Experience-based decision support methodology for manufacturing technology selection: a fuzzy-decision-tree mining approach

by

Liam Evans

BSc (Hons) MSc

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Abstract

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Manufacturing companies must invest in new technologies and processes to succeed in a rapidly changing global environment. Managers have the difficulty of justifying capital investment in adopting new, state-of-the-art technology. Technology investment accounts for a large part of capital spending and is a key form of improving competitive advantage.

Typical approaches focus on the expected return of investment and financial reward gained from the implementation of such equipment. With an increasingly dynamic market environment and global economic model, forecasting of financial payback can be argued to become increasingly less accurate. Subsequently, less quantifiable factors are becoming increasingly important. For example, the alignment of a technology with an organisations objective to fulfil future potential and gain competitive advantage is becoming as crucial as economic evaluation. In addition, the impact on human operators and skill level required must be considered.

This research was motivated by the lack of decision methodologies that understand why a technology is more successful within an environment rather than re-examining the underlying performance attributes of a technology. The aim is to create a common approach where both experts and non-experts can use historical decision information to support the evaluation and selection of an optimal manufacturing technology. This form of approach is based on the logic in which a decision maker would irrationally recall previous decisions to identify relationships with new problem cases. The work investigates data mining and machine learning techniques to discover the underlying influences to improve technology selection under a set of dynamic factors.

The approach initially discovers the practices to which an expert would conduct the selection of a manufacturing technology within industry. A defined understanding of the problem and techniques was subsequently concluded. This led to an understanding of the structure by which historical decision information is recalled by an expert to support new selection problems. The key attributes in the representation of a case were apparent and a form of characterising tangible and intangible variables was justified.

This led to the development of a novel, experience-based manufacturing technology selection framework using fuzzy-decision-trees. The methodology is an iterative approach of learning from previously implemented technology cases. Rules and underlying knowledge of the relationships in past cases predicts the outcome of new

decision problems. The link of information from a multitude of historical cases may identify those technologies with technical characteristics that perform optimally for projects with unique requirements. This also indicates the likeliness of technologies performing successfully based on the project requirements. Historical decision cases are represented through original project objectives, technical performance attributes of the chosen technology and judged project performance.

The framework was shown to provide a comprehensive foundation for decision support that reduces the uncertainty and subjective influence within the selection process. The model was developed with industrial guidance to represent the actions of a manufacturing expert. The performance of the tool was measured by industrial experts. The approach was found to represent well the decision logic of a human expert based on their developed experience through cases. The application to an industrial decision case study demonstrated encouraging results and use by decision makers feasible. The model reduces the subjectivity in the process by using case information that is formed from multiple experts of a prior decision case. The model is applied in a shorter time period than existing practices and the ranking of potential solutions is well aligned to the understanding of a decision maker.

To summarise, this research highlights the importance of focusing on less quantifiable factors and the performance of a technology to a specific problem/environment. The arrangement of case information thus represents the experience an expert would acquire and recall as part of the decision process.

Keywords manufacturing technology selection, decision support system, experience-based decision-making, data mining, fuzzy decision trees.

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Finally, I wish to thank all the friends and family who I have had the pleasure of spending time with during my tenure at University.

Dedication

This thesis is dedicated to my parents, Ruth and Stephen,

I thank them for their unconditional love and support,

And with thoughts to my Taid who sadly passed away recently.

Publications

The following list of publications has risen from this research activity:

Journals

Evans, L. Lohse, N. Summers, M. (2013) A fuzzy-decision-tree approach for manufacturing technology selection exploiting experience-based information. *Expert Systems with Applications,* Volume 40, Issue 16, 15 November 2013, Pages 6412-6426, ISSN 0957-4174, DOI:10.1016/j.eswa.2013.05/047

Evans, L. Lohse, N. Tan, K. Webb, P. Summers, M. (2012) Justification for the selection of manufacturing technologies: a fuzzy-decision-tree-based approach. *International Journal of Production Research,* Volume 50, Issue 23, 21 December 2011, Pages 6945-6962, DOI:10.1080/00207543.2011.638943.

Peer-Reviewed Conferences

Evans, L. Lohse, N. Summers, M. (2012) Intelligent Experience based Support Tools for Aerospace Manufacturing Technology Selection. *IEEE/AIAA Aerospace Conference,* Big Sky, Montana, USA. 3-10 March 2012.

Evans, L. Lohse, N. (2011) Optimized Fuzzy Decision Tree Data Mining for Engineering Applications, Advances in Data Mining. Applications and Theoretical Aspects. *In:* PERNER, P. (ed). *"The 11th Industrial Conference on Data Mining (ICDM)"*, Lecture Notes in Computer Science Series (LNCS), Vol. 6870, New York City, New York, USA: Springer Berlin / Heidelberg. 30 August – 3 September 2011.

Evans, L. Lohse, N. (2010) An intelligent technology selection algorithm for complex decision environments – a unique knowledge based approach, *The 7th International Conference on Knowledge Management (ICKM)* Pittsburgh, Pennsylvania, USA. 22 - 23 October 2010.

Evans, L. Lohse, N. Poad, M. Webb, P. (2010) Evaluation and selection of manufacturing technologies using the analytic hierarchy process in wing assembly, *Proceedings of The 8th International Conference on Manufacturing Research (ICMR)* Durham University, England, UK. 14 - 16 September 2010.

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List of Acronyms

AHP	Analytic Hierarchy Process	IRR	Internal Rate of Return
ANSI	American National Standards Institute	KBS	Knowledge-Based System
AI	Artificial Intelligence	KDD	Knowledge Discovery in Databases
AMT	Advanced Manufacturing Technology	KE	Knowledge Economy
ANP	Analytic Network Process	KM	Knowledge Management
BI	Business Intelligence	KPI	Key Performance Indicator
BIW	Body-In-White	MADM	Multi-Attribute Decision-Making
BSi	British Standards Institute	MCDA	Multi-Criteria Decision-Analysis
CAA	Civil Aviation Authority	MCDM	Multi-Criteria Decision-Making
CAD	Computer Aided Design	MF	Membership Function
CapEx	Capital Expenditure	MODM	Multi-Objective Decision-Making
CBR	Case-Based Reasoning	MoP	Measure of Performance
CIM	Computer Integrated Manufacturing	NGCW	Next Generation Composite Wing
CIT	Critical Incident Technique	NAS	National Aerospace Standard
CTQ	Critical To Quality	NN	Neural Networks
DBMS	Database Management System	NPV	Net Present Value
DEA	Data Envelopment Analysis	pp	Payback Period
DSS	Decision Support System	PRI	Primary Threshold
ES	Expert System	PV	Present Value
FAME	Financial Analysis Made Easy	QFD	Quality Function Deployment
FDT	Fuzzy Decision Tree	R&D	Research and Development
FID3	Fuzzy Interactive Dichotomizer 3	RBKS	Rule-Based knowledge system
FL	Fuzzy Logic	RI	Rule Induction
FMEA	Failure Mode and Effect Analysis	ROR	Rate Of Return
FMS	Flexible Manufacturing System	ROI	Return on Investment
FRIS	Fuzzified Rule-Induction System	RP	Rapid Prototype
GA	Genetic Algorithm	RPN	Risk Priority Number
GP	Goal Programming	SA	Single-Aisle
H&S	Health and Safety	SMART	Simple Multi Attribute Rating Technique
HOQ	House Of Quality	SME	Small and Medium Enterprises
HSE	Health and Safety Executive	TRL	Technology Readiness Level
I.T.	Information Technology	U.K.	United Kingdom
IE	Inference Engine		

Chapter 1

Introduction

1.1 Background

As organisations focus on growth and business development, the value of available information is crucial to making quick, rational business decisions. The consideration of new technologies can create information overload that leaves decision makers suppressed under a mass of inconsistent, irrelevant and inadequate data (A. T. Kearney, 2011).

Manufacturing organisations invest heavily in new techniques and processes to remain ahead of the competition in an increasingly competitive environment. The biggest hurdle in the adoption of manufacturing systems is the investment justification of capital equipment (Narain et al., 2007). The process is intensive from the identification and evaluation stage of a technology to the justification to senior management. It requires time and resource from employees to ensure they evaluate and justify appropriately. Manufacturing technology selection and justification has traditionally involved the analysis of a large number of economic (tangible) and analytical (intangible) factors in a decision support environment (Chan et al., 2000). The vast amount of available and potential information, when interpreted correctly, can provide a solid basis for decision-making. Investment opportunities tend to offer a wide range of capabilities that meet some but not all of the requirements. Subsequently, the investment trade-off requires careful consideration when the meaningful knowledge may be hidden among a vast set of information.

Industrial manufacturing managers are faced with the difficulty of identifying and implementing the single most appropriate technology system from a range of competing options. The level of information can be overwhelming and together with new production techniques, the complexity of the decision task can be daunting. The threat to an expert's reputation can limit the level of risk towards investment opportunities that bring added benefits over traditional technologies or sequential improvements.

Manufacturing technology selection is a complex decision activity and when not managed correctly can lead to the rapid decline in an organisations wellbeing (Garcia and Alvarado, 2012). Technologies can vary in terms of performance whilst offering similar performance capabilities. Aligning a solution to a problem is also difficult when many solutions may exist. It is frequently based on the subjective judgement of the decision makers involved. The experience and knowledge of the individual decision team members support each phase from evaluation to selection. The task is multifaceted, consisting of the evaluation of alternative options against a set of conflicting criteria and business requirements. The span of information and narrow expertise results in a challenging activity of justifying a technology that may not yet be fully understood. Much of the information is also immature and technologies selected based on expected performance attributes rather than proven capabilities. It is not always clear why a technology is or will be successful, and the choice is often reliant upon by the gut instinct of the decision maker based on the expected performance of the technology.

Advanced manufacturing systems can improve operational efficiency and be attractive to organisations wishing to attain higher profitability margins from existing products and processes. Although the ultimate selection and implementation of these technologies does not guarantee an advantageous effect, if conducted appropriately, organisations can invest wisely. Innovation and adoption of advanced technologies are crucial activities for today's manufacturing organisations. The competition is rife within the research and development (R&D) domain with small and medium enterprises (SMEs) challenging large organisations in the tendering of business to final product manufacturers. SMEs push technological boundaries in anticipation of developing advanced systems that bring strong revenue. This creates a progressively more difficult process of identifying the optimal manufacturing process due to the number of complex technologies that exist.

Some manufacturing organisations use the technology readiness level (TRL) guidelines to assess the maturity of evolving technologies in anticipation for application implementation, although it is often unclear at the outset how technologies were originally selected (Mankins, 2009). Technologies are not always acquired from third party vendors but often developed in-house and aligned to future requirements. This can enable technologies to be developed by research departments to be correctly aligned to organisations objectives. The lack of standard procedures for the evaluation and selection of alternative technologies can ultimately have a detrimental impact on the success of an organisation (Houseman et al., 2004). This lack of selection procedure for immature technologies also appears for mature, off-the-shelf systems.

Much of the literature has progressed in recent years from traditional economic models to hybrid combinations of managing economic, analytical and strategic factors. One downfall of the well-established multi-criteria decision-making (MCDM) tools is that they do not retain and reuse knowledge, and therefore managers are unable to make effective use of knowledge and experience of previously completed projects to help with the prioritisation of future cases (Tan et al., 2006). The lack of knowledge re-use can have a detrimental effect on new manufacturing investment opportunities where previous mistakes are not learnt.

For manufacturing organisations that are constantly making investment decisions, or large establishments where decisions are made at various sites, the re-use and sharing of knowledge can reduce the likelihood of investing in an inappropriate solution. A vast amount of information is created when evaluating and selecting a technology, therefore the re-use of potentially lucrative knowledge can support new manufacturing decision problems. Recently there have been advancements in knowledge-based approaches that bring added benefits to typical MCDM problems. The integration of such systems with industrial practices and support of managers has not yet been founded.

The literature suggests the need for further work in the area of manufacturing technology selection that is based on current practices and in line with theoretical developments. Much research has focused on solving the problem solely on the selection of a technology using MCDM techniques. Decision practices where the expert has a strong influence on the selection process tends to be the inclusion of historical cases where lessons are learnt and developed over time. This type of information and subsequent created knowledge has not yet been fully investigated. The requirement for a methodology is further driven by the potential implications of investing in an inappropriate technology. The investment cost through resource to select and implement a technology can easily be outweighed by the impact on production, product quality and customer impact. Investing in an inappropriate technology can effect production through the inability of a technology to perform, which subsequently can affect the end customer. Complex technologies account for a large portion of capital spending and organisations dedicate a lot of resource to secure the use of such equipment. Opportunities that are reverted back to traditional techniques are both severe pitfalls for business and customers.

Therefore, this research seeks to develop a new generic approach that better represents the decision practices of industry with the latest in theoretical developments. The representation of current practices and definition of an experience-based methodology similar to how an expert would apply their knowledge will be sought. The approach adopted is based on the understanding of current decision-making in industry and the techniques available within the literature.

1.2 Problem Statement, Research Definition and Motivation

The problem statement of this research is as follows:

Development of a decision methodology for manufacturing technology selection that is capable of extracting key information and knowledge from past technology implementation cases to learn from past achievements and mistakes to support new decision problems.

Medium complexity manufacturing technology selection decisions tend to be influenced by stages preceding technology selection (i.e. technology scanning), and stages after technology selection (i.e. acquisition and adoption). This is shown by Shehabudden (2001) in Figure 1.1 where the logical steps are conducted in order from selection to adoption.

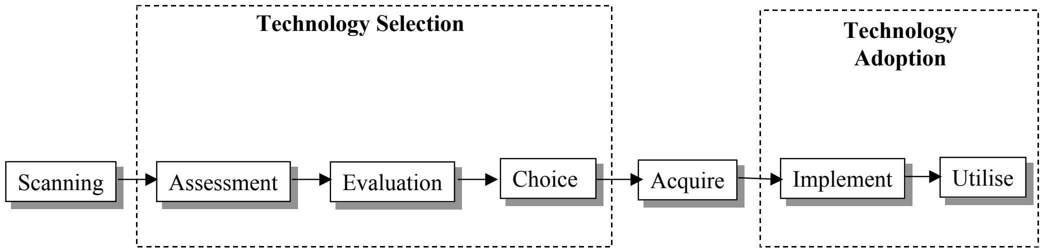

Figure 1.1 Technology selection process in context (Shehabudden, 2001)

The process necessitates two stages in the overall selection process. The initial scanning ensures a range of solutions is sought prior to the appropriate assessment being conducted. Each alternative is evaluated against one another and a choice is made. The chosen technology is then acquired, implemented and utilised within the business. The lack of knowledge feedback is apparent from the technology adoption phase to the technology selection phase. Current approaches typically use models which focus on prediction or expert opinion rather than past evidence/experience. This lack of direct objective knowledge support leaves open the possibility for inaccurate subjectivity of incorrect decision-making.

The focus of this work is mainly within the ‘technology selection’ phase highlighted in Figure 1.1. The assessment of alternative manufacturing technologies and the evaluation that leads to the choice requires further investigation. As highlighted by Shehabudden (2001), it is the preparation prior and the learning of technology adoption which influences the technology selection process and included in the development of such a methodology. The focus of a new model development using historical information from technology adoption cases should be sought. This defined and direct information can ensure decisions are accurately supported based on previous similar decisions. Linking the learning of past cases through tangible and intangible terms can support a knowledge-based heuristic approach to the problem.

Industrial approaches to decision-making appear to be more process ‘know-how’ and based on human expertise rather than a systematic framework to solving such a complex selection problem. The reliance on experts to appropriately evaluate and select the most optimal technology can be detrimental to an organisation when employees move firms, and the loss of investment knowledge can be severely costly. A structured process appears to not be coherently applied across organisations and similar decision problems can lead to different outcomes, both positive and negative.

This research focuses particularly on production technologies that include the investment in techniques and processes that contribute to the manufacture of a product. To meet the challenges of investing in production technologies, manufacturing companies have to select appropriate strategies, product designs, processes, work piece and tool materials, machinery and equipment, *etc.* for each particular activity. Manufacturing decisions are crucial and complex, and necessary conditions achieving efficient decision-making consist of understanding the current and upcoming events, and factors influencing the manufacturing environment. Understanding the form and nature of structuring the decision-making process is based on a wide range of issues related to manufacturing systems design, planning, and management, that contribute to the effectiveness of the approach (Rao, 2007).

The influential elements that assist in the evaluation of suitable systems are difficult for managers to consider due to a limited capacity of information processing and bounded rationality (Deng, 1996). The multiple attributes by which a technology can be evaluated is diverse from economic considerations such as return period and the technical performance, including operation and set-up time. These criteria can often be conflicting where increased technical performance would bring higher cost. Subsequently, the “evaluation approach is often not effectively carried out, as managers do not make effective use of their knowledge and experience of previously delivered technologies and projects as an input to the prioritisation of future projects” (Tan et al., 2006, p. 180). This can have a detrimental effect on an organisation, reducing their investment optimisation. The management view is that they are not confident that resources are being optimised and applied to a mixed portfolio of projects to maximise benefits.

Many methods are based on the concept of accurate measurement and evaluation, i.e. the measuring values must be exact and numerical. However, owing to the availability and uncertainty of information, it can often be very difficult to obtain the exact assessment data such as investment cost, gross income, expenses, depreciation, salvage value, flexibility, productivity, quality, *etc*. These factors, tangible or intangible, are mostly difficult and challenging to quantify (Georgakellos, 2007).

Many of the proposed approaches in the literature solve the technology selection problem through MCDM techniques. Whilst they provide a logical structure to the problem, they are limited through the tools lack of access to experts, reliability upon subjective judgment, lack of knowledge retention and re-use of knowledge, and experience within the decision-making process. Previous case information is not considered and the methods are unable to cope with high levels of complexity, such as a growing list of conflicting criteria.

MCDM tends to be the preferred option due to the ease in which an expert can make a judgement. Yet knowledge-based systems (KBSs) are expert-based approaches that capture the expertise from an expert for use by non-experts. A limitation of KBSs is the requirement for objective knowledge by an expert. The opinion of one expert may differ to another in the same field. This subsequently leads to discrepancies within the model. Acquiring this knowledge is also a difficult and lengthy activity.

It would appear easier to acquire knowledge from the original source of information an expert would use to develop their level of expertise. An expert develops expertise from their involvement in prior decision cases, and recalls this information when making judgement. This form of case remembrance is easier to define compared to acquiring direct knowledge from an expert for a KBS.

An expert would irrationally recall and record their experiences in the form of cases and formalise the underlying rules and knowledge. Therefore, merging multiple sources of "experience" (historical decision cases) rather than a lengthy subjective form of complex refinement and management process would be preferred. This type of approach would enable rules from different experts to be appropriately combined to support a decision problem. A case-based formulisation that captures the direct learning of case information has not yet been investigated for manufacturing technology selection.

In recent years there appears to be a trend in manufacturing organisations to increasingly acquire information. Through advancements in information technology (I.T.), data acquisition systems and storage technology, tools have enticed researchers to move toward knowledge discovering in databases (KDD). Within manufacturing organisations, data from almost all the processes are recorded (Harding et al., 2006). In particular, focus has been on functions where the accumulation of data is part of normal operations. The data is used to support decisions by reviewing information samples to identify useful knowledge patterns. These human-understandable patterns provide direction and support to decision problems.

Manufacturing organisations are expected to explore the types of information they can easily acquire. With advanced developments in data acquisition tools, new areas of operation include decision support where current acquisition techniques have not yet been applied. With recent advancements in business intelligence (BI) solutions, it is clear the domain is being directed towards data management systems to support new problems based on previous known information.

There appears to be a lack of reasoning using case-based approaches that represent the experiences of experts and manipulate the expertise to solve problems at an expert's level of performance. With existing literature and practices largely based on human intervention of an expert who recalls previous cases to make a decision, this research has set to explore a new and improved approach to the decision problem. Reflecting on an experience-oriented problem, the investigation into providing an efficient and supporting decision-making process through this form of information and knowledge is considered.

1.3 Research Domain

To gain a better understanding of industrial practices and provide an appropriate form of validation, this research has been supported and conducted in collaboration with the aircraft manufacturer Airbus. Aircraft assembly involves a series of critical and complex manufacturing stages which requires advanced techniques to meet the strict industrial regulations. Technology selection is particularly difficult due to the range of techniques required to achieve the demanding product requirements. The consequence of error or lack of performance in a technology can also have devastating effect on production, the consumer and organisation.

The modern aircraft wing is a complex structure that supports a number of functions including lift generation, flight control, engine mounting, transfer of engine thrust and storage of fuel. In addition to meeting the demanding structural requirements, it needs to be able to support functions through the integration of many different and complex subsystems such as electrical services, actuators, hydraulics, anti-ice and fuel management. In terms of producing such a multifaceted product, state-of-the-art manufacturing is essential.

Aircraft assembly is profoundly conducted using manual labour with low levels of automation carrying out tedious drilling and riveting tasks. Advanced manufacturing technologies (AMTs) such as laser measuring equipment, automated riveting centres and robotic arms are becoming increasingly common assisting in complex assembly tasks. As the industry advances, so does the number of available technologies and solutions for increased automation. Airbus has recognised the need for a significant step-change in optimising manufacturing processes through the investment in new technologies. Schneider (2010) notes how although the cost structure is effective, investing in new technologies can see a 10% reduction of the unit cost of the current single-aisle (SA) Airbus product family.

The level of complexity in the decision process can vary by product, process and industry. Aircraft manufacturing is large scale, manufactured in relatively low volumes and has a typical lifespan of 25 years in service. In terms of technology selection, decision selection is critical; a technology will be expected to remain throughout a products lifecycle from introduction through to maturity and end-of-life. Cost of change in aircraft assembly is high and can have a detrimental effect on an organisations product flow. Working to tight takt times on high value products for a dependable customer can create a challenging environment. Aircraft assembly processes are built around complex systems that require high analytical evaluation based on conflicting social/technical elements. For example, the trade-off between the technical performance of a technology and ability of a skilled operator needs to be considered. In addition, decision makers are often faced with this level of uncertainty in an unpredictable business environment that is susceptible to external affairs.

1.4 Scope of Research

The research is defined in the following scope:

- The research is focused on a decision support system for medium complexity manufacturing technology selection that considers the experience of historical technology implementation cases to support the selection of new decision problems

- The decision-making process of alternative manufacturing technologies within industrial practices is considered to support the development of the support system

- The decision approach is adapted from a defined case structure of previous decision problems where a project is defined similar to how an expert would recall a historical decision case in practice

- The technology selection process is targeted towards linking the learning of past decision cases acquired by an expert and defining this in both qualitative and quantitative terms for decision support, acquiring the information in a format which is both readable and re-useable

- The framework focuses on the heuristic approach of decision-making and uses the acquired information to form knowledge that does not exist in decision applications today within the field of manufacturing technology selection

- The research has been carried within the aerospace domain where complex manufacturing technologies support the assembly of an aircraft. The principles and methods defined are expected to be applicable to similar manufacturing technology problems in a multitude of domains

The major contributions from this research are:

- A decision support framework for industrial manufacturing managers to select a manufacturing technology supported by knowledge mined from a database of past decisions

- A link between the theory of data mining and industrial application of manufacturing technology selection that is predominately based on human expertise

1.5 Approach and Thesis Structure

The approach and contributions of this research is as follows:

- Industrial decision practice survey
- A study of information and knowledge transformation within the manufacturing technology selection process reflective to decision-making needs
- Key decision variables in capital investment of manufacturing technology for historical decision cases
- An experience-based decision framework for manufacturing technology selection
- Validation of framework through industrial case study

This thesis documents the research endeavour and within this presents a logical argument for the study. Initially, the problem is investigated, a solution is developed and applied within an industrial domain, and concluding is a critical discussion of the research findings. The thesis is structured as follows:

Chapter 2 Reviews literature on decision-making techniques and support systems to explore the scope of the research. It identifies intelligent decision support methods, data mining and provides a detailed literature analysis review. Knowledge gaps are also discussed.

Chapter 3 The research methodology describes how the research process is shaped and the systematic steps to analyse the problem leading to the validation. The aims and objectives identified from the literature and the research methods are addressed to provide a sound approach to the research problem. A definition of the hypothesis and detailed research methods are discussed.

Chapter 4 Reports the findings from an investigation into the decision-making practices at manufacturing organisations within the aerospace, automotive, defence and pharmaceutical industries. The review describes the preparation, execution and findings of a survey to confirm the gap in knowledge from an industrial perspective. The survey validates the requirement for a methodology and highlights existing methodologies and constraints.

Chapter 5 Presents the results of a study conducted to define the development and progression of data throughout the technology selection process. The context and process of information and knowledge is defined to fully understand the influences and requirements of experts within the decision-making process.

Chapter 6 Describes the study to define a modular set of decision attributes to represent the information structure of a historical decision case. It facilitates the identification of the tool evaluation elements of the decision support information.

Chapter 7 Presents an experience-based support system that uses factual information of historical decisions to calculate confidence factors of potential technologies for a given case. The chapter describes the design and development of the research solution. It outlines the main components of the decision tool framework, and provides a detailed description of the implementation procedure. A numerical example is also shown.

Chapter 8 Presents the application of the decision model to an industrial selection problem. The applied case study within Airbus supports a typical metrology decision process. Experts within the company evaluate the applicability of the model.

Chapter 9 Concludes the thesis with a review of the key findings against the research aims and objectives. The chapter critically discusses the contribution to theory and practice, outlining limitations in the research and recommendations for future work. The future direction of the research area is also noted.

Chapter 2

Literature Review

2.1 Introduction

This chapter presents an overview of the relevant literature considered as part of this research. It includes technology selection, decision-making, the theory of fuzzy logic and fuzzy systems, decision and knowledge-based support systems and data mining. The chapter concludes with an analysis of related publications and the identified gaps in the existing body of knowledge.

The scope of the literature review covers manufacturing technology selection within medium and large organisations. The focus includes advanced and medium complexity technology solutions for both manufacturing and assembly support. The chapter explores typical decision techniques discussed within the literature for multi-criteria decision problems, prior to reviewing both knowledge and information systems. The literature then explores fuzzy and data mining approaches that have been applied to similar problems. A state-of-the-art review summarises the standards and methodologies for manufacturing technology selection.

2.2 Manufacturing Technology Selection

Manufacturing technology selection is a decision-making exercise of selecting the most appropriate technology from a pool of available options. Specific organisation requirements may differ the criteria for selecting the best technology (Shehabuddeen et al., 2006). Technology selection is best defined by Gregory (1995), p. 351 as:

> "...the choice of technologies that should be supported and promoted within the organisation. Selection is critical as it may result in the commitment of large human and financial resources as well as limiting the company's future options."

The problem concerns new product introductions, competence and capability, and R&D management (Gregory, 1995). Building upon his earlier definition, Lamb and Gregory (1997), p. 206 advocates that technology selection involves "gathering of information from various sources about the alternatives, and the evaluation of alternatives against each other or some set of criteria". The authors discuss the concern of evaluation will often include risk, benefit and cost. Dussauge et al. (1992) regard the technology selection process as identifying the selection of a new or additional technology that the firm seeks to master. Whereas Gregory (1995) separates the ‘identification’ and ‘selection’ stages in first identifying the potential options before deciding on an alternative.

Shehabuddeen et al. (2006) notes that the premise among the alternative definitions is that technology selection is very much a ‘process’ linked within the business. It is often associated with the broader technological, organisational, and business environment.

Stacey and Ashton (1990) describe technology selection as a process of prioritising the technological investment alternative, suggesting that the decision should consider the risks involved for the business and technology in order to fulfil an organisational objective. This is reiterated by Matthews (1990) who views the process as a defining component of technology strategy development.

Typical technology selection is the ranking of alternative physical solutions based on the presumption that they do not require extensive research and development. For the purpose of this study, the following interpretation by Shehabuddeen et al. (2006), p. 325 is adopted:

> “Technology selection involves choosing a technology that a firm views as most suitable based on the consideration of its technological, organisational, and business environments.”

Technology selection comprises three phases:

<u>Assessment:</u> involves establishing the key features and influence of technologies to fulfil an objective. It is concerned with establishing the factors for evaluation and selection (Braun, 1998, Tipping et al., 1995).

<u>Evaluation:</u> involves comparing the key features and impact of technologies (Yap and Souder, 1993, Daim, 1997).

<u>Choice:</u> involves selecting a manufacturing technology that is most appropriate to the problem (Edosomwan, 1989, Saad, 1998).

In terms of the assessment and evaluation, many justification methods for manufacturing technologies have been applied. Karsak and Tolga (2001) presented a reorganised account of the original classification of manufacturing technology justification methods by Meredith and Suresh (1986) (Table 2.1).

The justification methods are divided into three types to ensure all aspects are considered. The economic techniques include critical financial information that understand how well a solution will perform financially, this includes techniques such as payback period (PP) and return on investment (ROI). The strategic factors consider how well a technology meets the business objectives. The analytic parameters consider tangible and intangible technical information through techniques such as scoring models and stochastic approaches.

To achieve manufacturing targets, organisations must select appropriate machinery and equipment, strategies, work piece and tool materials, product designs, processes, for each particular activity. The choice of most appropriate technology is complex and the decision activity challenging. Necessary conditions achieving efficient decision-making consists of understanding existing and forthcoming events, and factors including the complete manufacturing environment. Manufacturing decision makers face the difficultly of assessing a broad range of alternative solutions, and selecting a single solution based on a set of conflicting and tentative factors (Rao, 2007a).

	TECHNIQUES	ADVANTAGES	DISADVANTAGES
ECONOMIC	- Payback method - Return on investment - Discounted cash flow techniques (NPV, IRR)	- Ease in data collection - Intuitive appeal	- Do not take into account strategic and non-economic benefits - Consider a single objective of cash flows, and ignore other benefits such as quality and flexiblity
STRATEGIC	- Technial importance - Business objectives - Competitive advantage - Research and development	- Require less technical data - Use the general objectives of the firm	- Necesity to use these techniques with economic or analytic ones since they consider
ANALYTIC	- Scoring models (AHP etc.) - Mathematical programing - Integer programming - Goal programming - DEA - Stochastic methods - Fuzzy set theory	- Uncertainity of the furue and the multi-objectivity can be incopoated - Subjective cirteria can be introduced in the modeling phase	- Require more data - Usually more complex than the economic analysis

Table 2.1 Justification methods for manufacturing technologies (Karsak and Tolga, 2001)

The topic of manufacturing technology selection and in particular the investment techniques is well represented within the literature. In recent years, a number of literature review papers have provided a critical overview of the domain and the techniques that exist. In Chan et al. (2001)’s literature review article, the authors discuss that because of the high investments in manufacturing technologies and moderate-to-high risk involved in selecting and adopting such processes, there should be sufficient economic analysis and justification methods to assist companies in selecting the most optimal technology. Generally, the reported justification methods within the literature are shown within Figure 2.1.

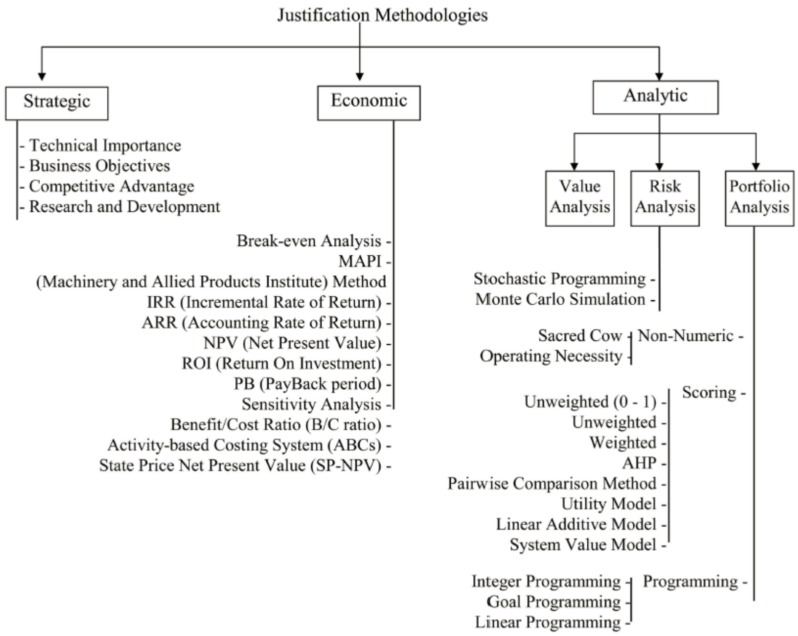

Figure 2.1 Justification methodologies (Chan et al., 2001)

A survey conducted by Small and Chen (1995) indicated that most researchers have focused on the justification of manufacturing technology dealing with the relationships between usages of different justification approaches. Determining the relationships between justification actions and the performance of a project are usually disregarded.

Firstly, Chan et al. (2001) discusses the strategic approaches within the literature. They tend to be less technical than the economic and analytical methods; the advantage is their direct tie to the organisations aims and objectives. The commonly used strategic approaches include: technical importance (i.e. project is a crucial follow-on activity), business objectives (i.e. project achieves firm's objectives or not), competitive advantage (i.e. signification gain over competitor) and research and development (i.e. fails to meet strategic objectives at this point in time but may do so in the future). The strategic approach is a set of plans to provide manufacturing output for some or all decision areas.

Subsequently, economic justification approaches are commonly used in combination with strategic techniques. Analytic techniques are rarely included. The authors note the common economic justification techniques include PP, ROI, cost-benefit analysis, net present value (NPV) and internal rate of return (IRR). The use of these is imperative to assess financial feasibility of the technology but cannot identify potential improvements.

The authors discuss the analytical approaches. They are often more complex and largely quantitative-based. They are applied when considering intangible benefits. They enable information to be collected, consider uncertainty and multiple measures. The common techniques shown in Figure 2.1 include value analysis for determining the potential value of a technology over a period of time, potential risk and portfolio analysis for determining an optimal portfolio of technologies.

In summary, the authors believe that some of the benefits, such as tangible and intangible, are difficult to quantify in financial terms and require consideration for the duration of the technology lifecycle. The review indicated the achievement of intended benefits requires systematic and integrated planning. More importantly, their survey revealed that some technology decisions are based on weighted averages by an expert or through decision maker judgement. The authors stress the importance to consider both subjective and objectives factors commonly evaluated by an experienced decision-maker.

In a more recent literature review study by Narain et al. (2007), the investment justification of capital equipment is further discussed as one of the biggest hurdles in the selection of manufacturing technology. Similar to the study by Chan et al. (2001), Narain et al. (2007) presents the range of techniques which consist of pure economic models, to strategic and complex assessment procedures (analytical methods). However, the authors also discuss two newly considered advanced methods, expert systems (ESs) and decision support systems (DSSs) (presented within Section 2.6). The benefits of applying ESs to the problem of technology selection are through their ability to integrate qualitative issues with strategic objectives, experience, judgement and intuition of the decision maker. However, the development and testing requires high resource to deliver optimal results. The authors discuss the effective and strategic use of DSSs. To support managerial judgement in all decision processes, their ability to combine strategic, analytical and economic models is highlighted through accounting the need for structuring a wide range of input data.

In summary, the authors believe no method thus far has been successful in providing a satisfactory and generally applicable approach. The combination of one or more techniques is apparent and many hybrid financial and strategic techniques exist. The stalemate problem still exists through new dimensions such as qualitative information being added. Also, despite its intuitive appeal, current research has not yet developed a sufficient technique for capturing experience and intuition of the decision maker.

2.3 The Process of Making Decisions

Decision-making is regarded as a process where the trade-off of alternatives is conducted. This can be conducted through a mental process or assisted through a series of decision support matrices. The process of making decisions is viewed as a methodology approach to deal with decision-making problems to reach an outcome. Clemen and Reilly (1999) describe this as a six phase process assuming that the decision maker develops the alternative (Figure 2.2).

The first phase for a decision maker is to identify the decision situation and understand the objectives in the situation. Understanding the exact problem and domain is important for understanding the situation. It is also vital to verify the boundaries of the domain to treat the problem correctly. Performance measures to analyse the effectiveness to solve the problem including factors, variables and data relevant to the problem must also be identified.

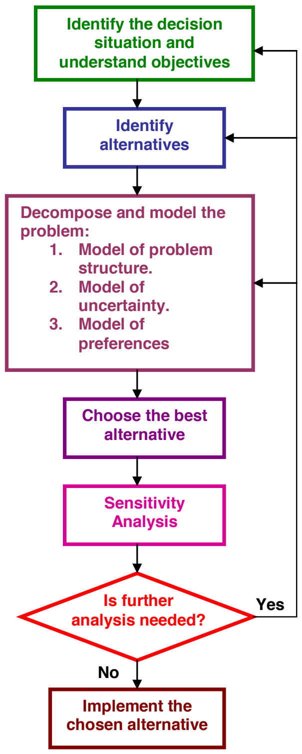

Figure 2.2 Decision-making process (Clemen and Reilly, 1999)

The second phase requires discovering and creating the alternatives. This may be done through a tendering process or conducted in-house of currently known alternatives. Understanding the objectives and careful examination of them will assist the decision maker to identity suitable alternatives.

Kabli (2009) explains how modelling is an important feature of the decision-making process. Analogue and symbolic models are used widely. Mathematics has a role to play in modelling, and the development of computers and computer systems has had a big impact on decision-making. The decision maker can use decision trees and hierarchies to structure the problem and represent relationships between different objectives and performance measures. Models of uncertainty use probabilities to inherent the uncertainty in the problem. Mathematical representation of subjective preferences can help indicate a 'preferred' alternative. The decision maker uses decision models in the next phase to choose the best alternative.

The evaluation and choice is often supported by theoretical models from within the literature (economic, MCDM model, *etc*). The following stage is to apply a sensitivity analysis. It is the study of how the variation (uncertainty) in the output of a mathematical model will change depending upon the input (Saltelli et al., 2008). The phase shows the consequences of selecting an alternative solution if the decision maker applies small changes to some aspects of the model. If these changes lead to changing the selected alternative, the decision is considered sensitive and the decision maker may need to reconsider carefully those aspects to which the decision is sensitive.

The final phase allows the decision maker to return back to the first, second and/or third phase to make modifications. If the decision reaches a satisfactory conclusion about an alternative, the final phase is to implement the chosen alternative. The decision methodology is extremely logical but lacks any form of iteration in which learning can easily be captured and used to support future decision problems. Learning's acquired during the "implement the chosen alternative" would provide useful information and knowledge able to support the "choose the best alternative" stage within Figure 2.1.

The basic method for a decision-making process is similar and coherent among most authors. Elbing (1970) best describes the five steps for a decision-making process:

1 *Perception* of the environment or situation: observing and becoming sensitive to potential problem situations.

2 *Diagnosis:* attempting to understand what is happening in a particular problem situation.

3 *Definition* of the problem to be solved: identifying and stating a problem in relation to organisational and personal goals.

4 *Determination* of alternative methods and solutions and choice of the best solution: selecting a course of action from a series of alternatives.

5 *Implementation* of the chosen solution: the entire process of actualising the chosen solution.

Understanding the problem, domain, objectives and boundaries are important factors that should be considered in a decision-making project. It is possible that a decision maker may decide the suitability of an alternative based on the incorrect understanding of the problem domain. There are many approaches to decision-making within the literature and depend upon the ideas and opinion of researchers and authors. Certain approaches are suited to particular domains whilst others depend on the type of data required for computation. MCDM explicitly considers multiple criteria within decision-making environments and similar to matrices, allows the trade-off of alternatives to be conducted. Within the following sub-section, the most popular MCDM techniques are presented and critically evaluated for the problem.

2.4 Multi Criteria Decision Making

MCDM, sometimes referred to as multi-criteria decision analysis (MCDA), is a discipline for supporting decision makers faced with making numerous and possibly conflicting evaluations. MCDM provides a structured approach to decision-making and is a set of tools that can highlight conflicts and forms of deriving a way to come to a compromise in a transparent process.

Rao (2007b) best summaries MCDM as two common techniques (Figure 2.3):

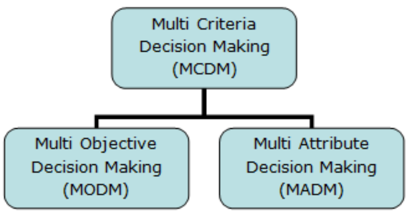

Figure 2.3 MCDM types (Rao, 2007b)

Multi-attribute decision-making (MADM) is the selection among decision alternatives that are defined by their attributes. It assumes that the problem has a predetermined number of decision alternatives. In multi-objective decision-making (MODM), it assumes that the decision alternatives are not given. Instead, MODM provides a mathematical framework for generating a set of judgement alternatives. Once identifying the decision alternative, each alternative is judged by how close it satisfies the objective.

To support a decision-making process, MODM and MADM techniques can be applied. Each technique is unique and supports decision-making in similar and diverse forms. Schaeffer and Lochow (2004) have classified the MCDM problem in the Figure 2.4.

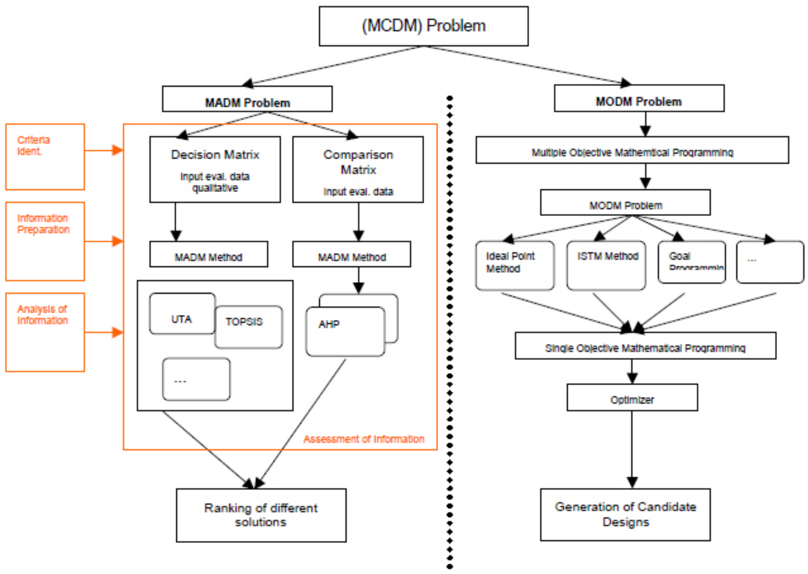

Figure 2.4 MCDM classification (Schaeffer and Lochow, 2004)

Schaeffer and Lochow (2004) classification show the difference between MADM and MODM problems. MADM requires the criteria identification and appropriate analysis of information to form a ranking of different solutions. MODM instead uses multiple objective mathematical programming as an optimiser to generate a candidate of designs.

The steps of the decision process in a MCDM approach are defined by Malczewski (1999) in Figure 2.5 and as follows:

- *Set of alternatives:* Are the alternative choices available to the decision problem. It is the matter of understanding whether or not the alternatives satisfy the problem objectives to be admitted as a feasible decision alternative.
- *Set of criteria:* Evaluation criteria represent measures for achieving those criteria.
- *Criterion scores:* Each score for the alternative represents the achievement of the product.
- *Decision table:* Represents the collection of criterion scores to provide a basis for comparing each alternative.

- *Aggregation functions:* Sometimes called decision rule. It computes an overall evaluation measure of each alternative by integrating decision maker preference with the criterion scores.
- *Sensitivity analysis:* It tests the stability of assessment measure of each decision alternative when weights and criterion scores are varied.
- *Final recommendation.* The choice of the most appropriate decision alternative(s).

The remaining sub-sections introduce a number of popular decision models described within the literature.

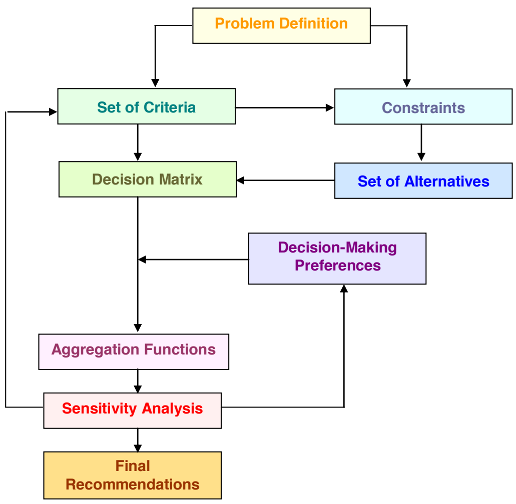

Figure 2.5 Steps of decision process in MCDM approach (Malczewski, 1999)

2.4.1 The Analytic Hierarchy Process

The analytic hierarchy process (AHP) is a "framework of logic and problem solving that spans the spectrum from instant awareness to fully integrated consciousness by organising perceptions, feeling, judgments and memories into a hierarchy of forces that influence decision results" (Saaty, 1994, p. 5)

The AHP technique is used to derive ratio scales on a variety of dimensions, both tangible and intangible from the application of paired comparisons in multilevel hierarchic structures. The comparisons are either actual measurements or taken from a fundamental scale that reflects the relative strength of preferences and feeling. Arranging these dimensions in a hierarchical structure allows for a breakdown of the decision problem into smaller parts that lead from simple paired comparison judgements to the priorities in the hierarchy. It is a structured technique that helps decision maker's deal with complex decisions by focusing on small areas of an entire problem.

AHP provides a comprehensive and rational framework for structuring a problem, for presenting and quantifying its elements, relating those elements to overall goals, and for evaluating alternative solutions (Saaty, 1980). AHP is classed as a multi-attribute decision model. Instead of prescribing a 'correct' decision, the AHP helps the decision maker find one that suits their needs and understanding of the problem.

Saaty (1980) describes the AHP method as a form of concentrating judgement on a pair of elements. With no concern for other properties, they are evaluated on a single property that assists in a sound decision. It facilitates decision-making by organising perceptions, feeling, and judgements in a framework that displays the forces for influential decision-making. It is based on mathematics and psychology, and has since been extensively studied and refined. The procedure is conducted in five stages:

1. Model the problem as a hierarchy noting the goal, alternative solutions and evaluation criteria.
2. Establish the priorities among criteria by conducting a series of pair-wise comparisons of the elements, e.g. when comparing cost and quality, an organisation may see quality as a more important criteria, thus, this must be considered as more important.
3. Synthesize these judgements to yield a set of overall priorities in the hierarchy. Each alternative rated against each criterion and summed together.
4. Check the consistency of judgements.
5. Select the alternative receiving the highest numerical rating.

Saaty suggests a fundamental scale of absolute values for representing the strength of judgements (Table 2.2). The AHP methodology is an excellent technique for dealing with complex, unstructured and multiple-criteria decisions. AHP has been applied to a variety of decision areas and suitable for situations in which the decision alternative can be inter-related by well-defined mathematical linear functions. AHP is able to handle multi-criteria problems by allowing experts to evaluate criteria in order to generate the appropriate weightings. It is similar to weighted matrices which are often used in practice today.

AHP in its current form does not yet enable knowledge or information to be captured for each decision iteration. Therefore when the methodology is applied, no learning is captured and the process relies on experts each time a decision is required. The technique can be extremely difficult to use in practice and understand when multiple criteria are required. For example, a set of ten criteria is manageable however, an increase in criteria brings increased complexity where decision makers can become confused when dealing with high numbers of criteria. In addition, decision-making involving ranking alternative in terms of attributes of those alternatives. It is an axiom of some decision theories that as the decision problem develops and new alternatives are added, the ranking of historical alternatives must not change, however the process is required to be conducted again from the start.

Intensity of importance on an absolute scale	Definition	Explanation
1	Equal importance	Two activities contribute equally to the objective
3	Moderate importance of one over another	Experience and judgement strongly favour one activity over another
5	Essential or strong importance	Experience and judgement strongly favour one activity over another
7	Very strong importance	An activity is strongly favoured and its dominance demonstrated in practice
9	Extreme importance	The evidence favouring one activity over another is of the highest possible order of affirmation
2, 4, 6, 8	Intermediate values between the two adjacent judgments	When compromised is needed
Reciprocals	If activity *I* has one of the above numbers assigned to it when compared with activity *j*, then *j* has the reciprocal value when compared with *i*	
Rationals	Ratios arising from the scale	

Table 2.2 Fundamental scale (Saaty, 1994)

2.4.2 Decision Tree

A decision tree is a decision support toolset that creates a tree-like graph that models decisions and consequences. Frequently used within operations research, they assist in identifying the best approach to reaching a goal. The graph can model a variety of parameters such as chance event outcomes, resource cost, utility, *etc.*

A decision tree is a chronological representation of the decision process. It utilises a network of two types of nodes: decision (choice) nodes and a state of nature (chance) nodes. Constructing a decision tree well utilises the logic of a decision problem. Decision trees are simple to understand and interpret and tend to have value with little data. Decision trees provide assistance to classification problems where nodes act as sub decisions of which a decision maker will select a leaf of a node to narrow down to an appropriate solution.

Safavian and Landgrebe (1991) denote any tree by *T,* see Figure 2.6.

Where:

C(t) – subset of classes accessible from node *t*

F(t) – feature subset used at node *t*

D(t) – decision rule used at node *t*

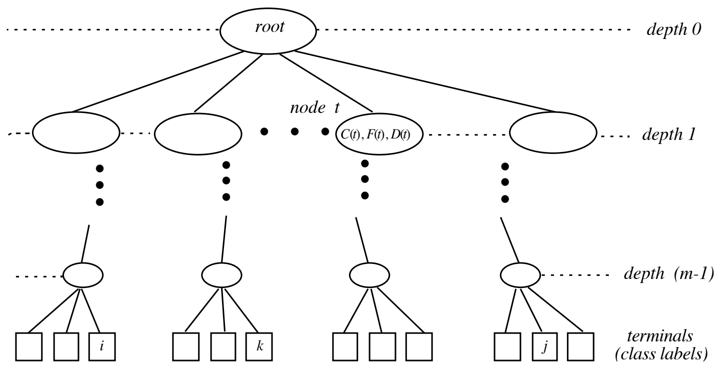

Figure 2.6 Decision tree (Safavian and Landgrebe, 1991)

Decision trees are simple to understand and interpret, and with very little hard data, important insights can be generated based on experts describing a situation. The ease at which decision trees demonstrate a problem in an easy to understand format is attractive when developing new decision methodologies. Understanding a problem and defining it through a decision tree can be extremely beneficial to manufacturing technology selection. The knowledge by which experts make decisions and information by which they consider may enable such techniques to be applied. Technology selection and the process by which a decision is made will often include a number of potential avenues where a trade-off among criteria (e.g. high performance, high cost/low performance, low cost) is required. Therefore, decision trees are extremely attractive to support the technology selection problem, not only for criteria evaluation but representing information and knowledge. They can also easily be combined with other techniques. Decision trees may be generated on a dataset of information such as previously implemented technologies/decisions.

