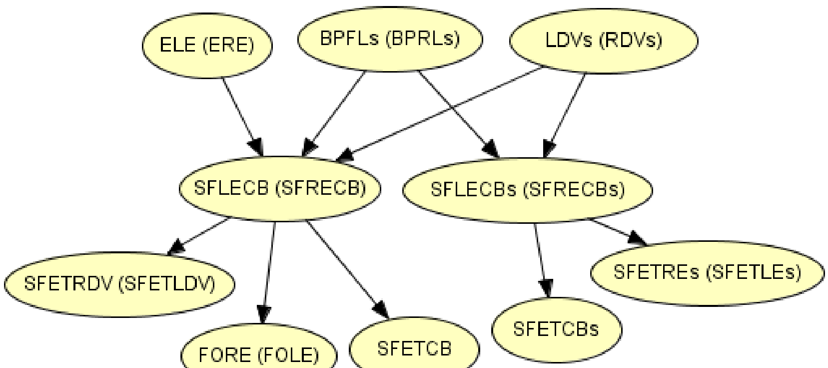

Figure F.5 Relationships of the nodes SFLECB and SFRECB (supply from left/right engine to centre bottom)

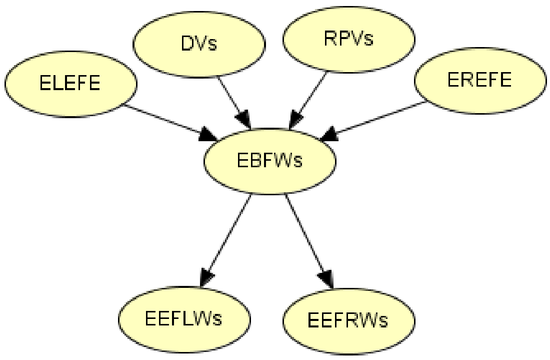

Figure F.6 Relationships of the node EBFWs (exit bottom from wings)

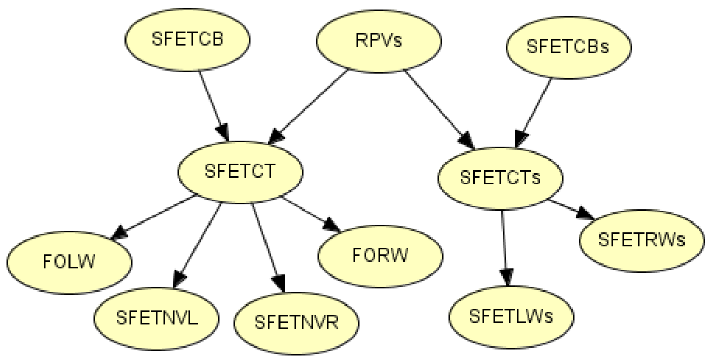

Figure F.7 Relationships of the nodes SFETCT and SFETCTs (supply from engines to centre top)

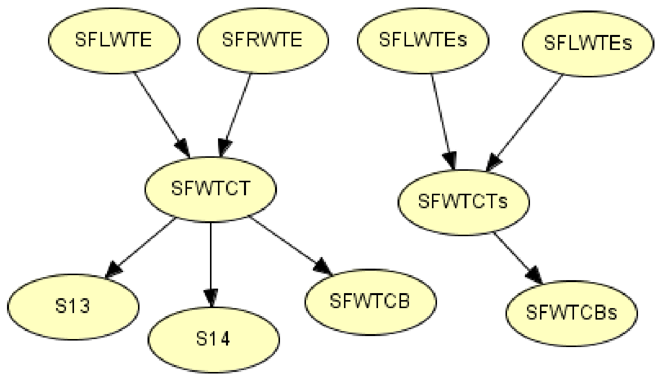

Figure F.8 Relationships of the nodes SFWTCT and SFWTCTs (supply from wings to centre top)

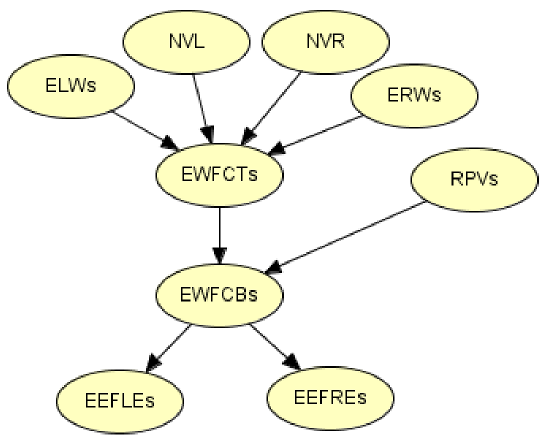

Figure F.9 Relationships of the nodes EWFCTs and EWFCBs (exit wings from centre top/bottom)

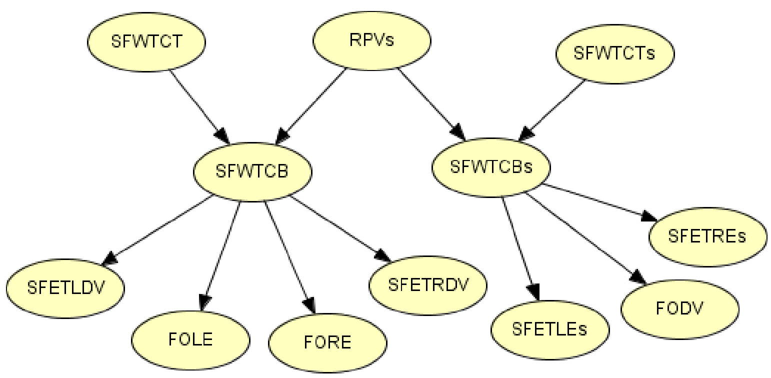

Figure F.10 Relationships of the nodes SFWTCB and SFWTCBs (supply from wings to centre bottom)

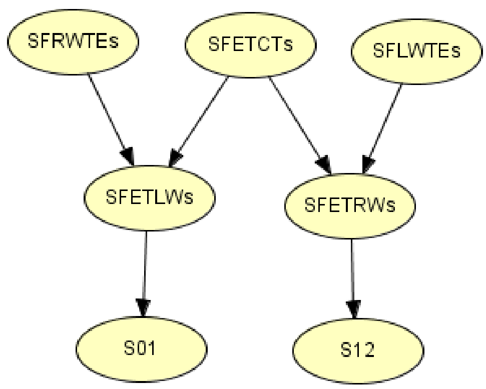

Figure F.11 Relationships of the nodes SFETLWs and SFETRWs (supply from elsewhere to left/right wing)

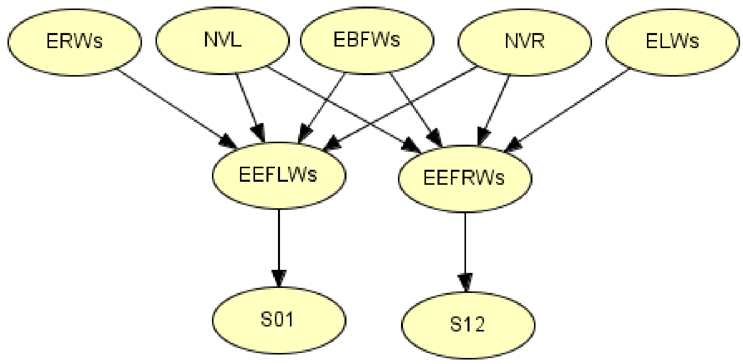

Figure F.12 Relationships of the nodes EEFLWs and EEFRWs (exit elsewhere from left/right wings)

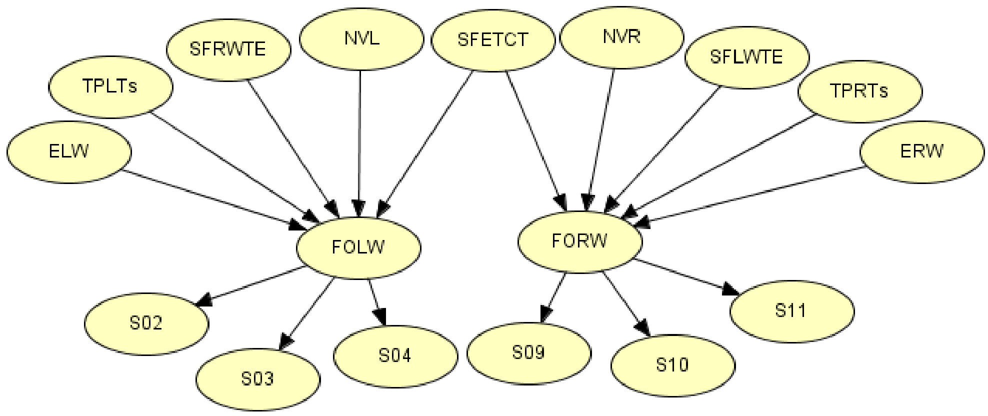

Figure F.13 Relationships of the nodes FOLW and FORW (fuel out left/right wing)

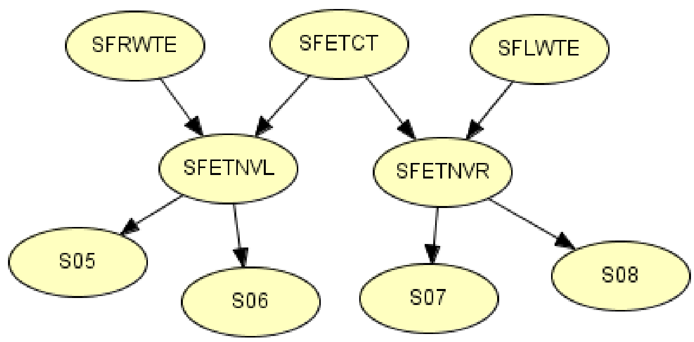

Figure F.14 Relationships of the nodes SFETNVL and SFETNVR (supply from elsewhere to NVL/NVR)

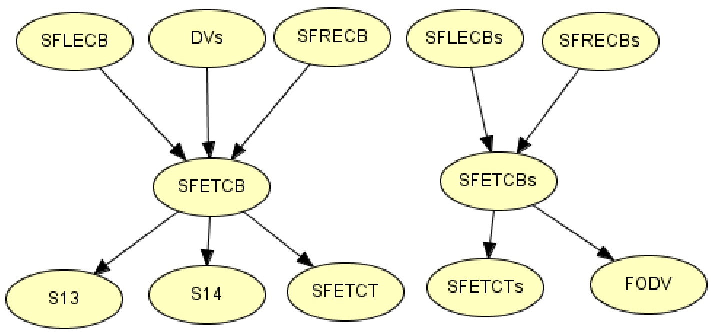

Figure F.15 Relationships of the node SFETCB (supply from engines to centre bottom)

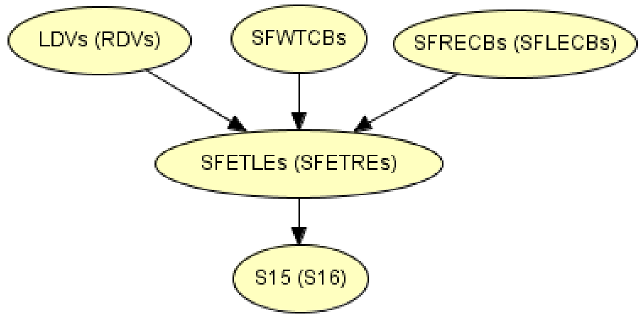

Figure F.16 Relationships of the nodes SFETLEs and SFETREs (supply from elsewhere to left/right engine)

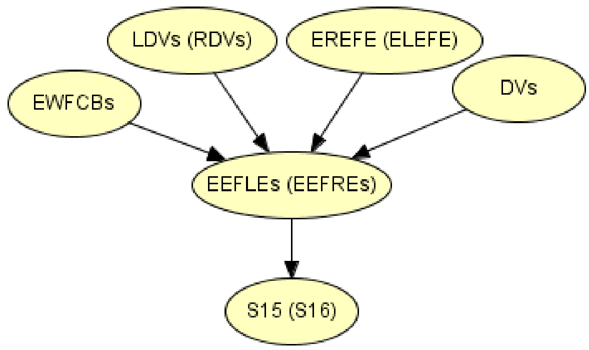

Figure F.17 Relationships of the nodes EEFLEs and EEFREs (exit elsewhere from left/right engine)

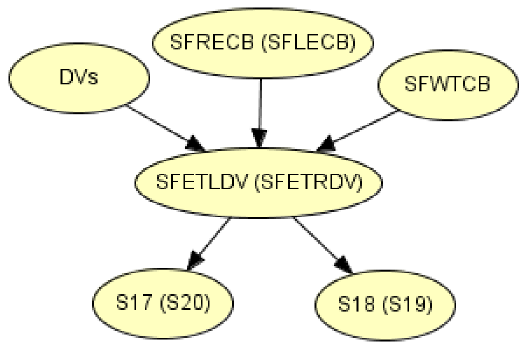

Figure F.18 Relationships of the nodes SFETLDV and SFETRDV (supply from elsewhere to LDV/RDV)

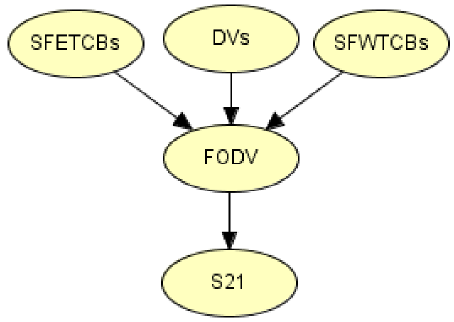

Figure F.19 Relationships of the node FODV (fuel out dump valve). Note, the relationship of node S21 is also presented in this figure.