2.4.3 Failure Mode and Effect Analysis

In an attempt to identify all possible failures in an alternative, the failure mode and effect analysis (FMEA) toolset supports the evaluation of a system. It defines the likelihood of a risk occurring and determines the probability that a failure will go undetected. FMEA provides a basis for classification or characteristics, i.e. for identifying critical to quality (CTQ) and other critical variables. Similar to a Pareto analysis, the FMEA toolset directs the potential resource towards the most favourable alternative. It assists in conducting a trade-off of potential consequences, when a serious unlikely failure may not be the best place to concentrate preventive efforts (Pyzdek and Keller, 2003).

The FMEA is an integral part of the early design process and placed during the design phase. FMEAs reflect design changes that make them useful in the control or verification phases. All recommend actions which result from the FMEA must be evaluated and formally dispositional by the appropriate implementation or documents rational for no action (Pyzdek and Keller, 2003).

Beauregard et al. (1996) describes the following procedure for constructing an FMEA:

1. Review the process.
2. Brainstorm potential failure modes.
3. List potential effects of each effect.
4. Assign a severity rating for each effect.
5. Assign an occurrence rating for each failure mode.
6. Assign detection rating for each failure mode and/or effect.
7. Calculate the risk priority number (RPN) for each effect.
8. Priorities the failure modes for action.
9. Take action to eliminate or reduce the high-risk failure modes.
10. Calculate the resulting RPN as the failure modes are reduced or eliminated.

A risk when investing in a manufacturing technology is the potential failure or impact on other production systems within an organisation. Often a technology is evaluated based on its technical performance and subsequently considered for implementation. A level of risk is apparent and the FMEA toolset is a disciplined approach to deal with such uncertainty. FMEA has been developed to reduce the possibility of the future failure rather than support the evaluation and selection of a technology. Technology decisions will include a level of risk and such should be considered during the decision process. However, the FMEA toolset alone is insufficient to deal with the requirements for a technology evaluation and selection process. It is dependent of the members of the committee which examines the products failures, unable to deal with the trade-off of multiple criteria and appropriately provide a recommendation of alternative solutions. It is appropriate for evaluating risk within a process and would be best integrated using another technique to fully align the technique to a decision process. FMEA also lacks iterative learning where risks associated with previously considered technologies can be reused when evaluating new alternatives in a simple manner.

2.4.4 Quality Function Deployment

Quality function deployment (QFD) is a comprehensive toolset for matching customer requirements to engineering characteristics of a product. It is an adaptation of some of the total quality management tools, as it was developed as a tool contributing to the attainment of Japanese quality standards in industry (Cohen, 1995). Akao (1990), p. 3 defines QFD as "a method for developing a design quality aimed at satisfying the consumer and then translating the consumers demands into design targets and major quality assurance points to be used throughout the production stage". The procedure is able to translate perceived or expressed needs of customers into the features for process and operational characteristics.

The QFD mechanism is designed in a manner to help designers to capture customer requirements and ensure that they are dealt with at the product design stage. The approach is based on a series of techniques that enable engineers to capture, prioritise and structure the broad intangible and immeasurable requirements into tangible objectives and relevant product specifications (Cohen, 1995). It is a process that translates the customer requirements into organisation requirements that can be incorporated in the research, development, engineering, manufacturing, and marketing of the product (Franceschini, 2002).

In order to translate the requirements of the customers into the entire product development process, the voice of the customer in the quality chart is cascaded through four stages. Where the "hows" of the preceding chart becomes the "whats" of the next. The "house of quality" (HOQ) is the first matrix used to describe the basic process underlying QFD. It is a very complex matrix in the sense that it consists of several matrices attached to each other, as shown in Figure 2.7.

QFD is a proven technique for transforming the customer needs into engineering characteristics for a product or service. Within the technology selection process a technology is often selected based on the requirements of the project, therefore the "needs" of the manufacturing or assembly process can be related to the product. QFD and the simplified form of the HOQ matrix are able to translate the needs of a process into the targets of a proposed technology. The matrix allows items of one list to be ranked based on their relationships with the items of another list. Similar to FMEA, where the technique alone is unsuitable to be used for technology selection, QFD can appropriately align the requirements of a process to an alternative to further understand the relation. Therefore, elements of QFD would be appropriate for technology selection.

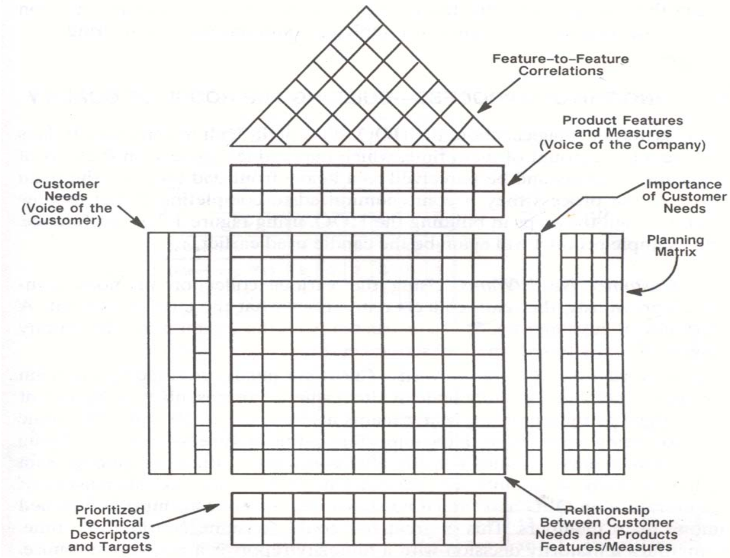

Figure 2.7 House of quality matrix (Shillito, 1994)

2.5 Fuzzy Logic and Fuzzy Systems

For many decision problems, several factors need to be considered simultaneously when emphasis towards a particular factor is not always clear. A trade off among criteria and alternatives is subsequently made. Fuzzy reasoning has been proposed in many instances as a solution to handling this type of problem, where a level of uncertainty exists within the decision process. The general framework of fuzzy reasoning facilitates the handling of such uncertainty. Fuzzy systems are used for representing and employing knowledge that may be unreliable, imprecise or uncertain (Asumi, 2011).

The concept of fuzzy was first introduced by Lotfi A. Zadeh, a mathematician at the University of California in his original paper on fuzzy sets (Zadeh, 1965). His research gained extensive interest in academic and industrial domains and has been applied to a wide range of disciplines and applications.

Fuzzy Sets and Membership Functions

Set theory is concerned with the concept of a set, a collection of objects which are defined as elements. It examines whether an object belongs, or does not belong, to a set of objects. Fuzzy sets can be considered as an extension to the theory of classical or crisp logic. In classical set theory, an object x is either a member of a set A, or not a member of set A. Thus, the membership $\mu_A(x)$ of x into A is given by:

$$\mu_A(x) = \begin{cases} 1, \text{if } x \in A \\ 0, \text{if } x \notin A \end{cases} \quad \text{Eqn. (2.1)}$$

When considering a parameter such as temperature, a person may say that 'less than 10°C is cold'. This account can be represented in the form of classical set theory as *cold* = $\{x|x \leq 10\}$ and demonstrated as a membership function in Figure 2.8.

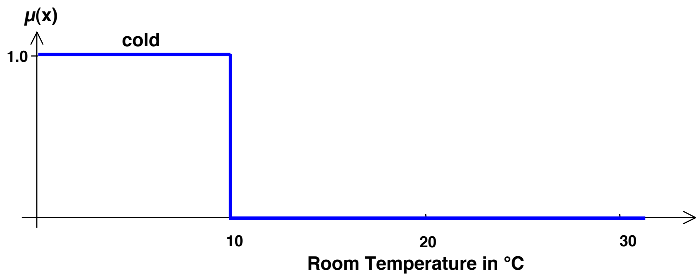

Figure 2.8 Membership function temperature (Asumi, 2011)

In distinction to classical set theory, the fuzzy set theory approach introduced the *'degree'* to the notion of membership. A fuzzy set A of a universe of discourse X (the range over which the variable spans) is characterised by a *membership function* $\mu_A(x) : X$ {0, 1} which associate with each element of x a number $\mu_A(x)$ in the interval {0, 1}, with $\mu_A(x)$ representing the *grade of membership* of x in A.

Returning to the previous example, the temperature statement can be represented in the form of a fuzzy set as shown in Figure 2.9. In comparison with the sharp boundaries in classical set theory, the concept of degrees of membership in fuzzy sets allows undefined or fuzzy boundaries to be defined. For example, it can be seen that a temperature of 11°C receives a degree of membership for cold but a lesser degree than 10°C (i.e. $\mu_{Cold}(x = 11) = 0.85$); whereas in classical set theory the degree of membership would be zero.

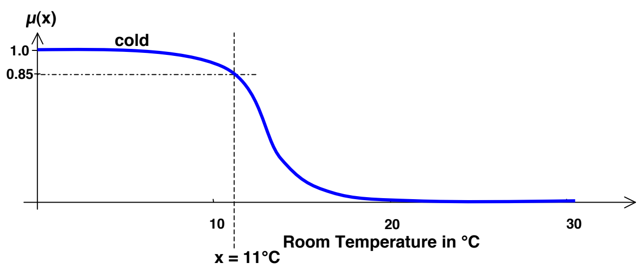

Figure 2.9 Fuzzy membership function temperature (Asumi, 2011)

Defining attributes in a fuzzy set assists in representing a problem in an everyday language, understandable by a human decision maker. The theory attempts to mimic human reasoning and decision-making by understanding the boundaries that exist between alternative sets within an evaluative variable.

Linguistic Variables, Values and Rules

Linguistic variables were introduction by Zadeh (1975) to refer to the sets within a variable that are best represented by linguistic expressions rather than as a numerical value. In the example shown in Figure 2.9, 'temperature' is a linguistic variable with a linguistic value 'cold'. Other linguistic values include 'moderate', 'warm' and 'hot'. Zadeh's theory suggests that each linguistic value is represented by a fuzzy set dependent on the domain of that particular problem. In relation to the temperature example, the characteristics of human reasoning may be interpreted as (Asumi, 2011):

- 'cold' is a temperature below 10°C
- 'moderate' is a temperature around 15°C
- 'warm' is a temperature around 20°C
- 'hot' is a temperature above 15°C

In the universe of discourse *U* = {0, 50}, which is associated with fuzzy sets with membership functions:

$$\mu_{cold}(x) = \begin{cases} 1, & \text{if } x \leq 10 \\ 1 - (x-10)/5, & \text{if } 10 < x < 15 \\ 0, & \text{otherwise} \end{cases}$$

$$\mu_{moderate}(x) = \begin{cases} 1 - |x-15|/5, & \text{if } 10 < x < 20 \\ 0, & \text{otherwise} \end{cases}$$

$$\mu_{warm}(x) = \begin{cases} 1 - |x-20|/5, & \text{if } 15 < x < 25 \\ 0, & \text{otherwise} \end{cases}$$

$$\mu_{hot}(x) = \begin{cases} 1, & \text{if } x \geq 25 \\ 1 - (x-30)/5, & \text{if } 20 < x < 25 \\ 0, & \text{otherwise} \end{cases}$$

The membership functions are represented graphically over the universe of discourse. The variable, temperature *T*, is assigned into four fuzzy sets – *cold, moderate, warm* and *hot* (Figure 2.10).

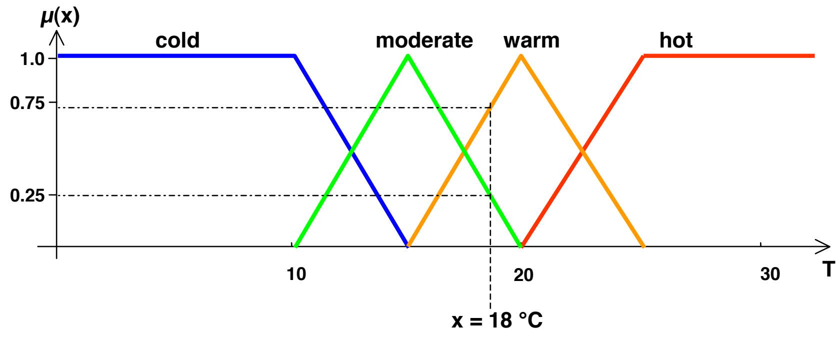

Figure 2.10 Fuzzy membership set function (temperature) (Asumi, 2011)

The fuzzy sets are overlapping which represent the degree of human reasoning for the fuzzy sets. It can be seen that a temperature of 18°C has a partial membership in both fuzzy set *moderate* and *warm*, where:

$$\mu_{moderate}(x = 18) = 0.25, \text{ and}$$

$$\mu_{warm}(x = 18) = 0.75$$

Fuzzy logic is a form of many-valued logic. It deals with reasoning that is approximate rather than fixed and exact. As discussed within Chapter 1 and Section 2.2, the manufacturing technology selection process is based on multiple criteria defined for both qualitative and quantitative parameters. Fuzzy logic is able to combine multiple opinions and express the undefined boundaries that exist in parameters. The theory of fuzzy logic appears to provide many benefits that are aligned to the current technology selection process. The varying degrees of truth and probabilities of the technical performance appear to be well suited to the numerous parameters discussed within the literature for technology selection.

Fuzzy Systems

Fuzzy systems generally consist of five interconnected components that form a complete system (Figure 2.11). Based on an input value, the fuzzification component computes a membership grade for each crisp input variable depending upon the defined membership functions within the system. The inference engine (IE) applies the appropriate fuzzy operator to determine a level of output. The final component transforms the output fuzzy set to a crisp output value, this is known as defuzzificiation.

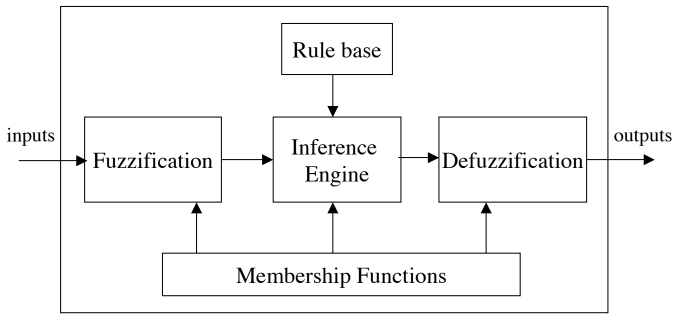

Figure 2.11 Component of fuzzy systems, adapted from Cordon et al. (1998)

The main phases in a fuzzy system design are:

- Examine and understand the problem in consideration.
- Determine the linguistic variables (inputs and outputs). Identify linguistic values and define fuzzy membership sets.
- Identify and define the fuzzy rule set.
- Choose an appropriate method for fuzzification, inference and defuzzification.
- Evaluate the system.

It is noted that the performance of a fuzzy system is highly dependent on the development of appropriate linguistic variables, membership functions and the fuzzy rule set. These phases ultimately provide the framework for the data and relate to the efficiency of the system.

2.6 Decision Support and Intelligent Support Systems

2.6.1 Decision Support Systems

A DSS is a class of information systems that assist organisations in decision-making activities. They are not limited to computerised systems, but are often interactive software based decision tools intended to aid decision makers compiling useful information from a combination of raw, technical, model, knowledge and documents, to identify, solve problems and make decisions.

DSSs are applied in a certain domain to support the analytical modelling of decisions by accessing a database of useful information. The system supports a decision maker by processing effectively in complex and ill-structured tasks. Petrovic (2008) explains that DSSs can support all phases of the decision-making process, they are adaptive and can be used by individuals or groups. Simple systems can be built by end uses and provide access to a variety of data sources, formats and types. Overall, decision makers can make more consistent decisions, better and in a timely fashion.

Figure 2.12 illustrates the common four components (Petrovic, 2008, p. 8):

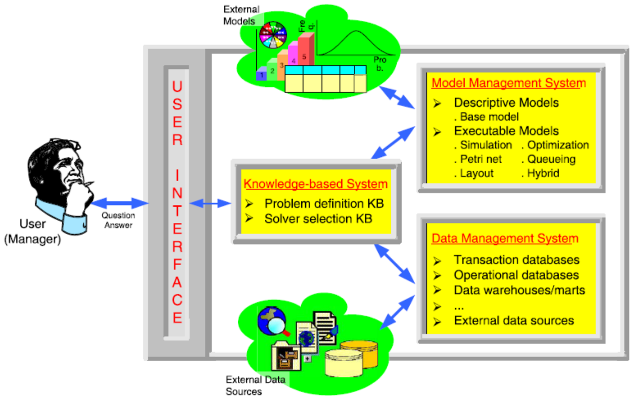

Figure 2.12 Decision support components (Delen and Pratt, 2006)

- "<u>Data management subsystem</u> includes the database, which contains relevant data for the problem.
- <u>Model management subsystem</u> includes financial, statistical, management science or other models and usually contains a modelling language for building custom models.
- <u>Knowledge management subsystem</u> provides intelligence to augment the operations of the other DSS components.
- <u>User interface</u> enables the user to communicate with the DSS."

2.6.2 Expert and Intelligent Support Systems

To solve complex decision problems, organisations often turn to experts for advice. These experts have specific knowledge and experience. They are often the best people to provide advice on matters such as which equipment to buy, merger and acquisitions, and advertising strategies. Typically, an ES or an intelligent system is a decision-making or problem-solving system that achieved a performance level comparable to an expert. They specialise in a field or narrow problem area. ESs attempt to mimic the decision thinking and logic of a human expert (Turban and Aronson, 2000).

KBSs are part of the group of artificial intelligence (AI) techniques that support demanding tasks that require intelligence. Through the availability of advanced computing facilities and other resources, KBSs are becoming more commonly available. The advantage of a KBS is that it can act on behalf of an expert, on demand at anytime. By leveraging the knowledge of experts, a higher level of consistency can be defined to a decision-making task. A KBS is a productive tool that advises collective knowledge of multiple experts (Akerkar and Sajja, 2009). Sajja (2000) outlines the differences between traditional computer-based information systems and KBSs in Table 2.3.

Traditional Computer-Based Information Systems	**Knowledge-based System**
Gives a guaranteed solution and concentrates on efficiency	Adds power to the solution and concentrates on effectiveness without any guarantee of solution
Data and/or information processing approach	Knowledge and/or decision processing approach
Assists in activities related to decision making and routine transactions; supports need for information	Transfer of expertise; takes a decision based on knowledge, explains it, and upgrades it, if required
Examples are TPS, MIS, DSS, *etc*.	Examples are expert system, CASE-based systems, *etc*.
Manipulation method is numeric and algorithmic	Manipulation method is primarily symbolic/connectionist and nonalgortihmic
These systems do not make mistakes	These systems learn by mistakes
Need complete information and/or data	Partial and uncertain information, data, or knowledge will do
Works for complex, integrated, and wide areas in a reactive manner	Works for narrow domains in a reactive and proactive manner

Table 2.3 Comparison of knowledge-based and computer-based systems (Sajja, 2000)

KBSs use and generate new knowledge from a defined database of data, information and knowledge. The systems are often capable of evaluating information to generate new knowledge where a decision task can be supported. Compared to traditional computer systems that do not know the data and information they process, KBSs are extremely promising.

The remaining part of this sub-section discussed further the collection of knowledge, representation of knowledge, and use of represented knowledge through reasoning and inference.

2.6.2.1 Knowledge Acquisition and Validation

Many practitioners have identified knowledge acquisition as a bottleneck that constrains the development of an ES (Turban and Aronson, 2000). It is the process of extracting, structuring and organising knowledge from one or more sources. Acquiring knowledge and deploying such knowledge is a powerful and valuable form of assisting decision makers to solve complex problems. It is a form of knowledge engineering (KE) that involves the co-operation of human experts that work within the domain and communicate with a knowledge engineer to codify and make explicit rules that a human expert uses to solve problems.

The KE process was defined by Turban and Aronson (2000) as five major activities (Figure 2.13):

- *Knowledge acquisition* involves acquiring knowledge from a variety of sources including: human experts, books, documents, sensors, or computer files.
- *Knowledge validation* is validating and verifying the knowledge to an acceptable form.
- *Knowledge representation* is organising the knowledge and coding it within the knowledge base.
- *Inferencing* is the computation to enable inferences based on the knowledge and the specifics of the problem to provide advice to a non-expert.
- *Explanation and justification* is designing and providing the ability to answer *why* and *how* questions to the system and draw conclusions.

The collection of knowledge is from a variety of sources such as books, films, computers, database, picture, maps, stories, *etc.* They can often be defined as either documented knowledge or undocumented knowledge. The undocumented knowledge tends to reside in an experts mind and requires extraction. The types of knowledge to be represented are shown in Figure 2.14.

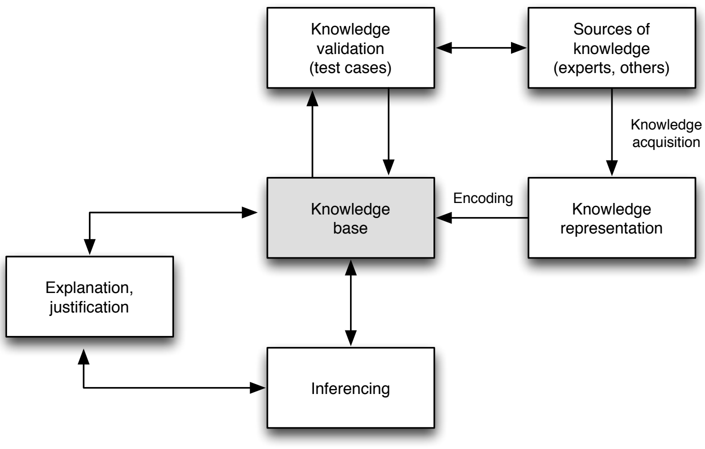

Figure 2.13 Process of knowledge engineering, adapted from Turban and Aronson (2000)

The acquisition of knowledge from an expert can be done manually or with the aid of computers. Manual methods tend to be structured interviews where a knowledge engineer elicits knowledge and codifies it within a knowledge base. Semi-automatic methods allow an expert to build a knowledge base with little or no help from a knowledge engineer. Automatic methods are often administered without a knowledge engineer and will rely solely on the expert.

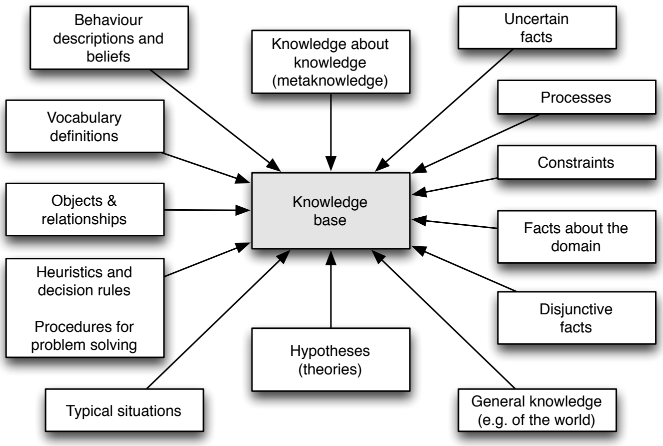

Figure 2.14 Types of knowledge. Adopted by Turban and Aronson (2000) from Fikes and Kehler (1985)

2.6.2.3 Knowledge Representation

Knowledge representation is a type of methodology by which a suitable structure is chosen to represent a given knowledge component to support storage, retrieval, inference and reasoning. It is a knowledge structure that enables easy operations on the knowledge it possesses. Data structures contain data and provide an access mechanism for reference, whilst a knowledge structure contains knowledge to provide reasoning and inference to achieve intelligent problem solving.

The knowledge representation scheme can be classified into broad categories: (i) factual knowledge representation and (ii) procedure knowledge representation. Factual knowledge representation is a form of formal knowledge and can be presented using first-order logic supporting constants, variables, functions and predicates. Procedural knowledge represents how to reach a solution in a given situation. It can be thought as 'know-how'. It is the steps in the procedure that represents the logic of an expert. Examples of procedural knowledge are rules, strategies, procedures and models (Akerkar and Sajja, 2009).

2.6.2.3 Inferences

Inference is an act or set of processing of deriving logical conclusions from certain premises of data or information known to be true. In deriving a conclusion, multiple observations are considered in which an assumption may either be correct, incorrect or contain a degree of accuracy. It is also known as 'inductive reasoning' that constructs or evaluates positions that are abstractions of observations or individual classes. The algorithm that controls the reasoning process is usually the IE or control program. It directs the search through the knowledge base and may involve the application of inference rules.

There are many specific inference techniques used in AI, here we introduce the commonly applied inference tree and case-based decision reasoning approaches.

Inference Tree

The inference tree provides a schematic overview of the inference process. Similar to an influence diagram or decision tree, each rule is composed of a premise and a conclusion. When building the inference tree, the premises and conclusions are shown as nodes, with branches connecting the premises and conclusions. Different operators, AND and OR can be used to reflect the alternative structures of the rules.

The tree is an excellent tool for visualising the process of inference and movement along the branches of the tree. The inference tree is assembled upside down, with the root at the top (end) and the branches point downward. Leaves are at the bottom of the tree and nodes are be a mixture of AND or OR nodes. The tree provides a guide for answering the *why* and *how* questions in the explanation process (Turban and Aronson, 2000). Figure 2.15 illustrates a typical inference tree.

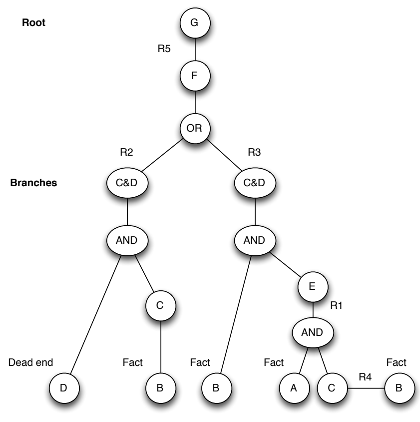

Figure 2.15 Inference tree (Turban and Aronson, 2000)

Case-Based Reasoning

Case-based reasoning (CBR) is a reasoning technique that retrieves and uses stored cases of past problems to support new decision problems. Stored in a case base, knowledge and experience from these cases support complex decision tasks. Previous solutions are adapted to new decision problems using the domain knowledge.

The new solved case is retained and reused. Cases are solved by retrieving the most relevant cases from a case repository that are adapted to fit new situations. Cases are represented as a contextualised piece of knowledge that expresses an experience of prior decisions to reach a goal (Leake, 1996). A typical case has two major parts: the problem itself defined with the context and environments and the solution of the problem (Qu, 2002).

CBR has been successfully applied to a wide range of problems (Kolodner, 1993) and a vast amount of work has been carried out concerning different techniques (de Mantaras and Plaza, 1997).

Aamodt and Plaza (1994) illustrate how CBR can be seen as a four RE's cyclic process: Retrieve, Reuse, Revise, Retain, as shown in Figure 2.16:

1. Retrieve – the most similar source cases efficiently
2. Reuse – the retrieved solutions to solve the target case (new case)
3. Revise – the solution concerning the new requirements
4. Retain – certain solved target cases into the case base

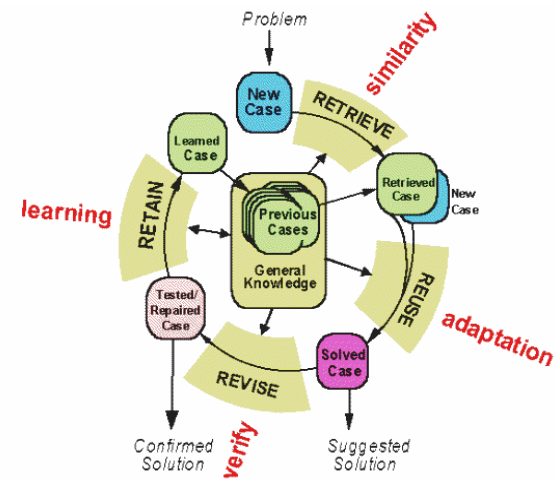

Figure 2.16 The case-based reasoning cycle (Aamodt and Plaza, 1994)

DDS toolsets and intelligent-based systems are suited to solving complex problems where the participation of multiple evaluators is needed. They are extremely advantageous for problems where the level of information and knowledge is unable to be considered by a single or multiple experts. The use of such a toolset integrated within an organisation and adaptable by multiple persons across different functions is beneficial where the decision process requires experts from different divisions within a company (e.g. finance, quality, manufacturing). The ease at which knowledge can be stored and considered through the evaluation of rules appears to suit the problem well. Although it is clear the extensive time and resource required to set up such a system, the long term benefits of knowledge developments is appealing where technology selection problems are expected to increase in complexity.

2.6.3 Data Mining

Data mining is a search technique of identifying new patterns in a defined dataset. The process is semi-automatic in which meaningful knowledge is extrapolated. The technique is used to create an economic or strategic advantage. Substantial quantities of data is often required to generate the best outcome (Witten and Frank, 2005). It is a branch of computer science that extracts patterns from datasets by combing methods from statistics and AI. The form of transferring data into BI is an essential tool to provide informal advantage.

This approach to recognising knowledge and patterns within datasets was first investigated as Bayes theorem (1700s) and regression analysis (1800s). The advancement in computer power has increased the proliferation of applications where models can handle increased data collection, storage and manipulation. Increased size datasets and complexity has brought the need for an automated data processing approach to data mining. Such techniques have been aided by discoveries in computer science. This includes clustering, GAs (1950s), decision trees (1960s) and support vector machines (1980s). The intention of data mining is to uncover hidden patterns using these techniques (Mehmed, 2003). Various data mining techniques and approaches exist within the literature, to provide further information related to this research study, this chapter will present the close relationship between rule induction (RI) and fuzzy decision trees (FDTs).

Rule Induction/Fuzzy Decision Trees

RI is part of machine learning where the extraction of a set of observations is achieved through formal rules. They may represent a full scientific model of the data, or merely represent patterns within the dataset. It is a form of intelligent analysis and often called *classification rule induction*.

Flach and Lavrac (2010), p. 1 define the classification rule-learning task as follows: “Given a set of training examples (instances for which the classification is known), find a set of classification rules that can be used for prediction or classification of new instances, i.e., cases that haven’t been presented to the learner before. A more formal definition of the classification rule-learning task has to take into account the restrictions imposed by the language used to describe the data (data description language) and the language used to describe the induced set of rules (hypothesis description language).”

Within the literature, many techniques support the construction of decision trees from a collection of examples (Safavian and Landgrebe, 1991). Yet there is still a difficulty of handling the vagueness and ambiguity associated with human thinking. The decision tree may be useful when building a knowledge-based ES and easy to understand, but the perception of a human when creating the tree is difficult to master (Yuan and Shaw, 1995). Decision trees are categorical and tend not to convey potential uncertainties in the classification calculation. Small changes in attribute values can result in sudden and inapplicable assignment classes.

It is these small changes in attribute values to sudden changes in the assigned class that FDT attempt to overcome. Crisp trees work well where class boundaries are non-overlapping and clearly defined. However, in reality, this is rarely the case when representing human thinking and reasoning. Fuzzy set theory allows the conversion of hard and crisp discrete partitions into soft and fuzzy divisions of the training set. The induction of FDTs applies similar steps to that of a classical decision tree with modified induction criteria (Janikow, 2002). In a fuzzy approach, the continuous attributes are partitioned into the defined fuzzy sets prior to creating the tree, which is based on expert opinion and data characteristics.

A crisp set *Ac* is expressed with a sharp characterisation function $Ac(a)$: $\Omega \rightarrow \{0,1\}$, $a\Omega$, alternatively a fuzzy set *A* is characterised with a membership function $Ac(a)$: $\Omega \rightarrow \{0,1\}$, $a\Omega$. The membership function $A(a)$ is called the possibility of *A* to take a value $a\Omega$ (Zadeh, 1978).

Generally hard discretion defined by a threshold generates two crisp sets. On the other hand, a soft discretion is defined by a fuzzy set pair, which forms a fuzzy partition. The soft discretion is defined with 3 parameters/functions, one is the cross point *T*, the other 2 are the membership functions of the fuzzy set pair *A1* and *A2*: $A1(a) + A2(a) = 1$ (Peng and Flach, 2001, Quinlan, 1987). The cross point *T*, i.e. the localisation of soft discretion, is determined based on the maximisation of the information gain in classification, and the definition of the membership functions of characterising each attribute in the dataset. To manage the uncertainty of the associated attribute, wide overlapping among the uncertain attributes is used among the data points (Bharti, 2004).

FDT induction has two major components: a procedure for FDT building and an inference procedure for decision-making (Lee et al., 1999). The building procedure, similar to classical decision induction, calculates the information gain, as the criterion to generate the best discretion for the corresponding attribute. After choosing the best attribute of all other attributes, it is placed as the root node. The inference procedure allows a data object to propagate across several paths down the tree falling into one or more leaf nodes with some certainty with possibly different classification decisions (Abu-halaweh, 2009). Various types of inference procedures have been proposed and the reader is referred to (Janikow, 2002) for a description of two inference methods:

- The first method corresponds to labelling the leaf node with the greatest membership class value
- The second value corresponds to labelling the leaf node with their membership values as class names

A FDT, as shown in Figure 2.17, consists of a number of nodes and leafs where each attribute is expressed as a fuzzy membership set. For instance, the root node, ‘receiver exist’ which contains 2 classifications, would be represented as a fuzzy set similar to Figure 2.9. Rules are extracted from the FDT and expressed in classification form IF-THEN. These rules are then applied to an inference technique in order to classify a new data set.

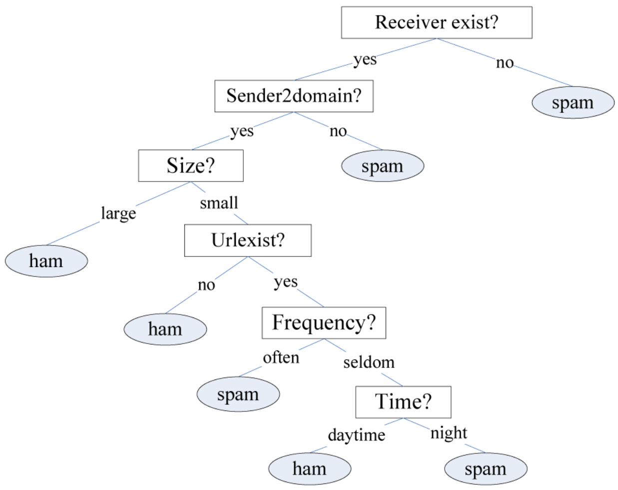

Figure 2.17 Fuzzy decision tree example (Meizhen et al., 2009)

Data mining is a powerful technique for discovering knowledge that would otherwise be unknown. The discovery of patterns in large data sets of exact information into an understandable structure for further use can be beneficial for supporting decision processes. The performance of such systems is well documented and automatic analysis of large-scale data shown to provide additional advantages compared with standalone techniques such as AHP and FMEA. The technique is suited to problems where a level of data exists and is likely to develop overtime. For example, where knowledge is likely to change as further information is acquired, data mining is easily able to interpret such information, with little input from experts. The approach relies on accurate information and data to generate knowledge that would otherwise require human expertise. For domains such as manufacturing technology selection where expertise and information is required, data mining is an appealing technique.

2.7 Literature Review Analysis

This section summarises the published literature in manufacturing technology selection and discusses the potential trend for the domain. Due to the popularity of the domain and the importance surrounding the investment justification of manufacturing technology, a number of review articles are discussed within the literature.

One of the most straightforward and natural approaches to technology selection is the economic approach. It has been widely applied within the literature. PP, ROI, NPV and IRR are frequent accounting justification methods used by managers in the evaluation of a project (Hynek and Janecek, 2007). Economic decision-making relates to the economic information that supports judgement for a decision problem. Related to the purchase and use of a product, economic models evaluate how well an investment will return and perform throughout its intended use, from purchase to decommission. The economic approach has long been popular in investment justification through the cost/benefit analysis that can easily be conducted. Economic models can improve a firm's ability to account for costs and benefits. In addition, where the level of risk and uncertainty make up the most critical elements of the justification process, caution can be calculated to ensure an organisation remains financially viable. Although the approach has much support, many academics argue that although the techniques are sensible in isolation, they are not always appropriate when considering a technology within its context (Chan et al., 2001).

Similarly, analytical approaches support more complex computations of predominately quantitative-based information. For intangible benefits, analytical approaches can provide a more realistic consideration of data by offering a better reflection of reality (Meredith and Suresh, 1986). Many approaches described within the literature include traditional optimisation techniques, scoring and ranking models, and risk analysis approaches. There appears to be a lack of consideration towards the transformation of the problem to the model that requires a great deal of simplification. In this case, many important factors are not considered. Furthermore, weighted approaches are vulnerable to the subjective judgement offered by a decision maker (Hynek and Janecek, 2007).

Strategic justification approaches tend to be less technical than economic and analytic methods and used in combination with them. Strategic objectives and vision tend to be defined in qualitative terms that are a combination of the goals to which a firm strives for and the means by which an organisation adheres to them.

They are extremely beneficial as they link the requirements with the goals of a company. Factors such as the retention of competitive advantage, the business objectives and industry leadership may be utilised. Although assigning too much weight towards strategic approaches may be unreasonable, a consideration of strategic together with economic and analytical is required (Hynek and Janecek, 2007).

Recent studies have promoted researchers to adopt hybrid approaches based on a combination of economic, analytic and strategic appraisal techniques. Often there are many roadblocks in the acquisition process; for the justification of advanced manufacturing systems, quantifying revenue or quality improvements is challenging, if not impossible. Practicing managers find that investments in advanced technologies is merited and advantageous, but find it difficult to articulate and translate this ‘gut’ feeling into the language of finance and accounting, which is a prerequisite to the funding and allocation of resources (Raafat, 2002)

The majority of existing publications in manufacturing technology selection is formed as two groups: MCDM and knowledge-based methods. The MCDM models tend to be deterministic in nature and reliant upon the subjective input values of the decision-maker. The knowledge-based approaches apply methods from within the AI and data-mining field; techniques formulate decisions through an acquired knowledge base in a subjective manner.

In terms of MCDM, Karsak (2008) introduced a decision model for robot selection based on QFD and fuzzy linear regression. QFD were applied to focus on delivering value by considering customer requirements whilst the relationship among system parameters was supported by fuzzy regression. Bayazit (2005) provided an insight into the use of AHP in evaluating flexible manufacturing systems (FMSs). The model was proposed to guide management of a tractor manufacturing plant and formed the most important factors, their relative importance and influences on the objective of the decision-making model. The author found that when dependences and interactions among the criteria exist, the analytic network process (ANP) model is more appropriate, yet AHP assumes linear independence of criteria and alternatives. Almannai et al. (2008) developed a decision support toolset based on QFD and FMEA for supporting management in addressing technology, organisation and people at the earlier decision-making stages. The developed decision tool was evaluated in industry and tested using data that produced a valid output.

A number of authors (Bayazit, 2005, Chang et al., 2007, Yang et al., 2009, Arbel and Shapira, 1986, Goh, 1997, Datta et al., 1992) have investigated the application of the AHP to a variety of selection decisions including vacuum pump technology, slicing machine, robot selection, justification of manufacturing systems, FMS, wafer fabricating and computer integrated manufacturing (CIM). The AHP provides a methodological approach to a decision-making problem that is reliant upon accurate expert judgments to form the final decision.

Myint and Tabucanon (1994) and Yurdakul (2004) both developed a hybrid approach using the AHP and goal programming (GP) in the selection of flexible and integrated manufacturing systems respectively.

Extending the use of a MADM approach using a combined AHP and GP technique, the model was able to consider multiple conflicting goals with limitations and dependencies. Lowe et al. (2000) developed a multi-attribute matrix analysis tool from the techniques of QFD. Applied to the evaluation of products within a innovative metal forming process, the model recorded the level of subjectivity necessary without substituting a comprehensive economic analysis. It recorded the level of subjectivity necessary in allocating characteristic settings, importance weightings and interrelationships scores. Nelson (1986) and Georgakellos (2005) both presented scoring models for considering each possible alternative based on a single score. The main advantages were that the approach is easy to understand and use, while being time and effort consuming.

Rao and Padmanabhan (2007) understood the need for a simple, systematic and logical scientific method to guide user organisations in a suitable rapid prototype (RP) selection decision. The authors considered graph theory and matrix approach to determine attributes that influence RP process selection. The matrix approach was useful in analysing the graph/graph models expeditiously to derive the system function and index to meet the objectives, whilst the graph/diagraph model proven useful for modelling and analysing various kinds of systems and problems. Rao and Patel (2010) helped to understand and solve the decision-making problem using the preference ranking organisation method for enrichment evaluations. The method supported real-life decision situations in an effective manner.

Since Zadeh's pioneering paper on fuzzy sets (Zadeh, 1965), a number of authors have attempted to incorporate fuzzy logic (FL) to improve existing decision models by relating closer to human reasoning than crisp logic. Abdel-Kader and Dugdale (2001) noted that is it conceptually possible to evaluate investments in AMTs using the mathematics of the AHP and fuzzy set theory. The integration of financial and non-financial factors based on a conceptual framework that combines the 3 dimensions of risk, financial return and non-financial factors was developed. In particular it draws on models based on the AHP and uses both fuzzy numbers and linguistic variables for AMT investment decision-making.

Liang and Wang (1993) proposed a robot selection procedure using the concept of fuzzy set theory, whilst Chan et al. (2000) quantified tangible and intangible benefits for technology selection in a fuzzy environment. Sener and Karsak (2007) presented a decision model based on fuzzy linear regression with non-symmetric triangular fuzzy coefficient and fuzzy optimisation for technology selection. Houseman et al. (2004) presented a technology selection methodology to quantify both tangible and intangible benefits of certain technology alternatives within a fuzzy environment. Decision makers expressed their opinions on comparative importance of various factors in linguistic terms rather than exact numerical values. The author discussed how using linguistic variable scales, such as 'very high' correlated to fuzzy membership sets and later defuzzified, become more meaningful to quantify a subjective measurement into a range rather than an exact value. Chu and Lin (2003) proposed a method for robot selection where the ratings of alternatives versus subjective criteria and the weights of all criteria are evaluated in linguistic terms. A closeness coefficient was defined to determine the ranking order of alternatives by calculating the distances to both the ideal and less appropriate.

The number of publications in manufacturing technology selection using knowledge-based decision models is somewhat less than MCDM, however, they provide an excellent insight into the suitability and advantages that can be obtained from using such techniques. Delen and Pratt (2006) reiterate the importance of structuring a problem based on a given set of symptoms by providing it with enough information needed to make a decision. To succeed in such a fast paced business environment, integrating intelligence in the decision-making process is required to provide the correct information and knowledge.

Shashikumar and Kamrani (1995) explains how research fields in AI accelerate and a greater number of experts are demanded by industry. In order to meet the technological sophistication in today's demanding environment, ESs can play a crucial role. Based on this assumption, the authors presented a viable solution to the problem of selecting an optimum robot by building a knowledge-based ES. The system asks the user several questions regarding the usage and requirements of the desired robot. It uses the knowledge base and rules to determine an optimum robot. If the analysis leads to more than one robot, a feasibility approach of computing economic values is performed to rank the alternatives. Masood and Soo (2002) presented an ES based on RP system selection incorporating 39 systems. The program was a rule-base ES and recommends the RP system along with its full specifications based on an interactive question-answer session with the operator.

Tan et al. (2006) developed an intelligent system integrating CBR and the fuzzy ARTMAP[1] (FAM) neural network (NN) model to support industrial decision makers in making an appropriate selection of manufacturing technology investment. The system comprised a case library that holds the details of past technology investment projects. Each case was characterised by a set of features determined by human experts to represent the technology alone. The framework uses historical case information to match features of a new proposal. Similar

[1] ARTMAP is a class of NN architectures which perform incremental learning of recognition categories and multidimensional maps in response to input vectors presents in arbitrary order

cases are retrieved and adapted, and information on those cases utilised to prioritise new projects. Similarly, Kraslawski et al. (1995) proposed a CBR approach for mixing equipment selection. Designed in two parts, the first presented the problem and retrieval stages, whilst the second the adaption, validation and realisation. The system provided a systematic documentation of cases and accumulated experience. The use of CBR for the problem was found to be very promising in the use of high quality, verified knowledge and ease to update.

Bayraktar and Gozlu (1994) proposed a technology acquisition framework to deal with issues such as sales, processes, cost and general policies through a knowledge-based approach. Questions generated by the system direct the user to identify the current position of the manufacturing organisation, determine the effect factors have on technology acquisition leading to a ranking of solutions.

Chtourou et al. (2005) presented an ES used in a simulated based approach in order to structure the solution search mechanism for machine selection. The rule based and object oriented tool permitted to obtain satisfactory preliminary results in the sizing of a simple machine selector. Similarly, Er and Dias (2000) developed a rule-based ES approach to process selection for cast components. The system progressively evaluated the user's specifications against the capabilities of various casting processes and in each level selected the processes that satisfy the design parameters specified. Formal IF-THEN knowledge rules are coded within the development environment to support the case process selection problem.

In summary, the achievement to date has significantly developed from the traditional financial models that were the main justification models for manufacturing technology selection. MCDM tools formed the next step forward by providing a systematic approach that considered additional factors rather than financial justification alone. The limitation of financial models is easily apparent from their sole consideration of financial performance. Whilst MCDM enables multi-criteria factors to be considered, their ability to be influenced by the decision expert limits the model in determining a timely and objective analysis. Rating scales and measurement values do not restrict the user and provide an output of the information provided. This could typically be biased information. MCDM tools are also unable to consider a form of defined knowledge learnt from prior cases. The outcome and suggestion of a decision is not captured to influence in any future decision problems.

More recently knowledge and intelligent based approaches have been developed and have begun to show a level of promise. Knowledge is acquired from a knowledge engineer. Their responsibility is to capture relevant knowledge and store in a suitable format for analysis. These toolsets are complex and required extensive resources to develop and use. In addition, they tend to lack a level of iteration as their knowledge was formed by the experts. This introduces a level of ambiguity where persons can influence the output by providing inaccurate or biased information. Rule-based reasoning attempted to restrict the complexity of expert knowledge; however, conflicting rules are difficult and extensive to define.

To further understand the problem and fully the narrative to support the development of a decision model, the following section explores current state-of-the-art practices within the industry. To identify the models and methodologies available within industry, an analysis of commercially available software, industry standards and supporting information is discussed in Section 2.8

2.8 State-of-the-Art Review

A state-of-the-art review was conducted to understand from an industrial perspective, the current technical support and software available for supporting technology selection in practice. The literature contains several references which discuss general methodologies and techniques for modelling and supporting technology selection. In contrast, relevant standards for technology evaluation and commercially available software for decision support were evaluated to understand to what extent theoretical models are currently applied in industrial practice and discuss possible reasons why.

Whilst the literature is abundant with techniques and methodologies, no regulatory standards are available for technology selection. The research evaluated similar standards within the area of manufacturing related to the decision process; two existing standards were identified. They focused on the facilitation of integrating manufacturing applications and the performance of manufacturing process capability. In relation to Figure 1.1, these two standards relate to the "evaluation" and "implement" stages of the technology selection process.

In terms of evaluation support, related standards from the British Standards Institute (BSi) and the American National Standards Institute (ANSI) exist. Whilst neither discuss general manufacturing technology selection and are relatively specific, they are the most related to this research in which ANSI B5.54[2] focuses on performance evaluation of computer numerically controlled machining centres and BS ISO 22400-2[3] key performance indicators for manufacturing operations management.

ANSI B5.54 defines common terms, machine types, position resolution, and operating modes to address the requirements of machining centers. The standard provides tests for evaluating machine accuracy performance as a machine tool. The value of these characteristics indicates the capability information of a given machine tool to

[2] ANSI/ASME B5.54 *Methods for performance evaluation of computer numerically controlled machining centres*
[3] BS ISO 22400-2 *Automation systems and integration – Key performance indicators for manufacturing operations management*

relate appropriately to a manufacturing process. The standard provides tests to evaluate such characteristics against the required performance.

BS ISO 22400-2 focuses on the key performance indicators for manufacturing operations management, defined as quantifiable and strategic measures that reflect a manufacturing organisations critical success factors. The standard relates to manufacturing operations management and includes a set of generic terms related to economic, business, logistic and financial factors.

Similar standards have also been developed by specific industries. For example, the National Aerospace Standard (NAS) 979[4] provides a set of performance attributes for the selection of cutting tests to evaluate the performance of conventional and numerically controlled machine tools. The standard establishes tests to assist characteristics such as accuracy, repeatability and cutting profiles.

The international standard BS EN ISO 19439:2006 specifies a framework for enterprise modelling to serve as a basis for computer integrated manufacturing. The standard provides a model-based decision support leading to model-based operation, monitor and control. Seven dimensions for enterprise modelling are indicated: domain identification, concept definition, requirement definition, design specification, implementation description, domain operation and decommission definition.

To summarise, the standards available provide very limited support for manufacturing technology selection. The standards which exist are generic and no methodology is available for evaluating and selecting alternative manufacturing technologies and systems.

The state-of-the-art review also considers commercially available software for decision support. It is apparent that no software exists specifically for supporting manufacturing technology selection. However, software does exist which can be used for supporting the process in practice. The weighted ranking of technologies by an expert can be conducted using spread sheet software such as Microsoft Excel[5] or iWork[6]. The software assists by allowing the calculations of multiple weighted alternatives to be normalised and summed. As discussed within the previous section, AHP is a popular method for decision-making. XpertRule® Miner[7] is commercially available software for applying the AHP toolset through a simple interface of multiple factors. The software allows multiple evaluative factors and technologies to be considered and displayed in a tree-like model. The software delivers an advanced business rule engine and expert system software to automate business decisions.

[4] NAS 979 Uniform cutting test – NAS series: metal cutting equipment specifications, National Stanard Association
[5] Microsoft Excel is a spread sheet application developed by Microsoft
[6] iWork is an office suite of desktop applications created by Apple Inc for OS X
[7] XpertRule® Miner is a data mining environment supporting data preparation, visualisation and knowledge discovery

Although the use of data mining techniques has not yet been applied for manufacturing technology selection, an abundant of software exists for applying the technique in practice. RapidMiner[8] enables multiple data mining techniques to be applied to a variety of decision problems. The software allows multiple parameters and datasets to be considered. The standalone application for data analysis has multiple operators for data integration, evaluation and mining. Economic factors are considered for all manufacturing technology decision problems. A multitude of costing tool software is available. TruePlanning®[9] by PRICE Systems provides support for ROI planning through cost analysis. In addition, COCOMO®[10] is a model developed by the University of Southern California that allows the estimation of cost, effort, and schedule planning. Whilst these costing tools are available within the marketplace, their use and development for manufacturing technology selection is limiting. Within practice, it is likely that spread sheet software would be used.

To conclude, the current state-of-the-art has demonstrated a lack of support for manufacturing technology selection in practice. Standards available are unrelated to fully support the decision methodology. Software available has been developed for a variety of applications and not specifically manufacturing technology selection. Whilst some can be adapted to the problem, the standards and software currently available are insufficient.

2.9 Knowledge Gaps

Despite the significant developments in the reported research areas, the available decision support methodologies do not appear to appropriately support decision-makers through the acquisition and retention of decision knowledge, where current approaches are reliant on the knowledge of experts. In addition, current techniques presented within the literature can be easily influenced by subjective judgement. The review of literature demonstrated an on-going trend towards hybrid multi-criteria models that utilise the judgement of a human decision maker to support the optimal selection of manufacturing technologies. In recent years, traditional economic approaches alone have been combined with analytical and strategic models to create a variety of approaches. However, these methodologies do not utilise the complex information and knowledge created through continuous iterations of the decision-making process.

Multi-criteria approaches lack learning and the re-use of past decision information is not possible. There are some reported approaches that support the selection process through the acquisition of knowledge for use within

[8] RapidMiner is freeware data mining software
[9] TruePlanning® is a cost estimation solution
[10] COCOMO is an algorithm software cost estimation model

specific manufacturing domains. Knowledge is acquired and expressed through a form of rules, frames, cases or procedures. It is however, difficult to extract from multiple experts and merge into a single framework for supporting technology classification. The systems are complex and industrial managers have difficulty using them in practice. In addition, they do not consider the direct decision information formed by each decision case. They rely on the interpretation of experience (involvement in prior cases) by a human expert, increasing the potential for a biased classification process.

The following gaps in knowledge have been identified within the current literature for manufacturing technology selection:

Limited insight into the techniques, standards and approaches supporting technology selection in practice; lack of definitive understanding of information and knowledge flow to support decision-making in practice

The manufacturing technology selection process is often described within industry as know-how, based on the judgement and experience of a human expert, in an ill-defined form. An understanding of the approach and practices within industry is lacking. The multi-criteria techniques reported within the literature which support industrial practices are unknown. To define a baseline of current industrial approaches and techniques, a review of practices is essential.

Furthermore, the process by which information and knowledge supports decision practices appears to be vast. Information and knowledge flow is apparent outside of the traditional evaluation and selection process. The content supporting technology selection is influenced by human rational due to the lack of definitive structure within the decision process. Subsequently, the alternative forms that combine to support manufacturing technology evaluation and selection require clarification.

Lack of performance measures for manufacturing technology evaluation and systematic approach of quantifying performance to support decision-making; no definitive form of representing historical manufacturing technology decision cases

The limited understanding of performance measures for manufacturing technology selection is apparent from the lack of industrial studies within the area. Whilst the literature describes several types of evaluation (financial, technical and strategic), there is a lack of classification of the most appropriate measures considered by industrial experts.

Furthermore, quantifying the qualitative and quantitative elements in an appropriate manner defines the performance of evaluation of an expert. Tangible and intangible benefits are difficult to quantify and the literature lacks a systematic approach of quantifying performance measures for which a technology can be evaluated. The structure an expert recalls knowledge is based on their prior involvement in decision cases. No standards appear to exist demonstrating the logic to which historical cases are referred. Previously considered decisions and implemented technologies provide factual background information and knowledge to support new problems. Experts form rules of the applicability of alternatives. Thus, understanding the relationship between rules and case information requires investigation.

There is a lack of definitive understanding how a technology decision case is defined within practice. Influential parameters exist however their logical definition is limited. The vagueness among decision languages requires uniformity across platforms for a consistent support process. Defining and characterising such information of recalled decision cases by an expert is required. Whilst the literature has proposed factors for technology evaluation, industrial validation and the quantification of measures does not fully quantify the ambiguity and biased view that exists today.

Lack of experience-based self-learning decision methodology; knowledge sharing across organisations to support technology capital investment, and ability to integrate quantitative and qualitative decision characteristics

Experience is a key component that supports the development and skill of an expert. Current practices rely on experts to recall previous examples and learned knowledge to support new decision problems. Missing within the current literature is a methodological approach to manufacturing technology selection that elicits and applies knowledge from past cases (experience). Knowledge sharing across organisations to support decision makers in manufacturing technology selection is also missing within the current literature. Methods that elicit decision rules for technology selection from formally defined and captured decision-making experience is lacking to support technology capital investments. The underlying logic and experience defined by a decision expert does not exist in a form to support manufacturing technology selection.

Furthermore, the capability to integrate quantitative and qualitative decision characteristics in a single platform is required to ensure the range of parameters considered is reflective of that of an expert decision maker. Quantifying qualitative performance factors and combining performance with tangible factors on a quantitative measure must be defined.

Chapter 3

Research Aim, Objectives and Methodology

3.1 Introduction

Chapter 2 investigated the literature and state-of-the-art to highlight the gaps in the existing body of knowledge. This in turn led to the development of the research hypothesis and methodology. This chapter defines the research aim and objectives, research methodology and purpose. Alternative research methods and data collection techniques are discussed, and the selected techniques justified. The research programme provides an overview of the research plan.

The vision behind this work is inspired by the need to formulate a systematic, decision-making process that results in a high quality, justifiable and knowledge supported technology selection process. An iterative environment is envisaged to create an efficient manufacturing technology selection approach that uses previous investment decisions during the later stages of technology evaluation and choice. The aim is to reduce the subjectivity in the decision-making process through the inclusion of factual historical decision information through a series of knowledge rules.

The new paradigm is best shown by adopting the technology selection process shown in context by Shehabudden (2001) in Figure 1.1 The iterative concept is developed in Figure 3.1 where the input information is applied at various stages to assist in each phase of the process. The knowledge learnt is captured and used to assist in the earlier phases of the decision process.

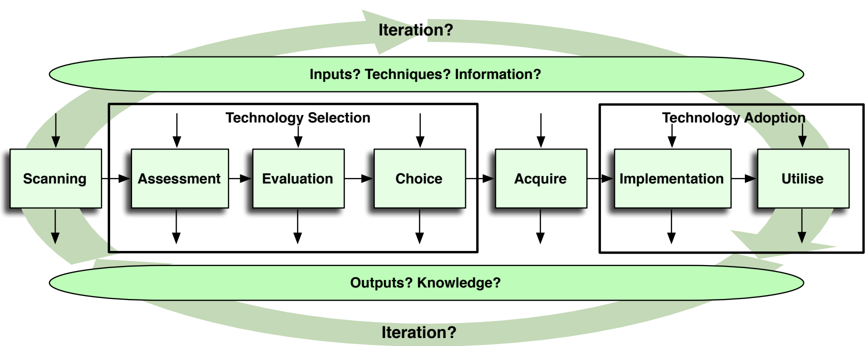

Figure 3.1 Generic framework for new paradigm adapted from Shehabudden (2001)

The process combines 3 phases: assessment, evaluation and choice. The approach to technology selection is linear and explicit in which each stage is data driven by an expert. Current methodologies lack consideration to the close integration of technology selection and adoption. Decision makers judge this as two processes in the overall selection method. Yet the experience and expertise used to make the 'choice' of a technology can be influenced by the stages preceding technology selection. In reality, the process is biased to the decision maker.

This confliction of innovation and experience against the structured approach to the process can be detrimental to the success of a selected technology. Decision makers involved tend to focus on satisfying the requirements of each stage rather than being innovative in combining the technology adoption issues with the selection of an optimal investment.

The innovation of developing this new paradigm is through historical case information transformed to knowledge to support the decision-making process. The iteration of capturing information and knowledge during the technology adoption phase and adapting this to support technology selection would reduce the current disregard for the activities adjacent to the selection process. Through an understanding of the input information and output knowledge, a rational level of know-how similar to the expertise of a decision expert would be developed. The development of the new paradigm in Figure 3.1 suggests that the logical linking of the complete decision process would provide factual support to the justification of new manufacturing technologies.

3.2 Research Aim and Objectives

The scope of this research is within the domain of decision-making for medium complexity single manufacturing technologies; evaluated independently and comparatively ranked. The research focuses on current practices across the decision-making process from initial technology requirements through to evaluation and selection. The research considers the decision logic of an expert through their use of past experiences. The form of representing the logic is presented. This chapter discusses the research methods and data collection approaches that enable each objective to be achieved.

Technology selection is a dynamic task where the application within the manufacturing domain has an ill-defined and ill-structured form. It owes to the various constraints and increases pressure on managers to select optimal investment projects. Industrial managers are often faced with the dilemma of choosing a single investment solution based on a large number of complex options. Decision makers must be familiar with the process and technology options to form judgement. However, due to lack of bounded rationality and limited capacity for information processing, the process is difficult to conduct.

The problem is that despite the importance of providing a methodology, existing literature fails to provide a resolution to key challenges of an objective approach and use of information and knowledge to support future decision-making.

Upon conducting a detailed review of literature, the aim of this research is:

"To develop, demonstrate and validate a decision-making framework that ranks and justifies manufacturing technologies using factual information through an evidence-based approach."

The literature has suggested that the development of an experts' expertise is based on their involvement in experiments/decision cases. This expertise can be represented in a number of ways and this research aims to define a factual form of representing decision information. This would subsequently support an evidence-based approach to rank and justify alternative manufacturing technologies.

The proposed decision-making framework provides a new approach based on an understanding of the existing literature and current industrial decision practices. The framework is a suitable foundation and trigger for further application development and industrial integration. The specific challenges that need to be overcome have been outlined in the discussion of knowledge gaps in Section 2.9.

The focus of this work is primarily on the development of a suitable methodology for the selection of an optimal manufacturing technology. The evaluation would be conducted from a range of alternative solutions using historical decision information to support the activity. The model will benefit from historical decisions to provide an objective approach for new decision-making problems. It has been assumed that an interactive software-based programme could be developed and deployed to support the integration within a manufacturing organisation upon a suitable methodology being developed.

The identified knowledge gaps in Section 2.9 have been converted to the following research objectives:

1. Define existing practices carried out within industry for manufacturing technology selection and identify potential areas for improvement to set a benchmark of the state-of-the-art principles
2. Investigate the transfer of information and knowledge at each stage in the manufacturing technology selection process
3. Study the key decision variables for representing historical manufacturing technology implementation cases and the characterisation of such parameters to define the structure for a case-based approach to the problem

4. Develop a technology selection methodology to support decision-making through the application of historical decision information
5. Verify the proposed methodology through an industrial case study and contrast with existing decision-making practices

3.3 Research Process and Strategy Design

This section describes the approach to the research and the development of the research strategy. The section concludes with an overview of the research programme.

The nature of this research is to understand the current manufacturing technology selection situation over a short period of time. As it is unlikely that the type of practices carried out within industry will change over a period of a few years, understanding the process and clarifying the decision-making during a single period is expected to be sufficient. Industrial manufacturing managers have been faced with the difficulty of identifying and implementing a single most technology for many years, and it is extremely unlikely that a significant breakthrough will be employed in such a short period of time. It is not expected to be a moving picture during the course of this research; therefore, a single snapshot conducted over a short period is most appropriate. The study period of time was less than one year.

3.3.1 Research Process

In order to meet the stated research objectives, a six-stage process was derived. Each stage is described within this section. Figure 3.2 shows how the corresponding stages are aligned to the chapters within this thesis. The research stages are further defined in four phases: the scope of the literature to define the research, an empirical investigation into the decision-making practices and understanding of the information context for historical decision cases, the design and development of the decision model, and the validation of the decision model.

Each of these phases was conducted in sequence with some concurrent overlap throughout the research project. Figure 3.2 shows the logical steps in which an understanding of the domain and approach to technology selection was well understood. The development of an information/experience-based approach is well justified and the sequence of events supports the development of the model.

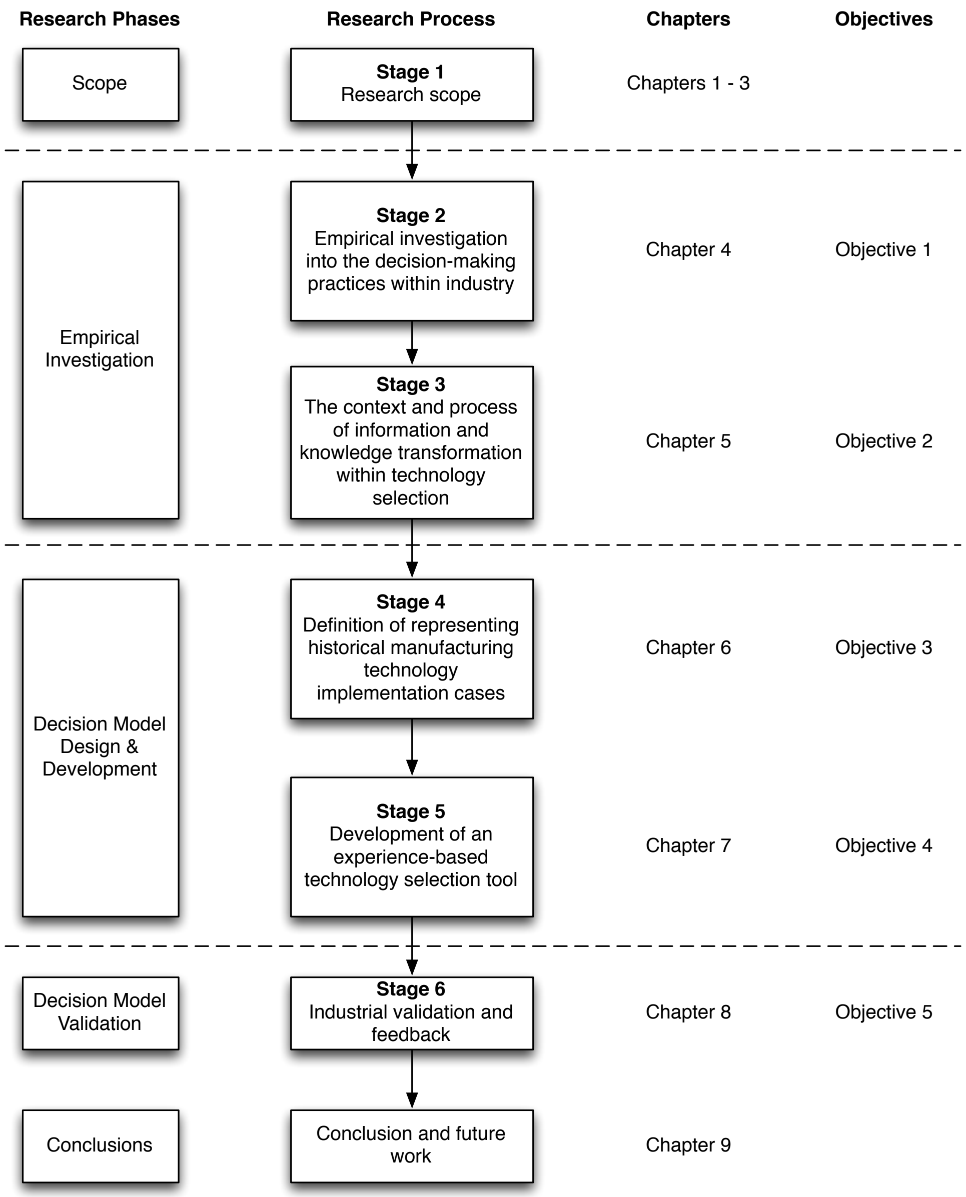

Figure 3.2 Six-stage research programme/framework aligned to research objectives

Stage 1: Research Scope

The initial stage of the research process involves conducting an appropriate review of relevant academic literature. This concerns defining a benchmark for manufacturing technology selection from within the theory. Understanding the approaches and techniques to the problem, forms of representing variable decision characteristics through discretisation and fuzzy logic, and approaches to facilitate knowledge representation through data mining are each conducted. The findings of the review are used to fully define the research aim and objectives. This initial stage forms the scope of the research work.

Stage 2: Empirical Investigation

The academic literature suggests that the application of theoretical decision techniques used to support manufacturing technology selection industry were lacking. Researchers referred to the industrial approach as "know-how" where a defined methodology is not apparent. There is subsequently a reliance on industrial experts to conduct an appropriate evaluation and selection of a new technology. The approach to the problem appeared to be influenced entirely by experts involved in the activity. An empirical study was conducted at manufacturing organisations within the Europe with the purpose of investigating current practices to determine a baseline of techniques/approaches within industry. This provides focus for the remainder of the research project.

This relates to research objective 1 to define the existing practices within industry and identify potential areas for improvement. To satisfy the overall research aim, developing a model based on the practices by an expert will ensure it relates well to the purpose and approach of a decision maker. Support from industrial managers is of paramount importance; a dependable tool useable by industrial decision makers is required.

The concluded outcome is subsequently able to identify potential areas for improvement where there is a discrepancy among the techniques and know-how approach to the problem. A definition of the techniques within the literature and irrational thinking to technology selection in industry can subsequently be supported in the development of an improved and novel approach to the problem. The main focus is on the phase of manufacturing technology justification. The characteristics of the problem are well defined and the concept of experience support for technology selection apparent.

Stage 3: Information and Knowledge Transformation

This stage was divided into two parts and conducted within the sponsoring company for the purpose of investigating information and knowledge transformation within the decision process. In the first part, a series of interviews were conducted to contextually define the technology selection map. The purpose of defining the map in detail was to understand the extent of the process. The second stage was to define a further understanding of the exact nature of information and knowledge that supports the different stages of the process. Although it was suggested that the approach is information driven, alternative categories of information and knowledge supporting each stage required investigation. This forms an appropriate understanding to investigate the nature and support of data, information and knowledge for manufacturing technology selection, satisfying research objective 2. The expression of fuzziness and natural logic of the decision support structure can be fully investigated.

Stage 4: Representing Historical Technology Decision Cases

The aim of stage 4 of this research is to define a structure of the information recalled by an expert to represent a historical manufacturing technology implementation project. This is deemed as a form of experience learned by an expert in the development of their expertise. In order to build the information framework of historical technology projects, a modular set of attributes for representing a decision case was required. This exercise commenced with a discussion of the conclusion from stage 3 to define the categories by which a decision case is best represented.

An initial review of literature was conducted to identify the decision attributes suggested. This led to an evaluation by experts within the sponsoring company to redefine a modular set of decision parameters. Modifications were made to the identified list to address any shortcomings and thereby render the list fit for use for an industrial problem.

The final phase of research stage 4 was to investigate the various options of characterising the identified decision variables. To reduce vagueness and uncertainty in decision problems, variables are required to be appropriately represented in a rational way. Characterising and quantifying them through a formal model contributes to the overall framework to ensure a rational approach is defined. The study modelled the decision variables for both qualitative and quantitative representations. The requirement for adapting fuzzy logic for defining the natural evaluative expression of decision-making is supported. This work addressed research objective 3 to characterise the variables for representing a decision case.

Stage 5: Development of the Decision Tool

The penultimate stage of the research process was to develop the decision model, which addressed the shortcomings to technology selection identified in the empirical study conducted in stage 2. As mentioned previously, the data and information driven process was defined in stage 4 and is featured in generating knowledge in the decision tool. The identification of qualitative and quantitative decision variables was applied for easy adoption within the framework. The work addressed research objective 4 which were to develop a methodology to support decision-making through the application of historical decision information.

The results from the study in stage 1 highlighted the lack of methodological approach to the problem. This led to the requirement of understanding the context and process of information and knowledge within the decision-making process. It was apparent the logic of information acquired by an expert to support their knowledge when making judgement. Stage 4 defined a modular set of decision parameters that combined both nominal and fuzzy characters. The conclusion from stages 2 – 4 strongly suggested the use of structured information that is typically represented in an unquantifiable form. The theory of fuzzy logic appeared to meet the requirements well. The concept of an experience-based approach to the problem is developed based on a fuzzy-case-based model. The characteristics of experience are defined to enable different technology selection cases to be comparable for decision-making. Decision makers can jointly benefit from sharing experience in large organisations. The decision model was subsequently developed.

Stage 6: Verification and Validation

The final stage of the research process was to implement and test the decision tool developed in stage 5. Verification of the decision model was firstly conducted to understand the accuracy of the output recommendation for particular known decision cases. Cases where the outcome was known were reapplied to the decision model and the accuracy recorded. Secondly, a validation exercise was carried out in the sponsoring company to validate the approach. The model was used to verify a recent decision problem and assessed for its applicability. Experts from within the company supported the activity and provided valuable feedback. The aim of the study was to verify and connect the findings of the research to an industrial problem, and contrast with existing decision practices. In addition, to validate the research further a number of industrial and academic publications support the development model and provide expert feedback.

3.3.2 Research Design

The purpose of the research is to develop a novel technology selection model through seeking new insights using existing approaches. The research is exploratory in which the purpose of enquiry is to find out what is happening in a little-understood domain; seek new insights and assess a new phenomenon in a new light.

To develop a new model for manufacturing technology selection, the practices within industry need to be fully defined. This understanding contributes to the development of a novel approach based on business and decision maker requirements. As the setting of the research is focused on challenges within industry and the lack of techniques presented within the literature, this research was conducted in collaboration with Airbus. To ensure the research was not limited or biased towards this environment and setting, the empirical survey in stage 2 was conducted at multiple manufacturing organisations and industries within Europe.

The research was identified through an initial review of literature and supported by the research group at Airbus. It was apparent that existing practices within Airbus required improvement and publications on technology selection did not appear to meet the industrial challenges of justifying technology investment projects.

The literature review presented in Chapter 2 provided evidence for the research and the following hypothesis was formed:

"Develop an experience-based methodology for manufacturing technology selection through the adoption of advanced decision-making, knowledge and data-mining techniques"

The research problem was motivated by the development of new products and improvement of existing manufacturing process where the selection of an optimal manufacturing technology is required. The linkage of the research to the aerospace industry attains some challenges that are unique, yet comparable with other industries such as automotive and pharmaceutical. Senior management always wish to ensure they select appropriate systems at the start of product lifecycles, as the cost of change mid-cycle can be high. Reducing this likelihood and requirement for change can reduce effort and cost.

In particular, the manufacturing process used in aircraft manufacture and the subsequent products it creates are highly regulated and changes are somewhat difficult to achieve. In addition, long life aircraft programmes of 25 years provide ill-affordable opportunity for change. Utilisation of high-value production equipment is important due to the large investment sums required. Similarly, industries such as defence, automotive and pharmaceutical wish to select the right technology at the right time and reduce the likelihood of change. Therefore, although sections of the development of the decision model are conducted in collaboration with an aircraft manufacturer, it is likely that the approach will be modular and the integration to other industries easy to conduct.

To define the framework in Figure 3.2, the researcher determined the appropriate research strategy. Robson (2002) explains that this will ensure there is a high compatibility between the research purpose, questions, methods and sampling strategy. When defining a design strategy, it can either be fixed or flexible.

The aim of this research was to develop a decision-making framework for manufacturing technology selection through an evidence-based approach. The development of such a framework is likely to be influenced by both literature and the industrial survey. Therefore, the approach will evolve during data collection.

The research strategy for this study is regarded as being a flexible design. A flexible design is considered less pre-specified and much more a ‘do-it-yourself’ type of approach. Typically, multiple qualitative data is collected that forms the research direction. Initial assumptions and characteristics are produced to guide the research at the beginning of the project, and lead it throughout. The research programme in Figure 3.2 was formed based on the outcome of stage 1, which was the scope of the overall research. The investigation into the decision practices led to determining the context and process of information and knowledge within the technology selection process. A relationship between the decision tools in the theory and the context of the information in the technology selection process guided the development of the decision model. The research evolution was greatly influenced by stages 1 – 4 defined in Figure 3.2.

The empirical investigation in Chapter 4 contributed greatly to the research as a defining way forward. Determining a baseline suggested that to develop and represent a methodology the information and knowledge transformation must be understood. The output from Chapter 5 subsequently suggested that the logic of a human expert was developed based on the experience of previous projects.

The development of the decision model began in Chapter 6 where representing historical manufacturing technology cases became apparent. The structure was suggested in Chapter 5 that led to an understanding of the key decision variables, which was supported by experts within the collaborating company. Understanding this information subsequently contributed to the development of the overall framework in Chapter 7.

The research pointed towards a form of quantifying both qualitative and quantitative information that guided the research to a fuzzy-based approach. The use of information based historical technology decisions suggested a case-based support system that would represent the learning of an expert. A decision support framework was subsequently developed based on the representative of historical decisions able to quantify both numerical and nominal attributes. The model is presented in Chapter 7.

3.3.3 Research Overview

From the exhaustive literature review of state-of-the-art techniques, the motivation and requirements for an optimised decision methodology for manufacturing technology selection was apparent. The reported research in the areas of manufacturing technology selection, MCDM, DSS and data mining was carefully reviewed. The well-populated literature of theoretical models and suggestions towards manufacturing technology investment decisions were analysed for their applicability. Despite the significant work in the area, there appeared a lack of experience-based approaches that resemble the decision practices of a technology as a historical decision case, where an set of initial requirements are well defined together with the success of a project.

The appropriately structured availability of quality information had been found to be the most promising approach to making quick, rational business decisions. A technology selection model has been developed that provides a fundamental structure for an iterative decision support approach to a typical know-how process. The applications of various subsets that form a decision model has been integrated to capture the relative information of historical decisions for supporting new decision problems (see Chapters 5 and 6). The developed model (see Chapter 7) has been applied to an industrial case study to demonstrate its applicability (see Chapter 8).

3.4 Research Method

The aim of this section is to define and justify the methodology for this research. The purpose of this study is exploratory that aims to find out about a particularly little-understood domain. For this research, it is the industrial decision practices for manufacturing technology selection. Robson (1993) suggests that the suitable research method for exploratory research is usually qualitative, but this is not necessarily applicable for all research programmes.

Research methods are commonly classed in two forms: quantitative (or scientific) or qualitative (or interpretative). Quantitative research concerns the collection and analysis of data in numeric form to measure variables and verify theories, hypothesis, or questions. Qualitative research concerns the collection and analysis of data in many forms, primarily non-numeric, to extract and examine information from the empirical materials. The use of words rather than numbers permits depth rather than breadth of meaning and understanding (Robson, 2002).

Research objective 1 aims to define the existing practices within industry. The process to define the approach focuses on the opinion of decision makers within each company and consists mainly of opened questions. Specific questions were not asked till the problem was defined. The investigation is conducted after the literature review and within the early stages of the research programme. It was therefore likely to evolve during the research programme. Some questions were definitive to ensure the required information was obtained, but the evolvement of new information assisted the development.

Research objective 2 aims to investigate the nature and support of information within the technology selection process. This activity is similar to research objective 1 in which an in-depth understanding of human behaviour is required. The study is conducted in small sample sets and seeks to answer questions like 'why is certain information captured' and 'how it is used'.

To satisfy research objective 3, measureable factors and events regarding the definition of historical manufacturing is captured. The way in which people construct, interpret and give meanings to experiences contribute to the definition of case information. Information given by the participants includes quantitative based properties and their relationship to the problem discussed.

The decision model is developed based on an understanding of the research conducted in stages 1 – 4. An understanding of the theory and the suitability to industrial practices support the development of a novel model for technology selection. This satisfies the overall research aim and objective 4. To appropriately validate the decision model, objective 5 must be satisfied. Experts within industry provide feedback on the model to support its applicability to the problem. The comparison of the suggested technology from the model is conducted against a previous decision case to compare the results.

The principle for applying a research method is the appropriateness of that method to answer the research question. The form of research question will vary and may extended across two types of questions (Robson, 2002, Yin, 2009). To best summarise the selection of a research method, Yin (2009) demonstrates the alternative forms of questions and their related methods in Figure 3.3.

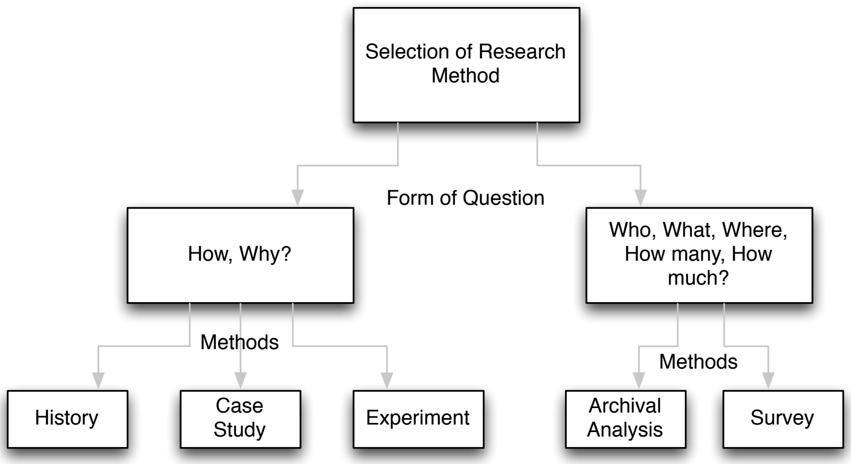

Figure 3.3 Research method based on the form of research question (Yin, 2009)

Since the research question of this thesis asks a 'how' question, this suggests the appropriate use of history, case study and experiment. However, there is a clear link to the 'Who, What, Where, How many, How much?'

type of questions that suggest archival analysis and survey. Although the survey is similar to the experiment, the use of archival analysis can support extensive and detailed areas of historical analysis.

In light of the research objectives set in Section 3.2, the purpose of this study is: (i) to identify/discover important variables, and (ii) to generate hypotheses for further research. Therefore, aligning the research purpose together with the objective, the following two research methods were selected: *survey* and *case study*.

3.4.1 Survey

The approach is well suited to this form of research for defining the decision practices carried out within industry. The research seeks to understand *who* is involved in current practices, *what* the process is and typically *where* it is conducted in the product lifecycle. Therefore, the nature and aim of this research is the adoption of the survey technique. The research necessitates the collection of data, which depends on eliciting the perceptions, policies, and experiences of people involved within the decision-making domain. A review of literature has identified the lack of methodological approach to the problem area. Collecting data directly from the decision makers involved in the process seems most appropriate. It is able to present a picture of what people think and do, which provide valuable knowledge for formulising the framework.

During the initial stages of this research, the main issue identified from the literature review is that there is a need to support manufacturing technology selection through an effective and methodological approach system. A survey was conducted to satisfy the following purposes: (i) to justify the research from an academic and industrial point of view, (ii) to focus the research on the particular area of decision-making, (iii) fully define the problem in its environment, and (iv) to outline a strategy for solving the problem. The following objectives were defined to:

- Identify existing industrial practices and analyse the strengths and weaknesses
- Identify the relevant findings to justify the requirements for this research
- Identify information (process, decision parameters, experts, persons involved, *etc*.) applicable to the problem area
- Evaluate and identify appropriate processes/techniques necessary for the optimal selection of manufacturing technology investments

The nature and aim of this research points towards the adoption of the survey technique. The research necessitates the collection of data, which depends on eliciting the perceptions, policies, and experiences of people involved within the decision-making domain. The review of literature identified the lack of methodological approaches to the problem and the collection of data directly from the persons involved as most appropriate. In addition, it is able to present a picture of what people think and do, that provides valuable knowledge for formulising the framework. The literature and state-of-the-review concluded the current lack of definition among practices within industry. Much of the literature discusses the process as know-how by experts. Standards do not explore such practices and the techniques used within the domain are not apparent.

3.4.2 Case Study

A case study is a ‘how? why?’ type of question. It is appropriate for this research as the method can indicate *how* well the developed decision model performed in its intended environment. In addition, reasons behind *why* it was successful can be made apparent. A case study is a “exploratory study of an existing situation as a means of creating and testing a hypothesis” (McBurney and White, 2010, p. 221). Case studies are typified by the varied nature of methods used to study the problem and the intensive description of a single individual or a single group of individuals (McBurney and White, 2010).

An evaluation study is performed to facilitate the assessment of the decision tool within an industrial environment. The goal is to evaluate the developed methodology of manufacturing technology selection by applying it to a real-life engineering problem. The collaborative company are also able to provide the appropriate information and form of validation for the case study. This validation strategy is most suitable as the methodology aims to mimic experts within an experience-based decision problem. Comparing directly and gaining feedback from experts provides the most accurate form of evaluation and verification. This justifies the practicality of the model and demonstrates the applicability of its use within the domain. The following objectives for the case study were determined:

- Identify a suitable case study and capture the relevant data for decision support
- Identify a number of experts to be involved in the process and determine parameters for initial evaluation
- Apply the decision model to an industrial problem and evaluate the recommendation with existing practices

- Verify the results of the methodology
- Identify further advantages and disadvantages of the manufacturing technology selection methodology

The above objectives are attained by means of an industrial case study. The methodology can be tested in an operations environment where engineers are considering investing in a new manufacturing technology. Subsequently, a questionnaire will check the applicability of the new methodology and a comparison of the results with and without the methodology provides further validation. The advantages and limitations of the new methodology can be shown within the case study. This is necessary to assess whether the model is practical for current decision practices.

The case study technique provides a suitable approach for analysing the outcome of this research as it involves demonstrating the decision tool to support manufacturing technology selection. Potential users perform an evaluation of the toolset against a real-life industrial case study to assess its performance. Data provided by the participating organisation form the basis of the decision platform and users evaluate through a criteria of applicability. A comparison is made against existing practices and feedback for refinement of the decision model. The case study relates well to evaluating the problem as the situation in practice is heavily reliant upon experts. Whilst it is possible to conduct a degree of mathematical verification, the opinion of an expert through the form of a case study is the most appropriate validation method.

3.5 Data Collection Approach

In order to appropriately carry out the research methods described in the previous section and to achieve the research objectives set out within Section 3.2, a series of data collection methods is required. Data collection is a term to describe a process of preparing and collecting data. The purpose is often to obtain information for record keeping, to analyse and make decisions, or to pass information onto others. The data collection methods described in this section focus on stages 2, 3 and 4 as defined in the research programme in Figure 3.2.

To define existing practices (research objective 1), a survey is suggested through a questionnaire where individuals are asked a series of questions related to the problem. Survey data is obtained through pre-determined questions designed to extract the required information. To satisfy objective 2, the data collection method interview and internal document analysis is suggested as the primary approach to investigating the nature of the technology selection study. It is the most appropriate way of finding out new things in a flexible and adaptable way. To satisfy objective 3, both a literature review followed by a focus group discussion appear most appropriate to determine a set of influential parameters for representing manufacturing technology cases suited to the research method. Three methods are discussed for their application in the following sub-sections:

3.5.1 Stage 2: Empirical Investigation – Questionnaire

The empirical investigation carried out to satisfy research objective 1 is to conduct a survey through a questionnaire at multiple manufacturing organisations. Little is currently known about the approaches used in the manufacturing industry for technology selection. The questionnaire method has subsequently been chosen to collect structured primary data to validate the requirement for a methodology. To clearly highlight existing practices and policies conducted within industry, acquiring information directly from the persons involved is more important. A vast amount of data is collected from diverse manufacturing industries and companies.

A survey is a technique of collecting and analysing data often conducted using a form of questionnaire. A questionnaire is a popular research instrument consisting of a series of questions and other prompts for the purpose of gathering information from the intended respondents. Neuman (2003) explains how it is a method of gaining information about people (called *respondents)* beliefs, opinions, characteristics, and past or present behaviour. They are appropriate for research questions about self-reported beliefs or behaviours, and how they test several hypotheses in a single survey. Surveys are often designed for statistical analysis of the responses, but this is not always the case.

A researcher may either employ a questionnaire or interview relevant persons. The interview schedule is a set of questions asked directly to the respondent, the interviewer on the questionnaire responds to the answers. The survey questionnaire is a set of questions read out by the interviewer, but filled in by the respondent.

A questionnaire was chosen as most appropriate as they can often be conducted over the phone, through postal mail or face-to-face. A survey tries to obtain responses from a large group of individuals who are difficult to locate and where whole cooperation may be difficult to obtain. This is most appropriate for the study as it is aimed at companies that are located at multiple locations throughout Europe. The face-to-face method will be preferred but the telephone and postal mail options will be considered when it is unreasonable to travel to the participant’s site or the participant has a preferred choice.

The evaluation of current state-of-the-art provided little indication of the approaches to technology selection in practice. The literature also appears to have not fully understood industrial decision approaches. The most in-depth study was carried out by Remer et al. (1993) almost 20 years ago focused on the design practices of automated manufacturing systems rather than the physical application and selection of manufacturing technologies. The survey concluded the high use of economic techniques and showed the shift from IRR to NPV and a decrease in the use of PP.

3.5.2 Stage 3: Information and Knowledge Transformation – Interview/Document Analysis

The collection of data to identify the nature and support of data, information and knowledge has been identified as best conducted by a combination of interviews and document analysis. The primary method is to conduct a series of interviews with experts in the collaborating organisation. The questions are qualitative based in which the participant is encouraged to discuss how their involvement in the decision process is influenced by the transformation of information.

To identify and detail the transformation activities and type of data-driven approach to manufacturing technology selection, it therefore seems most appropriate to interview the persons involved in the process. As the approach tends to be based on company know-how and personal opinion, speaking directly to the experts can ensure an accurate reflection of current practices is obtained. The expected complexity of the decision process and qualitative description of each stage is most suitable to be acquired through an interview technique.

Face-to-face interviews are excellent for asking complex and open-ended questions. The quality of the response is often good and the use of visual aids can assist in the quality of data obtained. The responses to questions of typical methods and approaches to technology selection are expected to be complex and open-ended where further elaboration will be required. Robson (2002) describes the types and styles of three face-to-face interview techniques.

In fully structured interviews, the interviewer will ask the respondent a list of pre-determined questions about a carefully selected topic. The interview may include open and closed questions, and be conducted in a face-to-face manner. Semi-structured interviews consist of open-ended questions based on the topic and domain, although there is an opportunity to discuss in more detail areas of interest and elaborate on responses that require further clarification. Unstructured interviews do not have a particular structure and often limited in the number of topics to discuss. An interviewer will ask a small number of questions and then ask further unprepared questions based on the interviewee's response. Unstructured interviews require the interviewer to have a good level of understanding in the topic area to elaborate on the response.

For this research survey, it was deemed appropriate to develop a semi-structured interview format, which would allow specific questions related to the field to be asked and the elaboration on the answers to be conducted. Many of the interview participants were encouraged to bring relevant documents to the interview or had access to a computer to obtain such information. This was particularly useful for the researcher to gain a better understanding of the problem. This led to the subsequent analysis of documentation. It is able to provide an insight into the methods and existing structure of documents of the technology selection process.

Due to the integration of the research within the collaborating company, the data collected were of critical importance to the research for the development of the technology decision-making model. Although much of the research has focused on the theoretical gap in knowledge from an academic point-of-view, the lack of understanding of published methodologies using industrial data does not fully verify the approaches.

Therefore, document analysis provides a unique window for understanding the structure and methods concerning the processes applied within an organisation. Whilst the current state-of-the-art provides no indication of the transformation of information, some studies have been conducted during the preliminary design phases. Through semi-structured interviews, Mountney et al. (2007) investigated the manufacturing knowledge required during each initial phase of the design process. The authors identified the high level of unstructured knowledge not recorded but communicated verbally. The quantification of parameters such as functional design requirements were difficult to determine. Similar research by Baxter et al. (2007) discusses the difficultly of acquiring such knowledge and the reuse for engineering design. To summarise, the current state-of-the-art and literature has not yet investigated information and knowledge transformation within the decision-making process. An understanding during the later stages of manufacturing technology selection and implementation requires understanding.

3.5.3 Stage 4: Representing Historical Technology Decision Cases – Literature Review/Focus Group

The investigation carried out to satisfy research objective 3 is to form a definition of representing historical manufacturing technology selection cases. It includes the identification of a set of decision variables for representing a decision case. A modular set of parameters was first identified through a review of literature.

A literature review is a systematic process that reviews available literature in the selected topic field. It is what is already known, and written down, relevant to the research project. It involves "systematically identifying, locating, and analysing documents containing information related to the research problem" (Robson, 2011, p. 51). These documents often include articles, abstracts, reviews, monographs, dissertations, books, other research reports, and electronic mail (Gay and Airasian, 2003).

The literature review had two functions during the research. First, to achieve a theoretical fountain on relevant topics related to the research for the development of an appropriate technology selection framework.

Secondly, to justify and define the key decision variables specified for the problem. This supports research objective 3 that is to define a set of influential factors for the evaluation of manufacturing technologies. In addition to determining the variables through the literature review, an in-depth definition of each factor is required to justify the selected measures for capital investment in manufacturing technology.

Upon the literature review, an industrial study based of a focus group was conducted within the collaborating company. Focus groups originated in market research in the 1920s, arising from the recognition that many consumer decisions were made in a social, group context (Bogardus, 1926). The generic term ‘group interview’ has tended recently to be used interchangeably with ‘focus group’ because of the latter’s popularity, even though it has similar characteristics. They are effectively interviews that take place in a group context. They offer great degrees of flexibility and input from more than one participant (Robson, 2011). Semi-structured focus groups allow the researcher to ask inviting questions and each participant is encouraged to become involved in discussions.

The focus group approach to data collection is most appropriate as it wishes to redefine the original list of attributes identified from the literature. The approach to a group style interview fits well within the requirement to understand the opinion of multiple experts. It allows for an open discussion where the concluded output is agreed by all and can be relied upon. The researcher guides the discussion and use of the pair-wise comparison toolset for down selecting the modular requirements identified from the literature. Discussions were also held to further understand the attributes that should and should not be included when representing a decision case.

Whilst many researchers have attempted to define knowledge for manufacturing design, current literature has not yet defined such understanding for supporting manufacturing technology selection.

3.6 Chapter Summary

This chapter introduced the research aims and objectives upon the consideration of the literature review. The research programme is presented and the stages that form the overall approach were discussed. For the purpose of identifying a feasible research methodology, quantitative and qualitative methodologies are also noted. Additionally, research methodologies and their inherent advantages and limitations are explained. A subsequent discussion of the selected data collection methods presents the applied approaches.

Chapter 4

Industrial Decision Practice Survey

4.1 Introduction

This chapter presents the findings of an industrial survey to validate the need for a methodology to assist businesses provide the required information and support to the decision maker in the selection of manufacturing technologies.

The following describes the design of the survey and results, followed by a discussion of the findings. Little is known about technology selection approaches in practice and this chapter aims to fulfil better this gap in knowledge.

The first research objective is to understand the existing decision practices to determine a baseline of techniques and practices within industry. The information is subsequently able to identify potential areas for improvement where a level of discrepancy exists among the techniques and know-how. It appears from the literature that limited decision support tools are considered in industry, yet an investigation into the techniques and approach to the topic has not recently been conducted. Some researchers refer to the approach as a 'know-how' where a methodology is not apparent; the approach is influenced entirely by the experts involved in the decision activity. Therefore, to fully understand the approaches/know-how, a review of technology selection practices has been conducted.

4.2 Overview and Technique

It is important to identify a data collection method that is in line with the type of questions which require answering. In addition, selecting an appropriate method aligned to the environment in which the data is collected is important. Including the information expected from individuals within various manufacturing organisations. These will typically be persons involved in the evaluation of potential investment projects where a new type of technology is being introduced. The questionnaire will include a number of multiple-choice questions together with qualitative-based answers where a further understanding of the problem can be acquired. A common approach to this sort of data collection activity is through an industrial survey.

From a review of the alternative survey methods, face-to-face interviews were chosen as the most suitable method. The self-administered method is the most cost effective technique, but due to the complexity of the questionnaire and questions, the approach would be unsuitable for this survey. A self-administered survey is poor in collecting open responses from respondents and more appropriate for closed questions, and therefore unlikely to be appropriate for the type of questions asked. Although the telephone interview approach is not appropriate for gaining an in-depth focus or asking complex questions, it is fitting for complex questionnaires with short and simple answers. Face-to-face interviews are suitable for complex, long and open-ended questions. The technique also enables the use of visual aids and the quality of recorded response is good. It allows complex questions to be asked whilst the length of the question is irrelevant and the control of the questions is very good.

The nature of the questions asked during the survey will be focused on both automated system design and manufacturing technology selection. They are aimed at the persons responsible for both activities and the factors considered during the process. Understanding the methods and techniques, and whether the decision-makers believe their current decision-making process to be satisfactory will each contribute to the overall understanding of the problem.

When considering the industry the survey is being conducted, it is apparent that visiting all intended manufacturing sites within Europe would be a costly and extensive task. Face-to-face is the preferred method for data collection, however, in instances where it may not be possible, the telephone interview is considered. Some organisations may not be able to dedicate such time to conduct face-to-face interviews, but valuable information can still be gained from conducting telephone interviews.

4.3 Questionnaire Design and Preparation

The research questionnaire is designed in such a way that the questions enable the respondent to gain a clear understanding of the objectives of the research, allowing them to relate this to company practices. Care was taken as to the flow of the questions, ensuring a gradual flow and focus towards the required information. Most questions were open-ended allowing the respondent to freely discuss the practices conducted at the company, based on their knowledge and experience of decision-making. The use of techniques in unstructured interviews was adopted for certain questions to explore an in-depth investigation of the areas of interest. Although the survey was designed to capture qualitative data, closed questions were used to collect relative quantitative information to assist in the analysis.

The survey was designed in four phases to ensure a structured approach was taken and concluded within a reasonable time period of one hour. The stages were as follows:

1 Administration issues (5 minutes)
2 Project briefing (5 minutes)
3 Questionnaire completion (45 minutes)
4 Debriefing (5 minutes)

Prior to conducting the industrial survey, the following activities were performed; industrial participant selection, questionnaire material and a pilot study.

4.3.1 Industrial Participant Selection

In an ideal world, the study would be conducted at all manufacturing organisations, where all findings will apply to the whole population. However, this would not be appropriate and therefore suitable methods for determining representatives of the population are required.

When conducting qualitative research, sampling techniques (e.g. probability) that are traditionally used in quantitative studies are rarely appropriate. It is however important to select an appropriate sample size as it is rarely practical to study whole populations. For a qualitative study, the accuracy of answers given by the participant is crucial rather than the number of responses. Selecting the appropriate sampling size is therefore of high importance.

Black (1993) lists five methods for determining representatives of a population:

1 Whole population, where all findings will apply to the whole population.
2 Random selection from a specified population.
3 Purposive sampling from a specified population, where some attempt has been made to select a reprehensive sample through characteristics related where variables are controlled.
4 Volunteers, where a sample is generated by a quota, accident, convenience, *etc*.
5 Unidentified group, where the description of the sample of sampling technique is not sufficiently clear either to indicate the population or to justify any generalisability.

The representative technique chosen for this research survey was based on method two. The random selection of organisations based on the specified population will form the target population. The organisations targeted for the survey were manufacturing producers that manufacture products using highly automated, various complexity and manually intensive systems. The study focused on companies within the aerospace, automotive, defence and pharmaceutical industries, to facilitate a generalised set of results.

To locate and select organisations within the identified industries, three approaches were used:

- University of Nottingham research contacts
- Internet search
- Financial Analysis Made Easy (FAME) database

The first approach was to make contact with persons whom a relationship with the University had already been established. This approach allows potential participants to be easily identified. Current research contacts are also more likely to be willing to participate as they are likely to have assisted in a similar academic exercises before. The second approach was to search the internet to identify relevant organisations that could provide the required information. Using internet search engines, graduate career websites and news articles, a number of organisations were identified for targeting.

The final approach was to use the FAME database. It contains financial information for more than 3.5 million companies, including public and private within the U.K. and Ireland. The database enables users to locate companies according to turnover, performance within their sector, the geographical area, the particular industry and the size of the organisation. To enable a better selection of organisations, the search focused on all companies that produced products for the aerospace, automotive, defence and pharmaceutical industries, had workforce not less than 250 employees, and an annual turnover in excess of two million pounds.

Having opted for face-to-face and as the secondary option telephone interviews, 75 organisations were identified from the search and targeted for interviewing. Based on the search of the database and internet, this was deemed sufficient to cover large and medium enterprises within the U.K. and a number of large reputable organisations within Europe. Firstly, all organisations where contact had not been identified, a telephone call were conducted to each company to identify the person(s) involved in the manufacturing selection process. The intention was to obtain the name of a contact and then conduct a formal approach via email or post.