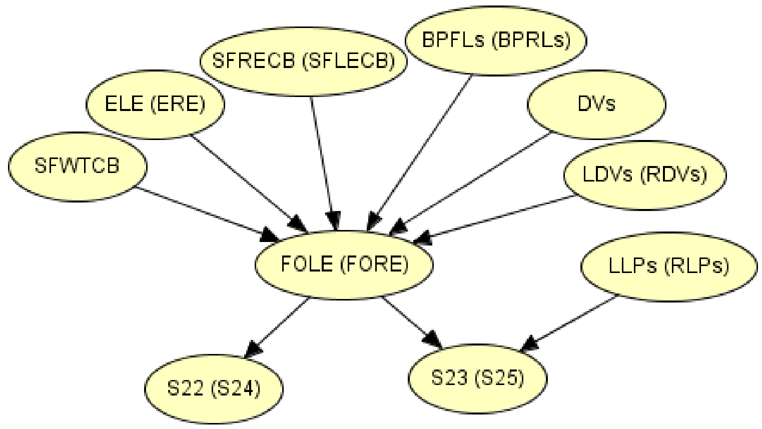

Figure F.20 Relationships of the nodes FOLE and FORE (fuel out left/right engine). Note, the relationships of nodes S22, S23, S24 and S25 are also presented in this figure.

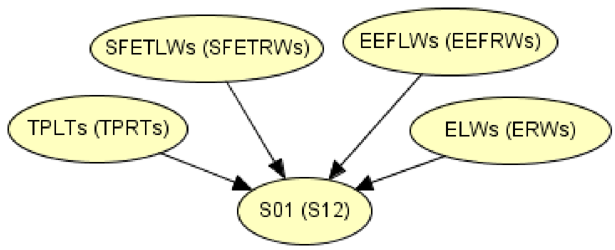

Figure F.21 Relationships of the nodes S01 and S12

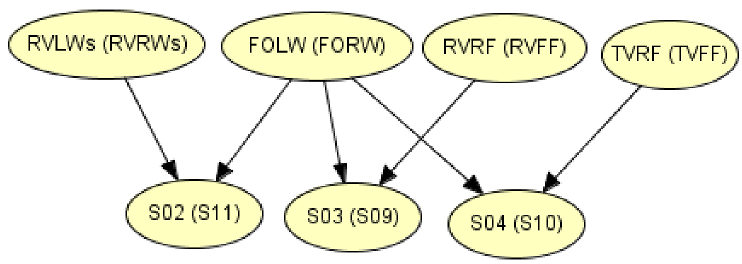

Figure F.22 Relationships of the nodes S02, S03, S04, S09, S10 and S11

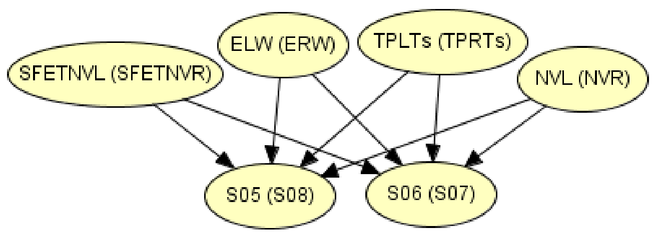

Figure F.23 Relationships of the nodes S05, S06, S07 and S08

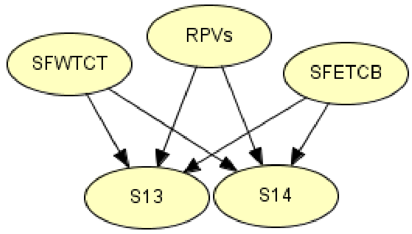

Figure F.24 Relationships of the nodes S13 and S14

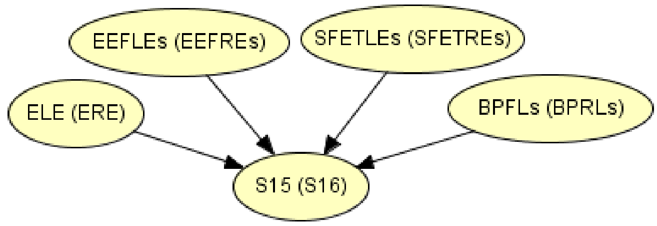

Figure F.25 Relationships of the nodes S15 and S16

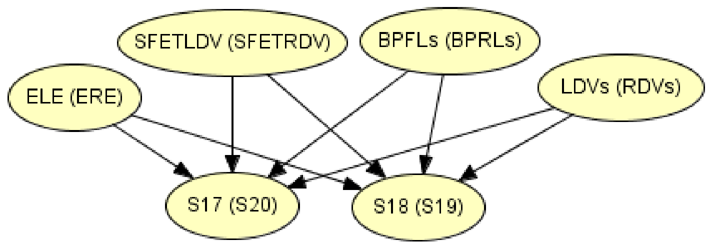

Figure F.26 Relationships of the nodes S17, S18, S19 and S20

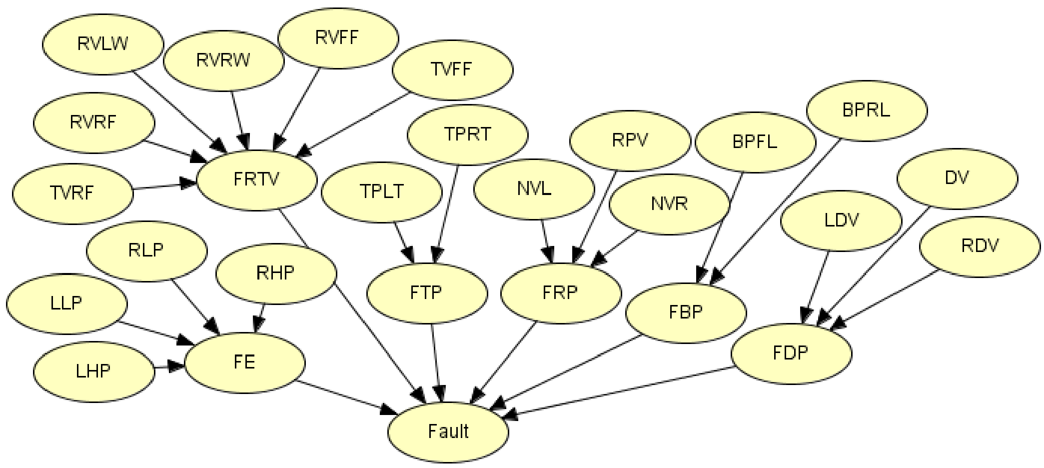

Figure F.27 Relationships of the fault nodes

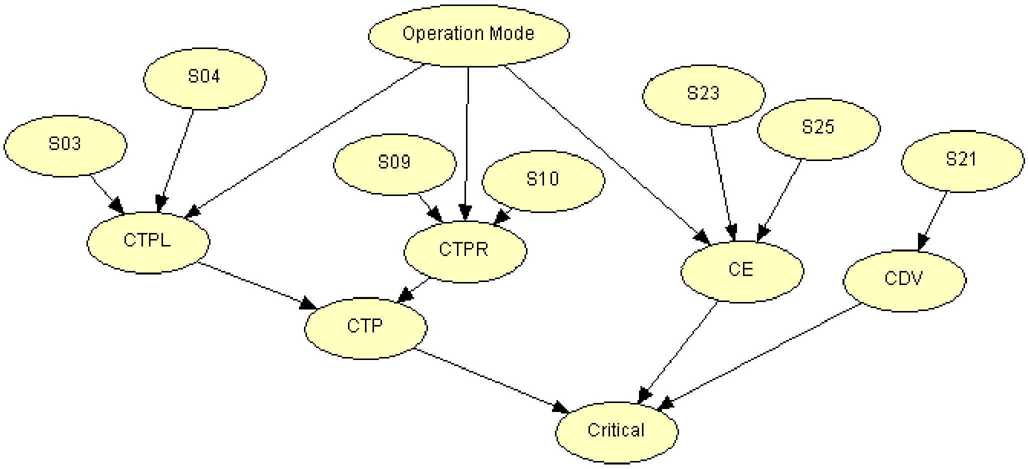

Figure F.28 Relationships of the critical nodes

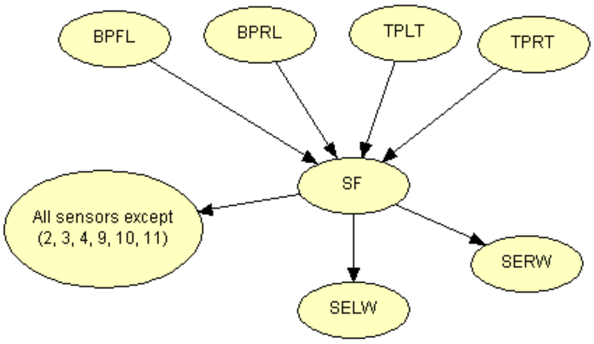

Figure F.29 Relationships of the supply of fuel node (SF)

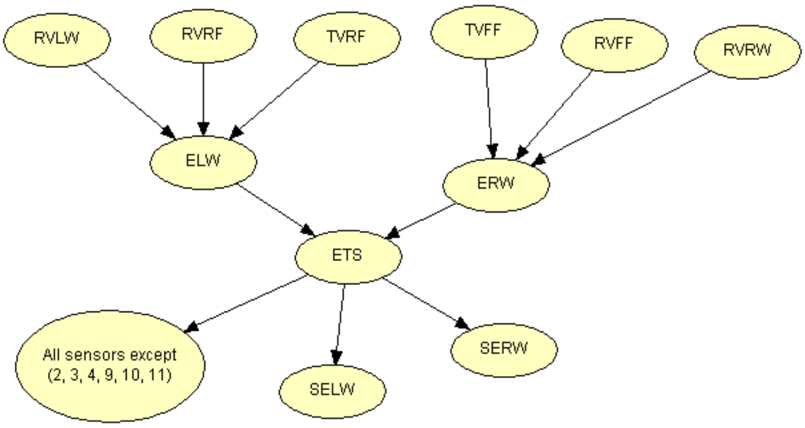

Figure F.30 Relationships of the exits in the top section nodes (ETS)

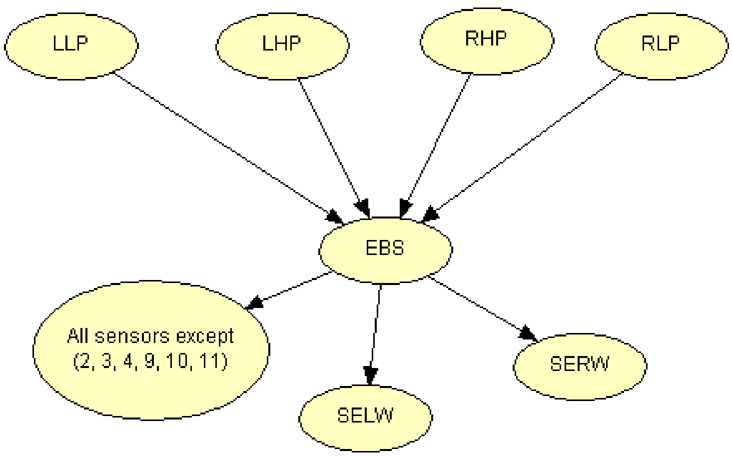

Figure F.31 Relationships of the exits in the bottom section nodes (EBS)

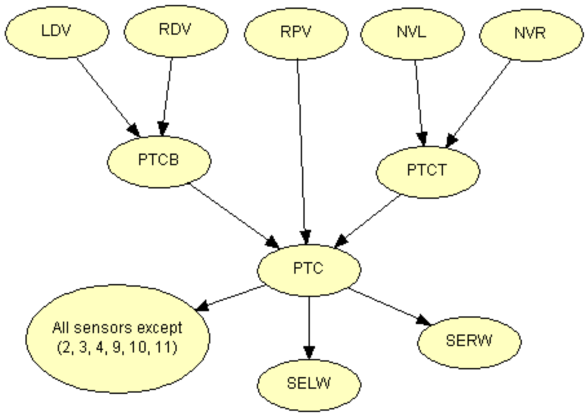

Figure F.32 Relationships of the path to centre nodes (PTC)

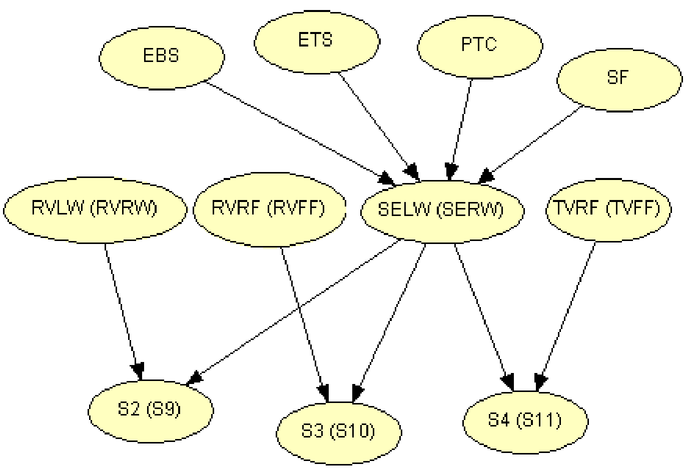

Figure F.33 Relationships of the supply per exit left/right wing nodes (SELW and SERW)

Appendix G

The C++ script for calculating the sensor reading for sensor S1 of the system considered in Chapter 4 is presented in this section. In this script, each of the components are represented by the label given in Table 4.1. The component states are represented by a number, where for the pumps, state 0 is working on, state 1 is failed on, 2 is failed off, and state 3 is working off, and for the valves, state 0 is the working state, state 1 is failed open, and state 2 is failed closed. Note, for the valves, only one working state is observed in the two considered operation modes, hence only three states are required for the valves. For the one directional valves, (NVL and NVR), state 0 represents the working state, state 1 represents the failed two-way mode, and state 2 represents the failed closed mode.