Formal emails and academic headed postal letters (see appendix A1) were despatched to the named contacts at each organisation. In total, 45 responses were received, of which 24 resulted in positive participation. The positive contacts were cited as willing to take part in the study. The number of responses was deemed sufficient to gain a reprehensive understanding of practices within industry. The target organisations were major manufacturing companies which were aligned to the scope of the study. The quality of the data is expected to be highly accurate. One-on-one discussions with experts will ensure the information collated is directly from the source and allow a two-way conversation to take place. The topic is also of interest to decision-makers as the number of participants per organisation is often more than one. Figure 4.1 presents a breakdown of the targeted industries and positive responses.

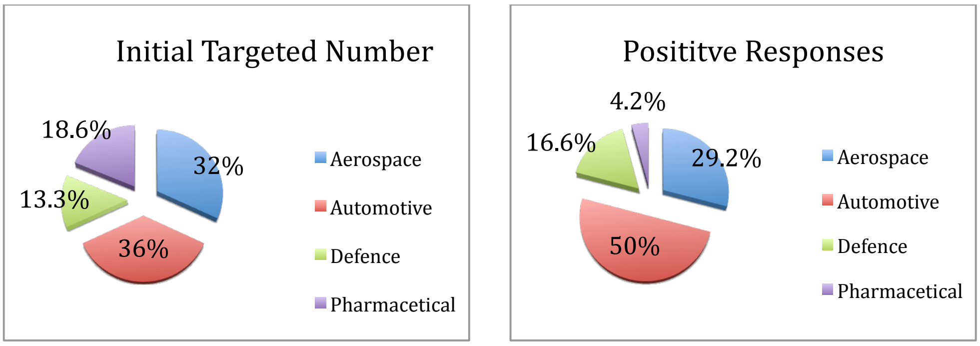

Figure 4.1 Research survey participant sample

The most positive responses were from the automotive and aerospace industries, receiving a positive response rate of 50% and 29.2% respectively. Companies from the pharmaceutical were least responsive with just 4.2% whilst organisations from the defence industry were 16.6%. The higher response rate for automotive and aerospace industries was assumed to be because the wealth of contacts the researcher and University had gained prior to undertaking this research activity.

4.3.2 Questionnaire Material

The interviews were conducted with the aid of a semi-structured questionnaire that can be found within Appendix A2. The questionnaire was developed to capture the current practices of manufacturing technology decision-making within industry. The introduction questions were developed based on the authors understanding of the area and through a literature research. The author was fortunate to be partially embedded within a collaborating aerospace organisation and had founded a good knowledge of industry and practices. The purpose was to investigate the decision-making process or know-how policies, and understand to what extent the analysis is conducted. The questions were developed from queries raised through the literature review and discussions with academics. The questionnaire was divided into three sections:

- *Company information* aimed at gathering general information about the company. It noted which sector the company manufactured for, the number of employees, the rate of manufacture and turnover. The first section aims to set the scene and gather quantitative data that can identify patterns related to the answers.
- *Automation justification/systems design* focused on determining the level of automation used at the company, the types of manufacturing methods and the main drivers for pursuing increased automation. The section intended to gather information of previous projects where automated equipment had been purchased but later reverted to a manual operation. The section also attempted to determine who is responsible for the design of a manufacturing system and the most important factors considered during the design phase.
- *Manufacturing decision-making practices* aimed at understanding the decision-making process of selecting manufacturing systems/technologies in a corporate environment. The persons involved in the process, and the tools and techniques assisting the decision makers. The criteria and influential parameters were considered in addition to the types of financial justification models. Questions regarding knowledge capture aimed to understand the format of lesson-learned techniques within the company. Subsequently, the questionnaire concluded by determining if the participants believed their decision-making process to be satisfactory and if they would consider a formalised decision methodology if one were developed.

The three types of questions enable a broad understanding of the topic to be defined. Acquiring general company information will enable a pattern and relationship to be determined for each decision-making technique. The drivers and reasons for why a technology is pursued for automation are also attained to link and understand the influence of these factors to the decision process. The tools, techniques, methodologies and general approach to the problem assist in fully understanding the practical requirements.

4.3.3 Pilot Study

Prior to running the study, a pilot was carried out to ensure it was structured appropriately and designed to gather the required information. Neuman (2003) describes how it is best to pilot-test survey interviews and questionnaires prior to implementation. A technique, known as cognitive interviewing, is used in pilot testing surveys where researchers try to learn about a questionnaire and improve it by interviewing respondents about their thought process or have respondents ‘think out loud’ as they answer survey questions. The questionnaire was first tested with colleagues and department staff at the University. The intention was to assess the readability and expected responses. It was apparent that the initial flow of questions required improvement; adjustments was conducted to allow the questions to flow from related higher-level answers to detailed understandings. Amendments to the questionnaire wording were also conducted. The initial estimated questionnaire time was also found to be accurate with a 10% allowance of the allocated 45 minutes.

Once the pre-test was complete and amended, a pilot study was carried out at the first 5 organisations. The aim was to understand how closely the questions and answers addressed the survey aims. It was found that some structured questions were limited through multiply choice answers and were amended.

4.4 Interview Process

Of the positive responses received, interviews were set up with each. Initially, issues regarding confidentially were addressed by informing the participant of their right to withdraw at any time and that any details discussed would be kept confidential between the University and the organisation under interview. The interviewer formally introduced himself through his former academic achievements, relevant internship employment and a brief introduction of the research. The interviewer expressed that the respondent is perfectly free to interrupt, ask for clarification throughout the interview or criticise a line of questioning.

The questionnaire comprised of 19 questions that were discussed throughout the 45-minute time period. The three sections of the questionnaire were briefly outlined followed by the questions in each section. The answers were recorded in all instances in a notepad and verified by the respondent. Upon completion of the survey, some organisations provided an observational tour of their manufacturing facilities and examples of automation backfire projects were discussed in detail. The final debriefing of the interview reiterated the answers and understanding determined by the interviewer.

4.5 Survey Result

Upon completion of the survey, the quantitative data was managed and presented through graphical charts. The use of bar charts enables the data to be placed within a single chart and compared for analysis. The qualitative data were formally typed with keynotes and wordings highlighted. The results were divided into the 3 stages of the questionnaire to provide a clear analysis of the data.

Company Information

The participants ranged from automotive, aerospace, pharmaceutical and defence industries. The rate of manufacture varied from as little as 10 products per month at a final stage aircraft producer to 9 million at a well-established pharmaceutical firm. It was noted that 19 organisations in the study had a workforce of more than 500 employees and the annual turnover ranged from £5 million to £20 billion. Additionally, positions of the participants varied from operation directors to engineering team leaders. One study at an aerospace manufacturer included four participants from quality, operations, manufacturing engineering and senior management. The actual names of the respondents were not noted within the questionnaire.

Automation Justification/System Design

This section aimed to determine the level and types of manufacturing automation at each of the organisations and to understand if there were patterns across the different industries. An understanding of the system design process and factors considered at this stage were noted, together with a ranking of important drivers for increased automation at each company. Automation was chosen particularly as there is much focus by technology developers to increase levels of automation in existing manufacturing processes. In order to optimise productivity, the development of new technologies tends to be through the use of automated machinery.

Each organisation was asked to indicate their level of automation, either as low, medium or high. These terms relate to the ratio of automated vs. manual technologies to support manufacturing and assembly. For example, an organisation which relies on skilled operators and uses very little automated equipment would be deemed as low.

The results indicated that less than half had either a medium or low level of manufacturing automation, whilst three organisations deemed their level to be high. Each of the organisations that suggested they had high levels of automation was from the pharmaceutical industry where the product manufacture rate is high and the complexity in the production process relatively low. Although the automated machines were complex, the tasks carried out were repetitive and did not require skilled persons. The respondents had judged their level of automation according to the ratio of manual and automated activities carried out within their plant. They also benchmarked their practices with other companies within the same industry. The results are shown in Figure 4.2.

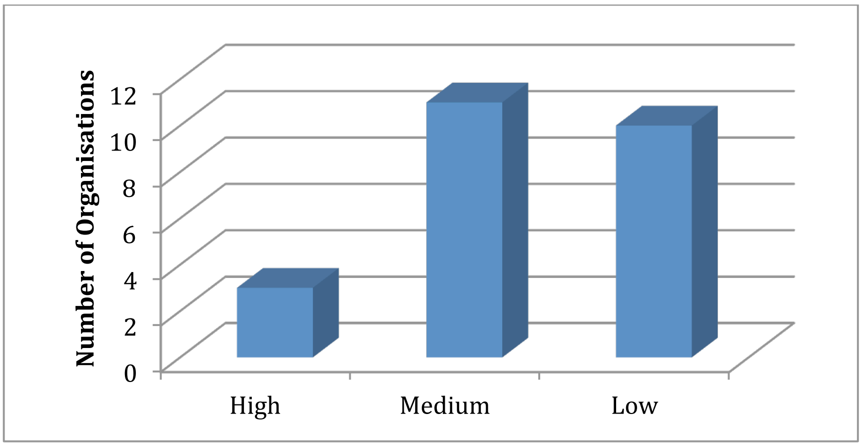

Figure 4.2 Level of automation within participant organisations

The types of automated systems varied from drilling and riveting, to packing lines and bottle filling. One automotive manufacturer relied heavily on automation in the body-in-white (BIW) division consisting of 97% automation for all bodywork assembly processes, although the same company relied 90% on manual labour for the final assembly of car manufacture. Equipping processes that include fitting harness adaptors, steering columns, seats and car doors were all part of manual systems that benefited from low gravity arms relieving the weight from the operator. A fully automated packing system was in place at a pharmaceutical distribution centre enabling pallets to automatically travel throughout the factory retrieving the required products. Examples of some of the qualitative answers obtained in the form of descriptive comments to types of automation were noted. The following qualitative quotes were selected as representative of the majority of responses received. They represent the opinion of multiple experts and noted by more than a single participant:

- *"Our levels of automation are low due to the complexity required to build the relative parts. There is a high level of dexterity involved in assembling our systems and as of yet we are unable to increase our levels of automation".*
- *"Recently we invested in automated machines to conduct the relevant environmental tests our products must undergo. Previous manual intensive systems have been replaced, increasing automation from 10% to 90%. We still require an operator to load, unload and monitor the machine, although they monitor a number of machines at one time to increase throughput".*

Various motives for automaton acquisition were discussed throughout the survey, each participant was asked to rank the drivers in order of importance. By determining the typical type of drivers for automation, this can be related to the objectives considered in a manufacturing technology selection case. To better understand the typical drivers and reasoning behind the focus to invest in automation, the persons were asked to rank a series of typical factors determined from the literature. With much focus on increased levels of automation in manufacturing businesses, this was able to form an understanding of why it was deemed as important to integrate such technologies in the business.

Reducing cost and increasing product quality were the most influential drivers, followed by health and safety (H&S). Additional drivers were customer requirements and process capability. These drivers aligned the technology to the customer and allowed greater future product potential and flexibility. Figure 4.3 illustrates the sum scored of automation drivers from the 1 – 5 ranking provided. Examples of some of the qualitative answers obtained in the form of descriptive comments to the main drivers for automation were:

- *"We always ensure we meet health and safety requirements to the best of our ability, after this, cost and quality are the most important drivers for automation".*
- *"Our customers expect us to be flexible in the products we manufacture. As we produce a variety of products, flexibility is top priority when considering automation options".*

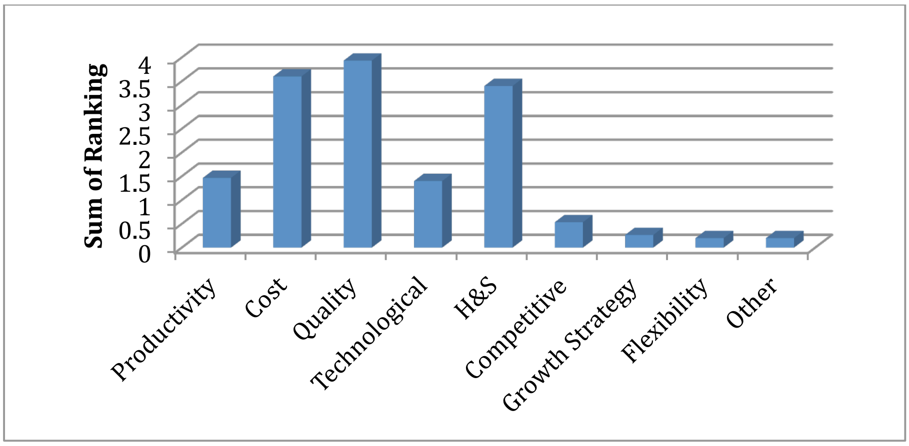

Figure 4.3 Main drivers for automation

The survey revealed that 25% of the participants had endured *'automation-backfire'* which refers to the purchase and implementation of automation equipment to replace a manual system that is later reverted to a manual process. The reason for returning to the original process varied from insufficient skilled labour, expected function of the equipment and lack of flexibility originally claimed in the specification. The most perceived backfire was the purchase of a £1.3 million robotic cell that was proven technically and financially but was unable to be implemented into the existing production facility due to unconsidered integration factors. An integration time of three months concluded prior to the equipment purchase which was based on build rates at that time, shortly after purchasing the equipment build rates increased and the implementation of the equipment whilst achieving build rates was impossible. The insufficient analysis of integration at the decision-making stage meant this was not considered for increased production rates.

To provide an overview of the manufacturing systems design approach, a number of questions have been combined into a single graph (Figure 4.4). It illustrates 15 respondents deploy cross-functional teams from design, manufacturing, management and operators to assist in the design process. Six followed a formalised methodology whilst three employed specialised experts during the design stage to aid in decision-making. Of the 24 respondents, 16 believed their design approach to be satisfactory.

The survey demonstrated that all companies understood the importance of a strong link between designers and manufacturing engineers when developing new products. It is proven to have a greater influence on the design for manufacturing issues and improve the overall quality of the product. Organisations that suggested their link to be less unified often proceed with generating designs to a certain level, then defining no further changes to allow manufacturing engineers to identify possible production methods. All companies agreed that a strong link between the designers and manufacturing engineers would benefit the final product, although only half believed their link to be satisfactory.

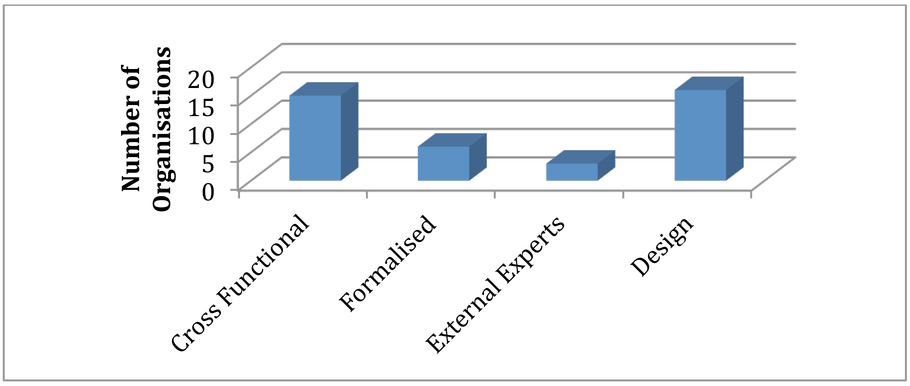

Figure 4.4 Organisations that adopt alternative manufacturing system design approaches

Each participant was asked to identify the most important factors considered during the design phase of a manufacturing system. H&S appeared to be the most important factor due to the cost of error through potential safety issues, followed by operation time and manufacturing flexibility. The main appeal of automated manufacturing systems was that they are capable of easily adjusting product designs and therefore flexibility was seen as a great advantage. Figure 4.5 presents the sum score of all the important factors considered during the design stage.

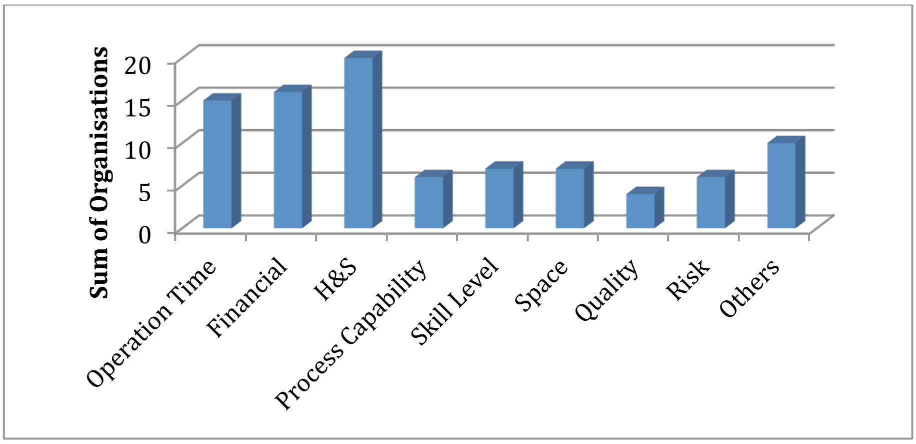

Figure 4.5 Important manufacturing system design considerations

A number of organisations were concerned with the required skill level for automated systems and the cost of employee training. The available space within the factory was also a consideration for some companies. However, this was dependant on the size of the existing factory and plan for future space. Other factors included issues with product flow and the alignment of the manufacturing system with the external supply chain.

Manufacturing Decision-Making Practices

This section aimed to understand the manufacturing decision-making procedure at each organisation. The results indicated that five respondents follow structured approaches that were noted to have adopted from design methodologies. Five deployed cross-functional teams to carry out the evaluation and selection of manufacturing technologies. Most interestingly, 12 combined a structured approach with cross-functional teams to carry out the decision-making process. Employees involved in the cross-functional teams included designers, manufacturing engineers, senior management, quality engineers and operators. Two organisations were reported to subcontract the process to external experts and sometimes the customer, in order to assist in areas of the decision-making process. The results are illustrated in Figure 4.6.

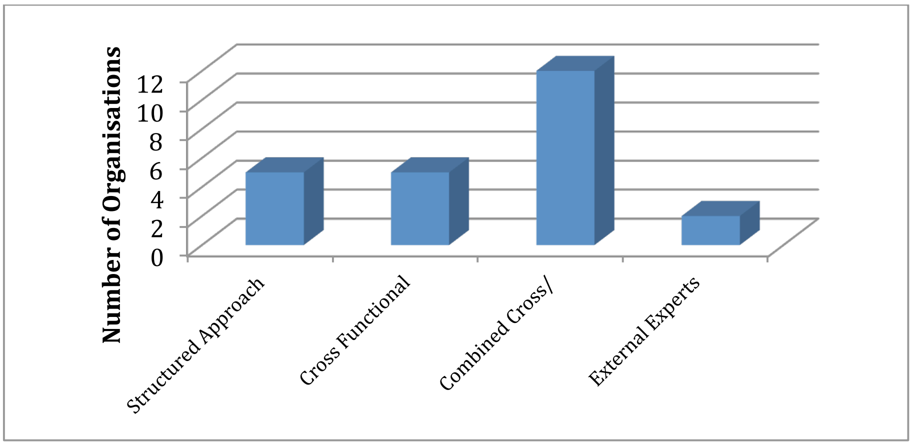

Figure 4.6 Organisations that adopt alternative decision-making approaches

Examples of some of the qualitative answers to the methods applied by the company were:

- *"We find it highly important that we have a clear and transparent structure within the organisation which allows us to share ideas and jointly reach a decision".*
- *"Due to the small size of the organisation and with our expertise in designing new products, we often employ a local consultancy firm to determine an appropriate manufacturing system".*

The uses of proven decision tools were common in most organisations. Twelve manufacturers explained how they use weighted ranking models and the FMEA toolset to evaluate and select manufacturing systems. Models such as the AHP and data envelopment analysis (DEA) were not used in any of the organisations and the responses indicated they knew very little of the techniques. Participants indicated that guidance was provided for the weighted scoring methodology but not on generating the criteria or numeric scores.

The use of computer aided design (CAD) software packages to digitally simulate a technology in practice was very common within the design stage and some organisations employed such tools for assisting in manufacturing operation selection. Simulation (e.g. using a CAD software package) of a process was often the most influential information to base a decision. QFD was a well-known decision tool applied once a technology had been selected. It was common for organisations to use more than one of the techniques with the weighted ranking and FMEA popular combined toolsets. The results are presented in Figure 4.7.

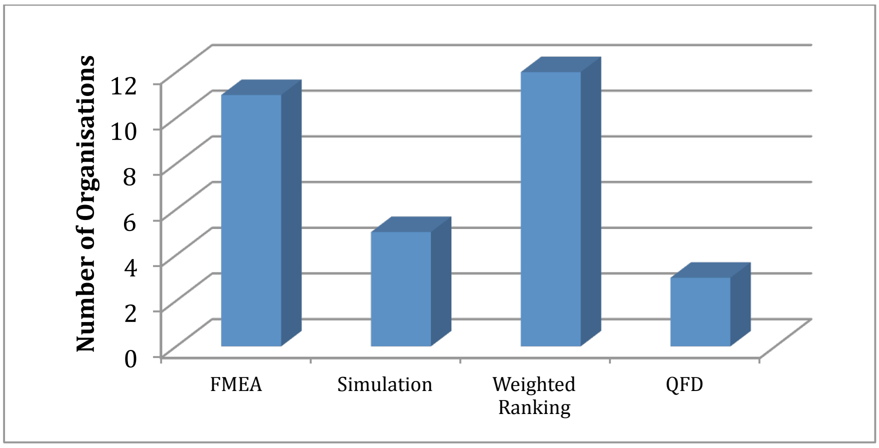

Figure 4.7 Organisations that adopt alternative decision-making models

The two most popular tools used for decision support are FMEA and weight ranking. Upon further questioning, FMEA was found to be a risk analysis toolset that focused solely on the potential level of risk for alternative potential failure modes in a technology. Although it was does conduct a trade-off of multi-criteria to support a decision process, engineers tended to consider the risk of a technology in order to make a subjective judgment of an appropriate solution. A weighted ranking tool was found to be as popular as FMEA when a selection among several alternatives was required. The technique was used when a decision was required by a group of experts. The influential parameters considered when evaluating manufacturing systems were discussed within the questionnaire. Question 14 was divided into two parts to identify and define key top-level criteria in the evaluation of manufacturing technologies.

The results were heavily based on technical specifications and sometimes related to the industry/production type objectives. One organisation noted a set of technical requirements for a new measurement process of large-scale products. Accuracy and process time were influential in the decision-making process and consideration was also directed to the influence it had on other processes. The alignment of technologies with long-term manufacturing strategy and corporate vision were deemed by engineers to be an important part of the process as it had the backing of senior stakeholders.

In terms of the key criteria provided in the first part of the question, technical ability was deemed one of the most important factors together with H&S. They were followed in the ranking with financial measures and production requirements.

Cost is often an important factor in any purchase. It can include the initial purchase cost and also the upkeep cost of the technology. Advanced technologies often have strict and costly maintenance schedules in order to maintain the state-of-the-art capability of the system. Part of the questionnaire aimed to understand the type of financial data that was required by stakeholders to approve new technology purchases. The data indicated that ROI, initial project cost and PP were deemed the most important factors. Some organisations noted that for certain projects such as improvement cases, a set ROI period often acts as an initial constraint for new investments. The popular key criteria and financial justification models are presented in Figure 4.8.

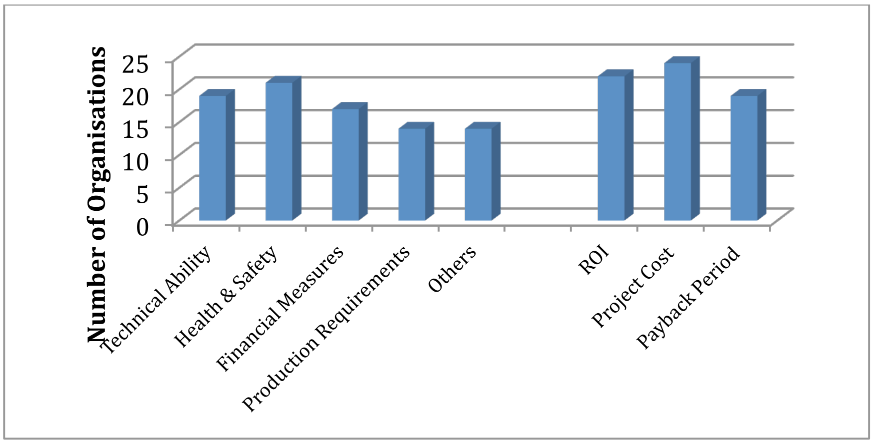

Figure 4.8 Manufacturing and Financial Factors

Question 16 aimed at understanding any knowledge capture practices that are undertaken within the organisation to assist in technology selection. The resultant understanding illustrated that all organisations captured cases in the form of capital expenditure documents that outline cost requirements. However, the access of such information was limited and not actively shared within any organisations. Many respondents indicated that experience and knowledge of historical projects assisted decision-makers in new projects and that such information was not available. Three organisations expressed that knowledge capture activities were being conducted but were focused on general on-the-job issues prior to employees leaving the company (e.g. retirement). When suggested that historical data could have a strong influence on future decision-making, all respondents agreed this to be true.

Examples of some of the qualitative answers obtained in the form of descriptive comments to the knowledge capture techniques were:

- *"Having a process in place which captured historical knowledge and previous decisions would provide us with the information to ensure we learn from mistakes".*
- *"Knowledge capture can be an expensive and exhaustive task, but to ensure we remain competitive, it would be a worthy investment".*

- *"As we are a large company, we often find similar projects being conducted across different sites but we have no knowledge sharing structure in place".*

The final questions concluded that 20% of the respondents believed their decision process to be satisfactory. Many believed the problem was due to lack of standardisation and gathering of technical and expert data. The respondents noted that they often conducted what they believe to be a rigorous evaluation process but the level of detail and study varied between individuals. Out of the 24 interviews, 19 agreed that they would use a formalised methodology that integrated strategic, financial and technical issues in a combined framework that would provide access to historical data to influence future decision-making. The remaining five were sceptical till they knew the full details of the approach.

4.6 Discussion

The results are discussed and analysed in this section to conclude the main findings of the survey, the discussion is set out in a similar form.

4.6.1 Company Information Analysis

The results from section 1 of the questionnaire demonstrated that most of the participants involved in the survey were manufacturing engineers or operation directors. Many of the organisations represented large workforces and were well-represented firms within their domain. This confirms that the survey was carried out within a suitable field and the data obtained from a set of appropriate people.

4.6.2 Automation/Justification System Design Analysis

The results from section 2 of the questionnaire revealed how the opinions of the respondents varied when asked what level of automation they possessed. The various definitions of 'automation' included software and hardware applications, many systems were manually controlled through a software program but automated in the actual performance of the part. Responses were based on the comparison of the company with other organisations within the industry and such rationale determined the level of automation. In addition, as illustrated in Figure 4.2, most respondents believed their organisation consisted of medium and low automation levels. In some instances respondents placed themselves at the medium level, even though they had an extremely high level of automation within the plant. This was particularly true at a manufacturing organisation where the level of automation in the initial stages of manufacture was extremely high; whilst in the later stages of assembly the levels were low.

The types of automated systems were mainly drilling and measurement operations in which the level of complexity was low and the process volume was high. Responses indicated that certain processes had no option but to be automated as it would be impossible to obtain such technical ability from a manual process. The responses of automated systems during final stages of manufacture, such as assembly, were extremely low with only high volume pharmaceutical manufactures investing in automated assembly lines. It was noted that in recent years such firms have invested in automated assembly systems, which were manually intensive with unskilled labour during the previous decade.

Figure 4.3 showed that quality, cost and H&S were considered the main drivers for automation in the respective order. Each of the elements discussed were deemed to have an influence on automation acquisition, but it was the intention to identity the main drivers for an accurate analysis of the objectives. Further investigation into the responses by the interviewee revealed that consideration for improvement in quality was through increased process reliability, repeatability and elimination of operator error. Initial cost was a major factor that was outweighed against future minimised labour costs for systems to achieve a break-even point. H&S had a large influence on automation acquisition to decrease the likelihood of injury. Of the suggested ROI periods, critical H&S upgrades had a disregard of such a constraints.

The discussion of automation-backfire instances resulted in a number of companies expressing previous failures that resulted from inadequate assessment being conducted on new technologies. These included an assembly system at a large automotive manufacturer where a technology that was believed to have developed to an adequate productive standard, was incapable of achieving takt time. The project required a large investment by stakeholders to ensure the project was not a complete failure.

It was clear that many respondents understood the critical issues of having a strong link between design and manufacture engineers. The most successful and confident responses were from organisations that pursued cross-functional teams to conduct the design process. The transfer of knowledge and experience during meetings was deemed as an appropriate and successful form of designing new products.

H&S issues in product design appeared to be one of the most important areas. The safety of the work environment and workforce was the area of first concern due to the potential consequences. Process time and financial factors were also important areas identified during the design. All the factors mentioned in Figure 4.5 were areas of focus during the design phase and reported according to the management aim and design approach.

4.6.3 Manufacturing Decision-Making Practices Analysis

Overall, 12 of the respondents believed they had a formalised decision-making process that consisted of a combination of weight sum and FMEA techniques. A small number of respondents indicated they were using CAD during the decision-making phase and QFD as a validation process. Although QFD is typically used in product design to deploy functions forming quality, it was found to be used in manufacturing systems design as a way in structuring the design problem and relating the requirements into engineering characteristics. A further investigation revealed that some of them were not decision support tools as such, although they could be used in the decision-making process. For instance, the FMEA toolset is a procedure used traditionally in product development for analysing potential failure modes within a product/system for classifying the severity and likelihood of those failures. The technique is often conducted once a solution has been identified and used to combat potential risk issues. Instances of FMEA focused solely on risk to help make a technology decision and did not include other parameters such as cost. Other tools mentioned were mainly design methodologies that were applied as a structural procedure in the design of manufacturing systems. The data shown that the respondents who mentioned the use of decision support tools were actually the same answers given for the design of a manufacturing system. The tools were therefore viewed as design support tools rather than decision support.

The persons involved in the manufacturing decision-making process resulted mainly in cross-functional teams that included project managers, operational support, operations, quality control and manufacturing engineers. It was deemed good policies to consider and involve employees from different divisions to gain a cross function of experience and ultimately identify any potential issues at the earliest stage.

The key criteria results confirm the importance of H&S to the respondents. This was both highly regarded as an important influential element in design and manufacturing decision-making. The importance of the technical ability and the financial justification techniques were illustrated in Figure 4.8. Most respondents mentioned project cost, ROI and PP with a common maximum PP of 2 years. What had not been anticipated were a number of least important factors in the decision-making process, which included social and managing change issues. Although they were deemed relatively low, social issues included the day-to-day effect on the operator, which was identified to affect productivity. Managing change issues of new product instalments was considered an issue to best incorporate new technologies and not necessary when deciding what equipment to purchase.

The amount of support provided across the respondent's organisations was deemed to be relatively low. The responses indicated that knowledge capture from historical cases was rarely conducted and although some information is available within capital expenditure reports, this information was not freely available and in some cases restricted. It was noted by some respondents that the process of locating information was so tedious they would not consider it. Reported responses on how useful it would be to them were the information available were that the information would improve their confidence and time required to make a decision.

The level of support observed from the respondents demonstrated their lack of confidence in their existing decision practices and a high level of interest to review the outcome of this research. Reported responses on how useful it would be to have a standardised, structured and knowledge database to support the evaluation and selection of technologies would provide additional reassurance to engineers and stakeholders. They believed it would create a level of ownership through the removal of subjective justification and emotional influences, which form part of every project. Comments also included how an improved process would decrease the decision time and allow focus on possible technologies to be extended to include a greater range of options.

Overall, this analysis provided a clear understanding of the important factors, constraints and weaknesses in the existing decision-making practices conducted within industry. It was obvious that there was an essential need to appropriately address a form of knowledge or information capture within the decision-making process, and provide a standard and optimised methodology.

4.7 Chapter Summary

It is clear that the highlighted policies within industry for technology evaluation and selection require improvement. The identified constraints include a lack of methodology and restriction of techniques for capturing lessons learned of previous projects. The key findings of the survey are presented in Table 4.1.

The outcome from this chapter raises further questions of the exact nature and approach to manufacturing technology selection, and the context and process by which it is conducted within industry. It is clear that decision makers are concerned by their practices and little guidance through a way of a structured methodology or techniques are provided by organisations. It was apparent that the process is data-driven where a vast amount of data is shared among decision makers to support the judgement process. In addition, the know-how appeared to be entirely supported by the expertise and experience of the decision-makers/experts involved in the selection process. Therefore, understanding the subsequent stages of the know-how process and transformation of information and knowledge appears to be a logical step forward in fully defining the process. This type of experience-based approach will subsequently be investigated in the following chapter.

Technology Automation / Justification System Design
1. Most of the organisations believed they had either a medium or low level of automation. 2. Reducing cost and improving quality were the main driver for increasing levels of automation. 3. 25% of participants had experienced automation backfire. 4. Cross functional involved in the decision-making stages of design were the most popular. 5. H&S was the most influential factor when evaluating design improvements.
Manufacturing Decision-Making Practices
1. Five respondents followed a structured methodology that was adopted from existing design approaches. 2. Two organisations instructed external experts to identify and select manufacturing systems. 3. A cross functional decision-making team was deemed the most appropriate and optimal decision-making practice. 4. FMEA and weighted scoring models were the most popular techniques used. 5. H&S, technical ability and financial factors were most influential in selecting new manufacturing automated systems. 6. Typical costing practices appeared to focus mainly on total investment costs (capital expenditure) with a reasonable return investment period required.

Table 4.1 Key survey findings

The types of key decision variables were not fully defined although some main drivers for automation were discussed. It is clear that single factor decision tools are not suitable and the problem is a multi-criteria decision process where an expert in a selection process considers a multitude of complex variables. Current approaches rely on financial analysis toolsets to support the justification of a new technology. Although these approaches provide an understandable level of quantitative justification, this alone is insufficient. Practices appear to use this quantitative information together with the subjective judgement of an expert to form an appropriate decision.

The findings of this research have been significant in which there is a clear understanding of the techniques and methods used in practice today. It is clear there is a reliance on human experts and existing collaborative approaches is common. The study has raised further questions regarding the process by which an expert would make a decision. Where decision tools are not used or techniques that rely on subjective weighting, the logic by which an expert would apply their expertise is not fully understood. To develop an accurate model for an approach similar to the information and knowledge of an expert, a further understanding of the domain is required.

The following chapters will seek the logic an expert would recall during the decision-making process and factors that represent decision cases to assist in manufacturing technology selection.

Chapter 5

A Study of Information and Knowledge Transformation within the Manufacturing Technology Selection Process

5.1 Introduction

Chapter 4 concluded that manufacturing technology selection is a decision activity based on the experience and knowledge of the personnel involved in the process. The approach is subjective where the skill of an expert has a strong influence on the selection of a investment opportunity. The know-how process of technology evaluation and selection is data-driven yet often not recorded and appropriately structured.

This chapter presents the results of a study to understand the context and process of information and knowledge transformation within the manufacturing technology selection process. The study was conducted at the collaborating manufacturing company through a series of interviews and review of internal documentation.

5.2 Study Objective and Technique

Whilst Chapter 4 presented the techniques and approach to technology selection in practice, the research was further required to understand the details of the process. It was apparent that understanding techniques was insufficient to support the development of a technology selection framework. The process is reliant on experience of experts and thus the techniques/approaches are often used as secondary support tools. Experts recall information and knowledge to support their decision-making judgement. Knowledge cannot be easily defined. It is a cognitive process where information process is an individual's physiological function (i.e. an expert recalls past information to support decision-making / technology evaluation). Therefore, the emergence of the study carried out within this chapter is to investigate the transfer of information and knowledge at each phase in the decision process by an expert.

In an attempt to engage with the current challenges and provide an appropriate step forward in the literature, the study of acquiring information and knowledge as part of inter-enterprise communication to support manufacturing technology decision-making is investigated. The research focuses on the presence towards industrial alliance and support, and forms the justification of the results.

As discussed in Section 3.6, this data collection activity represents a flexible, data-driven exploratory stage of the study that is aimed at defining a principle of manufacturing information/knowledge. It is concerned with the collection and analysis of qualitative and quantitative data from existing industrial practices of technology evaluation and selection. Upon designing the data collection activity, the following aspects were considered: the objective of the research activity, the form of collecting the data, the field and persons of whom to collect the data from, and how such data should be analysed.

This research views the data-information-knowledge hierarchy and manufacturing knowledge for decision support as technical; founded from engineering and scientific theorem involving highly structured and precise content. However, the approach by which this information/knowledge is acquired, used and reused during the decision process may be social and have tacit/explicit components.

Whilst there are many processes to support this form of research, interviewing and document analysis were subsequently chosen to investigate the area further. A theoretically focused study needs to choose carefully a target sample sited to the issues under analysis. This was available to the researcher as the study was conducted within an organisation where decision experts were available (see Section 5.2.2). The study area was partially known to the researcher; in-depth interviews provide the most appropriate form of further discovering the unexpected and uncovering the domain. Interviews are appropriate to collect information in a manageable form for later analysis and the interview questions can be altered as further understanding of the domain is understood. To guide respondents through a maze of life experience (their approach to a pre-dominantly experience-based decision process), effective interviews can be conducted in an orderly fashion and within a limited time period. This is accomplished by developing an incisive and probing interview schedule.

Experts often refer to material to support them during the decision process. Whilst this is a secondary tool, an evaluation of these documents would assist to further understand the domain. Analysis of these documents allows the critical examination of information that supports experts and the data to support multiple phases of the process.

5.2.1 Selection of Data Set

The data collection activity was designed to be an in-depth review and study of the manufacturing technology decision-making process. The interviews and observation activities were limited to small study groups/organisation structures within the collaborating company. They stop when saturation is achieved. As part of the study, there were two types of interview discussions. The first targeted investment leaders and senior engineering managers. The purpose of interviewing and studying these persons was to understand and generate a schematic plan of the decision process, from initial project identification to closure and review. The results from some initial discussions that formed the questions found the practices to be extremely broad and included a wide range of personnel from within the organisation. It was deemed appropriate to firstly understand the stages from the view of personnel who had knowledge of the process. The answers given in the first stage would also form the questions developed for the second set of interviews. In the first stage, interviews were carried out with 5 employees of whom the author did not know prior to the investigation. The 5 interviewees were 4 engineering managers and 1 investment manager. The engineering managers were responsible for the implementation technology and involved from the start of a project. The remaining interviewee was an investment manager who worked at a senior management level and was responsible for evaluating investments to conclude a go/no-go decision.

The experience of the interviewees varied widely with an average employment time within the organisation of 8 years. Most of the engineering managers had significant specialist experience in manufacturing and had progressed through the ranks within the organisation. The experience and time employed by the company was not explored further as it did not have any bearing on the key factors that emerged as part of the study. Participant experience had not been neglected; to ensure an appropriate range of personnel were consulted, persons with varying degrees of experience participated. The interests of the research were on specific situations and the events that occurred within them rather than of particular personnel. Also, to protect the identity of the individuals involved of whose anonymity was assured, personal factors were not noted. During the subsequent analysis of this study, these interviewees are referred to as Investment Manager 1, and Engineering Manager 1–4.

The first analysis and coding of the five interviews took place immediately after each interview. The aim was to schematically map the decision process, understand the relevant activities and personnel, and define the types of data-driven activities within the process. Once this was concluded, further interviews were required to validate and expand the detail of each element in the process.

The second phase of interviews targeted individuals who were involved in each element of the decision process and had knowledge of the activities and information shared. 11 interviews were subsequently carried out with representation from departments involved in the different stages of the decision process. They included 4 manufacturing engineers, 3 operation managers, and a representative from engineering management, procurement, quality and finance. The participants from the second group were referred to as Manufacturing Engineering 1 – 4, Operation Manager 1 – 3, Engineering Manager 5, Procurement Manager 1, Quality Manager

1 and Finance Manager 1. During the second session, 3 of the interviewees were known to the researcher prior to the study through previous work carried out within the company. The range of experience varied compared with the first study, including recent graduates and persons who had been at the organisation for less than two years. The average time of service within the organisation was five years. Similarly, personal experience and individual length of service remained anonymous.

Prior to running both phases of the process, a pilot study was undertaken to develop the interview questions, to understand the length of time required for each interview and decide on the method of coding the answers given by the interviewee. For the pilot study, two colleagues who were also working in collaboration with same company and were familiar with the research project took part. The first colleague had experience in manufacturing having worked as a manufacturing manager prior to undertaking further academic research. He was familiar with the TRL process and the process of technology development. The second colleague had a wealth of knowledge in manufacturing technologies and in particular the analysis of them for supporting assembly processes. The interviews with both colleagues focused on all stages of a manufacturing process from initial consideration to forming an overview of a new assembly process. All stages of a manufacturing technology decision process were discussed and the conversations were used purely for developing the study questions.

During the interviews many of the participants presented company documents to better explain the information of the decision practice. Many provided documents through email once the interviews had been conducted. These were subsequently analysed to provide further clarification and a better understanding of the decision process.

5.2.2 Study Field and Access to Study Setting

The research was undertaken within the manufacturing departments at Airbus sites in Filton and Broughton. In the first instance, the manufacturing engineering manager within the R&D group was consulted to discuss the feasibility of undertaking the study. Once permission and support was granted, accessibility within the company was straightforward. The researcher was given relatively unrestricted access to the company, provided with computer and telephone equipment, and given desk space to conduct the study. A short overview of the study purpose was developed and agreed by the industrial supervisor to be used as the first point of call for contacting potential observant and interviewees.

5.2.3 Design of the Interview and Documentation Analysis

A core list of questions was defined that allowed further scope for additional qualitative data to be extracted. This approach of data extraction was well suited to the grounded theory methodology as it provides useful tools to learn about individual's perception and feelings regarding a particular subject or actions.

The approach for this research is an adaption of the critical incident technique (CIT) which was originally developed for use in psychology (Flanagan, 1954). It has recently been applied to organisational research and is a method of collecting direct observations of human behaviour that have critical significance and meet methodologically defined criteria. An incident is any observable human activity that is sufficiently complete in it to permit inferences and predictions about the person performing the act. Although critical incidents can be gathered in various ways, typically respondents are asked to tell a story of a previous experience. This type of process is most suited to the research problem as respondents hold a wealth of information from experienced cases. Describing the process they went through will ensure an appropriate account is obtained.

To provide supplementary support and clarification of discussions within the interview, the participants were advised to bring documents they believed to be relevant to the study. As internal documentation alone can be difficult to interpret due to the type and level of data available, discussing this within the interview and having the data interpreted by a company employee was favoured. This method has further advantages that the researcher is able to review the documents once the interview is complete.

The interviews lasted one hour and each was transcribed upon them taking place. The researcher kept most of the internal documentation with the exception of highly sensitive information. To improve validation, the study had been designed through a means of data triangulation; ensuring the range of participants interviewed covered all potential areas. A set of core questions was developed for the first set of interviews and is shown in Table 5.1.

Background questions
Explain your position and responsibilities within the company. Summarise your experience/ background. What level of exposure have you had with the implementation of new technology? What area have you worked in?
Using a recent technology project as an example:
Describe your involvement in the implementation of a new technology. Are you aware of the process from initial project identification through to delivery? Consider the situation and the considerations that impact the outcome and process. What was the situation? Describe the project. Who was involved? What was the process?

Table 5.1 Core questions - first set of interviews

Following the first set of interviews, a second set of core questions was developed for the second set of interviews and is shown in Table 5.2. The second set of questions was influenced by the answers given during the first set of questioning. A further understanding of the steps of how a project is initiated and the information that supports the selection of a new investment opportunity were required. In addition, the information used to form a capital expenditure/business case was able to summarise how a technology was justified.

Background questions
Explain your position and responsibilities within the company. Summarise your experience/background. What level of exposure have you had with the implementation of new technology? What area have you worked in?
Based on your area of expertise and involvement in the project:
Describe the steps and actions carried out within initial project identification. Explain how the decision team, experts and project manager are selected. What is defined during the project launch meeting? What were the main business requirements and how were they determined? How are each potential technology identified? How is a technology selected? What data, information and knowledge is used to make a decision? How is the business case formed? What information is included in the business case? What stage does management give a go/no-go decision review? Who is involved in the implementation of the technology? How is the project closed? What information is captured? Are lessons learned recorded? Give an example of lessons learned.

Table 5.2 Core questions - second set of interviews

5.3 Interview Coding and Results

This section describes the outcome of the interviews. It presents the decision process map and emergence of information/knowledge themes in manufacturing technology selection. The key observations for each are noted including the definition of each category from the information supplied during the interview transcripts.

5.3.1 Contextual Technology Selection Map

Following from the first set of interviews, a decision process map was developed. Eight phases formed the process (Figure 5.1). The process map was developed upon completion of the first set of interviews. The identification of each phase within the process was apparent. This provided further clarity of each stage that forms the technology selection process; allowing an in-depth analysis of information and knowledge within each phase. To determine each activity and the key data-driven phases of each, the researcher explored further through semi-structured interviews (Table 5.2) a better understanding of each process. An overview of the results from each phase supported by transcribed quotes from the interviews is presented.

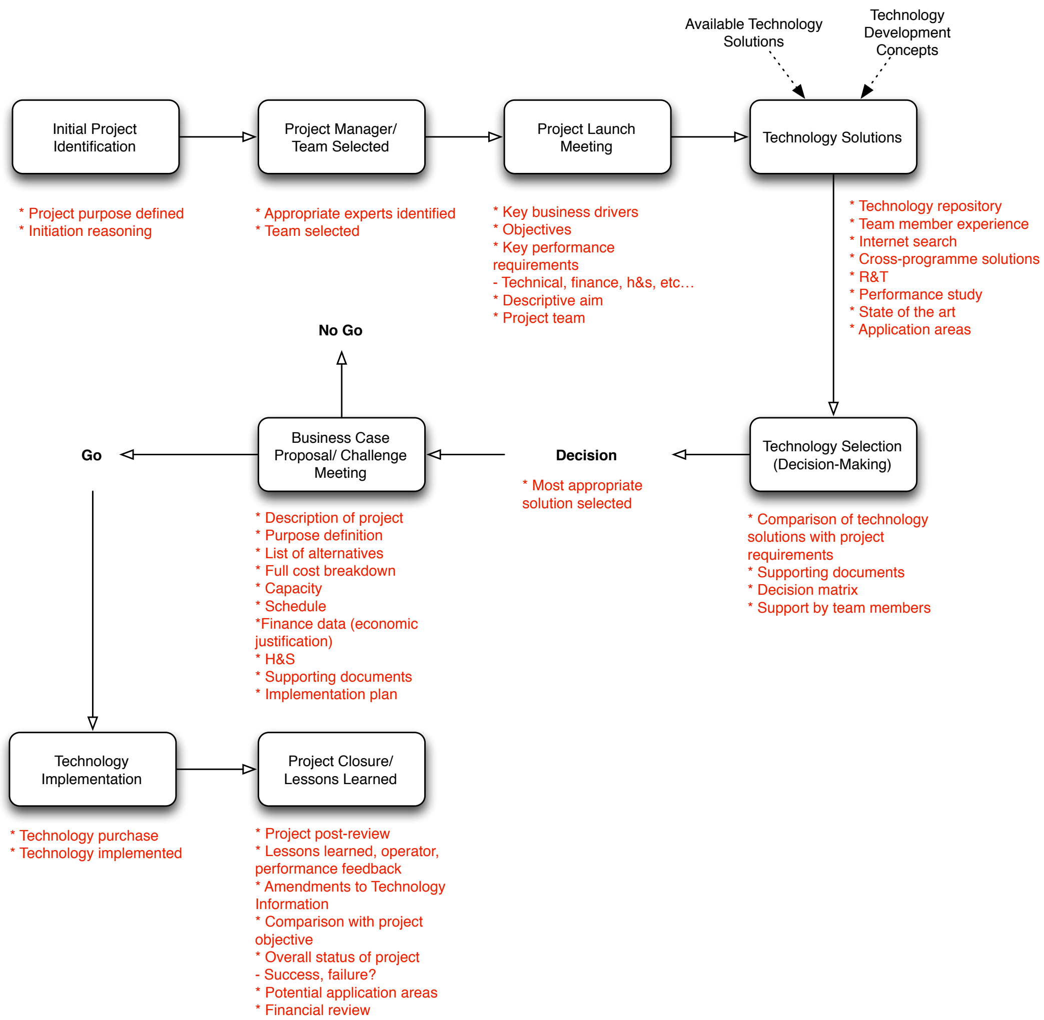

Figure 5.1 Eight phases of the technology selection process

Stage 1 – Initial project identification

The initial project identification stage is *"the activities and identification process by which the project is formed. It is during these stages where a manufacturing process is evaluated and identified as an area of improvement"* (Engineering manager 2). The process involves a number of engineers and internal experts that evaluate and decide on a new improvement project. The activities are conducted several times by an engineer and projects selected for development.

It is the phase where a project is founded by understanding the current manufacturing state and generating reasoning for improvement. The purpose is initially defined to provide a basis for further research.

Stage 2 – Project manager/team selected

Once a project has been identified and an initial case for further examination is agreed, the project team is formed. Depending upon the area of technology improvement, a number of experts are chosen from within the organisation and a project manager is selected. *"The project manager and team selection stage is the first phase where the project becomes official. Experts are identified based on experience and expertise, and each team members responsibilities are formed"* (Engineering manager 1).

Stage 3 – Project launch meeting

The project launch meeting is the first formal and recorded meeting between the team members. The engineer(s) involved in the initial project identification provide an introduction to the project and outline the research conducted. The purpose is to decide the aim and objective of the project. The responsibility of each member is also conveyed.

Investment manager 1 noted, *"A set of key project and business requirements are agreed by the project team through a group understanding of the problem"*. The aim is to decide on the planned outcome of the project. The project and business requirements can range between technical performance requirements of the technology, or business related requirements such as its overall goal or alignment to the organisational strategy.