The additional variables, ELE, ERE, EEFW, ELW and EFLW, represent Exit Left Engine, Exit Right Engine, Exit Elsewhere From Wings, Exit Left Wing, and Exit From Left Wing, respectively, i.e. detailing which sections of the system the fuel can exit in. Note, in each case, 0 represents that there is an open exit, and state 1 represents that there is not an open exit.

Note, for the sensor state, 0 represents the state E, -100 represents the state N, and any other number represents the amount of fuel passing through the sensor.

```
int (CalculateS1(int s1))
{
	if ((LLP == 0 || LLP == 1) && (LHP == 0 || LHP == 1))
	{
		ELE = 0;
	}
	else
	{
		ELE = 1;
	}
	if ((RLP == 0 || RLP == 1) && (RHP == 0 || RHP == 1))
	{
		ERE = 0;
	}
	else
	{
		ERE = 1;
	}
	if (RPV == 1)
	{
		if ((ELE == 0 && (LDV == 1 || (RDV == 1 && (CV == 0 || CV == 1)))) ||
			(ERE == 0 && (RDV == 1 || (LDV == 1 && (CV == 0 || CV == 1)))) ||
			DV == 1)
		{
			EEFW = 0;
```

```
		}
		else
		{
			EEFW = 1;
		}
	}
	else
	{
		EEFW = 1;
	}
	if (TVRF == 0 || TVRF == 1 || RVLW == 1 || RVRF == 1)
	{
		ELW = 0;
	}
	else
	{
		ELW = 1;
	}
	if (NVL == 1)
	{
		if ((NVR == 1 || NVR == 0) && (TVFF == 0 || TVFF == 1 || RVRW == 1 ||
			RVFF == 1))
		{
			EFLW = 0;
		}
		else
		{
			if (EEFW == 0)
			{
				EFLW = 0;
			}
			else
			{
				EFLW = 1;
			}
		}
	}
	else
	{
		EFLW = 1;
	}
	if (TPLT == 0 || TPLT == 1)
	{
		if (ELW == 0 || EFLW == 0)
		{
			s1 = 2;
		}
		else
		{
			s1 = -100;
		}
	}
	else
	{
		if (TPLB == 0 || TPLB == 1)
		{
			s1 = -100;
		}
		else
		{
			if (NVL == 0 || NVL == 1)
			{
```

```
                        if (NVR == 1 && (TPRT == 0 || TPRT == 1 || TPRB == 0 ||
                            TPRB == 1))
                        {
                            s1 = -100;
                        }
                        else
                        {
                            if (RPV == 1)
                            {
                                if (((BPFL == 0 || BPFL == 1 || BPFR == 0 ||
                                    BPFR == 1) && (LDV == 1 || (RDV == 1
                                    && (CV == 0 || CV == 1))))  || ((BPRL
                                    == 0 || BPRL == 1 || BPRR == 0 || BPRR
                                    == 1) && (RDV == 1 || (LDV == 1 && (CV
                                    == 0 || CV == 1)))))
                                {
                                    s1 = -100;
                                }
                                else
                                {
                                    s1 = 0;
                                }
                            }
                            else
                            {
                                s1 = 0;
                            }
                        }
                    }
                    else
                    {
                        s1 = 0;
                    }
                }
            }
            return s1;
        }
```

Appendix H

In this appendix, the relationships between the nodes of the BBN presented in Figure 5.7 are presented. Note, as in Appendix F, nodes that end in a lower case "s" have the same description as the nodes with same name, they just slightly simplify the conditional probability tables for the determination of states for other nodes. For example, the pump, BPFL has an additional node, BPFLs. BPFL has four states, working on, failed on, failed off and working off, but for most other nodes, it does not matter whether the pump is working on or failed on, only that it is on. Therefore, BPFLs is added and only has two states, on and off. The nodes in the network presented in Figure 5.7 are presented in Figures H.1 – H.36. Figures H.1 – H.36 are each of the sub-networks in the network. In the sub-networks, the nodes with the grey border are input and output nodes, with input nodes having a dashed border, and output nodes having a solid border. The output nodes can then be used as an input node for other sub-networks. A brief description of the input and output nodes in each of the sub-networks is presented after each figure. Note a description of the components are not given as they can be found in Table 4.1.

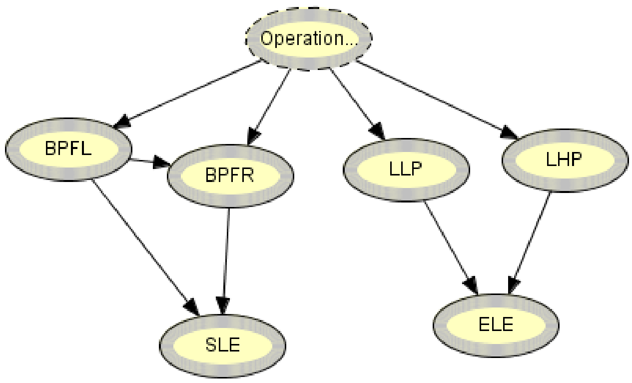

Figure H.1 Relationships of the nodes in the left engine section

- SLE (supply left engine).
- ELE (exit left engine).

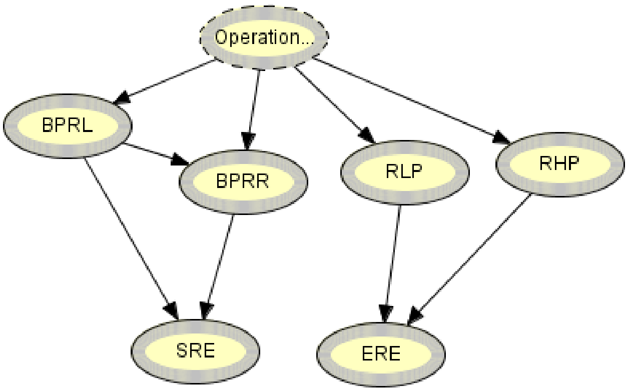

Figure H.2 Relationships of the nodes in the right engine section

- SRE (supply right engine).
- ERE (exit right engine).

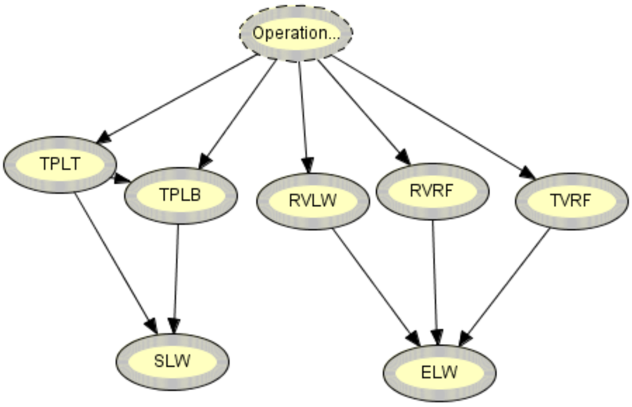

Figure H.3 Relationships of the nodes in the left wing section

- SLW (supply left wing).
- ELW (exit left wing).

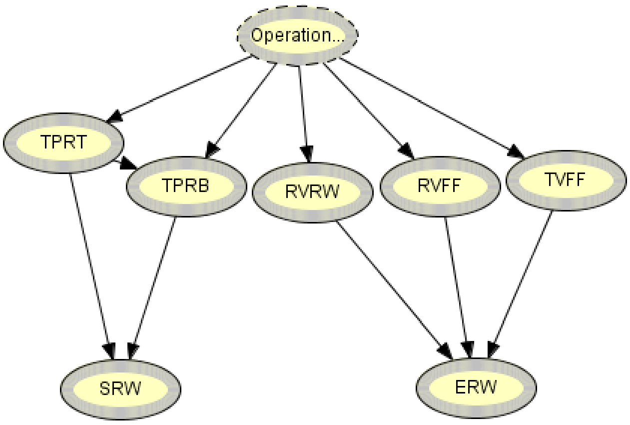

Figure H.4 Relationships of the nodes in the right wing section

- SRW (supply right wing).
- ERW (exit right wing).

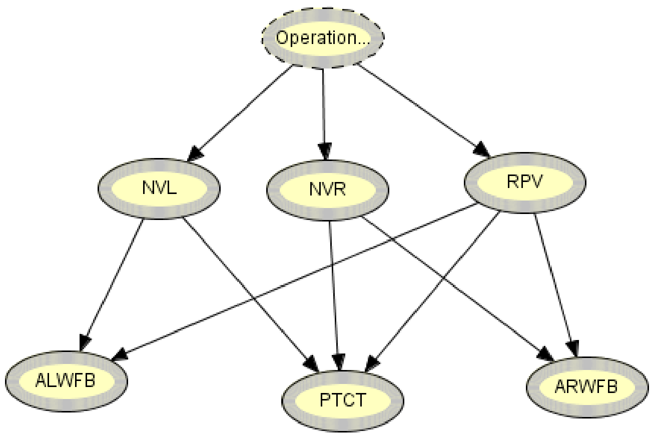

Figure H.5 Relationships of the nodes in the centre top

- ALWFB (access to left wing from bottom).
- PTCT (path to centre top).
- ARWFB (access to right wing from bottom).

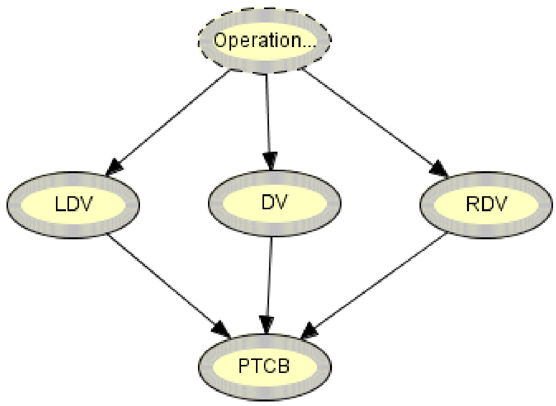

Figure H.6 Relationships of the nodes in the centre bottom.

- PTCB (path to centre bottom).

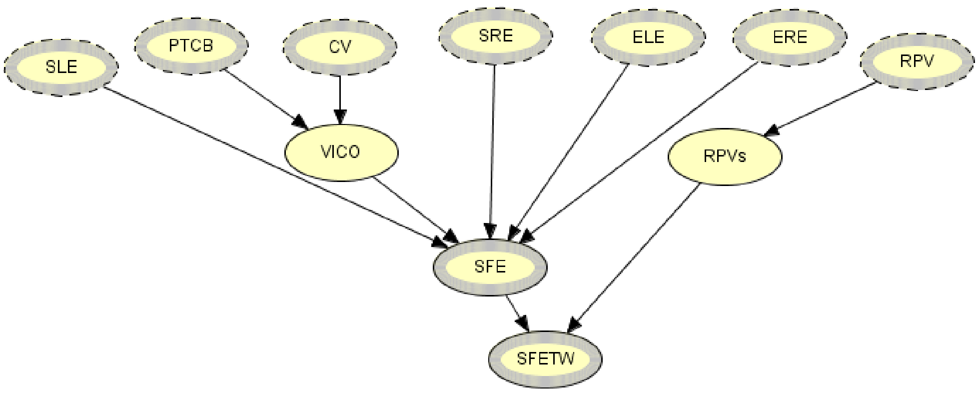

Figure H.7 Relationships of the nodes in supply from engines to wings

- VICO (valves in centre open).
- SFE (supply from engines).
- SFETW (supply from engines to wings).

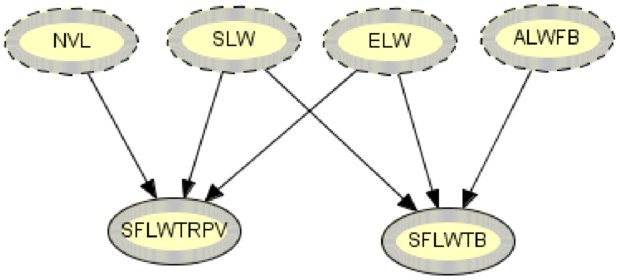

Figure H.8 Relationships of the nodes supply from left wing to bottom

- SFLWTRPV (supply from left wing to RPV).
- SFLWTB (supply from left wing to bottom).

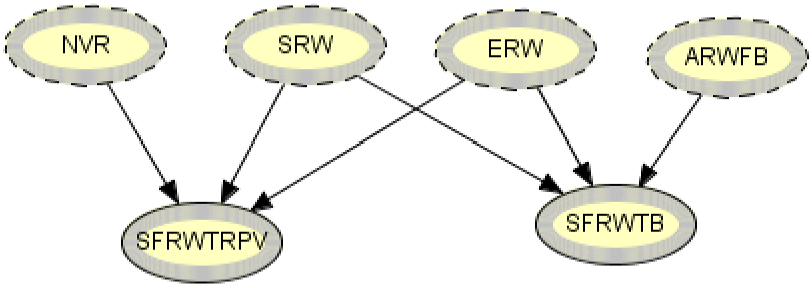

Figure H.9 Relationships of the nodes supply from right wing to bottom

- SFRWTRPV (supply from right wing to RPV).
- SFRWTB (supply from right wing to bottom).

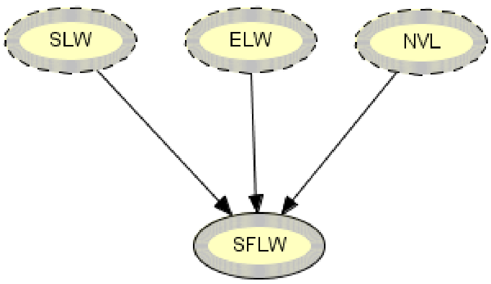

Figure H.10 Relationships of the nodes supply from left wing

- SFLW (supply from left wing).

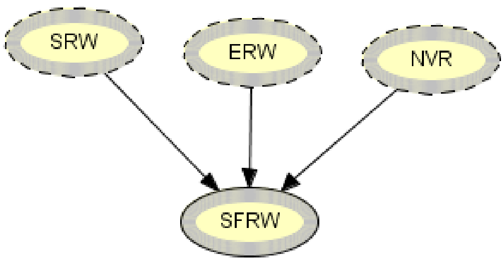

Figure H.11 Relationships of the nodes from right wing

- SFRW (supply from right wing).

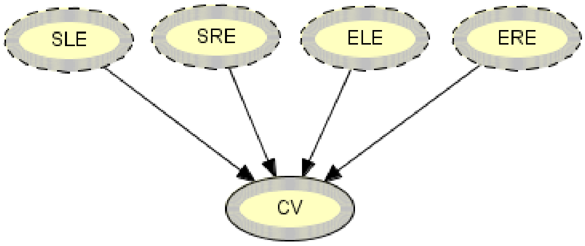

Figure H.12 Relationships of the cross-feed valve (CV)

- CV (cross-feed valve).

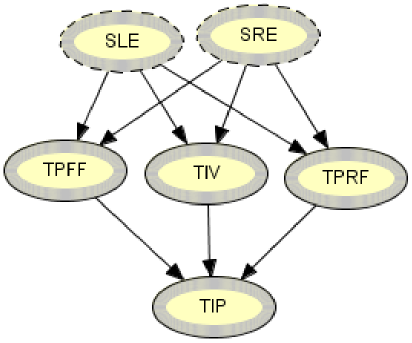

Figure H.13 Relationships for the tank interconnect path

- TIP (tank interconnect path).

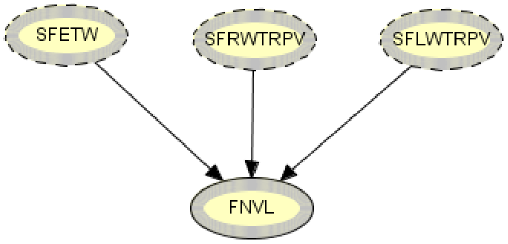

Figure H.14 Relationships for NVL

- FNVL (fuel through NVL).

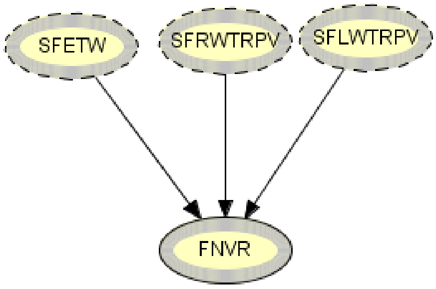

Figure H.15 Relationships for NVR

- FNVR (fuel through NVR).

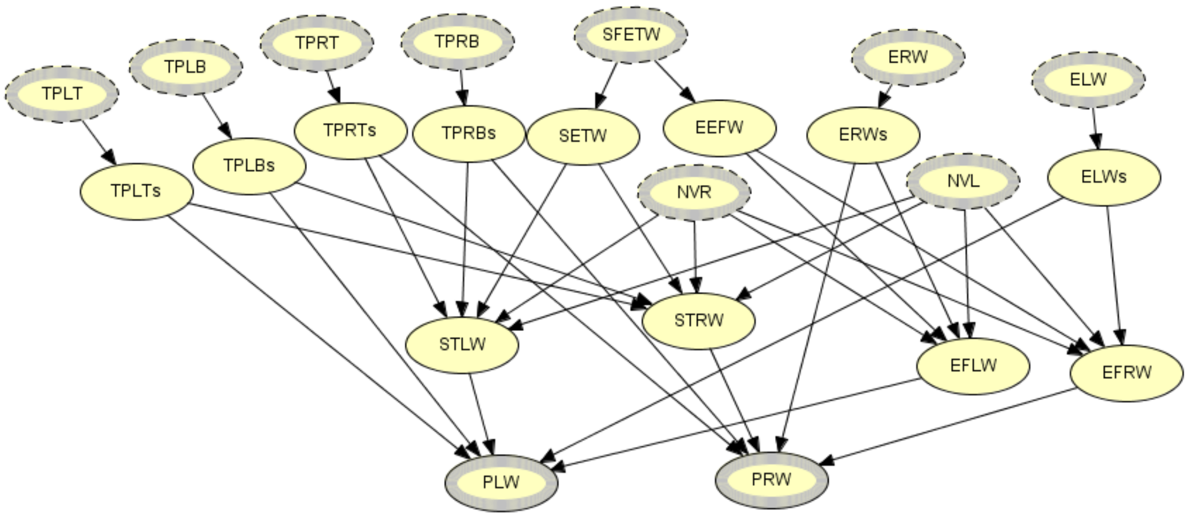

Figure H.16 Relationships for wing pumps

- SETW (supply from engines to wings).
- EEFW (engine exits from wings).
- EFLW (exits from left wing).
- EFRW (exits from right wing).
- STLW (supply to left wing).
- STRW (supply to right wing).
- PLW (pumps left wing).
- PRW (pumps right wing).

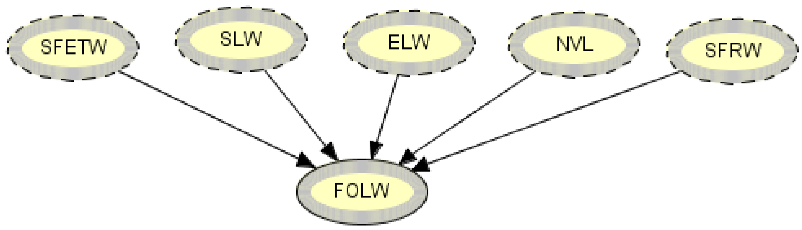

Figure H.17 Relationships fuel out left wing

- FOLW (fuel out left wing).

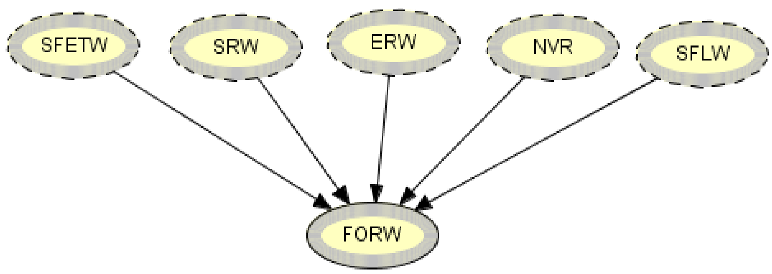

Figure H.18 Relationships fuel out right wing

- FORW (fuel out right wing).

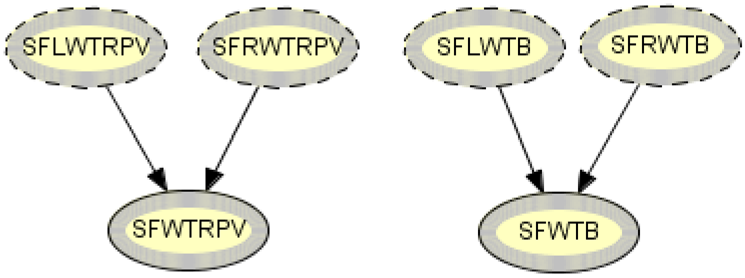

Figure H.19 Relationships for supply from wings

- SFWTRPV (supply from wings to RPV).
- SFWTB (supply from wings to bottom).

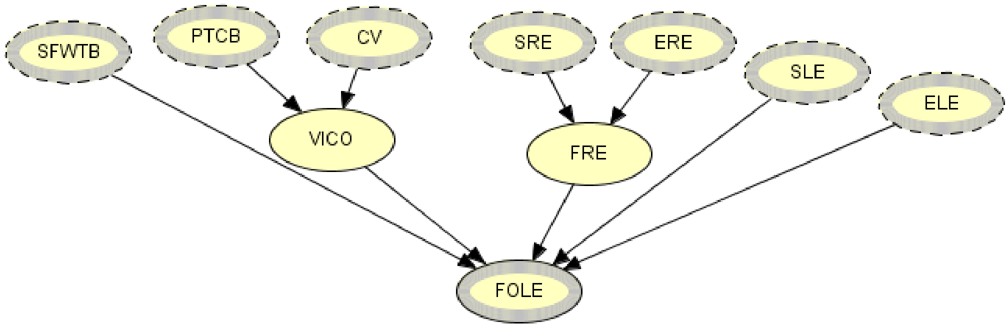

Figure H.20 Relationships for fuel out left engine

- VICO (valves in centre open).
- FRE (fuel right engine).
- FOLE (fuel out left engine).

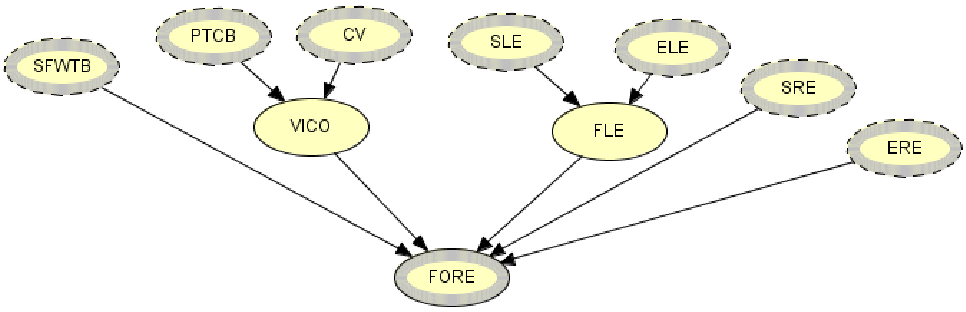

Figure H.21 Relationships for fuel out right engine

- VICO (valves in centre open).
- FLE (fuel left engine).
- FORE (fuel out right engine).