The launch meeting is the first group discussion where the experience and knowledge of the personnel involved have an impact on the direction of the project. The agreed activities for each member are typically to conduct a search of potential solutions.

Stage 4 – Technology solutions

Upon the project being officially launched, individual activities by each of the team members are undertaken. Due to the lack of technology repository-based systems, tasks are divided between the members of the group to conduct the extensive evaluation of potential solutions. The activities include a benchmark analysis of application areas, other businesses or industries. They include a review of internal documentation of previous studies or an internet search of state-of-the-art systems. The individual experience of previous projects strongly influence the direction of the research.

Alternative application areas are reviewed and the potential adoption of technologies is considered. Each team member considers the requirements previously discussed and together with their understanding of the problem, technologies are included in the initial consultation list or disregarded. Depending upon the suitability of the technology, the technology supplier may review the manufacturing process within the business to understand the alignment potential. *"Each individual conducts the technology solution search, and informal discussions of suitability and transparency is conducted within the group by email and phone"* (Engineering manager 4).

Stage 5 – Technology selection (decision-making)

The technology selection exercise is the second group discussion where the experience and knowledge of the personnel involved impact the direction of the project. Conducted as a group meeting setting, each project team member participants in the evaluation of each technology. The aim of the technology selection phase is to evaluate individually, the technology identified in the previous stage against the project/business requirements. By comparing the technical performance attributes of the technology against the requirements of the project, a group discussion and judgement is made to identify the most suitable solution.

"The involvement of a varied decision team is crucial to the evaluation as it ensures the appropriate experts support through their area of expertise. For example, a quality engineer will focus heavily and scrutinise the quality performance of a technology, whilst an operator will attempt to understand any implications of using the system on a daily basis" (Engineering manager 4).

Typically, the discussion will be conducted in two stages. Firstly, all technologies are considered and a filtering activity using a few criteria reduces the potential solutions to a manageable amount, often less than 10. The second stage conducts a full evaluation using an agreed list of factors for each technology that is compared to the project requirements. During both stages, it is the experience and intuition of each team member that conducts the trade-off of a technologies performance capability.

Stage 6 – Business case proposal/challenge meeting

Once a technology has been selected as being appropriate for the project, the business case is formulated. The business case provides the reasoning for initiating the project and is used as a form of presenting the project to senior management for financial approval. It is a well-structured document to provide a comprehensive justification of quantifiable characteristics of a proposed project.

The business case is formulated by the team and includes a description of the project, the alternatives considered, a full cost breakdown, intended capacity requirements, schedule, financial data, an H&S evaluation, and an implementation plan. Documents supporting each justification generated by the expert are also included.

The business case is used in a challenge meeting for which the proposal is considered by senior management. The meeting is a formal discussion between the project manager and an investment manager where a go/no-go decision is made.

Stage 7 – Technology implementation

Once a technology is given a go-ahead, an implementation plan of the system is created. The implementation of the technology is considered in the selection process and the realisation of the application is subsequently undertaken. Involving personnel from within the project and additional resource in the business, the process of purchasing the technology, implementation within the business and monitoring its initial use is conducted.

"Technology implementation is an important step in the overall process. Managing the change for the operator can be a sensitive and potentially unpredictable situation which requires consideration and planning" (Investment manager 1). The consideration and planning towards implementation is conducted before hand to ensure the smooth transition for all involved parties.

Stage 8 – Project closure/lesson learned

This is the third and final group discussion activity between the team. The post-project review includes a number of phases of which the project is evaluated. Firstly, to determine as a group the success of the project as a single entity, it is evaluated on a scale. By agreeing on the respective rating, the level of project success is recorded.

Understanding the changes in the performance characteristics of the technology compared to the predicted values. It is typical that a technology was selected based on predicted performance attributes. Understanding the variation to the actual performance capability can provide a better insight into how well it adapted to the problem. Reviewing operator feedback once the system has been implemented can also provide excellent advice of the performance and suitability of the technology. Changes in the technology performance and expected suitability for the business require consideration and understanding.

Engineering manager 2 noted how each of these activities is of *"crucial importance to a post-project review but the activities tends to be carried out on an informal basis rather than being documented and stored"*.

This concludes the transcripts obtained during the first set of interviews. The following sections discuss the results of the second interviews.

5.3.2 Information and Knowledge Themes

Upon transcribing the interview scripts, three information and knowledge categories emerged. The first were '*preparatory information'* that defines the objectives and requirements of a new project. In addition, it outlines the required performance specification to evaluate several technology alternatives. The second were '*support for evaluation and selection*' that incorporates the alternative data, information and knowledge forms for supporting the decision process. The third category were '*post-implemented learning*' that is the context acquired once a technology has been implemented and the types of lessons learned and how they are captured. A summary of the resultant information/knowledge categories is illustrated in Table 5.3. The relation of the information/knowledge categories to the selection process is also included.

The definition of each category and sub category are discussed in Sections 5.3.3 - 5.3.5. Similar themes were concluded from conducting the study and therefore a number of quotations by participants have been referenced. These are not "one-off" statements, rather individual quotations that were similarly mentioned by other industrial expert participants. For each sub-category, three levels of coding are described:

- *Definition* – a statement of meaning interpreted by the researcher from the interviews of the sub-type.
- *Occurrence* – the time and period when the event happens as noted by the interviewees.
- *Support form* – the form the data/information/knowledge as described and how it is applied and structured.

Information/ Knowledge Category	Definition	Sub Category	Definition	Phase of Selection Process (see Figure 5.1)
Preparatory information	Content acquired to support defining the problem and evaluation of technologies	Project requirements/ objectives Technology specification	Defined project aim/ objectives Predicted performance specification of technology	3 - 4
Support for evaluation and selection	Data, information and knowledge supporting the decision process	Expertise Selection guidance rules	Applied cognitive process Organisation support/ guidance for evaluation and selection	5 - 6
Post-implementation learning	Content acquired for implemented technology	Personal knowledge development Technology lessons learned	Learned empirical knowledge Updated performance specification of technology	7 - 8

Table 5.3 Summary of interview categories

5.3.3 Preparatory Information

For any manufacturing technology implementation project to be conducted, a series of preparatory information is collected prior to any decision being made. Content is acquired to support defining the problem and acquiring the information to conduct an appropriate evaluation.

Sub Category 1 – Project requirements/objectives

The process requirements of a technology are typically determined at the start of a project. A series of attributes are defined based on the assembly process requirements and/or the existing implemented technology. An initial set of requirements is identified early within the project before it is formalised. A manufacturing engineer studying a process will identify it as an area of improvement and thus determine an initial set of requirements. These are technical and related directly to the capabilities of the existing technology or the envisaged assembly process. Although it has yet to become formal, the engineer will record these and use this information as a benchmark for determining if a technology meets these requirements on a preliminary basis.

The defined attributes provide a foundation for the search of potential technologies that are near or identical to the requirements. This is best illustrated by the comment below which describes the actions of first evaluating a manufacturing process to determine a set of technical requirements.

"When employed as a manufacturing engineer you tend to embody yourself within the environment and get to know the operators well. It is during this time that the problems with a process become apparent. As you begin

to study an operation and learn about areas of improvement, you remember these key requirements. They may just be ideas like I want process X to be quicker, or let's reduce the required resource by 50%. Although they are important, they only assist in forming the potential list of technologies before a final set of requirements are decided" (Engineering manager 5).

Definition – during the early stages of a project before it is formed, an engineer will record a series of key process improvement requirements. It may include the attributes of a technology or the requirements of a process. Carried out by a manufacturing engineer, the process is unstructured whilst being initiative, informal and mentally recorded by the engineer. As the level of project importance progresses, so does the formality of the work.

Occurrence – the process occurs several times in a project during improvement cases. An engineer evaluates a manufacturing process to understand if it is an area of improvement, or focus on a project that is about to launch. The activity tends to occur very early within the overall project lifecycle, is informal and unstructured. Once the understanding of the process develops, an accurate set of definitions is established.

Support form – the approach of formalising the process requirements are supported by a variety of data and information. An expert uses personal knowledge and experience to review a technology and record it in the form of information. It is either documented on paper, on a computer or mentally stored. During the early stages of the process it is unlikely that the information is distributed.

It is the judgement of the engineer who will initially define the problem or perceived aim to satisfy the process of improvement. For example, a project may begin as quality errors have been recognised in the output of the process. This in turn may lead to an evaluation by the manufacturing engineer who also identifies the process as affecting the flow of other production activities. Subsequently, a reduction in process time may be identified as another aim of the project. These factors are discussed further within Chapter 6 of this thesis when defining a historical decision case.

<u>*Sub Category 2 – Technology specifications*</u>

The process of identifying a suitable technology is often based on premature technical attributes of a technology performing in an optimal environment. Technology companies provide technical specification sheets of their products including system specifications and typical performance attributes. Although this information is readily available online, it is generic and cannot be relied upon in the decision process.

Engineers use technical datasheets to firstly consider a technology before conducting a full evaluation. There are two stages to the information capture process. First, generic attributes that are readily available are considered. These are acquired through the supplier. A company will often demonstrate the technology at the potential client's site. The second is an in-depth analysis of the detailed attributes of the technology performing in its intended environment. Once the initial list is filtered to a manageable level, technology companies provide a detailed set of performance attributes.

Typically, a non-disclosure agreement is set-up and information between both parties is shared. The potential supplier visits the company to understand their requirements, how well their product fits the assembly process and determines an accurate set of performance capabilities.

Definition – technology information capture consists of two phases. The first is to acquire the information that is easily obtainable of a technology. Through an internet search, discussions with the potential suppliers and understanding of existing application areas each assist in determining an underlying level of knowledge for the technology. Once a list of potential solutions has been sought, a further information gathering exercise with the support of the supplier will determine the suitability of the technology to the application.

Occurrence – the phases occur twice during the early stages of the selection process. It is relatively fluid in that the supplier will maintain contact with the company and support further analysis if required. Maintaining a relationship of application studies and results provides initial support to engineers.

Support form – during the initial stages of information collection, the activity is based on the technology requirements defined in the first stage. As the level of information increases, the structure and type of data provided becomes more important. During the analysis stages it is essential that the data is comparable to make a judgement. Engineers typically use a spread sheet application and set of evaluative parameters for each technology to share information.

The type of information collected for each technology similar. The importance often surrounds the capital investment required to purchase the technology and the expected PP, which is a prerequisite for justification. In addition, it was noted that more qualitative-based requirements that are difficult to quantify are being included in the technical evaluation. Organisations are concerned with the type of skill level required to use a technology and how productive the equipment is within the business. These factors are discussed further within Chapter 6 when defining a historical decision case.

5.3.4 Support for Evaluation and Selection

In order to conduct the evaluation and selection of a technology, a set of activities where data, information, knowledge and experience combine together to assist in deciding on an appropriate technology investment. The approach to the problem will include a level of intuition and judgement based on a decision maker's previous experience. Through a combination of information and intuition, the evaluation of alternative manufacturing technologies is conducted. The key observation from the interviews was two types of supporting structure that assist in the decision process: expertise and guidance/rules. Expertise is defined as the heuristic knowledge experts acquire from previous experience, and guidance/rules as structured form of directing the process to a solution based on rules of thumb or predetermined guidelines. Both categories are now discussed in detail.

Sub Category 1 – Expertise

The skill of an expert forms their level of expertise. It consists of those characteristics, skills and knowledge of a person that is distinguished from a novice or less experienced individual. Manufacturing organisations employ field experts to assist in their decision-making tasks, they are likely to make better-judged decisions than persons with less or no experience. Expertise is the knowledge of or a skill of something. In manufacturing technology decision-making, it is the knowledge of previous events a person has been involved in. It is the accumulation of events through involvement in or exposure to historical technology implementation projects. It is the factual knowledge that is recalled by a decision maker. Many view experience as the key approach to selecting an optimal investment project. A person's experience gained over time includes projects they have been involved in, lessons they have learnt about technologies and processes which they have become familiar. Experts remember previous technologies and their performance level.

Engineers who work in a particular field for a great amount of time tends to become experts in that area. This can be good when they work in specialist areas of development, however, in terms of evaluating a range of technologies it can have an adverse effect on conducting a truly objective judgement. The decision process tends to be largely subjective in which experts have a preference towards a particular technology. The process of evaluation can be subjective and unstructured. It is difficult to fully represent the cognitive process of decision makers and record tacit knowledge. However, it is well noted that this type of experience is crucial in the current approach to decision-making.

A number of interviewees discussed how a technology alone and the comparison between two or more are not sufficient for conducting an appropriate decision task. It is often the comparison between the technology and the business/process requirements where the decision is made. The evaluation process tends to be a trade-off among performance. For example, a decision between a technology requiring two unskilled operators compared with another technology that required just a single skilled operator could be a typical choice.

In addition, the complexity and potential trade-off becomes more difficult as the technology parameters are technical and the business/process requirements focus on the overall aim of the project. A technology successfully applied to a project may have been successful because it met the project requirements well, this may not always be the case for a different project. Decision makers realise that for a similar project, a similar technology would have a better chance of success. Thus, the technology alone is not considered but the comparison of the technology and project requirements. Engineering manager 5 discusses this point:

"Although the technical properties of a manufacturing technology are important when conducting the alternative trade-off, it is the comparison in line with the business requirements where the decision is made. I was recently involved in a new investment project and we considered a technology that had been successfully implemented throughout the business. Although it looked like an obvious choice as the technology had a proven track record, it wasn't aligned to the business requirements and therefore not chosen. The technology we did select had similar attributes to a project previously applied within the business" (Quality Manager 1).

Definition – an expert who has gained experience over a period of time working in a particular area is most suited to assist in the evaluation of alternative manufacturing technologies. Their experience is difficult to extract as it is tacit and their approach to a decision problem based on intuition and gut feeling. The historical experience and involvement in similar cases acts as the main form of developing a deep level of expertise.

Occurrence – knowledge support by an expert in the decision process is continuous as the project develops. The remembrance of historical projects and technologies will be most apparent during the evaluation stages where a technology is chosen. The vast and broad range of knowledge held by an engineer is applied in many stages of the decision process.

Support form – the main support form is the collection of tacit and explicit knowledge an engineer gains through their involvement in projects. Although the decision is a form of intuition, explicit knowledge is transferable and can be acquired from the expert. Typically the information and knowledge is not recorded and the process is reliant upon the expert to remember similar situations.

The types of experiences are often in the form of previous manufacturing decisions where a technology has been implemented within production. They are remembered as specific case structures where the performance of the project was judged. Relationships between the objectives of the project and the technology may be apparent and stored by an expert. Individual investment projects are often easy to recall yet may be defined differently dependent upon the persons involved in the activity. A clear definition may also be made between the objectives of the project and the performance capability of the selected technology. It was apparent that a decision maker would recall past decision cases when supporting judgement of a new technology project. The definition of the case structure an expert would recall is investigated as part of the study within Chapter 6 of this thesis.

Sub Category 2 – Selection guidance rules

An extensive experience curve is necessary for a small number of persons alone to acquire the knowledge and experience needed for manufacturing technology selection. The experience support of an expert or a number of experts alone is not sufficient in the decision-making process. Rules and guidelines are a key part of the process. This may include financial guidelines of a technology, or limitations in manpower available or manufacturing constraints such as takt time.

Tools that guide the decision to increase the chances of acceptance by senior management and overall project success form as the secondary measure to ensure investments are optimised. These vary between financial guidelines set by senior management, company restrictions on suppliers or government agreements, and manufacturing restrictions such as space.

Manufacturing restrictions and rules form an important part of the decision process. Organisations have limited space and levels of resource available must be considered. For example, process takt time is an important factor to consider when seeking an alternative investment. Takt time sets the pace of the assembly line and the time needed to complete the work on each station must be less in order for the product to be completed within the allocated time. To ensure no bottlenecks are apparent in the process, the restriction on takt time can form the justification for selecting or discounting a technology.

In recent years government support and involvement in organisations has increased and has an effect on the investment policies of organisations. Financial arrangements and location-based deals form an important collaboration with the government when attempting to invest in areas to improve levels of employment. Also companies are tending to place restrictions on supplier selection by ensuring they are not reliant upon a single supplier in order to protect the business. Although there are advantages to using a single supplier, such as assured and consistent quality levels, in unforeseen circumstances, the loss of a supplier can affect the business.

Definition – levels of guidance and rules form an important part of the decision process. They range from financial guidelines, manufacturing restrictions and organisational boundaries. Adhering to these rules improve the chances of success for a project. Rules can easily be expressed as IF-THEN statements and guidelines vary depending upon its complexity.

Occurrence – this form of knowledge can appear throughout the decision process but have particular occurrence during the earlier stages of decision-making. The information is readily available and extractable when required.

Support form – they are expressed as structured statements, defined rules and within technical reports. Their definitive reporting and clarity ensure they are easily understandable and interpretable by the employees within the business.

For example, funds are often allocated to various products groups to assist in new improvement projects. As each financial year progresses, this allocation is reduced as money is dedicated to certain projects. Investment rules may be applied to reduce the overall cost of purchasing a new set of equipment. In addition, constraints such as manpower may be apparent within the business and would need to be taken into account during the consideration of a new technology. These can often be expressed as a set of rules. These guidance rules may also be similar to rules that are learned from previous investment projects. Although there structure may be less defined, it may only exist as a matter of know-how among certain personnel within the business. The benefit of using such rules is apparent within the business.

5.3.5 Post-Implemented Learning

The cognitive process of expertise is acquired often through the learning of implemented manufacturing technologies. It is the content acquired and learning which is gained from fully understanding a technology. They are a form of lessons learned that teach us important lessons about project practices and understandings. They are reflections of experiences that assist in future activities. The thought process prompts experiences, either positive or negative and uses such thought in new projects. The two type of post-implemented learning are personal knowledge developments and technology lessons learned.

Sub Category 1 – Personal knowledge development

The storing of empirical knowledge upon the completion of a technology investment project is capturing experience-based events that are stored by an expert and recalled to assist in similar future decision problems. Experience-based events are historical technology implementation projects where a previous decision was made and a particular technology was implemented, based on set project objectives. They are learned or remembered by an expert and recalled to assist in similar future decision problems. Individuals rely on their own personal experiences and apply these lessons to future activities.

It was well discussed within the interviews that recalling historical events is a key influence of a decision maker's assessment of unclassified cases. Historical cases influence the opinion of the decision maker and affect the logical approach to a decision problem. Employees value successful projects and attempt to identify resemblances of new projects with previously successful cases. This cognitive recalling of cases and reliance upon an expert is partly due to the lack of recorded information at the end of an investment project.

The personnel involved in a project keep up-to-date with progress even when outside their responsibility and original participants have a lasting interest in technologies they have been involved in. They have a preference towards cases they have been participated in and a subjective weighting towards their expertise can influence a project outcome. The desire to continue to learn is limited to the interests of the individual rather than the company. Subsequently, the lack of documented recording can have a detrimental effect on the company whilst the employees develop further knowledge.

A number of interviewees were asked to recall previous projects they were involved in. It was impossible to remember all details of a previous project and several interviewees discussed how they recalled key technical attributes of a technology. An example is given in the transcript below:

"About 2 years ago I was involved in a project of improving a number of processes on the assembly line. I've always remembered how a particular technology had a number of influential attributes that included requiring a single operator compared with 3 in the existing operation. Improvements in process time and estimated cost reductions were also factors that I tend to recall from previous projects. It is impossible to remember all of the details but a number of key factors always remain" (Engineering manager 5).

Definition – personal learning is developed over time through the involvement of project experiences. Individuals remember historical events that provide key influences in future decision activities. There is also a tendency to maintain knowledge about a project even when it is finalised to further increase the knowledge of the expert.

Occurrence – personal learning is constant in the decision process. From the stages of process evaluation to decision-making and implementation, each includes a different level of learning.

Support form – the supporting form is mostly psychological and comprises written technical documents of a project. These documents are stored on the company's intranet and include additional material maintained on the personal computers of the project members.

Decision rules are developed over time for an expert from their involvement in previous decision cases. For example, a decision maker may become familiar with certain projects and a set of themes become apparent. The rules learnt may change over time as their involvement in other projects increases. Relationships and reasons for a projects success/failure may also be concluded as part of a decision maker's involvement in a project. Key characteristics such as the overall aim of an investment may form a series of rules that have defined previous projects. This type of knowledge tends to develop as further information is learnt and is dependent on the context of the project.

<u>*Sub Category 2 – Technology lessons learned*</u>

A technology is often initially evaluated and sometimes selected on premature and expected performance information of how it will perform in its intended environment. Between the phase of selection and implementation, it is likely that changes in the technology performance will occur. These changes include the technical attributes of the technology or implications that only become apparent once a technology is implemented. They are each important features of learning.

Due to the reliance on the experiences of historical decision projects, it is important that an accurate reflection of a project is maintained. Decision teams constantly review the justification process of previous projects and relying on inaccurate information can have a detrimental effect on future activities. The importance is reiterated in the following interview transcript:

"It is common that during the technology selection process a number of people reiterate their experience from previous projects to justify a new investment. Primarily this is based on the experience that is recalled by the person and includes reviewing the capital expenditure documents to gain a better understanding of the reason for success. However, on a number of instances the information was found to be out of date, inaccurate and provide little assistance" (Engineering manager 5).

It is important to perform an end-of-project performance review and collect observations/lessons learned. Understanding the differences between technologies pre-selected and one that has been implemented is imperative. A change in the data and information of the technology throughout the process does have an effect on the project. Current practices to the approach are lacking and the only apparent update mechanism is monitoring the financial spending of the project. Although this is good practice, it is merely the responsibility of the finance department to ensure the project is within budget and the information is not maintained within the original capital expenditure documentation.

Learning occurs once the project is complete and on a personal level as described in the previous section. Although technical documents, process capabilities and assembly methodologies are updated to reflect changes, any realisation of attributes or technical capabilities related to the original decision requirements and projects remain unrecorded. It is also common that different people may be involved in the implementation and subsequent use of a technology. The original decision team have a better understanding of the financial viability but an operator or manufacturing manager will understand technical issues, which may not ever be recorded. As individuals move within the company, retire or leave, information related to a project is often lost.

Decision makers also learn more from previous unsuccessful cases than successful cases because they have to closely analyse why a decision that did not lead to a successful implementation. Unsuccessful cases are naturally better remembered, as the influence on the day-to-day activities of an engineer within the business will be more apparent. More focus is spent solving and analysing an unsuccessful implementation. Although an engineer will not forget unsuccessful cases, they tend to be brushed aside within the business. Discussions among members of the workforce attempt to ignore unsuccessful past cases and the persons involved are likely to reject any discussion about the failure of the project in detail. It is natural for people to express more freely successful cases they have been involved in. Although negative cases will naturally be part of the thought process when making judgement decisions.

Definition – post implementation technology learning is the approach and steps taken to record changes of a project that are influenced by the increased knowledge of learning. Existing practices have tended to lack in this area and focus is maintained by finance and business groups to ensure a project is within budget.

Occurrence – updating information is highlighted as severely lacking and its occurrence extremely rare. Financial managers become involved during the later procurement stages to monitor project spending.

Support form – financial information is stored and managed within database systems and financial management tools ensure projects are to budget. Performance attributes of a technology are sometimes recorded on the personal computers of the engineers involved in the technology and not freely shared.

5.4 Key Observations

Key observations were apparent from conducting the study into the information and knowledge transformation practices within the manufacturing technology decision process.

The decision process is data-driven from the initial technology data collection through to selection and implementation. The process begins by first defining the project, determining its intention, and generating a series of aims and objectives. It is based entirely on the judgement of the decision team members and their understanding of the project. By conducting the process in a group meeting scenario the activity is able to benefit from a wealth of experience that should improve output. The aims and objectives will often be described in a few sentences or as bullet points.

Upon all team members being aware of the project and its overall intention, members are tasked with conducting a search for an appropriate technology. This will include an internet search, review of implemented technologies across the business, state-of-the-art survey, input from the R&D group, *etc*. The aim is to capture a series of technical information and related supporting documentation that will support the comparison. Evaluative performance data of each technology is acquired for the potential options. Historical performance data, technical datasheets, predicted performance data from the supplier or the technical judgement of an expert forms a list of technical attributes for a technology. A period of time is allocated for the relative search to take place and to ensure supporting documentation is acquired.

The subsequent technology selection process compares each of the potential technology against the defined project requirements. The comparison between the attributes and requirements are considered to fully determine the relevancy between them. The process is conducted for each considered technology. The project requirements will likely remain the same throughout. The assessment is relatively informal and based on the judgment of the experienced decision-makers within the group. Their expertise of previously completed projects, which they mentally recall determines the potential success of each technology when compared to the process requirements.

Once the decision has been made, a business case is formed for the selected technology. An overview of the project, detailed information on the problem, the selected technology, other potential alternatives, financial data and a project plan is formed. All the supporting data, information and knowledge is compiled within the business case and submitted to senior management for approval.

At this stage the project is either given a go/no-go decision. If a project is rejected, the reasons for the rejection are presented back to the decision team to review and make any amendments they feel necessary. If a project is given approval, formal arrangements are made with the technology supplier and the technology is purchased. Terms are agreed and predicted performance terms included in formal negotiations.

The closing of the project is the final definitive phase of recording information. A post-project review is held between all team members to discuss the overall project outcome. Amendments to technology performance data are conducted and a review of each activity within the project. The recording of information tends to be relatively limited with most information solely focused on the actual performance data such as manufacturing characteristics or actual costs.

The minutes of the meeting are later shared among the group. The learned knowledge tends to be personal rather than systemically recorded within a database and difficult to access at a later point.

5.5 Chapter Summary

This chapter has detailed the investigation and key observations to understand the transfer of information and knowledge at each stage in the technology selection. The key observations highlight the lack of structured inter-enterprise communication and how the informal transfer of information is not appropriately stored. There is a large amount of information transfer and mental storage by the expert; however, there is a clear lack of techniques for the acquisition of information and knowledge to reiteratively support decision-making practices.

This understanding has subsequently raised the issues of which elements needs to be included in the decision-making framework. It would suggest that experience-based events learned by an expert could be appropriately stored based on a representation of the current practices. Different types of decision variables are included in a representation of a historical case with them either specifying the objective of the problem, or the technical ability of a technology.

The subsequent chapter will therefore investigate the key decision variables for representing a historical implemented technology case and an appropriate form of characterising the variables, replicating the logic of a human expert in practice. Whilst it is now known the alternative phases that use information and knowledge to support decision-making, the following chapter will define this of actual historical information /expertise recalled by an expert to support the developed decision-making framework.

Chapter 6

Key Decision Variables for Representing Historical Manufacturing Technology Implementation Cases

6.1 Introduction

To closely relate and develop a decision methodology for the practices carried out in industry, a structured approach to acquiring experience-based information is required. The investigation carried out previously concluded the logic by which an expert would pass judgement based on their involvement in prior cases. This chapter satisfies research objective 3 to identify the key decision variables for representing historical manufacturing technology decision cases. The scope of the research is within the field of medium complexity manufacturing technologies evaluated and selected for application in advanced manufacturing organisations. The application included a broad range of industrial experts within a large aerospace manufacturer. Experts from quality, finance, engineering and design were involved.

The study was conducted through a review and expert focus group to identify and represent historical manufacturing technology implementation cases. The key parameters and form of characterising such variables is presented.

6.2 Representing a Manufacturing Technology Implementation Case

Chapter 5 discussed the approach to technology selection as being data-driven and using information acquired by an expert based on historical decision projects. It would therefore appear appropriate to use a similar logic when developing a representative technology selection support system. The configuration is determined by the type and characteristic form of the decision variables for the manufacturing domain.

Decision parameters represent a set of measures focusing on those aspects of performance most critical for the current and future success of decision-making. They are a form of decision variable that provide an appropriate measure for evaluating alternatives. Organisations rarely spend a considerable and coherent amount of time identifying and defining new parameters. They rely on the judgement of experts to determine variables to evaluative alternatives. Measures can vary and range from non-financial measures, frequency measures, numerical/linguistic or an impact measurement, *etc.* (Parmenter, 2010).

An expert recalls a previously implemented technology in three phases. First, the initial project objective and the purpose for the investment are remembered, followed by the selected technology and its technical performance. Finally, the judged level of success is remembered. This success rating can differ by individuals involved in the project. The opinion of a project success can vary based on their involvement, industrial background and general optimism.

The acquisition of historical manufacturing technology implementation cases would therefore be represented the three phases:

1. Objectives of a manufacturing technology project
2. Manufacturing technology evaluative parameters
3. Project outcome

The objectives of a manufacturing technology project are the list of defined attributes that outline the initiation/aim of the project. These factors can be qualitative or quantitative that provides support and analysis for investing in a manufacturing technology. A cost-based objective such as reducing cost would provide a measure to evaluate potential technologies to understand if they meet such performance criteria. They are factors to justify the requirement for a technology investment and define the reasons for investment. They outline the purpose of a project and an understanding of its origination is well defined. The manufacturing technology evaluative parameters are a list of technical and non-technical factors used to represent a single technology. They are a type of specification to enable an appropriate comparison between two or more technologies. The project outcome enables the conclusion of the project to be appropriately represented. It allows the level of satisfaction of a technology to be compared by how well it performed aligned to the project requirements. The process is subjective and based on the opinion of members involved in the project. For example, a manufacturing engineer may deem a project a success whilst the financial manager may believe it performed poorly. These discussions are held at the end of a technology implementation and agreed by the decision team to represent the project. During the maturity of a new technology, this may change and the learning of information is crucial for future projects.

The process of identifying decision parameters involves an understanding of the relevant literature within the area of manufacturing technology selection. Much literature incorporating attributes for technology justification cover generic manufacturing technology, FMSs and AMTs (Abdel-Kader and Dugdale, 2001, Bayazit, 2005, Hynek and Janecek, 2007, Saleh et al., 2001). Hynek and Janecek (2007) stress that it is necessary if economic justification is considered, strategic and analytical implications should also be taken into account and utilised for a better understanding of the impact of a project. This suggests that some factors can easily be quantified. In terms of manufacturing technology selection, this is likely to include cost, process time or the required type of operators. Subjective based factors may include how well a technology aligns to an internal strategy or vision.

A decision parameter is a value that can be compared against an internal target, or an external targeting 'benchmark' to give an indication of performance. The value could relate to data collected or calculated from any method or activity. The selection of a range of performance factors appropriate to a particular company/manufacturing project must be considered together with strategic intentions, which will have been formed to assist the competitive environment that the business operates and the nature of the industry (Ahmad and Dhafr, 2002). A decision variable is an industry term for a type of measure of performance (MoP). They are commonly used by organisations to evaluate the success of a particular activity and define a set of values to measure against. Decision makers can judge investment opportunities and how they are likely to perform.

6.3 Manufacturing Technology Evaluative Parameters

The process to identify a defined list of manufacturing technology evaluative parameters was first conducted through a literature review. These were subsequently evaluated in a focus group using the pair-wise comparison technique. Experts finalised a shortlist of factors to be included in the technology selection framework developed in Chapter 7.

To ensure the parameters are coherent and appropriate, a screening process was established to identify from the literature the requirements of the intended environment. The following evaluations were considered: *appropriateness to manufacturing industry, relationship to manufacturing technologies* and *creditability.* Table 6.1 presents the outcome of the study and screening process. The outcome of the literature review for the manufacturing technology evaluative parameters was 27 factors that included nine sub-parameters, each categorised as six types.

Industrial manufacturing experts from Airbus were involved in a focus group study. The purpose was to define the most appropriate list of factors from the 27 defined from the literature review.

Type	Parameter	Sub-Parameter
Commercial	Technology Supplier	Vendor Support Delivery Lead Time Technology, Technical Capability
	Company Reputation	
	Environmental Considerations	
	Historical Project Experience	
Financial	Economic Calculation	Net Present Value Internal Rate of Return Payback Period Peak Exposure
	Initial Investment Cost	
	Recurring Cost	
	Predicted Non-Recurring Cost	
Health & Safety/ Personnel	Work Environment	
	Personnel Training	
	Skill Level	
	Supply of Machinery	
	Personnel Integration	User Interaction Workload Workstation Design
Managerial/ Operations	Change Management	
	Technical & Management Support	
	Product State/ Operational Effect	
	Supply Chain Management	
Strategic	Manufacturing Objectives/ Strategy	
	Manufacturing Vision	
	Longevity	
Technical - Process	Flexibility	Machine Flexibility Process Flexibility Project Flexibility Volume Flexibility
	Productivity	Capacity Efficiency Throughput Rate Process Time Set-Up Time
	Risk	Risk of Breakdown Risk of Product Damage
	Compatibility	Hardware Systems Integration Software Systems Integration
	Physical Effect	Floor Space Mobility
	Quality	Conformation to Specification Performance Reliability
	Maintainability	

Table 6.1 Manufacturing technology evaluative parameters

Once the purpose and rational of the study had been explained, the researcher provided each participant with a full definition of all the factors detailed in Table 6.1. This assisted the participants during the pair-wise analysis process to conduct the analysis. A trial version of Expert Choice[1] was used. To reduce any potential misunderstandings and uncertainty, the group agreed on a single appropriate intensity value using the absolute scale of 1 – 9 in both directions for the compared attributes. Table 6.2 outlines the activities and duration of the focus group.

Item	Description	Duration	Responsible
1	Purpose and rational of study	20 minutes	Researcher
2	Overview of identified literature review factors	15 minutes	Researcher
3	Pair-wise comparison analysis	1 hour	All
4	Review of results and down selection	30 minutes	All
5	Confirmation of defined list	15 minutes	Researcher

Table 6.2 Focus group

The first analysis was conducted on the six evaluative types to determine the relative importance of the parameters identified from the literature. The criteria were first arranged in an N*x*N matrix. For each row, the item in the row was considered to each item in the rest of the row. Within each cell, an intensity value was discussed among the group and selected. From the first evaluation, the decision team agreed on the values shown in Table 6.3. In total, 15 judgements were required.

	Commercial	Financial	H&S/ Pers.	Man/ Op.	Strategic	Tech - Process
Commercial	1	1/3	1/3	5	1	1/3
Financial	-	1	3	3	3	3
H&S/ Pers.	-	-	1	7	3	1
Man/ Op.	-	-	-	1	1/3	1/7
Strategic	-	-	-	-	1	1/3
Tech - Process	-	-	-	-	-	1

Table 6.3 Pair-wise comparisons of evaluative parameters

A value of 1 was deemed as having an equal level of importance whilst 9 had a positive level of importance. All values in between were intermediate. For example, if we considered the value given when comparing H&S/ personnel and managerial/operations, the decision team believed that H&S/personnel were 7 times more important and seen as having a strong level of importance. If the parameter opinion was reversed, a value of 1/7 is entered.

The pair-wise algorithm was subsequently applied (see Saaty (1980) for further details on deriving the overall attribute weightings) and the ranking of priority vectors calculated as follows:

[1] Expert Choice is a software application that enables teams to prioritise objectives and evaluate alternatives and achieve alignment, buy-in, and confidence around important organisational decisions (www.expertchoice.com).

Financial = 35.1%, H&S/Personnel = 21.1%, Technical – Process = 21.1%, Commercial = 9.9%, Strategic = 8.7% and Manager/Operations = 4.1%.

This in turn led to a discussion among the group of the results from the pair-wise comparison. It was clear that financial, H&S/personnel and technical – process was of high importance to the evaluation of manufacturing technologies and would be included in the framework. The group then discussed the remaining three factors. The importance of the commercial factor was highly reiterated as an influence in technology evaluation due to the supplier liability as a potential consequence on manufacturing. In addition, strategic factors ranked 5th were found to be a supporting factor when convincing senior management to invest in a new technology. The longevity and alignment to manufacturing objectives were highly regarded among the group. Managerial/operations were ranked last in the pair-wise comparison and this was supported by further discussions.

Change management is an important issue in new technology integration. However, it was not deemed as a key influential factor in the decision-making process. It is anticipated that transitioning for organisations, teams and individuals would be appropriately managed. In addition, issues regarding supply chain were expected to be controllable depending upon the severity of any potential issues. As the technology will likely be a one off purchase, supply chain concerns are low and may include maintenance and unpredictable breakdowns. Considering these factors, the group of experts decided that the managerial/operations KPI was not a key factor in the selection process and it was subsequently removed from the list. It was not deemed as key in the evaluation of a manufacturing technology. This led to a review of the remaining five evaluative parameters and 22 decision parameters. A number of comments were made that the list was far-reaching and included some factors that were likely to not be needed. Therefore, similar to the previous analysis, the pair-wise comparison technique was applied to each of the remaining five evaluative parameters to determine which parameters were appropriate.

Firstly, the commercial parameter that had four dependant parameters was reviewed. Although ‘technology supplier’ had four sub-dependant variables, it was deemed as a single variable in the matrix as the three sub-variables could appropriately be represented as a single measure. The results from the pair-wise comparison are shown in Table 6.4.

	Technology Supplier	Company Reputation	Environmental Considerations	Historical Project Experience
Technology Supplier	1	1/5	1/3	1/3
Company Reputation	-	1	3	3
Environmental Considerations	-	-	1	1/3
Historical Project Experience	-	-	-	1

Table 6.4 Pair-wise comparisons of commercial parameter

The pair-wise algorithm was subsequently applied and the ranking of priority vectors calculated as follows:

Company reputation = 50.8%, historical project experience = 26.5&, environmental considerations = 15.1% and technology supplier = 7.5%.

Company reputation was deemed as an important indicator prior to the investment of a new technology. A positive reputation indicates that the company is highly esteemed and worthy to collaborate. In addition, previous dealings with the company of historical experience were noted to provide a good indication of future work. The group of experts agreed that the remaining two factors did not hold a similar level of importance and could be disregarded in the selection model. Focus subsequently led to the financial parameter. Again, after reviewing a full definition of each decision and sub-decision parameter, the pair-wise comparison analysis was conducted. The experts agreed on an appropriate factor for each and the results are shown in Table 6.5.

	Economic Calculation	Initial Investment Cost	Recurring Cost	Predicted NRC
Economic Calculation	1	3	3	3
Initial Investment Cost	-	1	5	5
Recurring Cost	-	-	1	1
Predicted NRC	-	-	-	1

Table 6.5 Pair-wise comparisons of financial parameter

The pair-wise algorithm was subsequently applied and the ranking of priority vectors calculated:

Economic = 47.4%, initial investment cost = 33.5%, recurring cost = 9.6% and predicted NRC = 9.6%.

It was apparent that economic calculation and initial investment cost were key factors within the financial parameter. Discussions then led to the sub-variables within the economic calculation. NPV, internal ROR, PP and peak exposure (PE) were identified from the literature as the most important economic methods of justifying the economic investment of a manufacturing technology. However, the discussions were directed to PP being the most influential factor and a prerequisite for new investment projects. Participants noted that senior management would not approve a technology investment project without an appropriate PP, as it was a typical financial measure used within the industry. PP is the first factor a financial manager would check in a business case. PP alone would therefore be sufficient to replace economic calculation in a modular set of parameters. In this instance, the participants deemed PP and initial investment cost appropriate to evaluate a manufacturing technology.

The study then focused on the five decision parameters within the H&S/personnel category. The parameters related to the safety, health, welfare and requirements of an operator. It was concerned with the procedures that protect employees and the type of operator required for a process. After reviewing a full definition of each parameter and sub-parameter, the pair-wise comparison analysis was conducted. The experts agreed on an appropriate factor for each and the results are shown in Table 6.6.

	Work Environment	**Personnel Training**	**Skill Level**	**Supply of Machinery**	**Personnel Integration**
Work Environment	1	3	1/5	1	1
Personnel Training	-	1	1/5	5	1
Skill Level	-	-	1	5	1
Supply of Machinery	-	-	-	1	1/3
Personnel Integration	-	-	-	-	1

Table 6.6 Pair-wise comparisons of H&S/personnel parameter

The pair-wise algorithm was subsequently applied and the ranking of priority vectors calculated:

Skill level = 48.8%, work environment = 15.7%, personnel integration = 14.4%, personnel training = 14.0% and supply of machinery = 7.1%.

The results from the comparison demonstrate the importance of skill level in the selection of a new technology. Skill level concerns the measure of required labour ability for an operator to carry out a task. The differing level of complexity of the operation and technology would require alternative levels of operator skill/training. Skill level provides a good indication of anticipated labour cost and is aligned to the number of skilled operators within the business. Skill level was subsequently agreed as a key factor in the decision process.

Focus then began on the strategic parameter. It is the consideration of a plan of action designed to achieve a vision of gaining a position of advantage by exploiting emerging possibilities. It is a form of measure to determine how well aligned a potential investment technology is to the vision and objectives of the company. Each factor was subsequently considered and the results shown in the pair-wise comparison in Table 6.7.

	Manufacturing Objectives/ Strategy	Manufacturing Vision	Longevity
Manufacturing Objectives/ Strategy	1	3	1
Manufacturing Vision	-	1	1/5
Longevity	-	-	1

Table 6.7 Pair-wise comparisons of strategic parameter

The pair-wise algorithm was subsequently applied and the ranking of priority vectors calculated as follows:

Longevity = 48.1%, manufacturing objectives/strategy = 40.5% and manufacturing vision = 11.5%.

Longevity, which is the anticipated life span of a technology, was ranked as the most important strategic parameter. It concerns the expected use of the technology in the future and measured over the intended period of use. Due to high capital costs of investing in new technologies, the experts deemed it as one of the most important factors when investing in new equipment. For most manufacturing industries, this would also be considered a high priority factor. The ranking was subsequently followed by manufacturing objectives/strategy, which is the planned positioning or termination of investments in a response to market and environmental forces. Upon further discussions, manufacturing vision was ranked least important of the three parameters. The view of the participants was that as the manufacturing vision was a bridge between the mission, goal and strategy, it was difficult to define and contain a lengthy set of elements. Therefore, evaluating a technology against a set of diverse manufacturing vision elements would be difficult. Longevity and manufacturing objectives/strategy were subsequently chosen as key elements for evaluating the technical performance of a manufacturing technology.

The final part of the study focused on the technical – process parameter. In total, seven sub-parameters were evaluated using the pair-wise comparison technique. This was the most difficult comparison to conduct due to the number of elements involved. The participants mentioned that the sub-decision variables were too specific for an evaluation and that an appropriate number of parameters would be investigated. Similar to the previous study, the group decided on the most appropriate values when comparing two elements at a time. The pair-wise comparison is shown in Table 6.8.

	Flexibility	Productivity	Risk	Compatibility	Physical Effect	Quality	Maintainability
Flexibility	1	1/5	1/5	1	1	1/5	1
Productivity	-	1	1	5	3	1	3
Risk	-	-	1	5	3	1/3	1
Compatibility	-	-	-	1	1/3	1/3	3
Physical Effect	-	-	-	-	1	1/3	3
Quality	-	-	-	-	-	1	5
Maintainability	-	-	-	-	-	-	1

Table 6.8 Pair-wise comparisons of technical - process parameter

The pair-wise algorithm was subsequently applied and the ranking of priority vectors calculated:

Quality = 28.3%, productivity = 23.4%, risk = 19.3%, physical effect = 10.2%, compatibility = 6.8%, maintainability = 6.5% and flexibility = 5.5%.

Upon reviewing the resultant priority vectors, it was apparent that productivity, risk and quality were the most important factors among the seven identified from the literature. Quality was ranked the most important factor. It is a measure of excellence or the state of the output product that is free from defects and significant differences. Quality is deemed as playing a key role in manufacturing strategy and forms a company's reputation. Risk received 19.3% as the 3rd most important factor. It concerns the possible threats from purchasing a new manufacturing technology that could affect the organisation. It is considered at the earliest stages of evaluation and is conducted throughout the implementation process.

Productivity is the performance measure of a manufacturing technology and ranked 4th most important driver for automation during the industrial survey carried out in Chapter 4. Although there are alternative measurement types, the most common within the literature are capacity, efficiency, throughput rate, process time and set-up time. The participants agreed that each sub-decision variable held a similar level of performance and that the appropriate values for each would best be represented as a single value for productivity.

The participants subsequently reviewed each of the factors and concluded the following as the most important for representing the technical performance of a manufacturing technology:

Company reputation, historical project experience, payback period, initial investment cost, skill level, manufacturing objectives/strategy, longevity, productivity, risk and quality.

The identified parameters are applicable to a wide range of manufacturing technologies with differing process configurations. The findings can be used systematically in the decision process by incorporating both tangible and intangible attributes. Managers can subsequently use this consolidation to support the evaluation of a manufacturing technology.

Identifying the parameters is the first stage to determining an appropriate method of evaluating a manufacturing technology. Characterising each numerically or as alternative terms is required. Section 6.5 discusses the characterisation approach of each of the defined variables.

6.4 Objectives of a Manufacturing Technology Project

The outcome of the study conducted in the previous chapter was that a set of objectives is determined at the start of a new manufacturing technology implementation project. These attributes define the reason a project is initiated and relate to the envisaged capability of a new technology. The process to identify a set of defined objectives as part of this study was the review of internal documentation within Airbus. The documentation included a series of capital expenditure (CapEx) documents and project plan reports conducted as part of lifecycle development of new technology and improvement projects. The reporting formats were subsequently reviewed.

CapEx documents are financial-based reports that detail the anticipated spends and future benefits of investing in a new manufacturing technology. They are created once a technology has been chosen. These reports are generated to provide an overview of an investment with the purpose of securing financial backing from senior management.

A detailed overview of the project is included in a CapEx. This outlines a description of the project that includes background information of the investment opportunity. An overview of the problem and anticipated outcome defined. In order to categorise an investment project, the purpose is usually noted at the start of the project. A drop-down list of potential options including productivity, capacity, *etc* is provided. This enables the project manager to clearly define the main purpose of requesting investment funds.

In addition, the CapEx document is formulated in such a manner that the project manager can define the justification/benefits in a short format. Summarising the project in such a way is highly recommend during the early stages of the reporting process to provide an overview of the expected investment benefits. Financial data of the initial investment cost and PP (usually defined in years) is provided together with a breakdown of the overall costs. It is often to interpret if the overall objective is to reduce cost by reviewing the financial data and project aim.

For business improvement projects and new product introductions, a lifecycle methodology is provided to manage key milestones. Different phases and deliverables are well defined to support the selection process. Each phase defines the deliverables and the minimum criteria required to progress through each stage. The overall lifecycle is defined in four phases: generation phase, analysis and design phase, development and implementation phase, and materialisation phase. Each phase consists of a number of 'G document gates' reports that are the evaluation stages in the process from G1 to G10.

After reviewing the G reports, a standard set of required information became apparent. Similar to CapEx documents, the project objective and scope are defined. The report focuses heavily on defining the current state of a process/ product, and the intended future state (after improvement). Examples of defined future states are 'reducing cost' or 'improving productivity'. Further details and a more accurate account are defined as it progresses from G2 to G10. The expected savings for the set assumptions are recorded and potential risks noted. The risks noted within the earlier G documents are in a bullet point format, but as the project progresses, FMEAs are conducted and detailed. Specific technical performance information (as noted in Section 6.3) was often not included.

A CapEx document is created at the G5 stage in the product lifecycle. During the earlier G documents, a draft business case is created to estimate financial outlay and predicted savings from the investment project. The project scope lists the benefits, and any potential re-occurring and non re-occurring costs. A detailed description of the current process is provided to give the reader a better insight into the problem. Focus on the apparent shortcomings or problems are highlighted to support the reason a project was initiated. As a project progresses through the G stages (e.g. from G0 to G2), changes to the estimated benefits are recorded and an understanding of the development work can be understood. The project plan and required stakeholders are defined to fully realise the project.

Upon reviewing both internal documents, it was apparent that five alternative types of variables typically define a manufacturing technology project objective. They are generic definitions of which projects will typically satisfy more than one variable defining the purpose of a project. They are an important set of attributes that have a defining point in the decision process. The relationship of the technical attributes of a technology and the objectives of a project were well reported in the study conducted in Chapter 5.

The defined key project objectives concluded from the study were:

- Time objective – is the aim of the project to reduce time?

- Cost objective – is the aim of the project to reduce cost?
- Quality objective – is the improvement of quality a key parameter in the project?
- Purpose – what is the defining purpose of the project? e.g. productivity, *etc.*
- Regulation requirement – was the project initiated because of a regulation / H&S necessity?

Discussions were subsequently held with the participants of the focus group to confirm that the defined list represented a generic set of objectives for a new manufacturing technology selection. The participants agreed that the five variables represent typical reasons for investing in a new manufacturing technology. Upon analysing the internal documentation, it was apparent these factors were appropriate for a new technology investment project. Several participants noted that the reduction of cost was often the principle investment factor. Comments for options as part of the purpose attribute were added and discussed in Section 6.5.

6.5 Characterising Decision Variables

To reduce the vagueness in decision problems, the variables must be appropriately characterised and quantified i.e. adequately represented through a formal model. The interpretation may vary considerably depending on the area of interest. When modelling specific decision situations and variables, the decision maker feels overstrained when asked to provide precise numerical quotations concerning the objectives or constraints, whereas qualitative statements are easily given (Zimmermann and Zysno, 1985). This section focuses on an empirical study of modelling the decision variables identified in Section 6.4. It includes the determination of quantitative and qualitative representations of the defined parameters. A logical and objective approach to determining fuzzy membership sets for the appropriate variables is demonstrated.

To define the representative form of the decision variables, the focus group continued and through an open, unstructured discussion of each factor, a characterisation of each was formed. The first stage in the process was to identify which parameters would be best represented in nominal terms, e.g. as qualitative statements and which are best to be represented quantitatively (as a number which is later fuzzified). The review of literature in Chapter 2 concluded that using qualitative based factors would facilitate increased uncertainty and the concept of fuzzy reasoning was well justified. Therefore, the identified factors were first grouped into either nominal or fuzzy variables. Discussions were led among the group by the researcher and were appropriately agreed. An overview of fuzzy logic was provided to the participants. The characterisation of each variable is presented in Section 6.5.1 and 6.5.2. Each is shown in an appropriate category in Table 6.9.