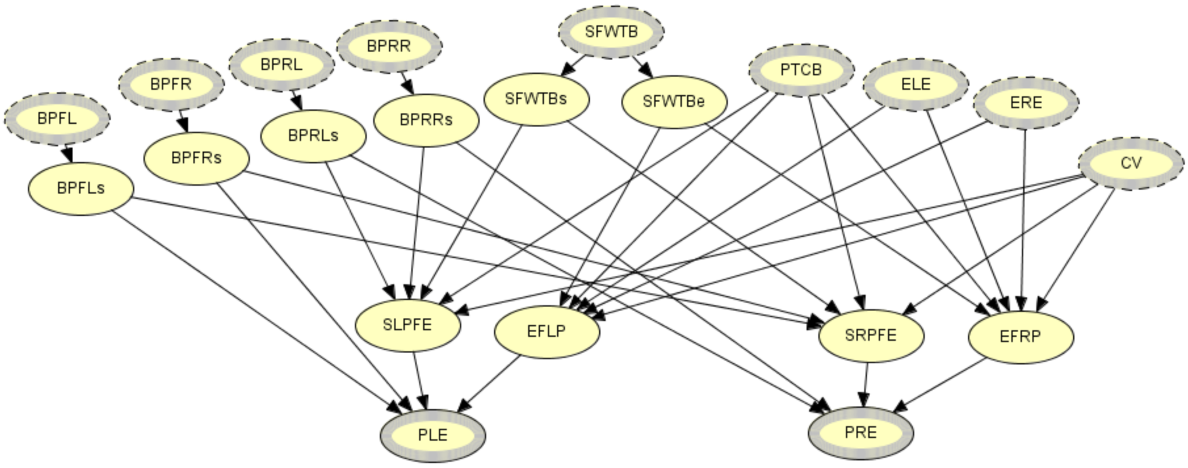

Figure H.22 Relationships for engine pumps

- SFWTBs (supply from wings to bottom supply).
- SFWTBe (supply from wings to bottom exits).
- SLPFE (supply left pumps from elsewhere).
- SRPFE (supply right pumps from elsewhere).
- EFLP (exits from left pumps).
- EFRP (exits from right pumps).
- PLE (pumps left engine).
- PRE (pumps right engine).

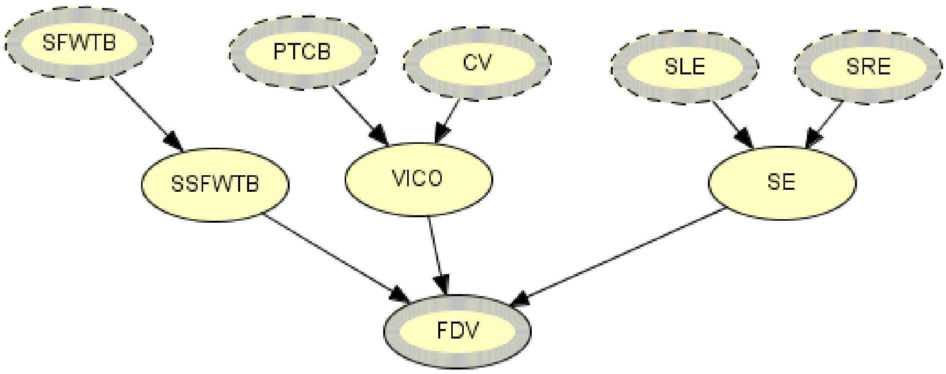

Figure H.23 Relationships at dump valve

- SSFWTB (simple supply from wings to bottom).
- VICO (valves in centre open).
- SE (supply engines).

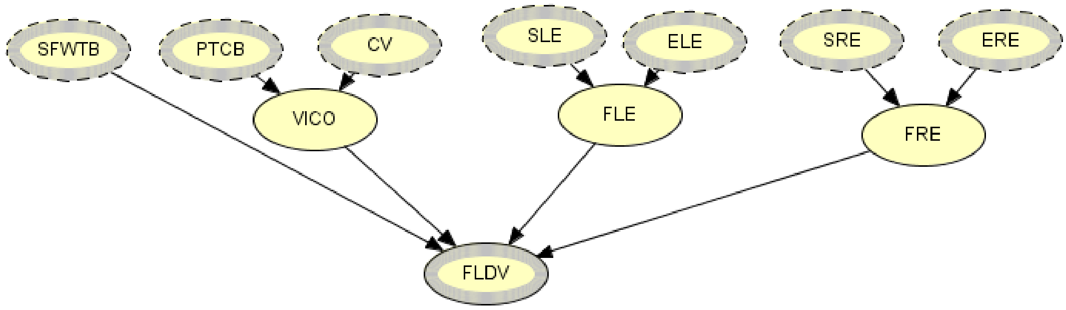

Figure H.24 Relationships at left dump valve

- VICO (valves in centre open).
- FLE (fuel left engine).
- FRE (fuel right engine).
- FLDV (fuel through LDV).

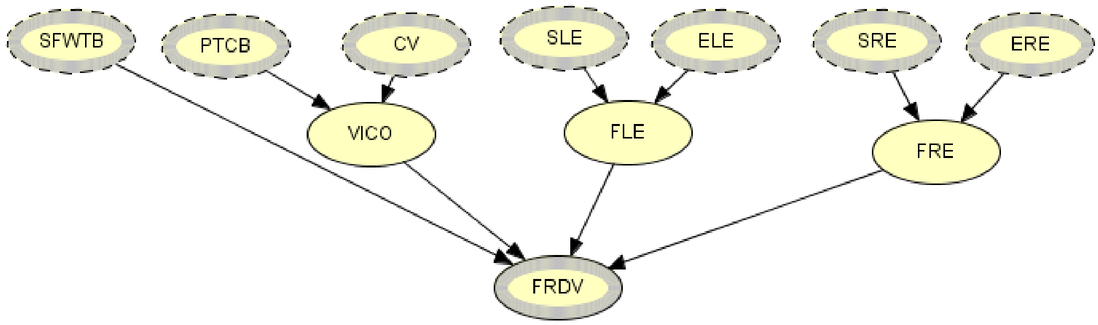

Figure H.25 Relationships at right dump valve

- VICO (valves in centre open).
- FLE (fuel left engine).
- FRE (fuel right engine).
- FRDV (fuel through RDV).

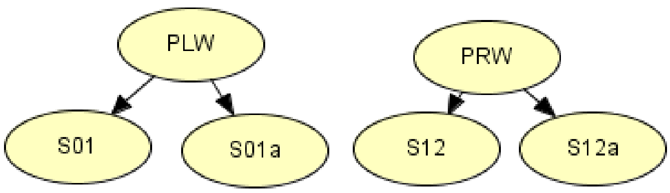

Figure H.26 Relationships for sensors S01, S01a, S12 and S12a

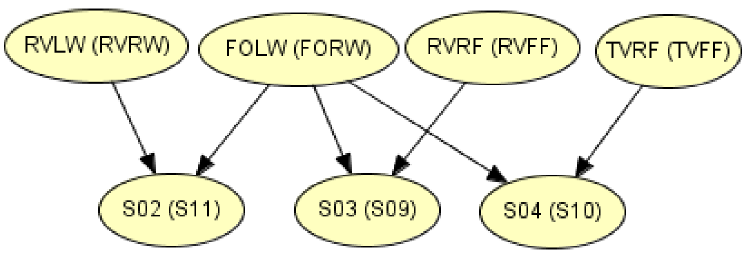

Figure H.27 Relationships for sensors S02, S03, S04, S09, S10 and S11

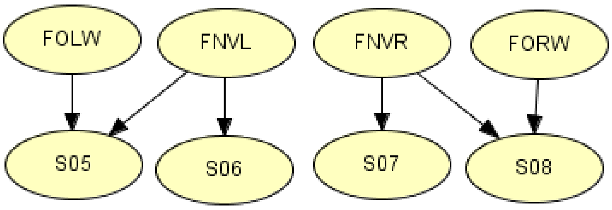

Figure H.28 Relationships for sensors S05, S06, S07 and S08

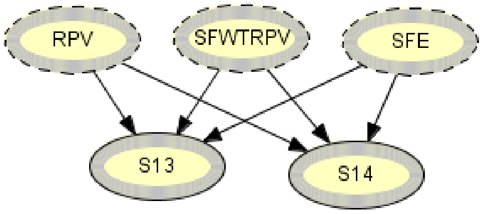

Figure H.29 Relationships for sensors S13 and S14

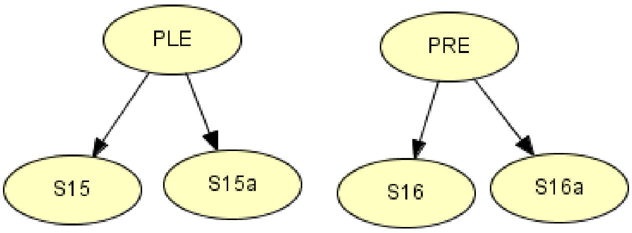

Figure H.30 Relationships for sensors S15, S15a, S16 and S16a

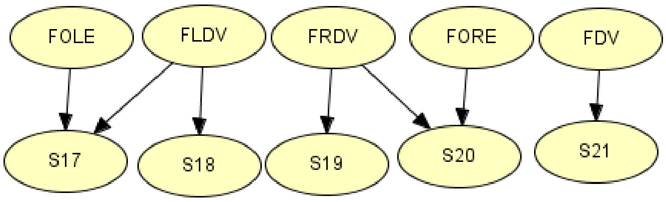

Figure H.31 Relationships for sensors S17, S18, S19, S20 and S21

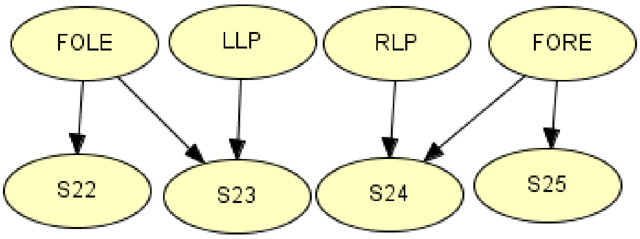

Figure H.32 Relationships for sensors S22, S23, S24 and S25

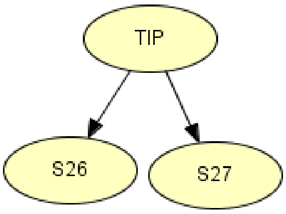

Figure H.33 Relationships for sensors S26 and S27

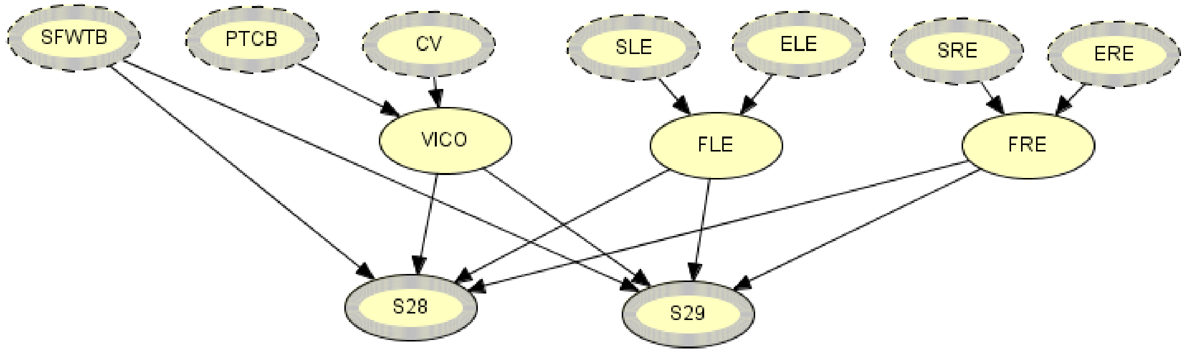

Figure H.34 Relationships for sensors S28 and S29

- VICO (valves in centre open).
- FLE (fuel left engine).
- FRE (fuel right engine).

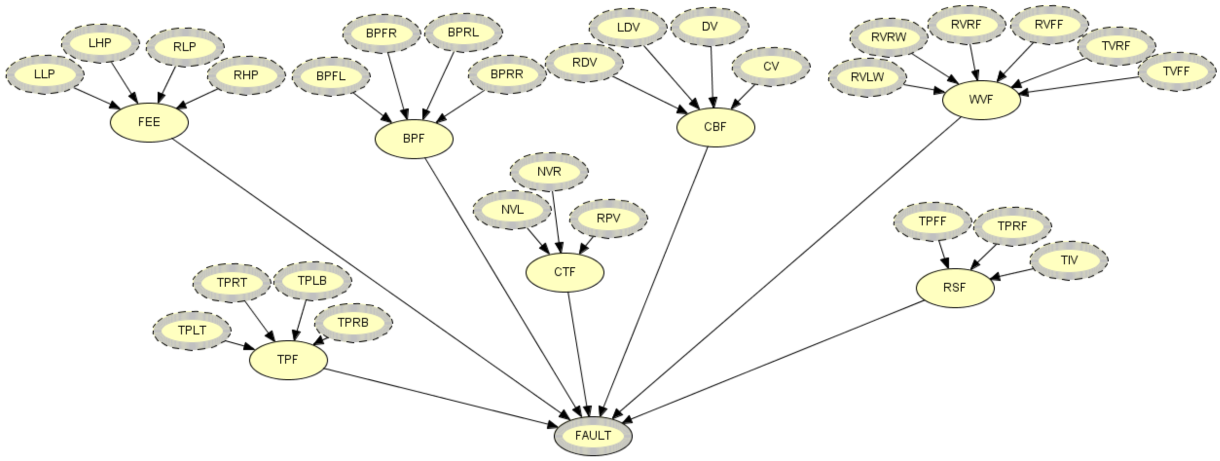

Figure H.35 Relationships for the fault node

- FEE (fault engine exits).
- BPF (booster pump faults).
- CBF (centre bottom faults).
- WVF (wing valve faults).
- TPF (transfer pump faults).
- CTF (centre top faults).
- RSF (tank interconnect section faults).