Nominal Variables (e.g. tangible)	
Project Objective	**Technical Technology Parameter**
Time	Historical project experience
Cost	Skill level
Quality	Manufacturing objectives/ strategy
Purpose	
Regulation requirement	

Fuzzy Variables (e.g. intangible)	
Project Objective	**Technical Technology Parameter**
-	Company reputation
	Payback period
	Initial investment cost
	Longevity
	Productivity
	Risk
	Quality

Table 6.9 Attribute categorisation (nominal/fuzzy)

When determining the characterisation of each decision variable, the participants were advised to determine the appropriate values based on their opinion of historical manufacturing decision projects. After an initial review of the two types of variables (nominal and fuzzy), it was apparent that the nominal factors would be represented based on generic terms. However, fuzzy representations were best determined based on actual historical projects.

Membership functions characterise the fuzziness in a fuzzy set – whether the elements in the set are discrete or continuous, in a graphical form for eventual use in the mathematical formalisms of fuzzy set theory. Just as there are an infinite number of ways to characterise fuzziness, there are an infinite number of ways to graphically depict the membership functions that describe this fuzziness (Ross, 2004). A demonstration of the selected approach is shown in Section 6.5.2. The nominal variables are discussed in Section 6.5.1.

6.5.1 Nominal Variables

From the identified list, eight factors were deemed best represented in a nominal manner. These are values assigned to each variable and selected to represent the factor in the overall historical decision case. An overview of the discussions from each is as follows:

<u>Historical project experience</u> enables an indication of any previous work undertaken with the company and to what level of success any involvement was. It is a measure of technology performance. A relative performance measure is selectively agreed by multiple persons assisted by a definition of performance evaluation. Three nominal values were defined: {good prior involvement, no previous dealings, disappointing prior experience}.

Skill level is the typical level of skill required for a process to use the technology. It provides an indication of necessary operators that can be compared with any financial/labour constraints within the business. It is a measure of technology performance. Three nominal values were defined: {unskilled, semi-skilled, skilled}.

Manufacturing objectives/strategy is a measure of how well a technology is in line with the defined objectives and strategy set by the company. It is a measure of technology performance. Three nominal values were selected: {non-related, partial, in-line with objective}.

Time is a project objective measure used to define if time reduction is an aim for the initiation of an investment project. Two nominal values were selected: {reduce time, non-applicable}.

Cost is a project objective measure to define if cost reduction is an aim for the initiation of a manufacturing improvement project. Two nominal values were selected: {reduce cost, non-applicable}.

Quality is a project objective measure to define if quality improvement is an aim for the initiation of a manufacturing improvement project. Two nominal values were selected: {improve quality, non-applicable}.

Purpose is an attribute to define the main driver of a project. A variety of motives may be representative of a project purpose. As part of this study, the focus group defined 5 related manufacturing attributes in an investment justification case. A single purpose is selected to define the reasoning for an investment project: {productivity, capacity, replacement, modification, new product}.

Regulation requirement is a classification if a project was initiated due to requirements as part of a set of regulations. This may include regulations set by the civil aircraft authority (CAA), internal H&S desires or guidelines set by the health and safety executive (HSE). Two nominal values were selected: {yes, no}.

This concluded the characterisation of the nominal factors for representing a historical manufacturing technology decision case. Representing the information as a nominal factor is relatively easy as the values are crisp. A single value can be selected for each variable.

6.5.2 Fuzzy Variables

For attributes where the reasoning is approximate rather than fixed or exact, and where they require representing in a valued logic, fuzzy logic is employed. To make the values comparable across a wide range of different value scales, they need to be normalised. From the identified list, seven factors were deemed best represented in a fuzzy manner. Fuzzification is a form of normalisation without crisp boundaries between values to indicate some un-sharpness of the normalisation.

Fuzzy logic is most appropriate for representing intangible variables of a manufacturing technology as the measure of such terms is approximate rather than fixed and exact. For example, measure of risk would include the likelihood of breakdown of a machine or damage to a product. Whilst this can be evaluated on a relative range, the terms by which a measure can be conducted (i.e. high, medium, low) would vary between experts. Similarly for an evaluation of a 0 – 10 scale. Whilst one expert may believe a score of 7 / 10 to be high, another may believe the same score to be medium. Fuzzy logic is able to deal with this discrepancy and uncertainty between relative performance measures.

Fuzzy logic is able to evaluate the undefined boundary of each measure and logically represent them as a fuzzy membership function. The approach is dynamic and able to deal with changes in performance measure overtime. It is most suited to the problem of manufacturing technology evaluation as the measures such as cost may change overtime. For example, a technology advances and production costs are reduced, the purchase of a technology today may be defined as 'low' but in two years as 'high'. Fuzzy logic is able to appropriately adjust according to these changes.

For variables that are best represented in a quantitative form and subsequently fuzzified, the appropriate membership values or functions to fuzzy variables are required. Since the membership function essentially embodies all fuzziness for a particular fuzzy set, its description is the essence of a fuzzy property or operation. Because of the importance of the 'shape' of the membership function, a great deal of attention has been focused on the development of these functions. Ross (2004) describes six popular procedures that have been used to build membership functions: *intuition, inference, rank ordering, neural network, generic algorithms* and *inductive reasoning.*

There are possibly more ways to assign membership values or functions to fuzzy variables than there are to assign probability density functions to rank variables (DuBois and Prade, 1980). This assignment process can be intuitive or based on some algorithmic or logical operation. The list defined by Ross (2004) are straightforward methods described in the literature to assign membership values or functions to fuzzy variables. Intuition, inference, rank ordering, NN, genetic algorithm (GA) and inductive reasoning were each reviewed for their relevancy to the problem and context.

Upon reviewing the advantages and disadvantages of each approach, and the suitability of representing manufacturing technology selection factors, it was apparent that inductive reasoning is most appropriate for the decision problem. Inductive reasoning is the automatic generation of membership functions derived from a general consensus of a particular situation. It is based on the idea that a number of experts will input knowledge of a subject in the database with objective validity and universal application. The approach is easy to understand and implement, and the objective nature of the approach is appealing.

The aim of this research is to develop an experience-based decision methodology that reduces the uncertainty of subjective judgement. Inductive reasoning is based on the opinion of many experienced personnel and the view of experts will reduce the potential for inaccurate judgement and uncertainty representing variables. Multiple experts are involved in decision projects and available within the business; combining multiple judgements will ensure each variable is coherently representative of many judgements.

Fuzzy membership functions are developed specifically for the domain in which they are applied. To develop such fuzzy membership functions based on numerical values, they are required to be domain specific. For example, generating a fuzzy function for the cost of a robot may differ to a drilling machine. Although the shape and position of the membership functions may be similar, the range of the *x*-axis may be diverse. For example, the technology shown in Table 6.15, the longevity of the technology considered is expected to not last longer than 25 years. In addition, the PP of the investment will always be less than 5 years. Therefore, the values along the *x*-axis will be different for attributes and the technology being considered. The advantage of fuzzy logic is that alternative attributes with differing values can be normalised for representation.

To generate the membership functions, this research was conducted alongside the case study in Chapter 8. The values were considered for investing in a new metrology system for a typical aircraft assembly improvement project. The values were determined for an improvement project of replacing a metrology technology for the measurement of aircraft wing jigs. The ranges of values were obtained from a number of experts within Airbus and are representative of the values expected for the type of technology.

The development of membership functions were conducted for each of the seven identified fuzzy variables. As an example, the following describes how the initial investment cost of a metrology technology was captured and developed as a fuzzy function.

To conduct an inductive reasoning approach, the entropy of each value of x in the region x_1 and x_2 expressed by Christensen (1980) is used. The entropy measure calculates the information gain to reflect the quality of an attribute as the boundary attribute. The smaller entropy value the greater the purity of the subset partition.

$$S(x) = p(x)S_p(x) + q(x)S_q(x), \quad \text{Eqn(6.1)}$$

where

$$S_p(x) = -[p1(x)\ln p_1(x) + p_2(x)\ln p_2(x)], \quad \text{Eqn(6.2)}$$

$$S_q(x) = -[q1(x)\ln q_1(x) + q_2(x)\ln q_2(x)], \quad \text{Eqn(6.3)}$$

where

$pk(x)$ and $qk(x)$ = conditional probabilities that the class k sample is in the region $[x_1, x_1 + x]$ and $[x_1 + x, x_2]$

$p(x)$ and $q(x)$ = probabilities that all samples are in the region $[x_1, x_1 + x]$ and $[x_1 + x, x_2]$, respectively

$p(x)$ and $q(x) = 1$

A value of x that gives the minimum entropy is the optimum threshold value. Entropy estimates of *pk(x), pq(x), p(x),* and *q(x),* as follows (Christensen, 1980):

$$p_k(x) = \frac{n_k(x)+1}{n(x)+1}, \quad \text{Eqn(6.4)}$$

$$q_k(x) = \frac{N_k(x)+1}{N(x)+1}, \quad \text{Eqn(6.5)}$$

$$p(x) = \frac{n(x)}{n}, \quad \text{Eqn(6.6)}$$

$$q(x) = 1 - p(x), \quad \text{Eqn(6.7)}$$

where

nk(x) = number of class *k* samples located in [*x1, x1 + x]*

n(x) = the total number of samples located in [*x1, x1 + x]*

Nk(x) = number of class *k* samples located in [*x1 + x, x2]*

N(x) = the total number of samples located in [*x1 + x, x2]*

n = total number of samples in [*x1, x2*]

l = a general length along the interval [*x1, x2*]

The induction is performed by the entropy minimisation principle, which clusters most optimally the parameters corresponding to the output classes (De Luca and Termini, 1972). After initial discussions with experts, metrology investment costs for a typical aerospace assembly application were deemed up to £250,000. Therefore, a range of £0 - £250,000 was defined on the *x*-axis of the membership set.

To develop the membership function for the initial investment cost attribute, five experts were required to give their opinion of a random set of cost values between the defined ranges. Overall, three fuzzy regions were first chosen as 'low cost', 'medium cost' and 'high cost'. To develop these functions, each expert were asked to indicate if a random cost of a technology would be represented in the 'low cost' or 'high cost' category. Each expert was asked independently and the values were random. The results are shown in Tables 6.10 (a-e).

Calculations for the selection of the partition point, the primary threshold (PRI) value are calculated using equations 6.1 – 6.7. Random PRI values are selected and partition points with the lowest entropy is chosen. From Table 6.11 (see checkmark at S = 0.4209), we see that the first partition point is selected at £95,000, and its location for determining membership function selection is shown in Figure 6.1. In this example, the most common triangular and trapezoidal shape approach was selected as utilised forms of depicting a fuzzy set due to their convenience of designating linear functions.

Expert 1	
Value	**Category**
£25,000	Low
£125,000	Low
£150,000	Low
£175,000	High
£225,000	High
£250,000	High

Expert 2	
Value	**Category**
£50,000	Low
£75,000	Low
£100,000	High
£200,000	High
£225,000	High
£250,000	High

Expert 3	
Value	**Category**
£0	Low
£25,000	Low
£50,000	Low
£75,000	Low
£150,000	Low
£225,000	High

Expert 4	
Value	**Category**
£50,000	Low
£75,000	Low
£100,000	High
£125,000	High
£175,000	High
£225,000	High

Expert 5	
Value	**Category**
£25,000	Low
£50,000	Low
£75,000	High
£100,000	High
£225,000	High
£250,000	High

Table 6.10 a/b/c/d/e Expert opinion input for investment cost

x	£70,000			£95,000			£115,000			£135,000		
p1	$\frac{8+1}{8+1}$	=	1	$\frac{11+1}{12+1}$	=	$\frac{12}{13}$	$\frac{11+1}{15+1}$	=	$\frac{3}{4}$	$\frac{12+1}{17+1}$	=	$\frac{13}{18}$
p2	$\frac{0+1}{8+1}$	=	$\frac{1}{9}$	$\frac{1+1}{12+1}$	=	$\frac{2}{13}$	$\frac{4+1}{15+1}$	=	$\frac{5}{16}$	$\frac{5+1}{17+1}$	=	$\frac{1}{3}$
q1	$\frac{6+1}{22+1}$	=	$\frac{7}{23}$	$\frac{3+1}{18+1}$	=	$\frac{4}{19}$	$\frac{3+1}{15+1}$	=	$\frac{1}{4}$	$\frac{2+1}{13+1}$	=	$\frac{3}{14}$
q2	$\frac{16+1}{22+1}$	=	$\frac{17}{23}$	$\frac{15+1}{18+1}$	=	$\frac{16}{19}$	$\frac{12+1}{15+1}$	=	$\frac{13}{16}$	$\frac{11+1}{13+1}$	=	$\frac{6}{7}$
p(x)	$\frac{8}{30}$			$\frac{14}{30}$			$\frac{15}{30}$			$\frac{17}{30}$		
q(x)	$\frac{22}{30}$			$\frac{16}{30}$			$\frac{15}{30}$			$\frac{13}{30}$		
Sp(x)	0.244			0.362			0.579			0.601		
Sq(x)	0.585			0.473			0.515			0.462		
S	0.4944			0.4209		***x***	0.5472			0.5409		

Table 6.11 Calculations for selection of partition point PRI

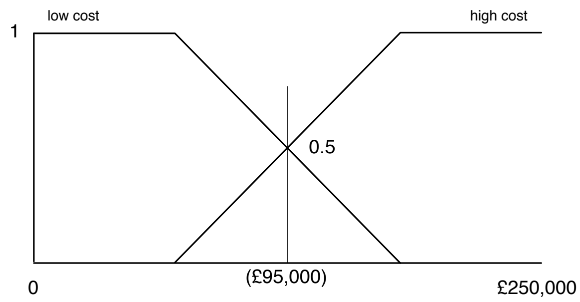

Figure 6.1 Partitioning of the variable $x = a/b$ into low cost and high cost partitions

The same process is repeated for the low and high cost partitions for different values of x. In determining the threshold value to partition the low cost side of Figure 6.1, Table 6.12 displays the appropriate calculations.

Table 6.13 illustrates the calculations to determine the threshold value to partition the high cost side of Figure 6.1. The partitions are selected based on the minimum entropy principle. The result fuzzy partitions are shown in Figure 6.2.

x	£20,000		£40,000	£60,000
$p1$	$\frac{1+1}{12+1} = \frac{2}{13}$		$\frac{4+1}{4+1} = 1$	$\frac{8+1}{8+1} = 1$
$p2$	$\frac{0+1}{12+1} = \frac{1}{13}$		$\frac{0+1}{4+1} = \frac{1}{5}$	$\frac{0+1}{8+1} = \frac{1}{9}$
$q1$	$\frac{11+1}{12+1} = \frac{12}{13}$		$\frac{7+1}{8+1} = \frac{8}{9}$	$\frac{3+1}{4+1} = \frac{4}{5}$
$q2$	$\frac{0+1}{12+1} = \frac{1}{13}$		$\frac{1+1}{8+1} = \frac{2}{9}$	$\frac{1+1}{4+1} = \frac{2}{5}$
$p(x)$	$\frac{1}{12}$		$\frac{4}{12}$	$\frac{8}{12}$
$q(x)$	$\frac{11}{12}$		$\frac{8}{12}$	$\frac{4}{12}$
$Sp(x)$	0.485		0.322	0.244
$Sq(x)$	0.271		0.439	0.545
S	0.289	**x**	0.399	0.344

Table 6.12 Calculations for selection of partition point low cost

Using the input values in increments of £5,000 along the *x*-axis, the fuzzy membership values for the each of the three partitions can be calculated. A fuzzy index table has been provided and shown in Table 6.14.

x	£135,000	£155,000	£180,000		£215,000
$p1$	$\frac{1+1}{5+1} = \frac{1}{3}$	$\frac{3+1}{7+1} = \frac{1}{2}$	$\frac{3+1}{9+1} = \frac{4}{10}$		$\frac{3+1}{11+1} = \frac{1}{3}$
$p2$	$\frac{4+1}{5+1} = \frac{5}{6}$	$\frac{4+1}{7+1} = \frac{5}{8}$	$\frac{6+1}{9+1} = \frac{7}{10}$		$\frac{7+1}{11+1} = \frac{2}{3}$
$q1$	$\frac{2+1}{13+1} = \frac{3}{14}$	$\frac{0+1}{11+1} = \frac{1}{12}$	$\frac{0+1}{9+1} = \frac{1}{10}$		$\frac{0+1}{7+1} = \frac{1}{8}$
$q2$	$\frac{11+1}{13+1} = \frac{12}{14}$	$\frac{10+1}{11+1} = \frac{11}{12}$	$\frac{9+1}{9+1} = 10$		$\frac{7+1}{7+1} = 1$
$p(x)$	$\frac{5}{18}$	$\frac{7}{18}$	$\frac{9}{18}$		$\frac{11}{18}$
$q(x)$	$\frac{12}{18}$	$\frac{11}{18}$	$\frac{9}{18}$		$\frac{7}{18}$
$Sp(x)$	0.518	0.64	0.616		0.637
$Sq(x)$	0.462	0.287	0.23		0.26
S	0.452	0.424	0.423	**x**	0.490

Table 6.13 Calculations for selection of partition point high cost

Value	Fuzzy Membership Score			Value	Fuzzy Membership Score		
(*x*-axis)	Low Cost	Medium Cost	High Cost	(*x*-axis)	Low Cost	Medium Cost	High Cost
£0	1.00	0.00	0.00	£130,000	0.00	0.59	0.41
£5,000	1.00	0.00	0.00	£135,000	0.00	0.53	0.47
£10,000	1.00	0.00	0.00	£140,000	0.00	0.47	0.53
£15,000	1.00	0.00	0.00	£145,000	0.00	0.41	0.59
£20,000	1.00	0.00	0.00	£150,000	0.00	0.35	0.65
£25,000	0.93	0.07	0.00	£155,000	0.00	0.29	0.71
£30,000	0.87	0.13	0.00	£160,000	0.00	0.24	0.76
£35,000	0.80	0.20	0.00	£165,000	0.00	0.18	0.82
£40,000	0.73	0.27	0.00	£170,000	0.00	0.12	0.88
£45,000	0.67	0.33	0.00	£175,000	0.00	0.06	0.94
£50,000	0.60	0.40	0.00	£180,000	0.00	0.00	1.00
£55,000	0.53	0.47	0.00	£185,000	0.00	0.00	1.00
£60,000	0.47	0.53	0.00	£190,000	0.00	0.00	1.00
£65,000	0.40	0.60	0.00	£195,000	0.00	0.00	1.00
£70,000	0.33	0.67	0.00	£200,000	0.00	0.00	1.00
£75,000	0.27	0.73	0.00	£205,000	0.00	0.00	1.00
£80,000	0.20	0.80	0.00	£210,000	0.00	0.00	1.00
£85,000	0.13	0.87	0.00	£215,000	0.00	0.00	1.00
£90,000	0.07	0.93	0.00	£220,000	0.00	0.00	1.00
£95,000	0.00	1.00	0.00	£225,000	0.00	0.00	1.00
£100,000	0.00	0.94	0.06	£230,000	0.00	0.00	1.00
£105,000	0.00	0.88	0.12	£235,000	0.00	0.00	1.00
£110,000	0.00	0.82	0.18	£240,000	0.00	0.00	1.00
£115,000	0.00	0.76	0.24	£245,000	0.00	0.00	1.00
£120,000	0.00	0.71	0.29	£250,000	0.00	0.00	1.00

Table 6.14 Fuzzy membership scores for three partitions of investment cost

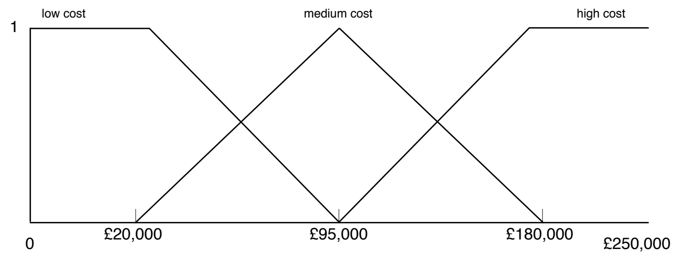

Figure 6.2 Investment cost fuzzy membership function

The method was subsequently applied to the remaining six fuzzy attributes for the metrology domain required for the case study (Chapter 8) and provided within Appendix A3.

6.6 Chapter Summary

This chapter has presented the results of a study to define the key decision variables pertaining to the selection of a manufacturing technology. The research focused on the technical performance attributes of a technology and the objective nature of justifying such investments. The defined decision parameters provide an insight into the importance of various criteria through a shortlisting approach. The study benefited from industrial experts in the evaluation of 27 decision variables identified from a literature review. The conclusion was 10 independent variables that are modular and applicable to a wide range of manufacturing technologies with differing process configurations. Through a document analysis the study also identified key project objective parameters for defining the typical reasoning for initiating an investment project.

Table 6.15 shows how the structure of a historical technology implementation case that is representative of the information recalled by an expert is defined. The overall project objective is defined in the following chapter as part of the proposed methodology.

The findings from this study can be used to systematically and quantitatively incorporate both the tangible and intangibles attributes in the decision process. Section 6.5 described the use of inductive reasoning to generate fuzzy membership functions for quantifying variables on a suggested scale. The approach is easy to conduct and reduces uncertainty and subjective judgement when creating the functions.

Case ID	12345	
Technology Name:	Technology ABC	
Technology Type:	Metrology	
Production Stage:	Final assembly	
Objectives		
Time	{Reduce time, non-applicable}	
Cost	{Reduce cost non-applicable}	
Quality	{Improve quality, non-applicable}	
Purpose	{Productivity, capacity, replacement, modification, new product}	
Regulation requirement	{Yes, No}	
Technical Performance		
Historical project experience	{Good prior involvement, no previous dealings, disappointing prior experience}	
Skill level	{Unskilled, semi-skilled, skilled}	
Manufacturing objectives/ strategy	{Non-related, partial, in-line with objective}	
Company reputation	{0 - 10}	{Poorly regarded, good, well regarded}
Payback period	{0 - 5 years}	{Low, medium, high}
Initial investment cost	{£0 - £250,000}	{Low, medium, high}
Longevity	{0 - 25 years}	{Short, average, long}
Productivity	{0 - 10}	{Low, medium, high}
Risk	{0 - 10}	{Low, medium, high}
Quality	{0 - 10}	{Low, medium, high}
Overall project performance	{Defined project success}	

Table 6.15 Example structured of defined experience case

Chapter 7

Experience-based Manufacturing Technology Selection Framework using Fuzzy-Decision-Trees

7.1 Introduction

This chapter presents an approach to manufacturing technology selection through information-based historical decision cases. The empirical studies carried out in previous chapters have guided the research towards an experience-based approach to technology selection. It acquires previous decision case information in a similar form how an expert would develop expertise. The relationship between different information items stored in a case base of historical technology decisions provides a new level of rational for optimal technology classification. Exploring the correlation of historical decisions enables the optimal manufacturing technology for a project to be selected based on previously implemented solutions.

7.2 Purpose and Problem Definition

The aim of manufacturing technology selection is to select an alternative technology that is most well aligned to project objectives. The technology must be technically capable of carrying out the process whilst aligned to business requirements. Each technology project is evaluated against two sets of attributes (as discussed in Chapter 5 and 6). The purpose of this research is to develop an improved methodology compared with industrial practices (defined in Chapter 4) and the reported literature (discussed in Chapter 2). Conclusions drawn from these studies suggest that decision information, as a form of experience, would be most suited to the problem and has not yet been explored.

Chapter 5 concluded that the technology selection problem is a challenging and information-driven decision activity. It relies upon by the experience of experts to form an appropriate judgement. Previous implemented technologies are recalled through the performance of historical decisions; experts conduct a subjective evaluation to select the optimal technology. The evaluation process is based on the consideration of multiple technology performance attributes against a set of specific project objectives. The purpose is to determine which technology and its related performance ability is best aligned to the requirements of a project.

As outlined in Chapter 6, the attributes are distinctive in which the project requirements represent the drivers of the project (e.g. reduce cost, reduce time, *etc*). Technical attributes of the technology represent performance-based characteristics (e.g. total investment cost, required operators, *etc*). Chapter 6 highlighted how historical decision information is recalled on the performance attributes of the selected technology, the original project objectives and judged project success. Therefore, it can be concluded that a combination of historical information is considered when evaluating multiple technology performance information against a set of requirements for a new project. The problem definition of current practices is best represented in Figure 7.1.

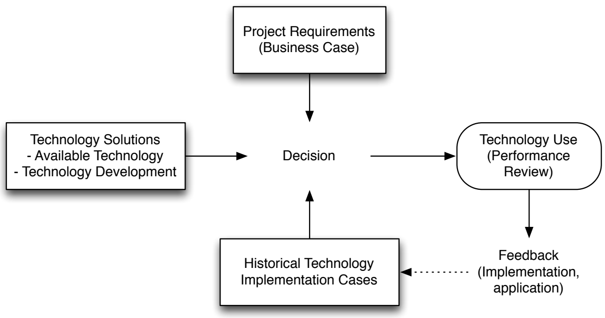

Figure 7.1 Problem definition of current practices

Each of the three information-driven activities is as follows:

- *Project requirements* is the information source phase in which a new problem is defined by the decision team. These are the attributes identified to represent the requirements of a new project that outline the overall objective and expectation of an investment. Chapter 6 concluded a set of 5 decision variables as representative of the requirements of a new case. The set of modular attributes enable a variety of projects to be defined similar to the information recalled by an expert.
- *Technology solutions* are an account of all potential manufacturing technologies in a project. Through a study of state-of-the-art technologies and previously implemented solutions, a list of potential solutions is defined. Each assessed through a modular set of criteria as outlined in Chapter 6. The performance of each technology is evaluated against the defined project requirements as outlined in Figure 7.1.
- *Historical technology implementation cases* are previously implemented decision cases. They are individual decisions represented by the original project objectives, technical attributes of the selected technology and the judged level of performance. An example of a historical decision case was concluded in Chapter 6 and represented in Table 6.15.

7.3 Concept

A typical problem-solving model provides a scheme for organising the reasoning of domain knowledge (experts, experience, rules *etc*.) to construct a solution to a problem task. As organisations attempt to solve a complex problem, experts provide advice and direction to an appropriate solution. One common form of this is a traditional ES approach. It directly elicits rules from an expert and typically stores them in the form of production rules (IF-THEN), as a decision tree or a flow chart of procedural knowledge. ESs store knowledge where a user is able to call on for specific advice as needed. The system requires experts who are widely considered as a reliable source of technique or skill, and often have prolonged experience through practice. Although some methods have been proven, they are reliant upon vast amounts of knowledge for use by a non-expert. Chapter 2 discusses how the knowledge acquisition process can be intensive, difficult and costly. An advantage of an ES approach is that the representation method is easy to understand by non-experts. Researchers agree that production rules, frames and objects are simple to derive, yet difficult to combine.

An alternative approach of using domain knowledge is through cases that are data-mined to create previously unknown production rules. Chapter 5 demonstrated that the expertise of an expert in technology selection is developed through previous cases, where the outcome of historical projects is learnt to provide an indicator to support future decision problems. Although structured case information is not commonly captured during the decision process, the approach is data driven where there is a high transfer of irrational information.

To further discuss three common knowledge-based decision techniques, Yang (1997) summarises the distinctive characteristics of an ES, CBR and RI (Table 7.1). Although ESs have an excellent explanation ability, they lack the learning capability of CBR and RI. ESs acquire knowledge through experts whilst CBR and RI rely on collecting and inducing from cases. The difficulty of development for RI is low whilst ESs and CBR is more difficult.

The ability to learn from existing data and induce knowledge from historical manufacturing decision cases suggests RI as the most suited approach to the problem. Historical decision cases are the primary learning method by which information is collected and interpreted by an expert. Although knowledge is difficult to capture, acquiring case information in a data-driven process can be the most accurate form of reflecting the experience and practice of decision-making. Each case would represent the problem (project objectives), the solution (technical attributes of the chosen technology) and an appraisal of the project (defined level of success). Developing a concept that represents knowledge through case information similar to existing practices reflects current practices and fits the problem.

Identities	ES	CBR	RI
Learning capability	Limited	Existing	Existing
Input format	Numerical / alphabetical	Numerical / alphabetical	Numerical / alphabetical
Input requirements	Complete information	Incomplete information	Incomplete information
Knowledge acquisition method	Acquiring from experts	Collecting from cases	Inducing from cases
Knowledge representation method	IF-THEN rule, frame, object, *etc.*	Cases with certain attributes	IF-THEN rule, decision tree
Property of knowledge representation	Transparent	Transparent	Partial hidden
Major difficulty	Knowledge acquisition	Collection of existing cases	Evaluation of induced rules
Explanation capacity	Excellent	Good	Good
Difficulty at development	Medium	Medium	Low

Table 7.1 Comparison of ES, CBR and RI techniques (Yang 1997, p. 36)

Much of the existing literature has focused primarily on the evaluation trade-off of alternative manufacturing technologies through a multi-criteria type of approach. This is based on the judgement of an expert that is ultimately an opinion formed from their involvement in prior cases. An objective approach would reduce the likelihood of sub-optimal decisions being made from personal bias. The concept of the proposed approach is defined in Figure 7.2. The figure demonstrates how the integration of historical case information (applied by a human knowledge source) closely links to the problem solving mechanism of a new decision task. The approach uses a form of machine learning to learn a set of rules (in the form of a decision tree) from raw case data (historical decisions).

The benefit of considering the relationship between historical information and knowledge is that the uncertainty in the information is greatly reduced, as it represents factual information. This information is a set of observations by which formal rules can be extracted. Previous technology implementations are structured in Table 6.15 and based on the opinion of the decision-makers involved in a project. This provides a reduced level of ambiguity compared with a typical ES approach that relies on the direct input of knowledge by an expert; the knowledge is subjective and based upon the opinion and judgement of a skilled expert.

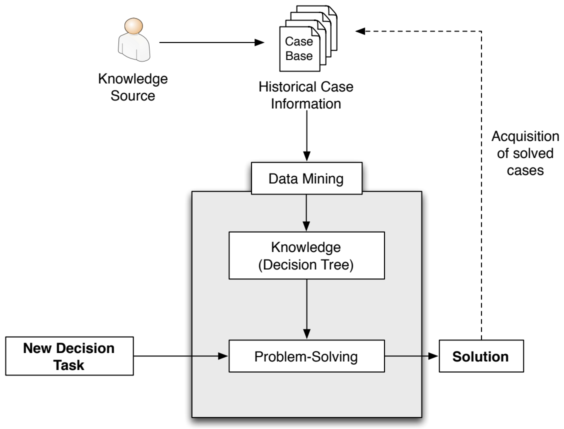

Figure 7.2 Model of relationships among knowledge, problem solving and solution concept

To develop a framework for experience-based manufacturing technology selection, the relationship of historical decision cases with new manufacturing decision problems must be defined. The model is required to classify/rank the most suitable technology for a new project based on previously implemented cases. The approach is not concerned with how a decision was made, but how the technology performed against the original project requirements. It is the relation between different information items that represent a historical decision case, and a new decision problem where a number of technologies require classification.

To discuss further, Figure 7.3 illustrates the concept of transforming information to knowledge for supporting manufacturing technology selection.

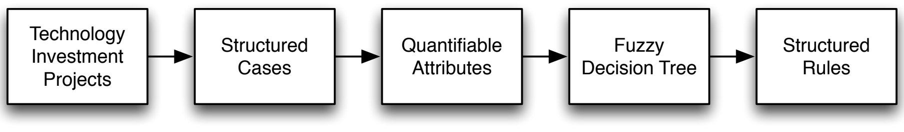

Figure 7.3 Transformation of information to knowledge

Benefits of combining and transforming case information to knowledge for technology classification are as follows:

- Information acquisition by collecting historical and new decision cases is more convenient than traditional acquisition methods. Also, the type of information can be easily captured once an appropriate structure is defined (as concluded in Chapter 6).

- Key decision variables used in the representation of historical cases can be both tangible and intangible. Quantifying attributes can be conducted as described in Chapter 6 for fuzzy and nominal decision variables.
- Although formal knowledge rules can be difficult to represent and acquire, patterns can easily be extracted from a database of historical information. Knowledge of multiple cases that would otherwise not be consolidated can be used to represent a full scientific model of data. A typical knowledge-based approach (e.g. directly acquired rules) would require multiple experts, which would bring increased levels of uncertainty. Combining rules is also more difficult when conflicts exist compared to case consolidation.

The concept is an iterative machine-learning model that transforms information to knowledge for supporting new decision problems. Overall, the model combines the capabilities of a database management system (DBMS), fuzzified rule-induction system (FRIS) and rule-based knowledge system (RBKS) to enable previous cases to act as knowledge sources and to induce rules for rule-based problem-solving. Figure 7.4 shows the relationship between the information transformation and integration tools in the developed model. The system architecture is shown within Section 7.5.

Appropriate technology investment projects act as raw sets of information related to previous decision cases. Cases are represented as frames of attributes or properties that detail project requirements and the technical performance attributes of a technology. A level of success is assigned to each project given at the end of the decision case. Structured sets of cases with modular sets of characteristics are represented in the case repository. Depending upon the type of attributes defined, non-crisp characters are fuzzified as suggested in Section 6.5. Subsequently, a FDT is created from the dataset with the most influential attributes being placed in the tree. Rules within the tree support classification.

To summarise, the concept iteratively captures or adds manufacturing technology cases to a database structured to represent experience. In domains such as technology selection where it would be difficult to capture and interpret precise human knowledge, cases reduce the subjective judgement by allowing multiple persons to contribute to a single set of case information. Knowledge patterns are extracted during model iteration using the available cases. The newly created knowledge is subsequently used to classify new decision cases by comparing each technology with the project objectives. Results of past implementation projects increase the likelihood of selecting an optimal technology for a new case.

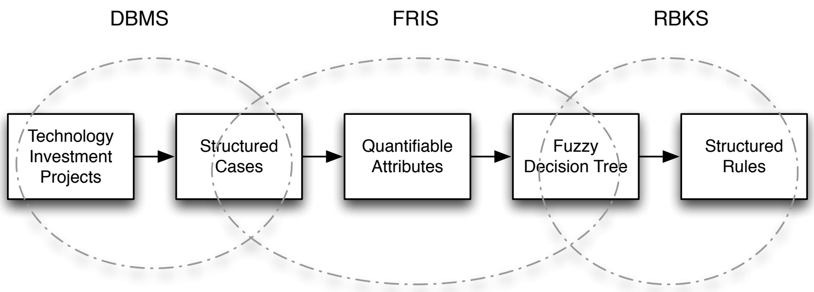

Figure 7.4 Integration tools

7.4 Manufacturing Technology Selection Approach

This research developed a framework for manufacturing technology selection that explores the relationship of historical decision cases for classifying new manufacturing problems. The aim of classification is to rank the most suitable technology based on previously implemented cases. The purpose is not to understand the decision that was made, but the performance of a technology for a similar problem. Reviewing potential technologies and determining the one with the highest level of success can identify the most appropriate solution for the problem. Hidden information patterns and knowledge are extracted from the case repository and used to support the classification of the decision problem.

The approach uses cases/experience information to choose the most appropriate technology based on the given requirements for the decision variables specified. The stages of the decision cycle are systematically linked to allow flow of information and data between each of the stages that form the overall decision process. Formed from the CBR framework of retrieve, reuse, revise and retain, the model adapts the case similarity inference with data mining and fuzzy rule-based reasoning techniques to provide an approach that identifies patterns within a decision dataset to solve new problem cases. Figure 7.5 outlines the methodology.

The methodology comprises two phases which can be applied consecutively or as separate entities for different roles. The upper section of Figure 7.5 is defined as the “unclassified case preparation” sub-system which main responsibility is to store/acquire manufacturing technology information or support the definition of a problem to be solved. The “experience-based inference support” sub-system provides the inference and data-mining capability to analyse the dataset of historical information to evaluate the presented decision problem. It also provides the capability to store and iteratively acquire historical case information.

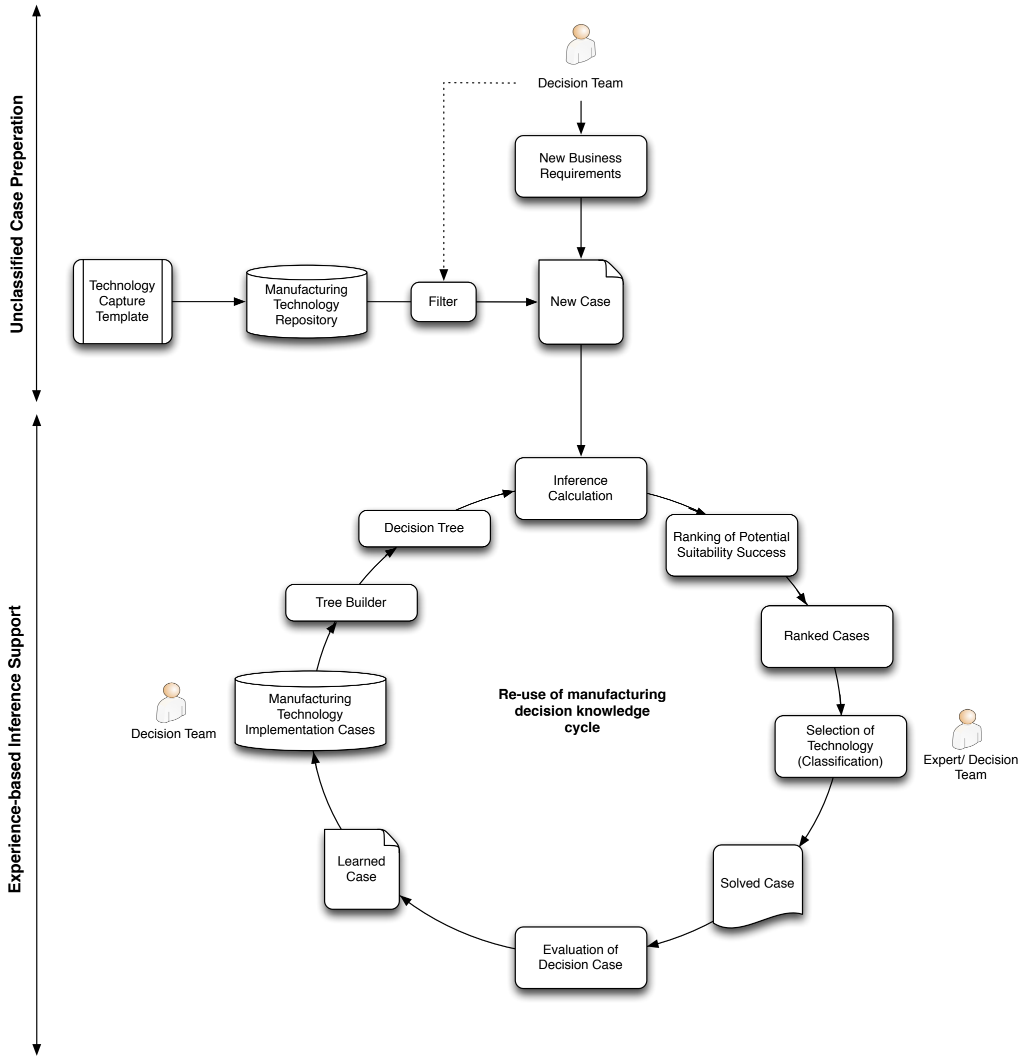

Figure 7.5 Experience-based decision methodology

The re-use of information and generated knowledge is apparent through the iterative methodology. The dataset of historically implemented technologies are considered again to develop a decision tree that represents all cases. The output form of the unclassified case preparation phase is directly linked to the inference support mechanism to evaluate the decision problem. This applies each potential technology to the tree and ranks the suitability based on the end leafs of the tree which were defined from historical cases.

The iterative design and multitude of technology information and knowledge is constantly generated as project information is added. The information is a form of expertise represented similar to how an expert wouldn't recall information and logically be evaluated to support decision-making. The ability to combine the quantitative and qualitative performance of a technology integrates economic, strategic and technical factors, in a single platform and approach.

The methodology is presented in detail in the following seven stages:

7.4.1 Stage 1 - New Case

In order to represent a new manufacturing decision problem, the information is formed as a new decision case *(C)*. The purpose of representing a problem through a case style matrix relates well to how an expert decision-maker would structure a new problem. An unclassified case is defined as:

C = {R, $T_{j,}$} with the objective to identify Y Eqn. (7.1)

where:

R = {r_1, ... r_n} is the set of requirements for the manufacturing decision case

r = is either a crisp/fuzzy attribute and defined within the context

T_j = {t_1, ... t_n}$_j$ is the set of technology attributes for technology j of the considered technologies

t_l^j = crisp or fuzzy attribute of the potential technologies (see Section 7.4.3)

Y = {y_1, ...y_n} is the technology confidence factor aligned to the context.

A decision case combines two forms of information: a set of requirements related to the problem or manufacturing process and a set of key technical properties of the identified manufacturing technologies. The key decision variables can be defined appropriately for both R and T_j, which is capable of handling crisp and fuzzy attributes. A technology confidence factor *(Y)* is calculated for each technology. Each decision case has a relationship between R and T_j and the calculated Y value combines to support the classification of technologies.

These two sets of attributes represent a new technology case. The study presented in Chapter 5 and in particular stages 3 and 4 of Figure 5.2 define how the two attributes are linked. Multiple technologies are compared to the set of project objectives to identify an optimal solution. This is similar to how an expert approaches a technology selection problem in practice.

To demonstrate further, Table 7.2 is a fictitious structure of a new decision case using attributes identified in Chapter 6. The purpose is to understand the relationship of Technology A, B and C to the set of project objectives, with the aim to identify a value of Y for each technology.

New Case *(C)*

Manufacturing Technology Implementation Project

Project Objectives *(R)*			
Time (r1) -	Reduce time		
Cost (r2) -	Reduce cost		
Down selected Technologies *(T)*			
	Initial Investment Cost (t1)	Longevity (t2)	Skill Level (t3)
Technology A	£50,000	25 years	Skilled
Technology B	£100,000	20 years	Semi-Skilled
Technology C	£250,000	5 years	Skilled
Confidence Factor *(Y)*			
Technology A	?		
Technology B	?		
Technology C	?		

Table 7.2 Fictitious example of new decision case

The example case has two objectives: reduce time and reduce cost. Three identified technologies are represented by initial investment cost, longevity and skill level. The aim is to determine a confidence factor for each technology.

7.4.2 Stage 2 - Manufacturing Technology Implementation Cases

The performance of technology investment projects is defined for each technology implementation case. Project feedback for a technology is captured to ensure lessons can be learned. The performance of previously implemented technologies provides vital feedback on the likelihood of the success of decision problems.

A single experience decision case is represented by:

$$E = \{R, T_j, S\} \quad \text{(Eqn. 7.2)}$$

where:

$R = \{r_1, \ldots r_n\}$ is the set of requirements for the manufacturing decision case

r = is either a crisp attribute or fuzzy attribute and defined mathematically within the context

$T_j = \{t_1, \ldots t_n\}_j$ is the set of technology attributes for technology *j* of the considered technologies

t_l^j = crisp or fuzzy attribute of the potential technologies (see Section 7.4.3)

S = the success rating of a project *{unsuccessful, neutral, successful}* is selected based on the recommended scale

For each case within the repository, it is evaluated on how well it performed. This is not the performance of the technology alone, but the performance of the technology for the project (e.g. how well the technical performance attributes of the selected technology performed for the project objectives). The study conducted in Chapter 5 described how the performance of a technology project is evaluated. During the development of this model, the research was directed to a similar approach that is easy to understand and define. A scale of 0 - 4 with three corresponding values, *unsuccessful*, *neutral* and *successful* was subsequently chosen.

As it is difficult to put an exact value on the judged performance of a technology project, a fuzzy representation with overlapped boundaries is suggested. A definitive boundary does not exist between the subjective judgements of multiple experts; the following fuzzy membership function was developed through discussions with a number of industrialists.

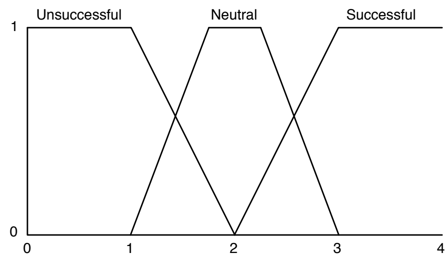

Figure 7.6 Technology project evaluation scoring (fuzzy membership function)

Whilst a positive outcome is more difficult to score, the developed membership function and scoring was defined and represented by industrial experts. The imprecise boundaries between each performance measure and correlation to the 0 – 4 rating adequately allows experts to select an accurate performance measure. In addition, the ability to determine an average score between 0 – 4 to compensate for multiple opinions ensures an accurate judgement is concluded.

A subsequent value can be selected on the scale to determine the level of success of a project. The type of characterisation is appropriate where multiple experts would evaluate a project individually and their opinions can be combined to determine an exact value. For example, if two decision makers review a project, one may judge the project unsuccessful and select a value of 1, where as a second decision maker may choose a value of 2. Therefore, an average value of 1.5 would be calculated. This would subsequently be applied to the fuzzy membership set for project evaluation (Figure 7.6) and be rated as shown in Figure 7.7.

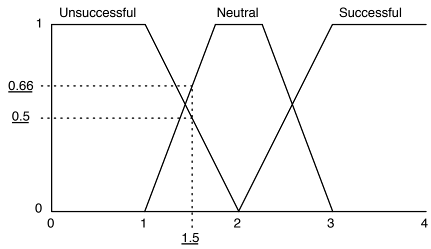

Figure 7.7 Defuzzification of technology project evaluation scoring (fuzzy membership function)

The defuzzification would subsequently provide a value for the three alternative categories: unsuccessful = 0.5, neutral = 0.66 and successful = 0. The combination of subjective judgement would ensure each case is evaluated appropriately based on multiple experts and compensate for the lack of defined boundary between alternative project success scores. The approach assists in representing the partial membership that would exist between the calculated project outcomes.

7.4.3 Stage 3 - Decision Variables

One of the benefits of a tree-based approach is the ability to represent multiple attributes in a decision-tree for simple interpretation. FDTs have the ability to represent attributes of either a discretization or fuzzification nature. This allows for context specific attributes to be appropriately dealt with for alternative decision problems. t_l^j can consider both crisp and fuzzy attributes and be universally applied to support pattern recognition. Crisp decision variables are defined for attributes that have a conventional set, wherein the degree of membership of any objective in the set is either 0 or 1. They are most appropriate for decision variables where the potential options may be represented as *yes* or *no*.

A fuzzy decision variable is an extension of a set, which the characteristic function that determines the membership function of an objective that is not limited to the values 1 or 0. These types of variables are suited to decision attributes that do not have defined boundaries within their set and can range between any value.

Chapter 6 concluded a modular set of decision variables for representing historical decision cases and both types can be quantified in the model. Figure 7.8 illustrates the difference between crisp and fuzzy values for this type of problem with appropriate representation.

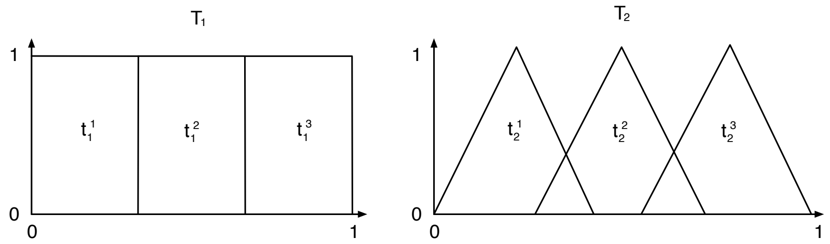

Figure 7.8 Crisp (discretization) decision variable set (left) and fuzzy decision variable set (right)

7.4.4 Stage 4 - Tree Builder and Fuzzy Decision Tree

Manufacturing technology implementation cases are represented through a set of attributes for the technical performance of the technology, the objectives of the business case and a judged level of success. This type of representation is found to be most suited to a tree-like model, where a series of decision nodes leads to a consequence/suggested recommendation during the final branch of the tree. For this type of decision problem, the concern is with the overall level of performance of a technology project, represented by *S*. However, it is the attributes that lead to that level that affects the value of *S*. This in turn provides guidance to a decision maker.

During industrial practices, an expert will typically be aware of a small number of projects to identify patterns among the attributes and performance of a project. For example, it may be apparent that projects between certain investment values always perform well, or a project where the supplier had no previous dealings with the company under performed. Decision makers have this difficulty of trying to identify patterns for a small number of projects that are complex and not explicitly defined.

This research therefore proposes to use the fuzzy interactive dichotomizer 3 (FID3) tree-building algorithm developed by Umanol et al. (1994) for the problem. The methodology adopts the algorithm from within the literature for building the tree and proposes a new inference classifier in Section 7.4.5. The FDT classification is well suited to support technology selection decisions due to the structure by which experience is represented. The tree builder is the decision algorithm used to generate a tree and applied for classification to assist decision-making. In this context, the decisions are the outcomes of historical cases whilst the consequences are a combination of technical properties of a technology and the business requirements related to that technology implementation case.

FDTs are able to handle a variety of crisp and fuzzy decision variables. It is an extension of the original tree-building ID3 algorithm and is able to generate understandable FDT using fuzzy and crisp sets defined by the user. The fuzzy ID3 algorithm although developed for fuzzy sets uses a similar information theory measure as ID3, the information gain calculation and entropy-base measurement identifies the key criteria in the data. At each internal node within the tree, the information gain associated within each feature in the dataset is calculated. The algorithm is easily adaptable to nominal data using the representative 0 or 1 values, in addition to the fuzzy scores for other decision variables.

FID3 partitions the historical dataset recursively based on a test attribute. In order to select the test attribute at a non-leaf node, an entropy-based measure called information gain is applied. The dataset is partitioned and the splitting feature is selected such that a certain information measure of separating data belonging to different classes is maximised (Janikow and Faifer 2000). The developed tree-like graph of decisions and their possible consequences is used to support decision-making where the consequences of a problem are unknown.

The algorithm is described as follows and the reader is referred to Umanol et al. (1994) for a more detailed definition. The representations have been changed to suit the structure of the historical decision cases as outlined in Section 7.4.2.

Assume we have a set of data *E*, where each data has r_n or t_n values for attributes $A = \{r, t_j\}$ and T_j and classified classes *S*. These have been chosen as an appropriate format of representing the potential classified outcome of a decision project. Each set within the function has a defined boundary and vary upon the judgement of the decision team.

The values for each attribute are expressed using a combination of fuzzy or nominal values. Let E^{Sn} to be a fuzzy subset/nominal set in *E* whose class is S_n and |E| the sum of the membership values or nominal values of the set of data *E*:

i. Generate the root node that has a set of all data, i.e., a fuzzy/nominal set of all data with the membership value 1 or > 0.
ii. If a node *t* with fuzzy/nominal set of all data *E* satisfies set conditions then it is a leaf node assigned by the class name.
iii. If it does not satisfy the defined conditions, it is not a leaf and the test node is generated.
iv. Class with the highest membership function is representative of the case for entropy calculations. The information gain *G*(A,E) for the attribute *A* by a fuzzy/nominal set of data *E* is defined by:

$$G(A,E) = I(D) - Entropy(A,E), \qquad \text{(Eqn. 7.3)}$$

where:

$$I(D) = -\sum_{k=1}^{n}(p_k \cdot \log_2 p_k), \quad \text{(Eqn. 7.4)}$$

$$Entropy\ (\mathrm{R/\ A}) = \sum_{j=1}^{m}\left(p_{ij} \cdot I\left(E_{F_{ij}}\right)\right), \quad \text{(Eqn. 7.5)}$$

$$p_k = \frac{|E^{C_k}|}{|E|}, \quad \text{(Eqn. 7.6)}$$

$$p_{ij} = \frac{|E_{F_{ij}}|}{\sum_{j=1}^{m}|E_{F_{ij}}|}. \quad \text{(Eqn. 7.7)}$$

The tree is expanded till one of the following is met:

a. No more attributes available to further partition the dataset;

b. The cases have an identical target role at the end node for the highest representative membership function;

c. The entropy calculations of the available attributes are zero;

d. The total number of cases at the end of node is less than the *total case threshold level*.

To demonstrate further, a small numerical example is shown. In the example, 8 decisions cases are represented by 2 project objectives, r_1 and r_2, characterised as discretization, and 3 technical performance attributes, t_1, t_2 and t_3, 2 characterised in fuzzy terms and 1 discretization. *S* is a value between 0 and 4. During this example, we define the success of each project based on the opinion of a single expert and using the defined scale in Figure 7.6. The database is shown in Table 7.3.

	Project Objectives		Technical Attributes			*S value*
Case ID	Time (r1)	Cost (r2)	Investment cost (t1)	Longevity (t2)	Skill level (t3)	
1	Reduce time	Reduce cost	£75,000	15	Semi-Skilled	2
2	Non-applicable	Non-applicable	£150,000	15	Semi-Skilled	2.5
3	Reduce time	Non-applicable	£150,000	20	Unskilled	1
4	Reduce time	Non-applicable	£50,000	5	Skilled	1.5
5	Non-applicable	Reduce cost	£250,000	15	Skilled	2
6	Reduce time	Reduce cost	£80,000	25	Skilled	3.5
7	Reduce time	Reduce cost	£150,000	20	Skilled	4
8	Non-applicable	Reduce cost	£50,000	20	Skilled	3

Table 7.3 Numerical example database

For an instance where identical information gains are calculated, one is either selected randomly or chosen based on its importance within the project. If a decision is unable to be made, a pair-wise comparison is recommended. In addition, only a single case can be represented in the tree and during the partitioning, the one receiving the highest function is selected for that particular criteria and subsequent branch.

Firstly, the attributes are fuzzified or represented in a discretization format; the corresponding fuzzy membership functions developed in Chapter 6 are used (Table 7.4).

Case	Project Objectives				Technology Technical Attributes												*S Value MF*		
ID	Time (r1)		Cost (r2)		Investment cost (t1)				Longevity (t2)				Skill level (t3)						
	Reduce time	Non-applicabl	Reduce cost	Non-applicable		Low cost	Medium cost	High cost		Short	Average	Long		Un-skilled	Semi-Skilled	Skilled	Unsu.	Neu.	Succ.
1	1	0	1	0	£75,000	0.27	0.73	0	15	0.00	0.33	0.67	Semi-Skilled	0	1	0	0	1	0
2	0	1	0	1	£150,000	0	0.35	0.65	15	0.00	0.33	0.67	Semi-Skilled	0	1	0	0	0.66	1
3	1	0	0	1	£150,000	0	0.35	0.65	20	0.00	0.00	1.00	Unskilled	1	0	0	1	0	0
4	1	0	0	1	£50,000	0.6	0.4	0	5	1.00	0.00	0.00	Skilled	0	0	1	0.5	0.66	0
5	0	1	1	0	£250,000	0	0	1	15	0.00	0.33	0.67	Skilled	0	0	1	0	1	0
6	1	0	1	0	£80,000	0.2	0.8	0	25	0.00	0.00	1.00	Skilled	0	0	1	0	0	1
7	1	0	1	0	£150,000	0	0.35	0.65	20	0.00	0.00	1.00	Skilled	0	0	1	0	0	1
8	0	1	1	0	£50,000	0.6	0.4	0	20	0.00	0.00	1.00	Skilled	0	0	1	0	0	1

Table 7.4 Fuzzified database

Using equation 7.4, the information of the technology outcomes is calculated. The fuzzy values were summed as follows for each category: unsuccessful = 1.5, neutral = 3.32 and successful = 3.5.

$$I(3.5\,successful, 3.32\,neutral, 1.5\,unsuccessful) = -\frac{3.5}{8.32}\log_2\frac{3.5}{8.32} - \frac{3.32}{8.32}\log_2\frac{3.32}{8.32} - \frac{1.5}{8.32}\log_2\frac{1.5}{8.32} = 1.500$$

Next, the information gain for each individual attribute is calculated. The attribute receiving the highest information gain is deemed as the most influential and placed at the top of the tree. Firstly, we demonstrate for one attribute, the information gain calculation of *investment cost* using equations 7.3 and 7.5.

$$H(investment\ cost, low) = -\frac{0.8}{1.67}\log_2\frac{0.8}{1.67} - \frac{0.87}{1.67}\log_2\frac{0.87}{1.67} - \frac{0}{1.67}\log_2\frac{0}{1.67} = 0.9987$$

$$H(investment\ cost, medium) = -\frac{1.9}{3.38}\log_2\frac{1.9}{3.38} - \frac{1.13}{3.38}\log_2\frac{1.13}{3.38} - \frac{0.35}{3.38}\log_2\frac{0.35}{3.38} = 1.3344$$

$$H(investment\ cost, high) = -\frac{1.3}{2.95}\log_2\frac{1.3}{2.95} - \frac{1}{2.95}\log_2\frac{1}{2.95} - \frac{0.65}{2.95}2.95 = 1.5309$$

Therefore:

$$G(S, investment\ cost) = 1.406 - [\left(\frac{1.67}{8} \times 0.9987\right) + \left(\frac{3.38}{8} \times 1.3344\right) + \left(\frac{2.95}{8} \times 1.5309\right) = 0.069$$

The information gain scores for the remaining attributes were calculated as follows:

G(*S, time*) = 0.110, G(*S, cost*) = 0.204, G(*S, longevity*) = 0.280 and G(*S, skill level*) = 0.549.

Subsequently, the attribute *skill level* has the highest information gain and is used as the initial splitting point in the tree. The first attribute in the tree is shown in Figure 7.9. To improve the accuracy of the decision tree, the learning must be stopped or pruned. Due to the size of the database, a threshold value of 30% was specified (the tree is stopped when an end leaf has 2 or less cases). For examples where the database is large, this is adjusted to reduce the overall size of the tree to focus on the most influential parameters without creating too large of a tree.

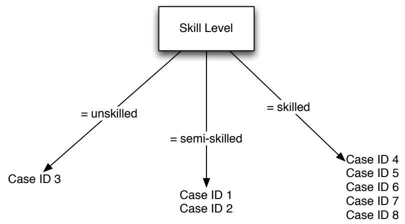

Figure 7.9 Sub-fuzzy decision tree

By reviewing the first stage of the decision tree procedure (Figure 7.9), the branch *skill level = skilled* has a decision threshold of 5 cases/8 total cases = 62.5%. Therefore, the expansion of the branch does not stop. In this example, the *skill level = unskilled* and *skill level = semi-skilled* branches has less than 2 cases after the first attribute and is stopped at this stage.

The remaining calculations of the decision tree builder were conducted and the overall result is shown in Figure 7.10. The larger the dataset, the larger the tree may be defined depending on the chosen threshold level.

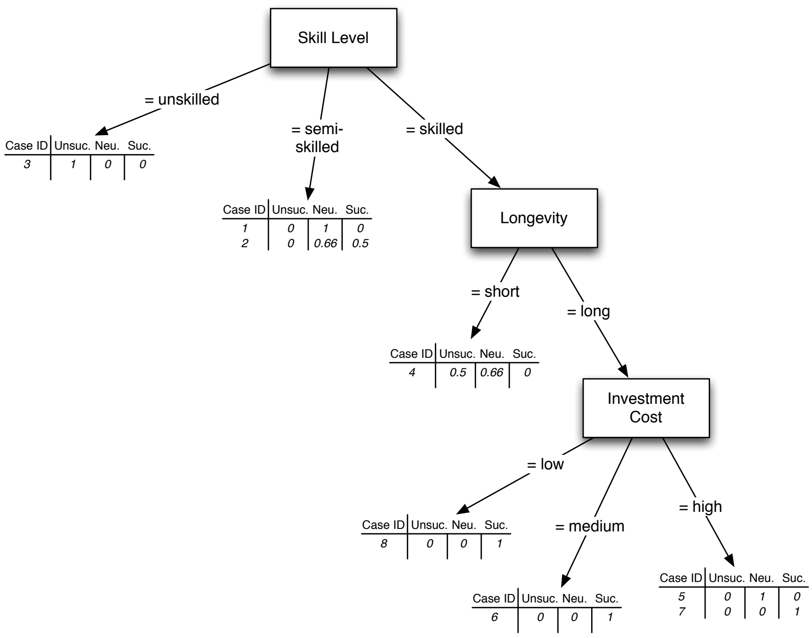

Figure 7.10 Fuzzy decision tree with membership values at each end leaf

Overall, six rules can be extracted from the tree of the end leafs that exist. Upon further examination, 2 end leaves contained more than 1 case from the repository. For this problem, an average for each classified category is calculated. For example, *skill level* = *semi-skilled* contains both cases IDs 1 and 2. Their defuzzified values are shown in Figure 7.11 and average conversion to represent a single value as the end leaf is shown.

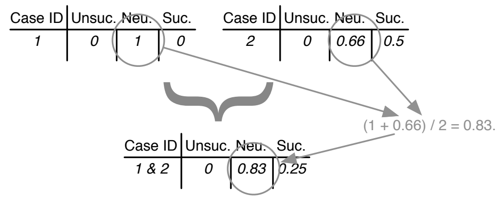

Figure 7.11 Multiple end leaf case calculation example

This concludes the building of the decision tree and the example tree is shown in Figure 7.12. The following section discusses the inference classification that applies each technology to the created decision tree.

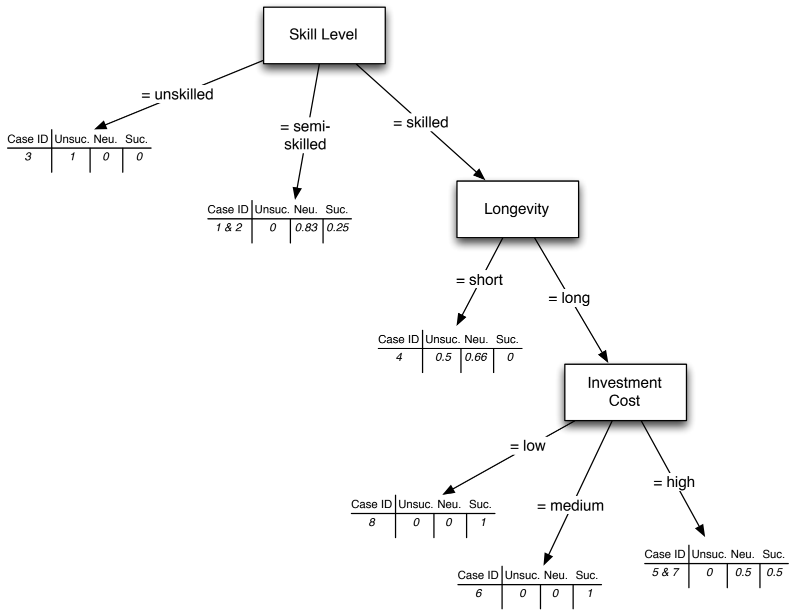

Figure 7.12 Final decision tree

Fuzzyness is introduced to the decision tree at each node that represents a decision variable. Each node has a defined fuzzy membership that is reflected as a branch within the tree. The fuzzy association with each branch may simultaneously assign more than one branch to the same instance with gradual certainty. The use of fuzzyness at each node preserves the symbolic structure of the tree and its comprehensibility. Real-valued output can easily be interpreted with gradual shifts in characteristics.

7.4.5 Stage 5 - Inference (Classification)

The purpose of the inference process is to use the created decision tree (as described in the previous sub-section) to calculate a confidence score for each potential manufacturing technology. The technical attributes of the down-selected technologies are identified and the objectives of the new project defined. The classification process appropriately applies each technology to the tree. The values are used to numerically evaluate several technologies based on their likely success for a project from a similar historical case.

The inference method for the manufacturing problem is as follows:

i. As the unclassified object propagates down the tree, crisp and fuzzy certainties are recorded at each branch;
ii. For each branch that leads to an end leaf, the certainties are multiplied;
iii. The certainties are multiplied by the end leaf fuzzy membership scores calculated during the tree build;

A corresponding value for each path is calculated:

$$\text{Technology } \{A, C, \ldots n\} = (A_1 \times A_2, .. A_n) \times \text{FMV } \{\text{unsuccessful, neutral, successful}\} \qquad \text{(Eqn. 7.9)}$$

where

$A_1 \times A_2, .. A_n$ is defined for each branch leading to an end leaf

$A_n = \{r_n, t_j\}$

FMV{unsuccessful, neutral, successful} is the defuzzified fuzzy membership values at each end leaf

To demonstrate, the decision tree from the previous sub-section is used to classify three manufacturing technologies for a new project as shown in Table 7.2. Table 7.5 first presents the defuzzified values of Technology A, B and C for each attribute. The relevant values were obtained from the fuzzy membership functions (see Appendix A3) for each attribute.

Tech.	Project Objectives				Technology Technical Attributes											*Y*
	Time (r1)		Cost (r2)		Investment cost (t1)				Longevity (t2)				Skill level (t3)			
	Reduce time	Non-applicable	Reduce cost	Non-applicable		Low cost	Medium cost	High cost		Short	Average	Long	Un-skilled	Semi-Skilled	Skilled	
A	1	0	1	0	£125,000	0	0.65	0.35	25	0.00	0.00	1.00	0	0	1	?
B	1	0	1	0	£100,000	0	0.94	0.06	20	0.00	0.00	1.00	0	1	0	?
C	1	0	1	0	£250,000	0	0	1	5	1.00	0.00	0.00	0	0	1	?

Table 7.5 Technology options with fuzzy values

We will demonstrate the first part of the inference mechanism using technology A from Table 7.5. The corresponding values for each attribute are taken from the table and applied to their respective branches within the tree. Figure 7.13 highlights the relevant values on each branch for technology A.

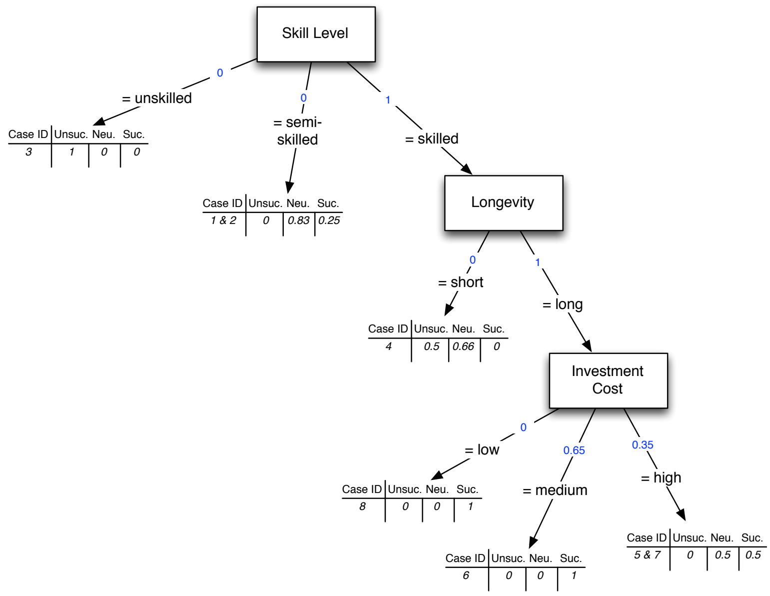

Figure 7.13 Decision tree with technology A applied

We can see from Table 7.5 that for the investment cost attribute, technology A received values 0.6, 0.4 and 0 for low, medium and high cost respectively. The values are highlighted in blue in Figure 7.13. Equation 7.9 is then applied to each branch and each end leaf is revised as shown in Figure 7.14.

To further elaborate on the change from Figure 7.13 to Figure 7.14, we discuss the 5th branch (skill level = skilled AND longevity = long AND investment cost = medium). The three values for technology A applied to the branches that lead to the end leaf are firstly multiplied (see equation 7.9). In this instance, it is 1 x 1 x 0.65 = 0.65.

The second stage of the inference is to multiple the calculated values by each of the respective fuzzy membership score for each of the classified categories (unsuccessful, neutral, successful). For example, in the 5th

branch the successful membership function was 1, therefore, 0.65 is multiplied by 1. The value is shown in Figure 7.14 (Case ID 6 end leaf – 5th branch) together with the remaining calculated values.

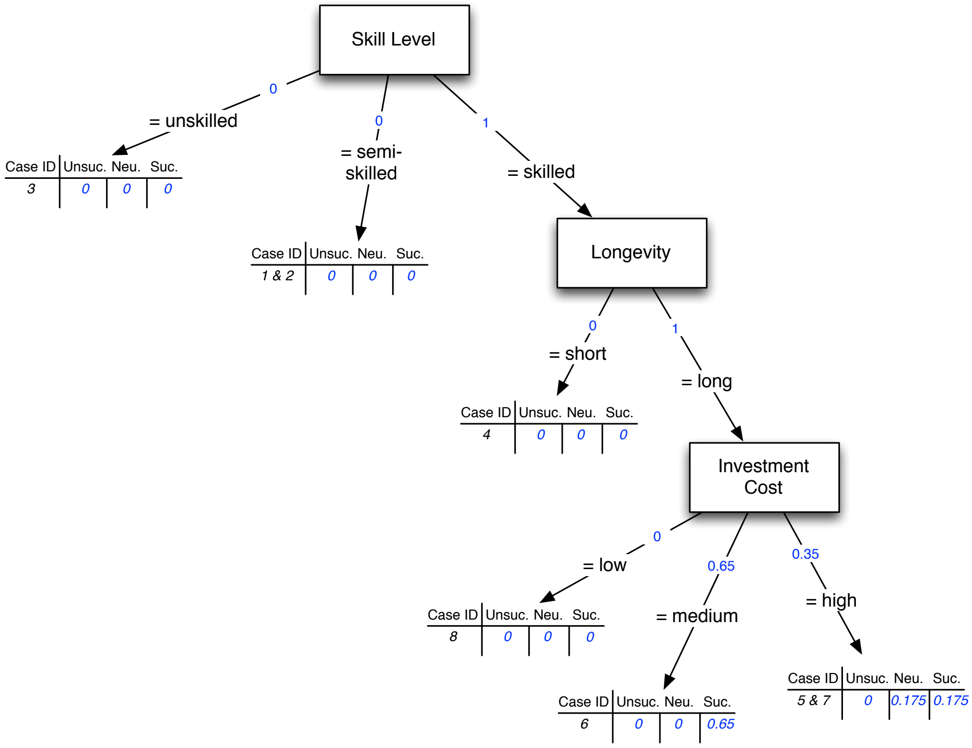

Figure 7.14 Decision tree with technology A applied to end leafs

The final stage of the inference process is to sum the unsuccessful, neutral and successful values in each end leaf:

Technology A - Unsuccessful = 0 + 0 + 0 + 0 + 0 + 0 = 0

Technology A - Neutral = 0 + 0 + 0 + 0 + 0 + 0.175 = 0.175

Technology A - Successful = 0 + 0 + 0 + 0 + 0.65 + 0.175 = 0.825

The process is subsequently applied to technology B and C and summarised within Table 7.6.

	Unsuccessful	Neutral	Successful
Technology A	0	0.175	0.825
Technology B	0	0.83	0.25
Technology C	0.5	0.66	0

Table 7.6 Summary of values for each technology

7.4.6 Stage 6 - Ranking and Technology Selection

To rank the available technologies, a confidence score is calculated for each technology. The factor assists in providing a level of confidence to the decision makers of all the available technologies that are likely to be most successful based on past experience. The relationship in past cases between the initial project requirements, the selected technology performance attributes and the concluded success provides an indication of potential success of an unknown case. Similar to the proposed project evaluation scoring in Figure 7.6, a weighing for each category is used. Successful cases are weighted mostly strongly with a weighting of x3, neutral and unsuccessful are weighted x2 and x1 respectively, as shown in Equation 7.10.

Technology confidence factor *(Y)* = (unsuccessful x 1) + (neutral x 2) + (successful x 3) (Eqn. 7.10)

The confidence factor of each technology is calculated as follows:

Technology A = (0 x 1) + (0.175 x 2) + (0.875 x 3) = 2.975

Technology B = (0 x 1) + (0.83 x 2) + (0.25 x 3) = 2.41

Technology C = (0.5 x 1) + (0.66 x 2) + (0 x 3) = 1.82

Once all technologies have been considered and the reflected confidence factor scores are calculated, the highest ranked technology/technologies are supported for selection. This provides an indication that the highest ranked technology is most likely to be successful for the defined project requirements based on historical implementation cases.

This type of classification corresponds well to the requirements of the decision-making problem. The technology with a higher ranking would suggest that based on previous cases, the technology has a higher chance of success as similar cases performed well. The ranking of a technology as a number is easy to interpret, as a decision maker is able to view the calculated confidence factor. It will be apparent that a particular technology is most optimal based on the numerical value calculated. Alternatively, a number of technologies that received similar/identical classification values may suggest a number of technologies are most appropriate.

The advantage of this approach is that the numerical ranking is based entirely on known historical decision information. Decision-makers are able to easily evaluate several technologies and a conclusion is apparent. To further demonstrate the ranking, the results are shown in Table 7.7.

Rank	**Technology**	***Y***
1	Technology A	2.975
2	Technology B	2.41
3	Technology C	1.82

Table 7.7 Results ranking

It is apparent that technology A is the highest ranked technology and would be selected. The confidence factor confirms that the highest ranked technology is most likely to be successful based on the cases within the repository. More cases within the repository will give a better quality classification with increased levels of certainty from the number of defined classifications. For example, an end leaf with multiple cases will be more reliant than a end leaf represented by a single case.

7.4.7 Stage 7 - Solved and Learned Case

Once a decision case is classed as solved, the technology is purchased and implemented within the business. Upon the project being completed, its success/failure is considered. Using the rating scale in Figure 7.6, a score is calculated to represent the decision case and selected by the decision team. The case is then classed as a learned case and subsequently captured and applied to the repository. The case is retained and represented in the database. As the implementation of the technology progresses, revisions in the data can be made to ensure the information is up-to-date. This can allow for precise values to replace initial estimates. It allows better preparation for future decision-making and provides an accurate case repository.

To illustrate, if two decision makers involved in the project independently review the overall success on a scale of 0 – 4 and selected ratings are 2 and 3, an average would be calculated. The average value (2.5) would then be applied to the proposed fuzzy membership function (as discussed previously in Figure 7.6) and a defuzzified value for each category would be calculated (as shown in Figure 7.17).

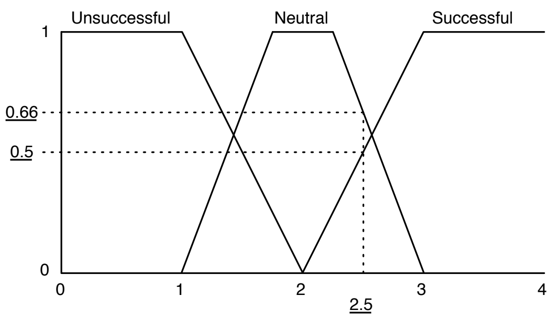

Figure 7.15 Final project evaluation – defuzzified values

Unsuccessful = 0, Neutral = 0.66, Successful = 0.5

The purpose of an iterative approach is to learn from new technology decisions that are made within the business. The inclusion of a new case would require the data-mining approach to be applied again as the tree may differ. The learned case is shown in red as case ID 9 in the new database (Table 7.8).

	Project Objectives		Technical Attributes			
Case ID	Time (r1)	Cost (r2)	Investment cost (t1)	Longevity (t2)	Skill level (t3)	*S value*
1	Reduce time	Reduce cost	£75,000	15	Semi-Skilled	2
2	Non-applicable	Non-applicable	£150,000	15	Semi-Skilled	2.5
3	Reduce time	Non-applicable	£150,000	20	Unskilled	1
4	Reduce time	Non-applicable	£50,000	5	Skilled	1.5
5	Non-applicable	Reduce cost	£250,000	15	Skilled	2
6	Reduce time	Reduce cost	£80,000	25	Skilled	3.5
7	Reduce time	Reduce cost	£150,000	20	Skilled	4
8	Non-applicable	Reduce cost	£50,000	20	Skilled	3
9	Reduce time	Reduce cost	£125,000	25	Skilled	2.5

Table 7.8 Database with new solved case

7.5 Manufacturing Technology Selection Framework

This section outlines the expected system architecture for the implementation of the model and describes the level of interaction by the user. Although no final working prototype of the system was developed, some interactive components were developed that required manual handling by the researcher. The proposed structure of the system for the decision model is based on a typical ES.

7.5.1 System Architecture

The information-based DSS architecture for the decision model is shown in Figure 7.16. It comprises of two parts: the development environment and the consultation environment. The development environment enables the model to build and comprise the components and knowledge set in the repository system. The environment allows refinements and lessons learned to be applied in the repository. The development environment is mainly consulted and developed by an expert. A non-expert or expert interacts with the consultation environment in order to obtain advice and expertise on individual problem tasks. It provides an opportunity for feedback where changes or recommended actions can be applied back to the development process.

The structure of the system is explicitly split into two roles. There are two modules, the knowledge module, known as the information base, and the control module, known as the inference mechanism. The separation of knowledge from the inference makes it easier to add new information either during program development or in light of expertise captured during systems deployment. Although the knowledge module is dynamic and ever changing, the structure of the inference mechanism will mostly remain unchanged. The advantage of this type of structure is that the approach is straightforward. The knowledge module represents knowledge explicitly whilst no implicitly remains within the structure of the program. Therefore, historical decision cases of information can be altered with relative ease.

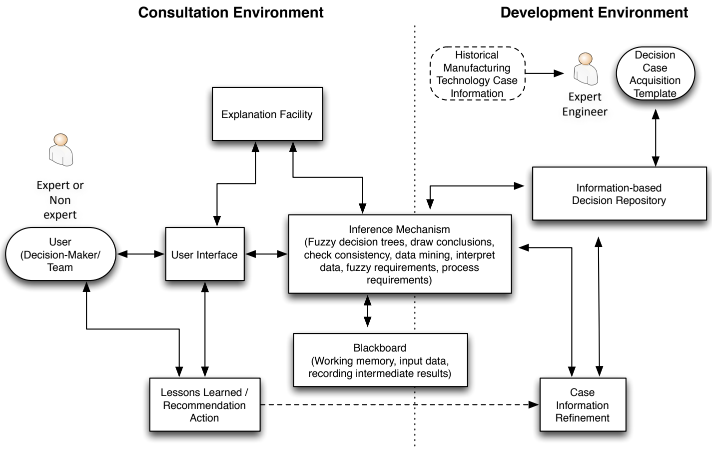

Figure 7.16 Experience-based decision support system architecture

The following six components form the decision model architecture as discussed as follows: *information-based decision repository, inference mechanism, blackboard, explanation facility* and *user interface and lessons learned / recommendation action.*

Information-based Decision Repository

Capturing historical manufacturing decisions in a structured information form is an excellent method of replicating the same information an expert would use to solve a problem. The information-based decision repository is a structured database of previous manufacturing technology investment decisions. An expert or knowledge engineer inputs the required information using the decision case acquisition template and provides a coherent set of information.

The system provides a platform for capturing and refining manufacturing technology cases. It is appropriate for resolving experience-oriented problems where existing experts use their expertise gained from prior involvement in cases to analyse a decision problem. It is the ability earned from previous cases that support new technology problems.

A prototype system for acquiring historical decision case information was developed in Microsoft Access and is discussed in the following section. It assists in the acquisition of decision information for the case study.

Inference Mechanism

The inference mechanism is the control structure of the model. It is connected to both the consultation and development environment, and is a communication between them. It provides a method of reasoning about the concluded knowledge and in combination with the blackboard, is able to formulate conclusions regarding unique tasks. The mechanism (see Section 7.4.4 and 7.4.5) is a combination of RI and FDT that enables project and technical manufacturing technology requirements given by the user to be considered against the generated knowledge rules.

By acquiring project objective and technology performance information, the fuzzified and nominal information is applied to the decision tree for each potential technology and a ranking is sought. A prototype system for computing the entropy values of a case dataset to develop the decision tree was developed in Microsoft Excel. It is discussed in the following section to generate the decision tree building information from the case information gathered.

Blackboard

The blackboard acts as the working memory during reasoning when input data is considered and the results are displayed to the user. It enables slight changes given by the user to record intermediate results for a decision-maker to understand the changes in output as the input value changes. For this model, alternative manufacturing technologies can be applied and a suitability score for each is concluded. In addition, the blackboard supports a sensitivity analysis to study how the variation in data will affect the outcome.

Explanation Facility

The explanation facility provides the ability to justify the conclusions from the inference mechanism and interaction with the user interface. It enables a level of interaction between the inference mechanism and interface by providing further information of classified technologies. Although the inference is conducted in either nominal or fuzzy terms, the explanation facility can provide further information on the assessment of cases such as exact costs, estimated requirements or full details of decision cases. It behaves interactively by answering a variety of questions put by the user. The purpose is to provide a trace of the selected technology to the case repository without making changes to the data unless required.

User Interface

The model provides a friendly user interface containing language processor for problem-oriented communication between the user and the decision system. The user interface is developed to allow the decision maker to specify process requirements in either numerical or linguistic terms easily.

Lessons Learned/Recommendation Action

An integral part of an intelligent decision model is the ability to self-learn. As new manufacturing technologies are considered and the decision team determine the resulting success or failure of the project. The lessons learned module enables structured decisions to be refined and placed within the information-based repository. The module also enables changes in technology attributes and project requirements.

7.5.2 User Interface Flowcharts

In order to further outline the stages of the experience-based model proposed within Chapter 7, this section presents the decision flow chart that defines the activities from a user perspective. Alternative perspectives can easily be identified for both the consultation and development environments. The consultation environment is aimed at the end user that requires a new decision problem solving, whilst the development environment is focused on capturing the relevant information and generating the knowledge to support the classification of a new technology project. Three user perspectives were identified for both user environments:

Development Environment

1. New technology capture
2. Manufacturing technology implementation case capture

Consultation Environment

3. New case

The first level of interaction by the user is to capture a series of case information that is stored within the manufacturing technology repository. Figure 7.17 shows a schematic overview of the process. The storage of information is structured appropriately for easy comparison and consideration by the decision model. Each technology is represented using the pre-defined and coherently agreed evaluative attributes concluded in Chapter 6. They include a combination of nominal or fuzzy values represented in linguistic terms.

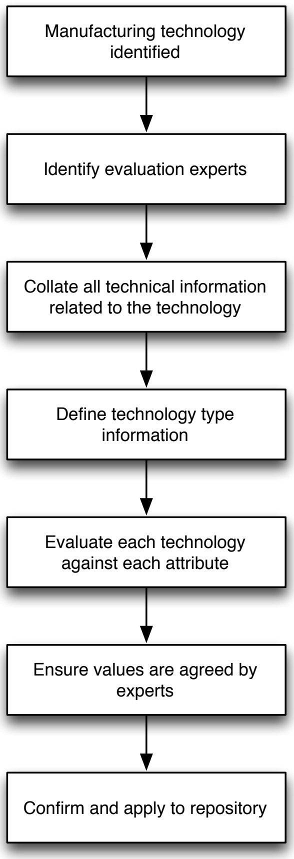

Figure 7.17 New technology capture flowchart

The first phase is the identification of an appropriate manufacturing technology. Once a technology has been selected for evaluation, experts from within the business are consulted to locate the appropriate personnel for conducting the evaluation. Technology experts or the related process experts are consulted first. All the appropriate technical information related to the technology is collated to support the evaluation. The expert first defines the technology type related to the expected manufacturing process method. A series of key technical performance attributes of the technology are agreed or have previously been defined. All manufacturing technologies are subsequently evaluated against each attribute and corresponding values are recorded for the alternative factors. The technology information is captured and applied to the repository.

The second level of interaction within the development environment is the manufacturing technology implementation case capture. Figure 7.18 shows a schematic overview of the process. The proposed model is reliant upon case information of historical manufacturing technologies and capturing this information at the start of model development is crucial to the decision case repository. To deal with this, a template is developed for acquiring the appropriate information.

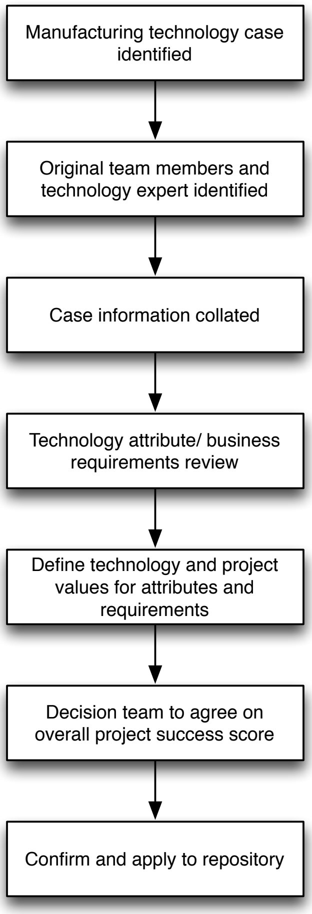

Figure 7.18 Manufacturing technology implementation case capture

Upon a historical manufacturing technology case being identified, the original team members and technology experts are identified. All case information is first collated to understand the technical properties of the technology and the business requirements that form the project. The pre-defined technology attributes and business requirements are reviewed to understand the type of information required. Reviewing each attribute one at a time, expert's select the appropriate evaluative values for each of the technology attribute and business requirements. An overall project success score is subsequently chosen, the case is confirmed and saved within the repository.

The final and most complex flow of information is applying a new case to the model and drawing together a justification for the most optimal technology among a set of available options. Figure 7.18 shows a schematic overview of the process. Once a project has been identified, the first phase is to identify an appropriate decision team. A decision team will consist of a variety of personnel from within the business and contain a cross reference of diversely skilled people. The team is responsible for the project by ensuring an appropriate technology is chosen through a detailed and appropriate evaluation process.

As with any new project, a set of key business requirements is first defined to represent a new decision problem. Using the pre-defined requirement factors, the appropriate linguistic values are chosen to term the project to a particular type. The business requirements include a number of factors that defines the overall aim and objectives of the project. They detail the main purpose of the project and ultimately the outcome that should be concluded. To decide on the business requirements, all attributes are reviewed and appropriate values assigned to the requirements. These are values of which the overall project purpose can be defined (Chapter 6).

At this stage, the manufacturing technology repository is reviewed to ensure any specific technologies are included in the evaluation. The database contains a wealth of information of different technologies and this phase provides the opportunity to store new technologies in the database. Using the appropriate template, new technology alternatives can easily be added to the database. The manufacturing technology repository is subsequently filtered and constraints applied to draw a list of potential solutions related to the new case.

With the key business requirements already defined and the technology repository concluded, the technology requirements are recorded. The decision team review each of the required parameters and subsequent fuzzy numbers for selecting appropriate values for the technology. Prior to applying the inference mechanism, the type of technologies for the application is specified within the implementation case repository and filtered to reflect the type of technology being sought. The FDT builder is then run and decision tree created.

With the decision tree built based on the case repository, and the technology and business requirements selected, the inference mechanism is applied for each technology and an appropriate ranking is concluded. A sensitivity analysis is applied to ensure the result is stable and the decision team reviews the top ranked technologies to select the most appropriate. The technology would subsequently be purchased and implemented. The final stage is to evaluate the project. The project is reviewed, predicted performance information is confirmed and an overall level of success is defined.

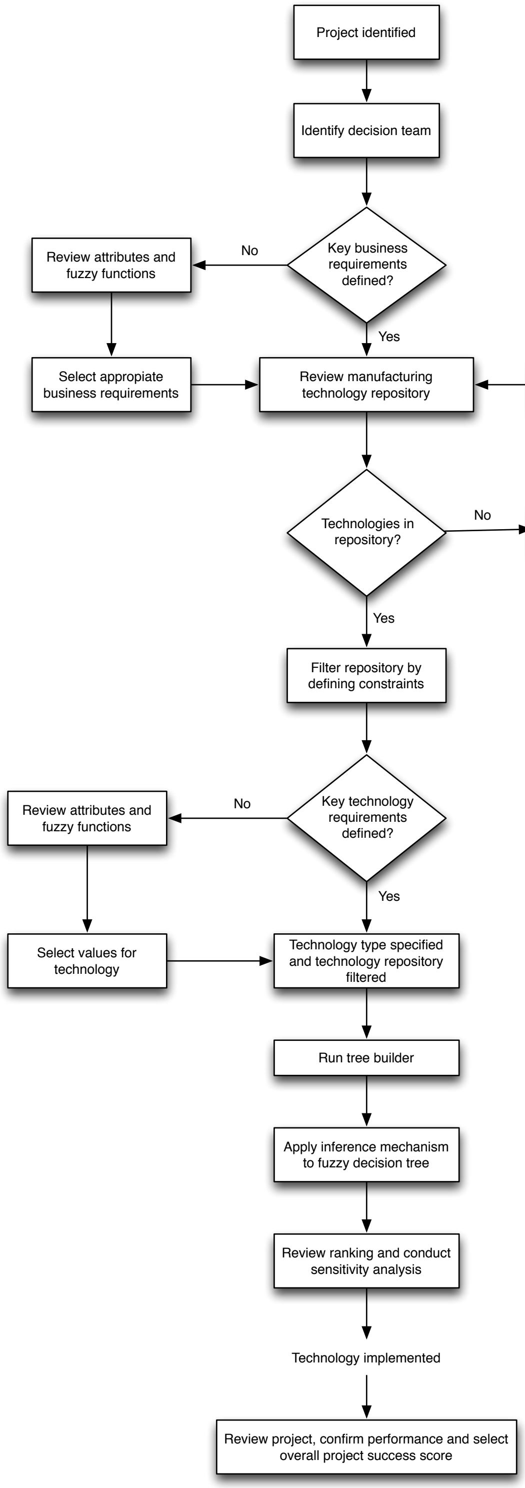

Figure 7.18 New case flowchart from project identification to acquisition of decision case information

The decision flowcharts provide a further understanding of each stage the decision maker would undergo to conduct an evaluation and selection of a new technology using the proposed framework.

7.6 Chapter Summary

This chapter presented the developed decision methodology for manufacturing technology selection. The methodology replicates the experience developed by an expert through their involvement in historical decision cases. The information-based approach uses structured technology information of previous implemented cases to support new decision problems. The iterative approach to technology selection is suited where the learning of previous implementation solutions supports new justification.

FDTs were found to be a better alternative than CBR formalisms as the learner portions the dataset based on the most influential attributes. The approach performs well in identifying the key differences in similar case information. The interpretation of a dataset as a decision tree is easy to understand by a decision maker to provide further confidence based on several cases, compared to a small number of similar cases in a CBR approach. The learning in CBR is associated with specific newly solved cases and thereby fails to discover more general domain knowledge relevant to the problem.

Existing literature has focused on multi-criteria decision techniques and little has been explored through information-based knowledge representation methods. Directly acquiring knowledge from experts is a difficult task and it appears more appropriate to use structured information that is less reliant upon an expert's judgement. The approach reduces uncertainty as multiple experts/decision team members agree on the values to represent the case.

Through the selected FDT data-mining algorithm, patterns create a new knowledge representation method of key information that influences the success/failure of a project. This unknown information can be applied across organisations and used to support similar projects. The tree-like graph models the decision stages of a technology (attributes) and is able to include the event outcomes of a project (success rating). The knowledge can be used to identify a strategy that is most likely to achieve a goal. For this problem, the likelihood of a project achieving a successful outcome is most important.

Chapter 8

Industrial Case Study

8.1 Introduction

This chapter presents an overview of the developed model to support an industrial case study. The purpose is to verify the developed decision model and certify the proposed approach against existing industrial decision practices. The experience-based technology selection methodology supports the selection of a recent industrial decision case. A metrology selection problem within Airbus was chosen to support the performance evaluation of the model.

The stages of the decision model are presented to demonstrate the workings of the methodology for the case study. The results and applicability outcome of the model is discussed to verify and connect the findings of the research to the problem. First, the analysis of the output results is evaluated in terms of accuracy and evaluation based on multiple decision tree thresholds. Secondly, the model and results from the case study is discussed by multiple industrial experts. The performance of the model and suitability is discussed.

8.2 Empirical Study

This section describes the empirical study of applying the proposed model to a metrology technology selection problem within Airbus.

8.2.1 Project Scenario

Over the past 10 years there has been significant developments in composite wing technology through existing research and product developments. There is a need to continue future development to establish and maintain a competitive product environment, and to address the economic and environmental performance requirements of future aircraft. The next generation composite wing (NGCW) programme led by Airbus aims to ensure mature technologies are available to enable the design, development, validation and manufacture of an aircraft wing.

A research project within the NGCW programme is to evaluate alternative types of metrology systems for rapid recertification of aircraft wing assembly jigs. Current full jig recertification takes around 1–3 weeks depending on size and condition of the jig, and is carried out once every three years. The future paradigm aims to monitor the jigs in real-time or quasi-real-time to a suitable accuracy, reducing the need for full recertification and jig down time.

To validate the decision model developed in Chapter 7, it was applied to verify the previous evaluation work carried. The experience-based decision model relies on accurate accounts of historical implementation cases where a similar technology has been previously applied and its conclusion evaluated. Airbus were interested to verify a previous decision activity. The original decision was based on the opinion and expertise of the decision team involved. The team members had established a criteria set of 10 parameters to evaluate each technology and through a weighted matrix approach, the technologies were ranked accordingly.

The model presented in Chapter 7 enables new technologies and their respective project requirements to be evaluated based on the performance of previously implemented metrology systems within Airbus. As this data was not readily available, a case information acquisition framework was developed in Microsoft Access (see Section 8.2.3 for further details). A database was subsequently obtained for the model.

Metrology is becoming a key manufacturing process. They are used in the manufacture of large products including tool setting, product verification and flexible metrology enabled automation. The metrology task is highly complex due to the range of applications and instruments available (Muelaner et al., 2009). This particular project was selected as it represented a typical technology selection problem that experienced engineers faced on a regular basis. In addition, previous metrology applications within the business were available to capture. It was appropriate as a wealth of knowledge and investment had been dedicated to application specific metrology development as an optimised process of measurement. Metrology systems are becoming part of standard processes for aerospace assembly and their use is expected to expand into future aircraft assembly methods.

Selecting a metrology system is difficult because they have their specific advantages and disadvantages. It is often impossible to define one best system for all measurements (Cuypers et al., 2009). The difficulty of selection and novel approach of using historical metrology cases to support the decision process provides an objective-based approach where the decision would traditionally be based on subjective judgement of the decision team.

To validate the applicability and also make the approach more understandable and clear, the concept is implemented to an industrial decision-making problem. A database of 51 cases was collated within Airbus where previous metrology technologies had been considered and implemented. Each of the applied metrology systems had been implemented during the previous 15 years. For this study, the researcher used the key parameters identified in Chapter 6 to evaluate the alternative systems. The study assessed the five metrology technologies considered in the initial evaluation. The aim was to rank five metrology technologies to determine the most appropriate for the project. The study is presented in the following seven stages:

8.2.2 Stage 1 – New Case

To fully develop and test the proposed methodology, the key decision variables identified in Chapter 6 were used to define the selection problem. As the model is being applied to a previously conducted technology selection activity, defining the new case was relatively easy as the information was available in previous documentation. Firstly, persons involved in the original decision activity were consulted and the project objectives were defined. Secondly, each of the five manufacturing technologies was evaluated against the 10 technical parameters (identified in Chapter 6) with assistance from the original decision members. The decision case is represented in Table 8.1.

New decision case					
Technology Type:	Metrology				
Production Stage:	Wing Build Tooling				
Objectives					
Time	Reduce time				
Cost	Reduce cost				
Quality	Improve quality				
Purpose	Replacement				
Regulation requirement	No				
Technical performance	**Option A**	**Option B**	**Option C**	**Option D**	**Option E**
Historical project experience	Good prior involvement	Good prior involvement	Good prior involvement	Good prior involvement	No previous dealings
Skill level	Skilled	Skilled	Semi-Skilled	Skilled	Skilled
Manufacturing objectives/ strategy	In-line w/obj.	Partial	In-line w/obj.	Partial	In-line w/obj.
Company reputation (0 - 10)	9	7	7	6	5
Payback period	2 years	3 years	2.5 years	3 years	1.25 years
Initial investment cost	£100,000	£250,000	£100,000	£50,000	£25,000
Longevity	15 years	15 years	10 years	10 years	15 years
Productivity (0 - 10)	9	9	8	7	9
Risk (0 - 10)	1	2	3	2	2
Quality (0 - 10)	8	6	9	6	8
Technology confidence factor (Y)	?	?	?	?	?

Table 8.1 New metrology selection case

The aim is to identify a value for the technology confidence factor *(Y)* of each manufacturing technology. Airbus asked for certain aspects of the project to remain confidential and each technology remained anonymous. Each metrology was subsequently noted as Option A–E.

To provide a further insight into the type of metrology systems considered in the model, two were established within the business, whilst another two had been used in a similar capacity. The final technology was a simulated solution using an off-the-shelf camera system where accurate predictions of the technology performance were conducted. The five potential solutions were evaluated using the 10 technical decision parameters defined in Chapter 6. Out of the 10 attributes, three were given linguistic ratings. The remaining seven were evaluated on a numerical scale or given an accurate measurement for the required attribute (e.g. cost, payback period and longevity). Defining the case enables the information to be well summarised for evaluation.

8.2.3 Stage 2 - Technology Implementation Cases

The proposed methodology described in Chapter 7 is based on the accumulation of historical decision information that is a representation of the case-based information a decision-maker would store and recall. It was apparent that no database of historical metrology applications existed within Airbus; a database of historical decision information was required. To develop this, the case structure of previous cases defined in Table 6.14 (Chapter 6) was used.

Firstly, a review of all metrology system applications across the business was required. In total, 51 cases were identified. A data collection activity was conducted to collect all information of implemented technologies. Engineers involved in the projects assisted in the acquisition activity. The template page is shown in Figure 8.1.

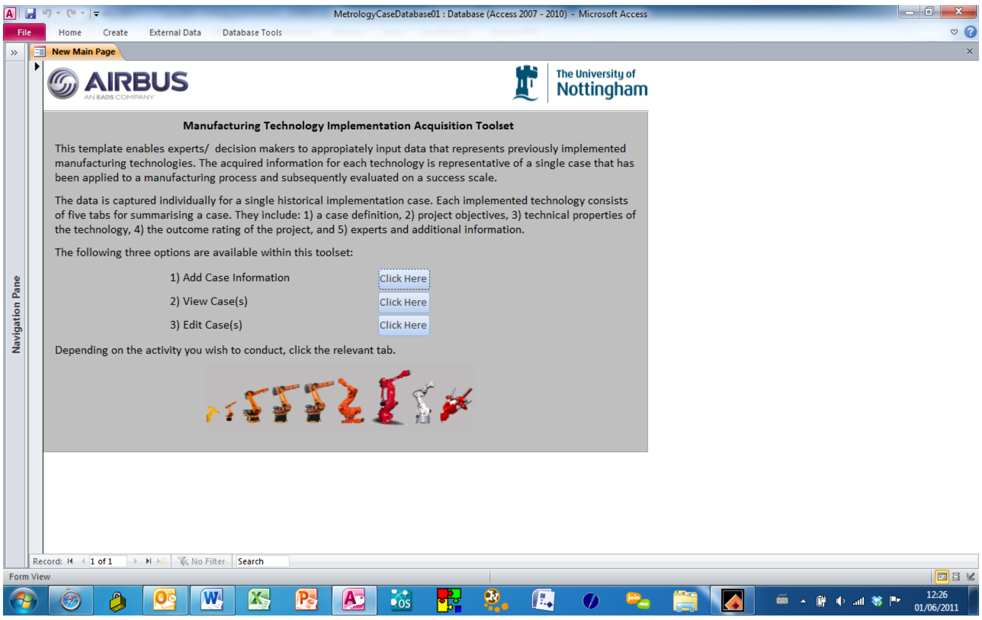

Figure 8.1 Case acquisition template – main page

It provides an overview of the purpose and how each technology case is represented. Three options are available to the user: add case information, view case(s) or edit case(s). The user will initially add case information that will guide them to the main technology case acquisition page. The additional options allow the user to view the cases already in the database or make amendments to existing decision cases.