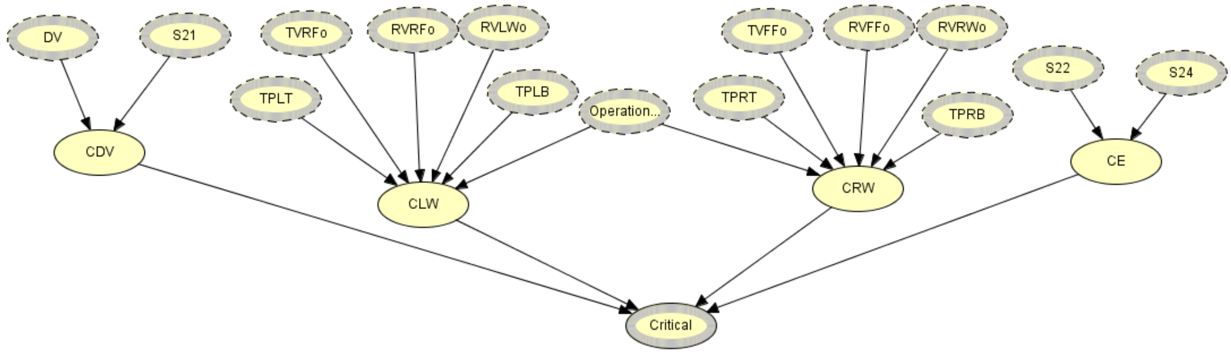

Figure H.36 Relationships for the critical node

- CDV (critical dump valve).
- CLW (critical left wing).
- CRW (critical right wing).
- CE (critical engines).

Appendix I

In this appendix the diagnostic results from section 6.5.3 are presented. The components are grouped into six groups; engine feed (EF) pumps, fuel transfer (FT) pumps, dump (D) pumps, engine feed (EF) valves, cross-feed (CF) valves, and dump and refuel (DR) valves. Tables I.1 – I.6 present the results of the diagnostic process for each of the groups of components, respectively. As in Chapter 5, the probability that each component is in the failure mode is presented after each of the component failures. This is equal to the probability of each failure occurrence divided by the probability of all component failures that produce the observed symptoms, respectively, i.e. P_{mli}/P_{sri}. For example, if the probability in the tables is 50%, then there is a 50% likelihood that the component has failed. In the tables, "a% - b%" refers to a confidence of diagnosis of "a%" initially, but at a later time in the mission, a confidence of diagnosis of "b%" is achieved, where "b" > "a". Some of the component failures are not detected as soon as they occur, therefore, "a%d" refers to a confidence of diagnosis of "a%" but the failure is not detected at the time of occurrence, i.e. there is a delayed detection, $t_d \neq t_f$. Note, details of the length of the delay in detection are not presented due to the number of different variations observed. This is also the case when the confidence of diagnosis changes from "a% - b%", as discussed before. Also note, "0%" diagnosis confidence is used to represent hidden failures.

As before, for brevity, the details of the failures are presented in the form TO-1, where the text before the dash represent the description of the failure, and the text after the dash represents the phase of the mission in which the component fails, i.e. as presented in Table 6.3.

Table I.1 Diagnostic results for the engine feed pumps

Group	Probability	Number	Description
1	100%	262	• L1P1, C/2 all phases, TO-1, TO/2-1, C-1, T-1, T/2-1. • L2P1, TO, TO/2, C/2, T, T/2, 0 all phases, C-1. • R1P1, C/2, 0 all phases, TO-1, TO/2-1, C-1, T-1, T/2-1.

			• R2P1, C/2, all phases, TO-1, TO/2-1, C-1, T-1, T/2-1. • L1P2, TO all phases. TO/2-1, C-1, C/2-1, T-1, T/2-1, T/2-2, T/2-3, T/2-5, T/2-7, T/2-9, T/2-11. • L2P2, TO, TO/2, C, C/2, T, T/2, all phases. • R1P2, R2P2, TO, T/2, all phases, TO/2-1, C-1, C/2-1, T-1.
2	100%d	4	• L1P1, L2P1, R1P1, R2P1, TO-1.
3	50%	240	• L1P1, R1P1, R2P1, TO, TO/2, T, T/2, phases 2 – 11. • L1P2, R1P2, R2P2, TO/2, C, C/2, T/2, phases 2 – 11.
4	16.66%	22	• L1P1, 0, all phases – *Diagnosed incorrectly.* • R2P1, 0, all phases – *Diagnosed incorrectly.*
5	0.707% - 100%	4	• L1P2, L2P2, T/2-4, T/2-6, T/2-8, T/2-10.
6	0%	84	• L1P2, L2P2, R1P2, R2P2, 0, all phases. • L1P1, L2P1, R1P1, R2P1, C, phases 2 – 11.

In Table I.1, all of the failure occurrence times are determined correctly. The component failures in group 2 are detected at the beginning of the next phase, but the correct failure occurrence time is determined. The component failures that are in group 3 are either the primary pump (except L2P1) failing or the corresponding secondary pump (except L2P2) failing in phases 2 – 11. Note, the pump supply rates are different in each case, but always in pairs, for example, either the primary pump is outputting the fuel at the take-off supply rate, or the secondary pump is outputting the fuel at the transfer supply rate. The component failures in group 4 are diagnosed incorrectly. These are the only failures in the system that are not diagnosed correctly. In each case, the corresponding engine feed valve failing closed (i.e. LEV1 for L1P1) results in the same set of symptoms. As the valves have a higher failure rate than the pumps, the failure is diagnosed as the valve failing closed. However, if evidence is introduced to the system that the valve is open, the correct failure will be diagnosed correctly with 100% confidence. The component failures in group 5 are diagnosed incorrectly initially, with 14 other components each having a probability of approximately 3.55% of being in two different states. The components are the dump and refuel valves. At the start of the next phase, the sensor reading changes and the failure is then diagnosed correctly with 100% confidence. The hidden failures in Table I.1, group 6, are the secondary pumps failing off, i.e. the state they are supposed to be in, and the primary pumps failing supply the fuel at the rate normally supplied during the cruise phase in phases 2 – 11, i.e. the state they are supposed to be in. The reason that the pump failure supplying the fuel at the rate that is supplied to the engines during the cruise phase are not hidden in phase 1, is because the pumps should supply fuel at a different rate in the first phase of the mission, i.e. take-off rate.

Table I.2 Diagnostic results for the fuel transfer pumps

Group	Probability	Number	Description
7	100%	45	• LOTP, ROTP, TO/2-10, C-10, C/2-10, T/2-10, 0-10. • LTP, RTP, TO-8, TO/2-8, C-8, C/2-8, T-8, T/2-8. • LMTP, RMTP, TO/2-6, C-6, C/2-6, T/2-6, 0-6. • LITP, RITP, TO/2-4, C-4, C/2-4, T/2-4, 0-4. • LMTP, TO/2-10. • LITP, RITP, C/2-2.
8	100%d	6	• LITP, RITP, 0-1, 0-3. • LTP, RTP, 0-8.
9	50% - 100%	52	• LOTP, ROTP, TO-2, TO-4, TO-6, C/2-2, C/2-4, C/2-6, T-4, T-6, T/2-4, T/2-6. • LOTP, TO/2-4, TO/2-6. • LMTP, RMTP, TO-2, TO-4, C/2-2, C/2-4, T-4, T-6, T/2-4, T/2-10. • LMTP, TO/2-4. • LITP, RITP, TO-6, C/2-6, T-2, T-6, T/2-6, T/2-10. • LITP, TO/2-6.
10	33.33% - 100%	29	• LOTP, ROTP, TO-8, TO-10, C-8, C/2-8, T-2, T-8, T/2-2. • LOTP, TO/2-8.

			• LMTP, RMTP, T-2, T/2-2, T/2-8. • LITP, RITP, TO-4, C-6, T/2-2, 0-2.
11	33.33% - 50% - 100%	16	• LOTP, ROTP, C-4, C-6, T/2-8. • LMTP, RMTP, TO-6, C-4, C/2-8. • LITP, RITP, C/2-8, T/2-8.
12	50% - 100%d	2	• LITP, RITP, T-4.
13	25% - 100%	4	• LOTP, ROTP, C-2. • LITP, RITP, TO/2-2.
14	14.26% - 100%	2	• ROTP, TO/2-4. • RITP, TO/2-6.
15	14.26% - 16.64% - 100%	2	• ROTP, TO/2-6. • RMTP, TO/2-4.
16	14.26% - 50%	2	• RMTP, TO/2-8. • RITP, TO/2-10.
17	12.49% - 16.64% - 100%	1	• ROTP, TO/2-8.
18	12.49% - 33.33% - 100%	3	• ROTP, TO/2-2. • RMTP, TO/2-4. • LITP, C-2.
19	12.49% - 50%	2	• RMTP, TO/2-8. • RITP, TO/2-8.
20	7.68% - 12.49% - 100%	2	• LOTP, TO/2-2. • LMTP, TO/2-2
21	8.33% - 100%	84	• LTP, RTP, TO, TO/2, C, C/2, T, T/2, phases 1 – 7.
22	2.77% - 100%	26	• LOTP, ROTP, TO/2-9, C-9, C/2-9, T/2-9. • LMTP, RMTP, TO/2-5, C-5, C/2-5, T/2-5. • LITP, RITP, TO/2-3, C-3, C/2-1, C/2-3, T/2-3.

23	2.77% - 25% - 50% - 100%	4	• LMTP, RMTP, C-1. • LITP, RITP, TO-1.
24	2.77% - 33.33% - 50% - 100%	16	• LOTP, ROTP, C-3, C-5, T/2-7. • LMTP, RMTP, TO-5, C-3, C/2-7. • LITP, RITP, C/2-7, T/2-7.
25	2.77% - 25% - 100%	4	• LOTP, ROTP, C-1. • LITP, RITP, TO/2-1.
26	2.77% - 33.33% - 100%	30	• LOTP, ROTP, TO-7, TO-9, TO/2-1, TO/2-7, C-7, C/2-7, T-7, T/2-1. • LMTP, RMTP, TO/2-1, T/2-1, T/2-7. • LITP, RITP, TO-3, C-1, C-5, T/2-1.
27	2.77% - 50% - 100%	62	• LOTP, ROTP, TO-1, TO-3, TO-5, TO/2-3, TO/2-5, C/2-1, C/2-3, C/2-5, T-1, T-3, T-5, T/2-3, T/2-5. • LMTP, RMTP, TO-1, TO-3, TO/2-3, C/2-1, C/2-3, T-1, T-3, T-5, T/2-3, T/2-9. • LITP, RITP, TO-5, TO/2-5, C/2-5, T-1, T-3, T-5, T/2-5, T/2-9.
28	2.77%	36	• LOTP, ROTP, TO-11, TO/2-11, C-11, C/2-11, T-11, T/2-11. • LMTP, RMTP, TO-11, TO/2-11, C-11, C/2-11, T-11, T/2-11. • LITP, RITP, TO-11, TO/2-11, C-11, C/2-11, T-11, T/2-11.
29	2.77% - 50%	18	• LOTP, ROTP, T-9. • LMTP, RMTP, TO-9, TO/2-9, C/2-9, T-9. • LITP, RITP, TO-9, TO/2-9, C/2-9, T-9.
30	2.77% - 33.33% - 50%	20	• LMTP, RMTP, TO-7, TO/2-7, C-7, C-9, T-7. • LITP, RITP, TO-7, TO/2-7, C-7, C-9, T-7.
31	50%	15	• LOTP, ROTP, T-10. • LMTP, RMTP, TO-10, C/2-10, T-10. • LITP, RITP, TO-10, C/2-10, T-10.

			• LITP, TO/2-10.
32	20%d	10	• LMTP, RMTP, 0, phases 1 – 5.
33	11.11%d	18	• LOTP, ROTP, 0, phases 1 – 9.
34	14.26%d	14	• LTP, RTP, 0, phases 1 – 7.
35	33.33% - 50%	18	• LMTP, RMTP, TO-8, C-8, C-10, T-8. • LMTP, TO/2-8. • LITP, RITP, TO-8, C-8, C-10, T-8. • LITP TO/2-8.
36	25% - 50% - 100%	4	• LMTP, RMTP, C-2. • LITP, RITP, TO-2.
37	8.33%	36	• LTP, RTP, TO, TO/2, C, C/2, T, T/2, phases 1 – 7.
38	7.67% - 12.48% - 16.64% - 100%	1	• RITP, C-2.
39	0%	32	• LOTP, ROTP, 0-11. • LTP, RTP, 0, phases 9 – 11. • LMTP, RMTP, 0, phases 7 – 11. • LITP, RITP, 0, phases 5 – 11.

In Table I.2 the component failures in group 7 are all detected and diagnosed correctly, at their time of occurrence. Each of the different component failures in this group are when the components fail in the phases in which they are supposed to be active. In group 8, the failures are not detected immediately, they are detected at the start of the next phase of the mission, i.e. when the component is supposed to be active. In group 9 there are initially two possible component failures that could have caused the failure, two different pumps located on the same side of the system, for example, LOTP and LITP. At a later point in the mission, (within the same phase), the confidence of diagnosis changes, and the correct component failure is diagnosed. The next group, group 10, is the same as the previous group, except that when the failure is first detected, there are three possible component failures. The following group, group 11, is when there are three possible failures when the failure is first detected, but at a later stage in the mission, there are two possible failures, and then at a later step only one possible failure, i.e. similar to the previous two groups, but three steps rather than two. The failures in group 12 are similar to the failures in group 9 except that they occur in a phase where the pumps are supposed to be in the state that they have failed in, and therefore, the failures are not detected until the start of the next phase, i.e. when it deviates from its normal operational behaviour. Group 13 follows the same pattern as groups 9 and 10, except that there are four possible failures when the failure is first detected, but then at a later time of the mission, the exact failure is determined. The next group, group 14, consists of component failures which are initially diagnosed incorrectly, with two failures with the probability given in the table, and one with approximately 71% confidence given as the possible solutions. However, within the same phase of the mission, the failure is diagnosed correctly with 100% confidence as the number of possible solutions is reduced. The next group, group 15, is similar to the previous group, except with an intermediate step, where one of the component failures with 14.26% can no longer occur, increasing the probability of the other two failures. The following group, group 16, begins like the previous groups, but the minimum number of possible failures it reduces to throughout the mission is two, both of which are equally likely to occur, therefore resulting in a maximum probability of correct diagnosis of 50%. The next set of groups, groups 17 – 19, are similar to the previous set of groups, groups 14 – 16. The first group, group 17, has four possible failures when the failure is first detected, i.e. three with a probability of 12.49% of being the failure. In group 18 there are four possible failures, three with a probability of 12.49% and one with a probability of approximately 62%. At a later stage in the mission, the failure with approximately 62% probability is no longer possible, making each of the other failures equally likely to have occurred, before the correct failure is diagnosed at a later time step. The final group in this set, group 19, only reduces down to two possible failures throughout the mission, both of which are equally likely to occur. The following group, group 20, has five possible failures initially, three with 7.68% probability, and two with higher probability. At a later time step, one of the failures with higher probability can no longer be the cause of the symptoms, increasing the probability of the other failures. At a later time step, only the actual failure produces the observed symptoms, and is therefore diagnosed with 100% confidence. For the next group, group 21, when the failure is first detected, it can be a failure of one of two components, in each of the 6 states, but the time of failure is diagnosed correctly. In each of the cases, at the start of the 8th phase, the correct component failure is determined. For the next group, group 22, initially the failure can be one of six components failing in six different states, hence a probability of 2.77% initially, but at a later time in the mission, i.e. in the phase where the failed component is supposed to be used, it will be diagnosed correctly. The next group, group 23, begins with the same possible component failures, but at a later time step, there are only four possible failures, followed by two possible failures, followed by the correct failure being diagnosed with 100% confidence at later time steps, respectively. The next group, group 24, is very similar, but instead of four possible failures, there are three possible failures at the second step. The next group, group 25, skips the third step of the previous groups, i.e. from four possible failures to the actual component failure. The group after that, group 26, is the same, except it goes from three possible failures, to the actual failure, and group 27 goes from two possible failures, to the actual failure. The next group, group 28, begins with the same possible failures, but the diagnosis is not improved at a later time in the mission. The next two groups, groups 29 and 30, begin with the same possible failures as the previous groups, but the minimum number of possible failures obtained at later stages of the mission is two. The following group, group 31, is when two component failures produce the same symptoms so there are two possible failures which are equally likely to occur. There is no increase in diagnosis confidence throughout the mission. The following group, group 32, corresponds to a situation when five possible failures could cause the observed symptoms. However, these five failures are the same component failure, just occurring at different times in the mission. The failures are detected at the start of the sixth phase. The same is the case with group 33, except that there are nine potential times of the same failure occurring, and the failures are detected at the start of the tenth phase of the mission. Group 34 consists of seven different failure times for the same component failure, which is detected at the start of the eighth phase, i.e. the component failure is known, just not its time of occurrence as in the previous two groups. The failures in group 35 are when initially there are three possible failures, but at some point later on in the mission, it reduces to two possible failures. The next group, group 36, consists of cases where there are four possible component failures that produce the observed symptoms initially, but at a later point in the mission, only two component failures produce the same set of observed symptoms, and finally, at a later point in the mission, only one component failure produces the symptoms, and is therefore diagnosed correctly with 100% confidence. Group 37 consists of one of two component failing in any of 6 modes, therefore, there is a 50% probability that the correct component will be inspected initially. The penultimate group, group 38, is similar to some of the earlier groups, in that initially there are five possible failures, three with a probability of 7.67% and the other two with probabilities of approximately 38%. At a later point in the mission, one of the failures that initially had a probability of approximately 38% no longer produces the observed symptoms, and is therefore not one of the possible solutions. After this, the group is the same as the group, “12.49% - 16.64% - 100%”, except a different component has failed than is in that group. The final group, group 39, is the failures that are not detected by the sensors. The failures are the component failing in the off failure mode after they have transferred the fuel to a different tank, i.e. when the pumps are no longer required.

Table I.3 Diagnostic results for the dump pumps

Group	Probability	Number	Description
40	4.167%	264	• LMDP, LIDP, RMDP, RIDP, TO, TO/2, T, T/2, C, C/2, all phases.
41	0%	44	• LMDP, LIDP, RMDP, RIDP, 0, all phases.

In Table I.3, all of the component failures that are detected produce the same set of symptoms, therefore, each of the 4 components can fail in any of 6 modes in which they output fuel, and the selection of sensors cannot distinguish between them. Therefore, there is a probability of 25% that the component that has failed is inspected first. All of the component failures are detected as soon as they occur. The hidden failures in Table I.3, group 41, are the pumps failing off, i.e. in the state they are supposed to be in.

Table I.4 Diagnostic results for the engine feed valves

Group	Probability	Number	Description
42	100%	22	• LEV2, REV1, Cl, all phases
43	83.44%	22	• LEV1, REV2, Cl, all phases
44	0%	88	• LEV1, LEV2, REV1, REV2, Op, Op/2, all phases

In Table I.4, the component failures are all detected as soon as they occur. The component failures in group 43 correspond to the other failure that has actually occurred in the group, "16.66%" in Table I.1, the group where the failure is diagnosed incorrectly. Therefore, these component failures are diagnosed correctly as they are more likely to occur than the corresponding pump failure. The hidden failures, group 44, can be split into two categories, the first of which is where the valves fail open. These failures are hidden because the components fail in their normal operating state. The other category is when the valves fail half open. These component failures are not detected because there are no other valves that are open in parallel with these components, and therefore, all the fuel must pass through these valves, the failures are not detected.

Table I.5 Diagnostic results for the dump and refuel valves

Group	Probability	Number	Description
45	100%	52	• LOTV, ROTV, Op/2-2. • LMTV, RMTV, Op/2-2. • LOETV, Op-2, Op/2-2, Op/2-4, Op/2-6, O/2-8, Op/2-10, Cl-4, Cl-6, Cl-8, Cl-10. • ROETV, Op/2-4, Op/2-6, Op/2-8, Op/2-10. • LIEV1, RIEV1, Op/2-4, Op/2-6, Op/2-8, Op/2-10, Cl-4, Cl-6, Cl-8, Cl-10. • LIEV2, RIEV2, Op-4, Op-6, Op-8, Op-10, Op/2-4, Op/2-6, Op/2-8, Op/2-10. • FTTV, Cl-8. • TTDV, Cl-8.
46	100%d	55	• LOTV, ROTV, Op/2-1, Cl-1, Cl-2. • LMTV, Op-1, Op/2-1. • RMTV, Op/2-1. • LOETV, Op-1, Op/2-1, Op/2-3, Op/2-5, Op/2-7, Op/2-9, Cl-5, Cl-7, Cl-9. • ROETV, Op/2-3, Op/2-5, Op/2-7, Op/2-9, Cl-5, Cl-7, Cl-9. • LIEV1, RIEV1, Op/2-3, Op/2-5, Op/2-7, Op/2-9, Cl-5, Cl-7, Cl-9. • LIEV2, RIEV2, Op-3, Op-5, Op-7, Op-9, Op/2-3, Op/2-5, Op/2-7, Op/2-9.
47	71.47% - 100%	1	• ROETV, Cl-10.
48	38.49% - 100%	1	• RMTV, Op-2.
49	71.47% - 83.36% - 100%	2	• ROETV, Cl-4, Cl-6.
50	62.56% - 83.36% - 100%	1	• ROETV, Cl-8.

51	38.49% - 62.56% - 83.36% - 100%	1	• ROETV, Op-2.
52	62.56% - 100%	1	• LMTV, Op-2.
53	50% - 100%	33	• LOTV, ROTV, Op-4, Op-6, Op-8, Op/2-4, Op/2-8, Op/2-10. • LMTV, RMTV, Op-4, Op-6, Op-8, Op/2-4, Op/2-6, Op/2-8. • ROETV, Op/2-2. • LIEV1, RIEV1, Op-2, Op/2-2. • LIEV2, RIEV2, Op-2, Op/2-2.
54	50% - 100%d	31	• LOTV, ROTV, Op-5, Op-7, Op/2-3, Op/2-5, Op/2-7. • LMTV, Op-5, Op-7, Op/2-3, Op/2-5, Op/2-7. • RMTV, Op-1, Op-5, Op-7, Op/2-3, Op/2-5, Op/2-7. • ROETV, Op-1, Op/2-1. • LIEV1, RIEV1, Op-1, Op/2-1. • LIEV2, RIEV2, Op-1, Op/2-1.
55	50%	16	• LOTV, ROTV, Op-10, Op/2-10. • LMTV, RMTV, Op-10, Op/2-10. • FTTV, Op-2, Op-4, Op-6, Op-10, Op/2-2, Op/2-4, Op/2-6, Op/2-10.
56	50%d	14	• LOTV, ROTV, Op-9, Op/2-9. • LMTV, RMTV, Op-9, Op/2-9. • FTTV, Op-1, Op-3, Op-5, Op/2-1, Op/2-3, Op/2-5.
57	33.33%d	12	• LOETV, ROETV, Cl-1, Cl-2, Cl-3. • LIEV1, RIEV1, Cl-1, Cl-2, Cl-3.
58	25% - 33.33%d	6	• LOTV, ROTV, Op-1, Op-2, Op-3.
59	25% - 100%d	2	• LMTV, RMTV, Op-3.

60	25%d	16	• LFVP, RFVP, Op-1, Op-3, Op-5, Op-9, Op/2-1, Op/2-3, Op/2-5, Op/2-9.
61	25%	20	• LITV, RITV, Op-8, Op/2-8. • LFVP, RFVP, Op-2, Op-4, Op-6, Op-10, Op/2-2, Op/2-4, Op/2-6, Op/2-10.
62	5.55% - 25%d	4	• LFVP, RFVP, Op-7, Op/2-7.
63	5.55% - 7.15%d	14	• DTV, Op, Op/2, phases 1 – 7.
64	16.66% - 50%	2	• DTV, Op-8, Op/2-8
65	16.66% - 25%	4	• LFVP, RFVP, Op-8, Op/2-8.
66	16.66%d	6	• FTTV, Op-7, Op-8, Op-9, Op/2-7, Op/2-8, Op/2-9.
67	14.3%d	14	• FTTV, Cl, phases 1 – 7. • TTDV, Cl, phases 1 – 7.
68	3.57%d	140	• LRV, RRV, Op-1, Op-3, Op-5, Op-7, Op-9, Op/2-1, Op/2-3, Op/2-5, Op/2-7, Op/2-9. • LODV, RODV, Op-1, Op-3, Op-5, Op-7, Op-9, Op/2-1, Op/2-3, Op/2-5, Op/2-7, Op/2-9. • LDV, RDV, Op-1, Op-3, Op-5, Op-7, Op-9, Op/2-1, Op/2-3, Op/2-5, Op/2-7, Op/2-9. • LOEDV, ROEDV, Op-1, Op-3, Op-5, Op-7, Op-9, Op/2-1, Op/2-3, Op/2-5, Op/2-7, Op/2-9. • LMDV, RMDV, Op-1, Op-3, Op-5, Op-7, Op-9, Op/2-1, Op/2-3, Op/2-5, Op/2-7, Op/2-9. • LITV1, RITV1, Op-1, Op-3, Op-5, Op-7, Op-9, Op/2-1, Op/2-3, Op/2-5, Op/2-7, Op/2-9. • LITV2, RITV2, Op-1, Op-3, Op-5, Op-7, Op-9, Op/2-1, Op/2-3, Op/2-5, Op/2-7, Op/2-9.
69	3.54% - 3.57%	112	• LRV, RRV, Op-4, Op-6, Op-8, Op-10, Op/2-4, Op/2-6, Op/2-8, Op/2-10. • LODV, RODV, Op-4, Op-6, Op-8, Op-10, Op/2-4, Op/2-6, Op/2-8, Op/2-10.

			• LDV, RDV, Op-4, Op-6, Op-8, Op-10, Op/2-4, Op/2-6, Op/2-8, Op/2-10. • LOEDV, ROEDV, Op-4, Op-6, Op-8, Op-10, Op/2-4, Op/2-6, Op/2-8, Op/2-10. • LMDV, RMDV, Op-4, Op-6, Op-8, Op-10, Op/2-4, Op/2-6, Op/2-8, Op/2-10. • LITV1, RITV1, Op-4, Op-6, Op-8, Op-10, Op/2-4, Op/2-6, Op/2-8, Op/2-10. • LITV2, RITV, Op-4, Op-6, Op-8, Op-10, Op/2-4, Op/2-6, Op/2-8, Op/2-10.
70	3.57%	28	• LRV, RRV, Op-2. • LODV, RODV, Op-2. • LDV, RDV, Op-2. • LOEDV, ROEDV, Op-2. • LMDV, RMDV, Op-2. • LITV1, RITV1, Op-2. • LITV2, RITV, Op-2.
71	3.57%d	28	• LTTV, RTTV, Op, Op/2, phases 1 – 7.
72	0%	473	• LRV, RRV, Op-11, Op/2-11, Cl-1, Cl-2, Cl-3, Cl-4, Cl-5, Cl-6, Cl-7, Cl-8, Cl-9, Cl-10, Cl-11. • LODV, RODV, Op-11, Op/2-11, Cl-1, Cl-2, Cl-3, Cl-4, Cl-5, Cl-6, Cl-7, Cl-8, Cl-9, Cl-10, Cl-11. • LDV, RDV, Op-11, Op/2-11, Cl-1, Cl-2, Cl-3, Cl-4, Cl-5, Cl-6, Cl-7, Cl-8, Cl-9, Cl-10, Cl-11. • LOEDV, ROEDV, Op-11, Op/2-11, Cl-1, Cl-2, Cl-3, Cl-4, Cl-5, Cl-6, Cl-7, Cl-8, Cl-9, Cl-10, Cl-11. • LMDV, RMDV, Op-11, Op/2-11, Cl-1, Cl-2, Cl-3, Cl-4, Cl-5, Cl-6, Cl-7, Cl-8, Cl-9, Cl-10, Cl-11. • LITV1 RITV1, Op-11, Op/2-11, Cl-1, Cl-2, Cl-3, Cl-4, Cl-5, Cl-6, Cl-7, Cl-8, Cl-9, Cl-10, Cl-11.

- LITV2, RITV2, Op-11, Op/2-11, Cl-1, Cl-2, Cl-3, Cl-4, Cl-5, Cl-6, Cl-7, Cl-8, Cl-9, Cl-10, Cl-11.
- LOTV, ROTV, Op-11, Op/2-11, Cl-3, Cl-4, Cl-5, Cl-6, Cl-7, Cl-8, Cl-9, Cl-10, Cl-11.
- LOETV, ROETV, Op-3, Op-4, Op-5, Op-6, Op-7, Op-8, Op-9, Op-10, Op-11, Op/2-11, Cl-11.
- LIEV1, RIEV1, Op-3, Op-4, Op-5, Op-6, Op-7, Op-8, Op-9, Op-10, Op-11, Op/2-11, Cl-11.
- LIEV2, RIEV2, Op-11, Op/2-11, Cl-1, Cl-2, Cl-3, Cl-4, Cl-5, Cl-6, Cl-7, Cl-8, Cl-9, Cl-10, Cl-11.
- LMTV, RMTV, Op-11, Op/2-11, Cl-1, Cl-2, Cl-3, Cl-4, Cl-5, Cl-6, Cl-7, Cl-8, Cl-9, Cl-10, Cl-11.
- LFVP, RFVP, Op-11, Op/2-11, Cl-1, Cl-2, Cl-3, Cl-4, Cl-5, Cl-6, Cl-7, Cl-8, Cl-9, Cl-10, Cl-11.
- DTV, LTTV, RTTV, Op-9, Op-10, Op-11, Op/2-9, Op/2-10, Op/2-11, Cl-1, Cl-2, Cl-3, Cl-4, Cl-5, Cl-6, Cl-7, Cl-8, Cl-9, Cl-10, Cl-11.
- FTTV, Op-11, Op/2-11, Cl-9, Cl-10, Cl-11.
- TTDV, Op-1, Op-2, Op-3, Op-4, Op-5, Op-6, Op-7, Op-8, Op-9, Op-10, Op-11, Op/2-1, Op/2-2, Op/2-3, Op/2-4, Op/2-5, O/2-6, Op/2-7, Op/2-8, Op/2-9, Op/2-10, Op/2-11, Cl-9, Cl-10, Cl-11.
- LSV, RSV, all hidden.

In Table I.5, the first group, group 45, consists of component failures that are detected and diagnosed with 100% confidence at their time of occurrence. The failures in this group are all when the transfer pumps are active. The components in the next group, group 46, are all diagnosed correctly with 100% confidence, but all occur in phases where the transfer pumps are not active, and are therefore not detected until the start of the next phase of the mission. In the following group, group 47, initially there are three possible failures that produce the observed symptoms, one of which has a probability of 71.47% and the other two have probabilities of approximately 14%, at a later point in the mission, the other two failures no longer produce the observed symptoms, and therefore, the failure is diagnosed with 100% confidence. The same is the case with the next group, group 48, except that there are two failures with a probability of 38.49% and three other failures with a probability of approximately 7%. At a later point in the mission, only one of the failures produces the symptoms observed, and therefore, the failure is diagnosed with 100% confidence. The next group, group 49, has three possible causes for the symptoms when the failure is first detected, but at a later time, one of the failures no longer produces the observed symptoms, and then later, another failure no longer produces the observed symptoms, resulting in a diagnosis confidence of 100%. The following group, group 50, is the same as the previous group, except that there are initially four possible failures that produce the observed symptoms. Group 51 is the same as group 50 except that initially there are five possible failures, but at a later time one of the failures is no longer possible, at which point, it is the same as the previous group. When the failure is detected for the next group, group 52, there are four possible failures that produce the observed symptoms, one of which has a probability of 62.56%, and the three others have probabilities of approximately 12%, but at a later time step in the mission, the other three failures no longer produce the observed symptoms, and the failure is then diagnosed with 100% confidence. The next group, group 53, is cases when the observed symptoms can be produced initially by one of two failures, but at a later time in the mission, only one of the failures produces the observed symptoms, and the failure is therefore diagnosed correctly. The failures in this group occur when the transfer pumps are active. The next group, group 54, is the same as the previous group, except the failures occur in phases of the mission where the transfer pumps are not active, and the failures are therefore not detected until the start of the following phase, when the transfer pumps are active. The next group, group 55, consists of cases when there are two possible causes for the failure, and the failure occurs when the transfer pumps are active. In this case, the failures are one component failing in one of two possible modes, i.e. the correct component is always diagnosed, but the mode is not known. The other failures in this case are when it is one of two components that has failed. The next case, group 56, is the same, except that the failures occur when the pumps are not active, and are therefore not detected until the start of the next phase. In the next group, group 57, there is only one possible failure, but the failure is not detected until the start of the fourth phase, and therefore it is not known which phase the component failed in, i.e. the component failure is always known, but the time of occurrence is not. The next group, group 58, is when the failure is detected at the start of the fourth phase, and can be one of four component failures, three of which are the same component failing in different phases. At a later time, the fourth possible failure can no longer produce the observed symptoms, and the component is therefore diagnosed correctly, it is just the time of failure occurrence which is not known. The next group, group 59, is when the component failure is the fourth failure from the previous group, and therefore, at a later point in the mission the failure is diagnosed with 100% confidence. The next group, group 60, consists of cases where there are four possible failures that can produce the observed symptoms, two possible failures for each component occurring at the same time, i.e. 50% probability of selecting the correct component. The failures in this case occur in a phase where the transfer pumps are not active, and they are detected at the start of the next phase. The failures in the following group, group 61, are the same, except that they occur in a phase where the transfer pumps are active and are detected as soon as they occur. The next group, group 62, is when there are three potential components that could have failed, one of which has fourteen potential failures, and the other two have two potential failures. At a later point in the mission, the fourteen failures produce different symptoms to those observed, and result in a case similar to the previous group. The following group, group 63, is the opposite way round to the previous group, i.e. at a later point in the mission, the other four failures produce a different set of symptoms to those observed. Therefore, the component will be diagnosed 100% correctly, but the time of failure occurrence, and the mode in which the component has failed in, is not determined. When the failures in the next group, group 64, are first detected, there are three possible components that produce the observed symptoms, two failures for each component, but at a later time, only one component can produce the observed symptoms, and the component is therefore diagnosed correctly, but the failure mode of the component is not known. The next group, group 65, is similar except that at the later stage in the mission there are two possible components that could have failed. Group 66 is a case where only one component can produce the observed symptoms, but the failure can be at three different times in two different modes. Therefore, the failed component is diagnosed but the failure mode and time of occurrence is not determined. The next group, group 67, is when there is one component failing in one failure mode, but there are a number of possible times of failure occurrence, i.e. the failure and failure mode is known, but the time of occurrence is not. The next group, group 68, consists of symptoms that can be produced by fourteen different components, each failing in one of two modes. The following group, group 69, is when there is an additional component that has potentially failed when the symptoms are first observed, but at a later point in the mission, that component no longer produces the same set of symptoms, therefore, one of the fourteen components has failed, as in the previous group. The next group, group 70, is where one of the same fourteen components has failed, but the failure is detected as it occurs. This is when the failure occurs in the second phase of the mission. The penultimate group in the table, group 71, consists of cases when one of two components has failed, in one of two modes at one of seven times in the mission. Therefore, there is a 50% probability of correctly diagnosing which component has failed. The final group, group 72, is component failures that are not detected. These are components failing in modes that they are in during normal operating conditions, or failures in sections of the system that are not normally used.

Table I.6 Diagnostic results for the cross-feed valves

Group	Probability	Number	Description
73	50%d	10	• CCV, Op-1, Op-3, Op-5, Op-7, Op-9, Op/2-1, Op/2-3, Op/2-5, Op/2-7, Op/2-9.
74	12.5%	48	• LCV1, LCV2, RCV1, RCV2, Op-1, Op-3, Op-5, Op-7, Op-9, OP-11, Op/2-1, Op/2-3, Op/25, Op/2-7, Op/2-9, Op/2-11.
75	10% - 12.5%	40	• LCV1, LCV2, RCV1, RCV2, Op-2, Op-4, Op-6, Op-8, Op-10, Op/2-2, Op/2-4, Op/2-6, Op/2-8, Op/2-10.
76	10% - 50%	10	• CCV, Op-2, Op-4, Op-6, Op-8, Op-10, Op/2-2, Op/2-4, Op/2-6, Op/2-8, Op/2-10.
77	0%	57	• LCV1, LCV2, RCV1, RCV2, CCV, Cl, all phases • CCV, Op-11, Op/2-11.

In Table I.6, the component failures in group 73 are detected at the start of the following phase. This is because they are only detected when there is fuel being transferred between tanks. In this case, the component that has failed is known, just not which failure mode the component has failed in. The component failures in group 74 can be of the four cross-feed valves to the engines (LCV1, LCV2, RCV1, RCV2) failing either open or half open, in phases in which fuel is not being transferred between tanks. The component failures in the next group, group 75, are the same component failures as the previous group, with the addition of CCV also failing open or half open when the failures are first detected. The failure in this group occurs in a phase where the fuel is being transferred between tanks. When the operation phase changes to a phase where the fuel is not being transferred between tanks, the possible component failures changes to the possible component failures of the previous group, i.e. group "12.5%". The following group, group 76, is a failure of CCV, but when it is first detected the possible failures are the same failures as in group "10% - 12.5%". However, when the phase changes, only the failures of CCV are possible. The final group, group 77, the hidden failures, are all the failures for all of the valves failing closed, i.e. the mode they are supposed to be in. In addition, CCV failing open or half open in the final phase of the mission is hidden. Failures of CCV failing open or half open are only detected in phases of the mission where fuel is being transferred between tanks. However, there is no fuel being transferred between tanks in the final phase of the mission, and therefore, the failures are not detected. Note, the other phases where the fuel is not transferred between tanks is followed by another phase where fuel is transferred, and the failure can be detected in those phases.