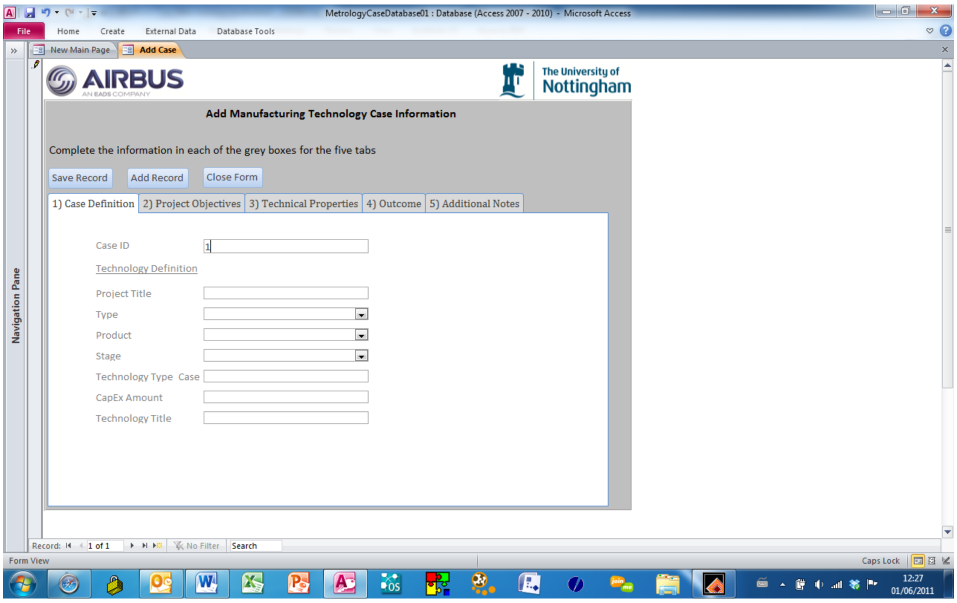

Figure 8.2 Case acquisition template – add technology information

The user is presented with the view in Figure 8.2. The five options that form the page are: case definition, project objectives, technical properties, outcome and additional notes. The definition has been based on the conclusions of Chapter 6 for defining the case information of a historical technology case. In addition, Airbus had asked that case definition and additional notes were added. Although they were not required for the model, the information was captured to ensure amendments to each case were conducted appropriately and could be used to further understand case information. It was worthwhile to collect this information at the same time the project and technical parameters were collated.

Once the definitive information of the project is specified, the parameters related to the project objectives were defined (Figure 8.3). Using a series of drop-box lists, the available options were presented to the user as shown in Figure 8.4.

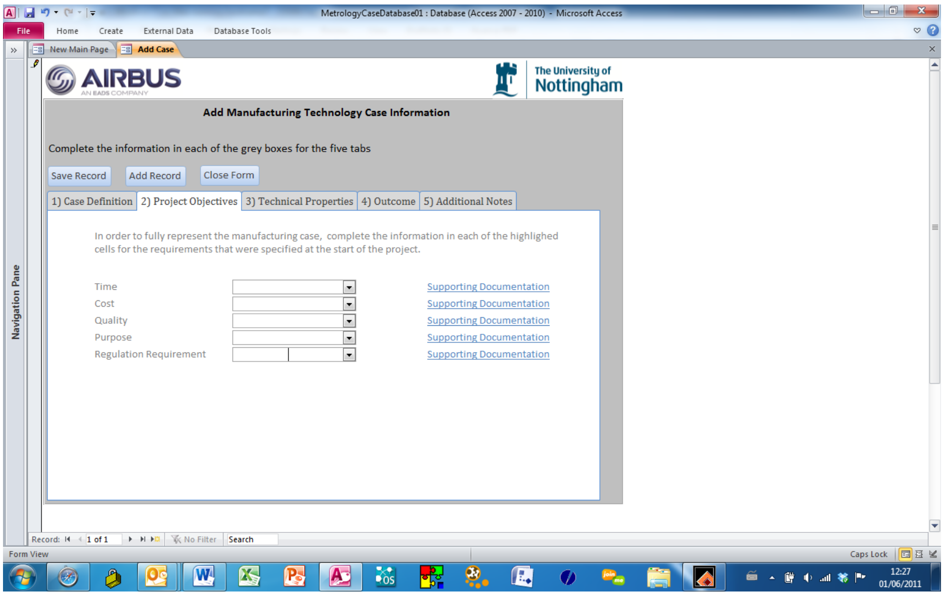

Figure 8.3 Case acquisition template – project objectives

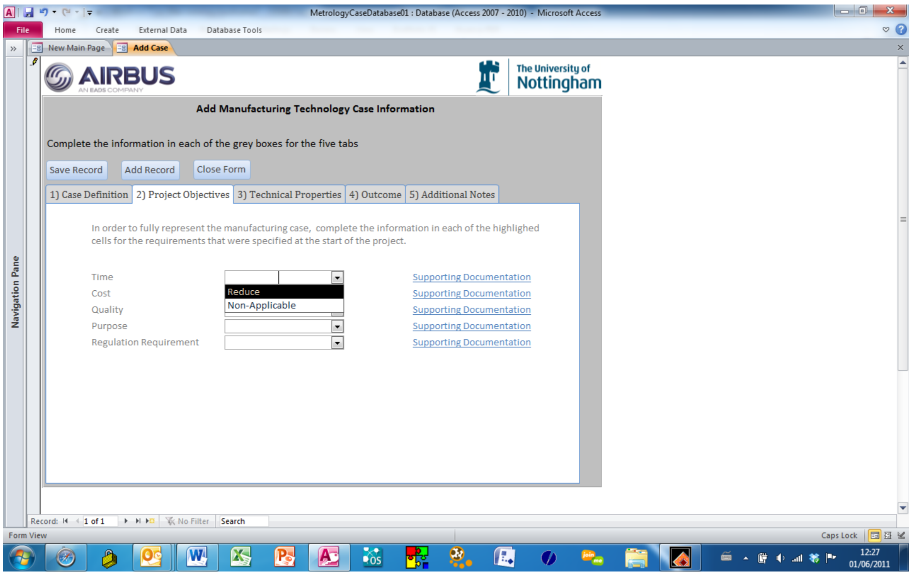

Figure 8.4 Case acquisition template – project objectives (2)

Once the project objectives were specified, the technology attribute information is required (Figure 8.5). The parameters consist of both linguistically defined options and numerical values. To provide assistance to the decision maker, guidance notes were also provided (see example in Figure 8.6).

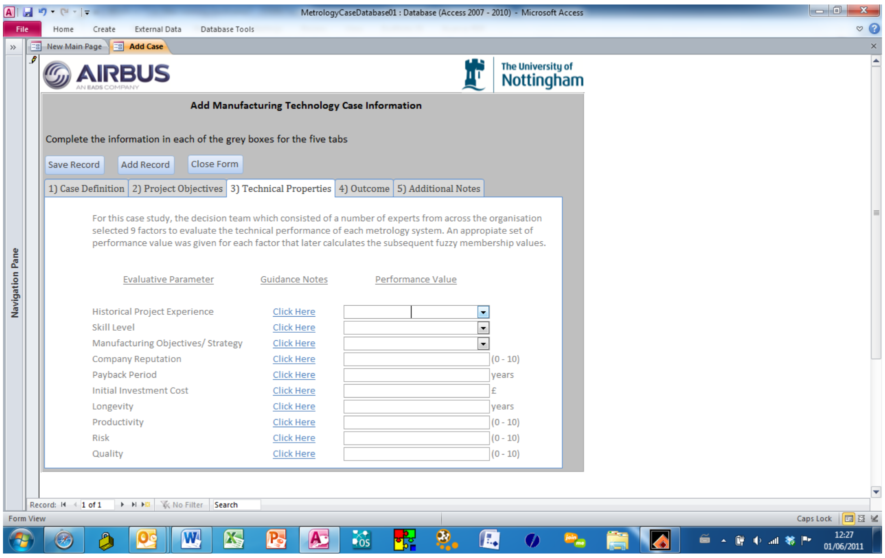

Figure 8.5 Case acquisition template – technical properties

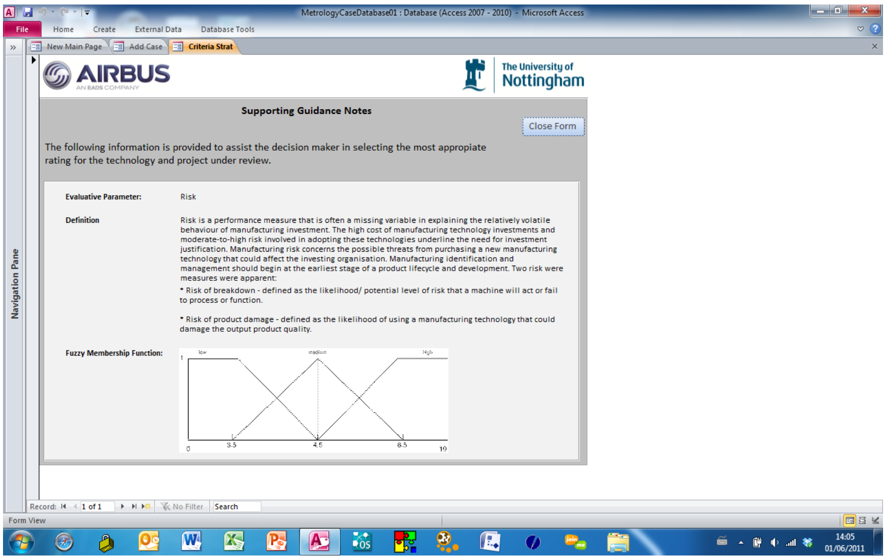

Figure 8.6 Case acquisition template – supporting guidance notes (risk)

Each provides a definition of the parameter to support the decision maker in appropriately choosing a definitive value. Upon the technical properties being specified, the project outcome page is completed using the guidelines from Section 7.4.2. A value is chosen to represent the technology project as shown in Figure 8.7. The weighted scale is explained.

During this case study, due to the difficult of acquiring the information of past historical decision cases, the performance of a project was given as a single crisp value. Unlike the proposal in the Chapter 7 which discusses how multiple persons can select a value between 0–4 and an average is calculated, in this example three linguistic values (unsuccessful, neutral, successful) were adopted and use the peak of the fuzzy membership function of 1 to represent the project outcome. This ensured that projects where personnel was not available to give multiple values to calculate an average, a single value was agreed and given. The value represented in the end leafs for the linguistic values will therefore be either 0 or 1 (unless a case is divided between branches), with a value of 1 representing a single project outcome term.

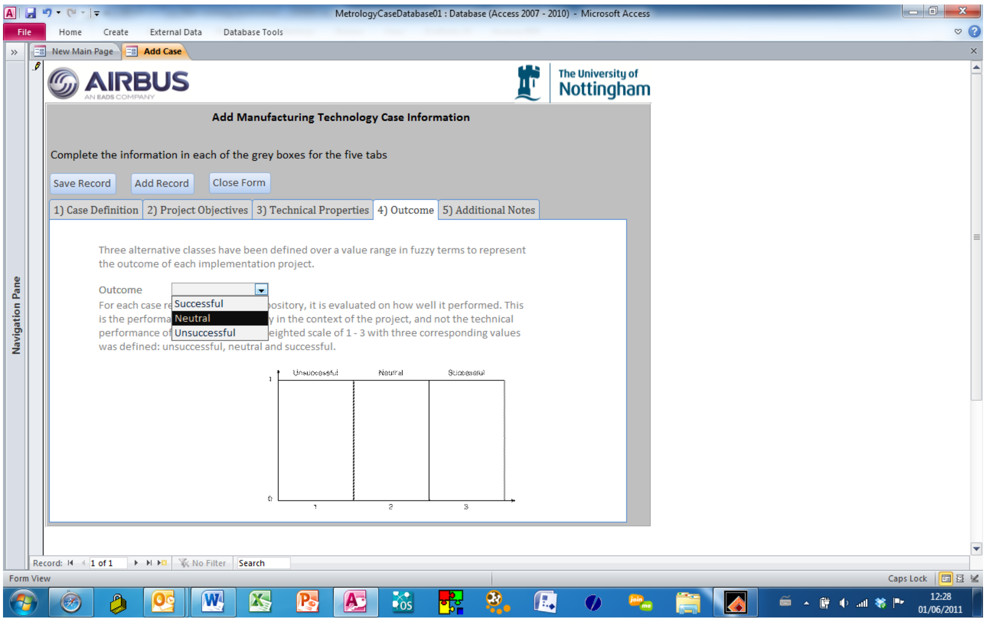

Figure 8.7 Case acquisition template – outcome

The final step of the acquisition process was developed to document supplementary information related to the project (Figure 8.8). Although the proposed decision model did not require it, it was worthy of collate the information during the acquisition process. Information of the experts involved in the technology project, free text notes for decision makers/experts to complete and an option to add documents were each included. Many employees noted how they were often aware of previous technology projects but did not know the persons involved in the activity and the search often took a large amount of their time. Therefore, the option was added and direct queries to the person(s) could easily be conducted. Adding supporting documentation such as CapEx documents, test results and communication with the supplier can also be supported. Further screenshots of the Microsoft Access template can be found within Appendix A4.

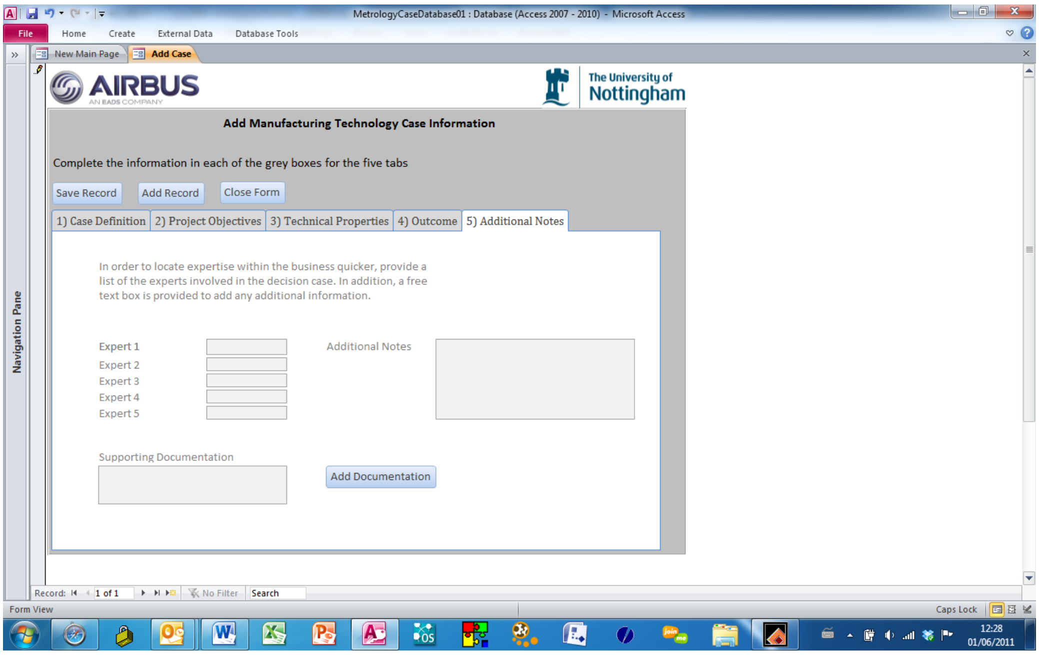

Figure 8.8 Case acquisition template – additional notes

Upon the template being developed and a list of metrology applications identified, a database of 51 historical technology implementation cases were concluded. The decision cases were for a variety of metrology applications within Airbus comparable as a potential technology for the original decision problem. Once the software was established and the relevant persons from the projects identified, the database was concluded. All case information is shown in Table 8.2.

It was apparent the variety of cases with different project comes. In total, 27 cases were identified as being successful, representing 52.9% of the database. 12 were concluded as neutral, which is defined as the case being not successful but neither unsuccessful. An additional 12 cases were unsuccessful as deemed by the decision team members.

The initial investment cost of the technologies ranged from £25,000 to £250,000. The average value within the database was £133,039 and the median £125,000. It was also apparent that only one case was implemented because of a regulation requirement, whilst the purpose of most cases was due to a new product being introduced.

Case Definition	Project Requirements					Technology Technical Attributes										
Case ID	Time	Cost	Quality	Purpose	Regulation Requirement	Historical Project Experience	Skill Level	Manufacturing Objectives/ Strategy	Company Reputation	Payback Period (years)	Initial Investment Cost	Longevity (years)	Productivity	Risk	Quality	**Project Outcome**
1	Reduce	Reduce	Improve	Replacement	No	Good prior involvement	Skilled	In-line with objective	6	2	£115,000	15	4	6	8	Unsuccessful
2	Reduce	Reduce	Improve	Replacement	No	Good prior involvement	Skilled	In-line with objective	6	1	£185,000	15	7	3	9	Successful
3	Reduce	Reduce	Improve	Replacement	No	Good prior involvement	Skilled	In-line with objective	6	1	£150,000	15	7	3	9	Successful
4	Reduce	Reduce	Non-Applicable	Capacity	No	Good prior involvement	Skilled	In-line with objective	6	1.5	£75,000	15	8	5	8	Successful
5	Reduce	Reduce	Non-Applicable	Capacity	No	Good prior involvement	Skilled	In-line with objective	6	1.5	£75,000	15	8	3	8	Successful
6	Reduce	Reduce	Non-Applicable	Capacity	No	Good prior involvement	Skilled	In-line with objective	6	1.5	£75,000	15	8	3	8	Successful
7	Reduce	Reduce	Non-Applicable	New Product	No	Good prior involvement	Skilled	In-line with objective	8	2	£150,000	20	9	2	8	Successful
8	Non-Applicable	Reduce	Non-Applicable	New Product	No	Good prior involvement	Skilled	In-line with objective	8	2	£100,000	20	8	3	7	Successful
9	Reduce	Reduce	Improve	Modification	Yes	No previous dealings	Semi-Skilled	Partial	5	5	£250,000	10	5	8	5	Unsuccessful
10	Reduce	Non-Applicable	Non-Applicable	New Product	No	Good prior involvement	Skilled	Partial	8	2.5	£150,000	15	8	2	9	Successful
11	Reduce	Non-Applicable	Non-Applicable	New Product	No	Good prior involvement	Skilled	Partial	8	2	£150,000	15	8	2	9	Successful
12	Reduce	Non-Applicable	Non-Applicable	New Product	No	Good prior involvement	Skilled	Partial	8	2	£150,000	15	8	2	9	Successful
13	Reduce	Non-Applicable	Non-Applicable	New Product	No	Good prior involvement	Skilled	Partial	7	3	£150,000	10	6	5	7	Neutral
14	Non-Applicable	Non-Applicable	Improve	New Product	No	Good prior involvement	Skilled	In-line with objective	8	2	£100,000	15	7	3	8	Successful
15	Non-Applicable	Non-Applicable	Improve	New Product	No	Good prior involvement	Skilled	In-line with objective	8	2	£100,000	15	7	3	8	Successful
16	Non-Applicable	Non-Applicable	Improve	New Product	No	Good prior involvement	Skilled	In-line with objective	8	2	£100,000	15	7	3	8	Successful
17	Non-Applicable	Non-Applicable	Improve	New Product	No	Good prior involvement	Skilled	In-line with objective	8	2	£100,000	15	9	3	8	Successful
18	Non-Applicable	Non-Applicable	Improve	New Product	No	Good prior involvement	Skilled	In-line with objective	8	2	£100,000	15	6	3	8	Successful
19	Non-Applicable	Non-Applicable	Improve	New Product	No	Good prior involvement	Skilled	In-line with objective	8	2	£100,000	15	6	3	8	Successful
20	Non-Applicable	Non-Applicable	Improve	New Product	No	Good prior involvement	Skilled	In-line with objective	8	2.5	£100,000	15	8	3	8	Successful
21	Reduce	Reduce	Improve	Productivity	No	Good prior involvement	Semi-Skilled	Partial	7	1.5	£60,000	20	8	1	8	Successful
22	Non-Applicable	Non-Applicable	Improve	Replacement	No	No previous dealings	Unskilled	Non-related	5	1	£50,000	10	3	5	2	Neutral
23	Reduce	Reduce	Non-Applicable	Replacement	No	No previous dealings	Semi-Skilled	Partial	8	2	£125,000	10	5	5	6	Neutral
24	Reduce	Non-Applicable	Non-Applicable	New Product	No	Good prior involvement	Skilled	In-line with objective	8	2	£150,000	15	8	4	8	Neutral
25	Reduce	Reduce	Non-Applicable	New Product	No	No previous dealings	Semi-Skilled	Partial	6	1	£25,000	10	7	1	6	Successful
26	Reduce	Reduce	Non-Applicable	New Product	No	No previous dealings	Semi-Skilled	Partial	6	1	£25,000	15	7	1	6	Successful
27	Non-Applicable	Non-Applicable	Non-Applicable	Replacement	No	Good prior involvement	Skilled	In-line with objective	8	1.5	£125,000	15	8	3	8	Successful
28	Non-Applicable	Non-Applicable	Non-Applicable	New Product	No	Good prior involvement	Skilled	In-line with objective	8	2	£125,000	15	9	3	9	Successful
29	Reduce	Reduce	Non-Applicable	Productivity	No	Good prior involvement	Skilled	In-line with objective	8	1.5	£100,000	15	9	3	8	Neutral
30	Non-Applicable	Reduce	Non-Applicable	New Product	No	Good prior involvement	Skilled	In-line with objective	8	3	£125,000	20	6	4	4	Unsuccessful
31	Reduce	Non-Applicable	Non-Applicable	Replacement	No	Good prior involvement	Skilled	In-line with objective	8	2.5	£125,000	15	8	3	8	Successful
32	Non-Applicable	Non-Applicable	Improve	Capacity	No	Good prior involvement	Skilled	In-line with objective	8	2.5	£125,000	15	7	1	8	Successful
33	Reduce	Non-Applicable	Improve	Productivity	No	Good prior involvement	Skilled	Partial	8	2	£150,000	15	8	3	6	Unsuccessful
34	Non-Applicable	Non-Applicable	Improve	New Product	No	No previous dealings	Skilled	Partial	6	3.5	£150,000	10	7	1	7	Successful
35	Non-Applicable	Non-Applicable	Improve	New Product	No	No previous dealings	Skilled	Partial	6	3	£125,000	10	7	4	5	Neutral
36	Non-Applicable	Non-Applicable	Improve	New Product	No	No previous dealings	Skilled	Partial	6	3	£125,000	10	7	4	5	Neutral
37	Reduce	Reduce	Non-Applicable	Replacement	No	Good prior involvement	Skilled	In-line with objective	7	3	£250,000	15	7	3	9	Successful
38	Non-Applicable	Non-Applicable	Improve	New Product	No	Good prior involvement	Skilled	In-line with objective	7	4	£250,000	15	4	4	7	Neutral
39	Reduce	Reduce	Improve	New Product	No	No previous dealings	Semi-Skilled	Partial	7	3.5	£125,000	15	7	5	6	Successful
40	Reduce	Reduce	Improve	Replacement	No	Good prior involvement	Skilled	In-line with objective	8	2	£125,000	15	6	4	7	Unsuccessful
41	Reduce	Reduce	Improve	Replacement	No	No previous dealings	Semi-Skilled	Non-related	6	5	£250,000	25	3	10	10	Unsuccessful
42	Reduce	Reduce	Non-Applicable	New Product	No	No previous dealings	Semi-Skilled	Non-related	6	5	£250,000	25	7	10	10	Neutral
43	Reduce	Reduce	Improve	Replacement	No	No previous dealings	Skilled	Partial	7	3	£125,000	15	7	7	8	Unsuccessful
44	Reduce	Reduce	Improve	Replacement	No	Good prior involvement	Skilled	In-line with objective	8	5	£250,000	15	6	6	7	Unsuccessful
45	Reduce	Reduce	Improve	Replacement	No	Good prior involvement	Skilled	In-line with objective	8	3	£150,000	15	6	6	7	Unsuccessful
46	Reduce	Reduce	Improve	Replacement	No	Good prior involvement	Skilled	In-line with objective	8	3	£150,000	15	5	6	8	Unsuccessful
47	Reduce	Reduce	Improve	Replacement	No	Good prior involvement	Skilled	In-line with objective	8	3	£150,000	15	5	6	8	Unsuccessful
48	Reduce	Reduce	Non-Applicable	New Product	No	Good prior involvement	Skilled	In-line with objective	6	3	£150,000	20	7	4	8	Neutral
49	Reduce	Reduce	Non-Applicable	New Product	No	No previous dealings	Skilled	Partial	7	3	£125,000	15	7	7	9	Neutral
50	Reduce	Reduce	Improve	Replacement	No	Good prior involvement	Skilled	In-line with objective	8	3.5	£125,000	10	8	6	6	Neutral
51	Reduce	Reduce	Improve	Replacement	No	Good prior involvement	Skilled	Partial	8	3.5	£125,000	20	8	4	6	Unsuccessful

Table 8.2 Database of previous metrology applications within Airbus

8.2.4 Stage 3 - Decision Variables

The decision variables used in the classification of the problem and historical decision cases were concluded as part of the study in Chapter 6. Sets of both crisp (discretization) and fuzzy variables were included from the literature and discussion with experts from within Airbus. The characterisation of each variable was conducted in Chapter 6 alongside the case study to solve this problem.

8.2.5 Stage 4 - Tree Builder and Fuzzy Decision Tree

The first stage of the tree builder is to numerically characterise the values in the dataset as either a fuzzy or discretization form. This is dependent upon the variables. The five project objective variables are each classed in nominal terms whilst the technical performance attributes consist of three nominal and seven fuzzy parameters. The decision case repository is numerically defined and can be found within Appendix A4. To demonstrate for case ID 1, Table 8.3 has numerically characterised each parameter.

The corresponding numerical values for each fuzzy membership function concluded in Chapter 6 were used to generate the values, shown as membership function (MF) in Table 8.3. In order to generate a FDT from the dataset, equations 7.3 – 7.7 are used.

Firstly, the information *(D)* of the complete dataset is calculated using equation 7.4. It is based on the alternative number of classed samples in the dataset (outcome results). During this case study, successful = 27, neutral = 12 and unsuccessful = 12. The calculation is shown in the equation below.

$$I(27\ successful, 12\ neutral, 12\ unsuccessful) = -\frac{27}{51}\log_2\frac{27}{51} - \frac{12}{51}\log_2\frac{12}{51} - \frac{12}{51}\log_2\frac{12}{51} = 1.468$$

Next, the information gain for each individual attribute is calculated. The attribute receiving the highest information gain is deemed as the most influential and placed at the top of the tree. Due to the computation required to calculate the information gain of each attribute, the algorithm was implemented in Microsoft Excel to assist in the calculation.

The values for each information gain attribute were subsequently calculated and the highest receiving attribute is underlined:

Time = 0.0802, cost = 0.1290, quality = 0.1296, purpose = 0.3294, regulation requirement = 0.0419, historical project experience = 0.0724, skill level = 0.0429, manufacturing objective/ strategy = 0.0908, company

reputation = 0.0140, payback period = 0.1760, initial investment cost = 0.0710, longevity = 0.0785, productivity = 0.2150, risk = 0.4200 and quality = 0.1162.

Case ID		1
Technology Type:		Metrology
Objectives		
Time		Reduce time = 1, non-applicable = 0
Cost		Reduce cost = 1, non-applicable = 0
Quality		Improve quality = 1, non-applicable = 0
Purpose		Productivity = 0, capacity = 0, replacement = 1, modification = 0, new product = 0
Regulation requirement		Yes = 0, No = 1
Technical Performance		
Historical project experience		Good prior involvement = 1, no previous dealings =0, disappointing prior experience = 0
Skill level		Unskilled =0, semi-skilled = 0, skilled = 1
Manufacturing objectives/ strategy		Non-related = 0, partial = 0, in-line with objective = 1
Company reputation	6	(MF) Poorly regarded = 0, good = 0.5, well regarded = 0.5
Payback period	2 years	(MF) Low = 0, medium = 0.75, high = 0.25
Initial investment cost	£115,000	(MF) Low = 0, medium = 0.76, high = 0.24
Longevity	15 years	(MF) Short = 0, average = 0.33, long = 0.67
Productivity	4	(MF) Low = 1, medium = 0, high = 0
Risk	6	(MF) Low = 0, medium = 0.25, high = 0.75
Quality	8	(MF) Low = 0, medium = 0, high = 1
Overall project performance		Unsuccessful

Table 8.3 Case example ID1

Using the decision tree building rules specified in the previous section, the first stage of the tree was subsequently built. Due to many attributes defined as fuzzy membership functions and the likelihood of attributes having an equal value across two sets, the outcome of the decision case is applied to both branches appropriately weighted by half the original weight. The first stage in the tree build is shown in Figure 8.9. The IDs and cases divided by two branches are shown. The purpose of this is not to replicate a decision case twice within the end leaf but divide them accordingly as the tree and attributes split.

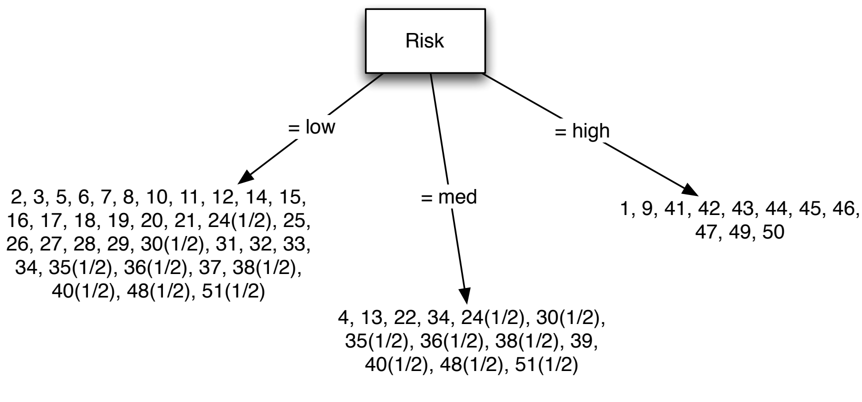

Figure 8.9 Leading attribute sub-fuzzy decision tree

Using the algorithm set up in Microsoft Excel, the FDT was generated. A total case threshold level was defined to generate a decision tree according to the size of the database. Initially a value of 15% was specified which stopped when an end leaf reached less than 8 cases. This was found to produce a small tree of only 15 rules. When considering the size of the database of 51 cases and number of attributes available (15), a larger size tree would produce a better output. Tests were conducted with a threshold of 10% and 5%, which produced trees with 23 and 28 rules respectively. When considering the size of the database, a threshold value of 5% was specified. The selection of this threshold is discussed further within the results analysis in Section 8.3.1 and alternative size trees are shown within Appendix A4.

The decision tree is defined based on a number of attributes required to appropriately divide the dataset. The end leafs represent the project outcomes of alternative cases from the original repository. All cases are included in the tree and some end nodes contain more than 1 case. This is dependent upon the pruning rules specified in Section 7.4.4. Figure 8.10 demonstrates the built decision tree with each end leaf represented as the case IDs. For cases that are divided between two branches, their weighting is appropriately divided.

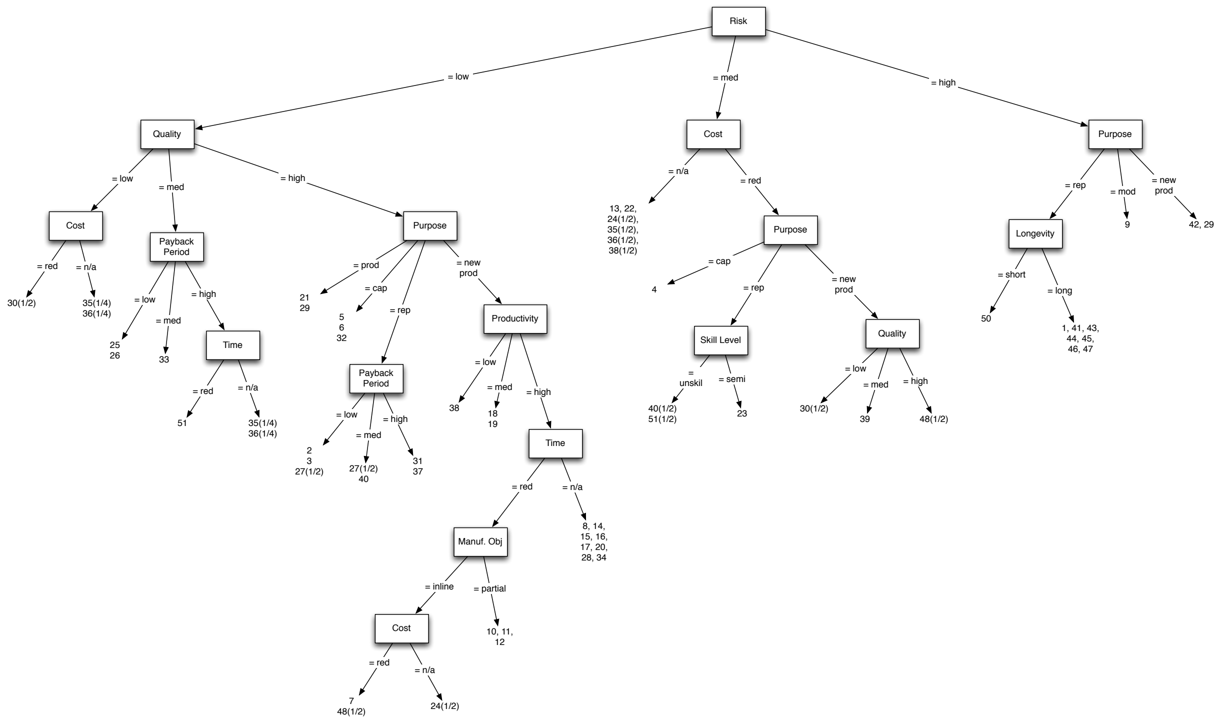

Figure 8.10 Generated decision tree with case ID end leafs

For example, case ID 30 received a fuzzy membership score of 0.5 for both the low and medium values of the risk attribute. As more than two values are the highest membership values, the case is split between the two branches. Its weighting is appropriately divided by two in the final end leaf. The final decision tree with the average FMV {unsuccessful, neutral, successful} is shown in Figure 8.11.

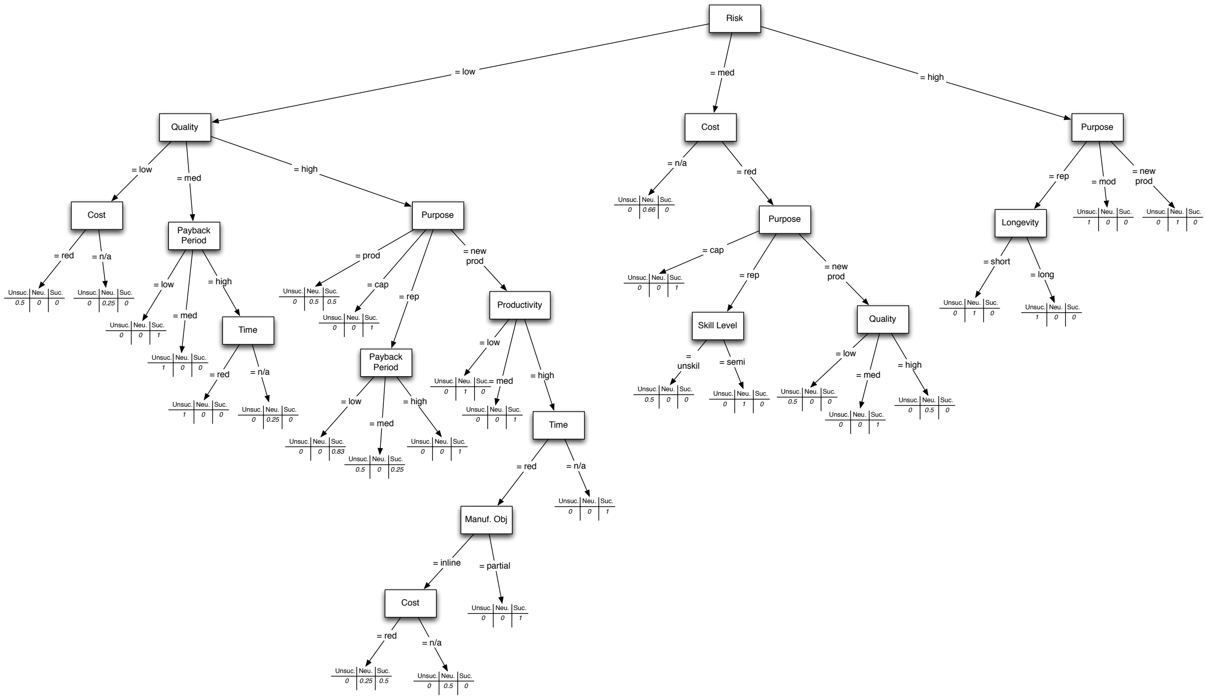

Figure 8.11 Generated decision tree with representative fuzzy end leafs

To discuss further, by reviewing the 10th end leaf from the left, the following rule can be extracted:

IF risk = low, AND quality = high, AND purpose = replacement, AND payback period = medium, THEN "unsuccessful = 0.5, neutral = 0, successful = 0.25"

The rule defines that a sample which meets each attribute value will have a probability of being unsuccessful by 0.5, neutral 0 and successful as 0.25.

8.2.6 Stage 5 - Inference (classification)

Upon the decision tree being built, the following stage is to conduct the inference of each technology within the new case. The inference is conducted initially using Equation 7.9.

To demonstrate, option A from Table 8.1 is applied to the generated decision tree using the fuzzified values of attributes in Appendix A3. The tree is redrawn with the corresponding project objective and technical numerical values placed at each branch, as highlighted in Figure 8.12. The values defined in the end leaf are multiplied by the multiplication of the values calculated prior in the branches. For any branch that contains zero, the values in the end leaf will always be zero. For option A, the end leafs which have all branches greater than zero only appear twice. These are shown as dashed branches within Figure 8.12. To demonstrate for the following rule:

IF risk = low, AND quality = high, AND purpose = replacement, AND payback period = medium, THEN unsuccessful = 0.5, neutral = 0, successful = 0.25

For option A, risk = low is valued at 1, quality = high is valued at 1, purpose = replacement is valued at 1 and payback period = medium is valued at 0.75, therefore "$A_1 \times A_2$,.. A_n" is calculated for each branch as: 1 x 1 x 1 x 0.75 = 0.75

Subsequently, 0.75 is multiplied by each of the unsuccessful, neutral and successful membership functions that represent that end leaf. The 10th end leaf is therefore numerically valued as: Unsuccessful = 0.75 x 0.5 = 0.375, Neutral = 0.75 x 0 = 0 and Successful = 0.75 x 0.25 = 0.1875

To demonstrate for the second end leaf where all branches leading to the end leaf are greater than zero, the 11th branch from the left is as follows:

IF risk = low, AND quality = high, AND purpose = replacement, AND payback period = high, THEN unsuccessful = 0, neutral = 0, successful = 1

For option A, risk = low scored 1, quality = high 1, purpose = replacement 1 and payback period = medium 0.25, therefore: 1 x 1 x 1 x 0.25 = 0.25. Subsequently, 0.25 is multiplied by each of the unsuccessful, neutral and successful membership values that represent that end leaf. The 11th end leaf is therefore numerically scored as: Unsuccessful = 0.25 x 0 = 0, Neutral = 0.25 x 0 = 0 and Successful = 0.25 x 1 = 0.25

The decision tree with option A is applied as shown in Figure 8.13 and the result of the final inference stage for option A calculated: Unsuccessful = 0.375 + 0 = 0.375, Neutral = 0 + 0 = 0 and Successful = 0.1875 + 0.25 = 0.4375

The remaining technologies were applied to the tree and inference calculations were as follows (Table 8.4). This concludes the inference. Appendix A4 shows option B - E applied to the decision tree.

	Fuzzy Membership Values		
Technology	**Unsuccessful**	**Neutral**	**Successful**
Option A	0.375	0	0.4375
Option B	0.75	0	0.25
Option C	0.125	0	0.8125
Option D	0.75	0	0.25
Option E	0	0	0.83

Table 8.4 Technology fuzzy membership values

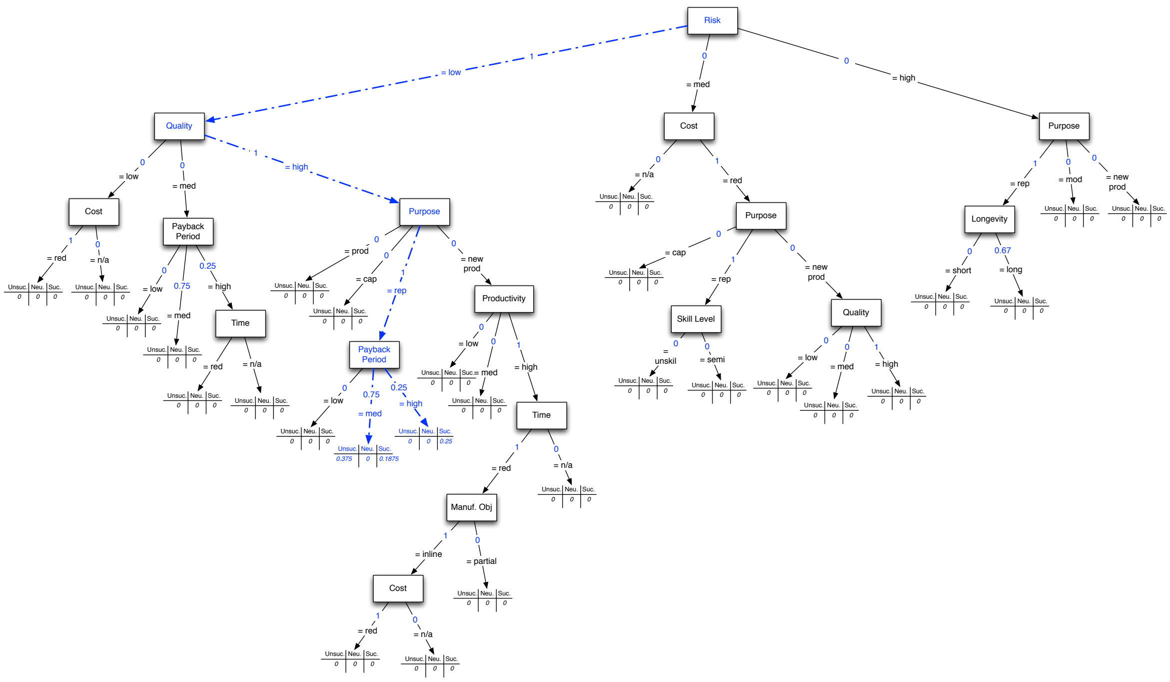

Figure 8.12 Option A applied to decision tree

8.2.7 Stage 6 - Ranking and Technology Selection

To rank each technology, a confidence score is calculated for each technology using Equation 7.10. Each is calculated as follows and ranked within Table 8.5.

Option A (Y) = (0.375 x 1) + (0 x 2) + (0.4375 x 3) = 1.6875

Option B (Y) = (0.75 x 1) + (0 x 2) + (0.25 x 3) = 1.5

Option C (Y) = (0.125 x 1) + (0 x 2) + (0.8125 x 3) = 2.5625

Option D (Y) = (0.75 x 1) + (0 x 2) + (0.25 x 3) = 1.5

Option E (Y) = (0 x 1) + (0 x 2) + (0.83 x 3) = 2.49

Rank	Technology	*Y* Factor	Normalised %
1	Option C	2.5625	26.31%
2	Option E	2.49	25.56%
3	Option A	1.6875	17.33%
4	Option B	1.5	15.40%
4	Option D	1.5	15.40%

Table 8.5 Ranking of technologies

Option C received the highest and was ranked 1st. Option E was also highly ranked in 2nd place. Both technologies performed well compared to option A, B and D when using past decision cases to determine which technology would most likely be successful for the project objectives. From an initial review of the results, option C would be selected whilst option E considered further. It is unlikely that the remaining three technologies would be selected as they performed low compared.

To further investigate and confirm the most appropriate technology, a sensitivity analysis was conducted. This is presented and discussed within Section 8.3.1.

8.2.8 Stage 7 - Solved and Learned Case

The final stage of the decision model requires the purchase and implementation of option C. Upon the case study being conducted, Airbus concluded that the same technology was also chosen during the initial analysis but had not yet been purchased. Due to the short time constraints of this research project and vision of the research group focusing on technology implementation for future aircraft, it was unlikely that the technology would be purchased in the short term. However, if the technology had been purchased and implemented, the project would be evaluated using the suggested scale as described in Section 7.4.2 and the case stored within the repository. Subsequently, the repository would contain an additional case and be included in the analysis of any future projects.

8.3 Verification and Validation

This section is presented two sub-sections. First, the verification of the decision model is discussed followed by the validation of calculated results by industrial experts. Verification deals with the process of evaluating a behavior model to determine whether the products of a given phase satisfy the condition imposed at the start of that phase. Validation deals with the process of evaluating a system or component during or at the end of the development process to determine whether it satisfies specified requirements. It is concerned with ensuring that the model meets the requirements of the customer.

8.3.1 Verification

The verification of fuzzy decision models can be conducted in multiple forms. It is concerned with the analysis of the underlying processes of constructing the fuzzy model to ensure they follow logical analysis principles. The proposed methodology described in Chapter 7 is the application of the FDT algorithm developed by Umanol et al. (1994), therefore the verification is concerned with the application of the algorithm to the described problem.

Three verification techniques were conducted:

1) Performance accuracy
2) Measurement adjustment for a single decision parameter (sensitivity analysis)
3) Pruning of the decision tree

The performance-based accuracy method analyses the performance of the model as a measure to the degree of measurements of a quantity to that of the actual value. This is the accuracy to which the output of a known decision case is the same as the output from the decision tree. The second verification method is the measurement through the adjustment of a single decision parameter to understand how the uncertainty in the output of the model can be apportioned to the different sources of uncertainty in its inputs. This is the ability to accurately predict the same decisions for slight changes in the performance measures of a technology. The third verification method is pruning of the decision tree. The aim is to reduce the size of the tree without compromising the classifying instances, thus forming a better predictive accuracy. This approach is typically used for large data sets where the number of attributes and cases is vast. Whilst the number of cases within the case study is small, we test alternative thresholds to further understand the impact pruning has on the output result.

In the first verification method, all 51 cases were individually applied to the original output decision tree. The approach was to use each known case and compare the calculated output by the decision tree with the known conclusion of the decision case. All 51 cases which comprised 22 successful, 16 neutral and 13 unsuccessful cases were analysed (Table 8.6). It was found that 100% of the successful cases were accuracy recognised. This was lower for neutral cases at 81.3% and higher for unsuccessful cases at 92.3%.

Case Outcome	# Cases	# Cases Correctly Scored	# Cases Incorrectly Scored	Accuracy
Successful	22	22	0	100.0%
Neutral	16	13	3	81.3%
Unsuccessful	13	12	1	92.3%
Overall	**51**	**47**	**4**	**91.2%**

Table 8.6 Performance accuracy of model

The accuracy results demonstrate the high level of performance achieved by the decision model. Although they also reiterate the difficulty of ranking a technology case as neutral. The judgement by an expert was reported within Chapter 6 to be difficult for cases which were deemed neither successful nor unsuccessful. This definitive boundary between the two performance measures was apparent during the development of membership functions in Section 6.5.2. The resultant low accuracy for neutral cases was likely contributed by the fuzzy membership function where the core upper boundary of the function ($y=1$) is narrower than the successful and unsuccessful performance measures. It is therefore less likely that a performance where a technology is ranked as neutral achieves the maximum score of 1 for the fuzzy membership functions. The lack of definitive boundaries leads the outcome towards successful or unsuccessful measures.

To further investigate and confirm the most appropriate technology, a sensitivity analysis was conducted. For this applied case study, the technical attributes of the technology which contained fuzzy attributes were altered. Five performance measures were selected based on their influence on the decision tree. For each factor, the measurement performance was adjusted +1 increment or -1 increment as shown in Table 8.7. The alternation in performance measure for each factor enables a simulation of the sensitivity analysis to be conducted. This output accounts for misjudgments in evaluation.

Factor	Adjustment
Quality	+ 1 *increment*
Initial Investment Cost	-£25,000
Risk	+ 1 *increment*
Productivity	- 1 *increment*
Payback Period	+ 1 year

Table 8.7 Measurement adjustment

The analysis was conducted to alter the selected technical values for all technologies. The change for a single performance measure was conducted and the technology rating by the decision tree re-evaluated. The results of each sensitivity analysis are shown in Table 8.8.

	Original Ranking		Quality (-1)		Investment Cost (-£25,000)		Risk (+1)		Productivity (-1)		Payback Period (+1 year)	
	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score
Option A	3	1.6875	3	1.51525	3	1.6875	3	1.6875	3	1.6875	1	3
Option B	4	1.5	4	0.75	4	1.5	4	1.5	4	1.5	4	1.4
Option C	1	2.5625	2	2.5625	1	2.5625	2	2.28125	1	2.5626	1	3
Option D	4	1.5	4	0.75	5	1.3906	4	1.5	4	1.5	4	1.5
Option E	2	2.49	1	2.6175	2	2.49	1	2.49	2	2.49	3	2.125

Table 8.8 Measurement adjustment

The results are further illustrated in Table 8.9 to demonstrate the change in technology ranking for the alterations in performance measure values.

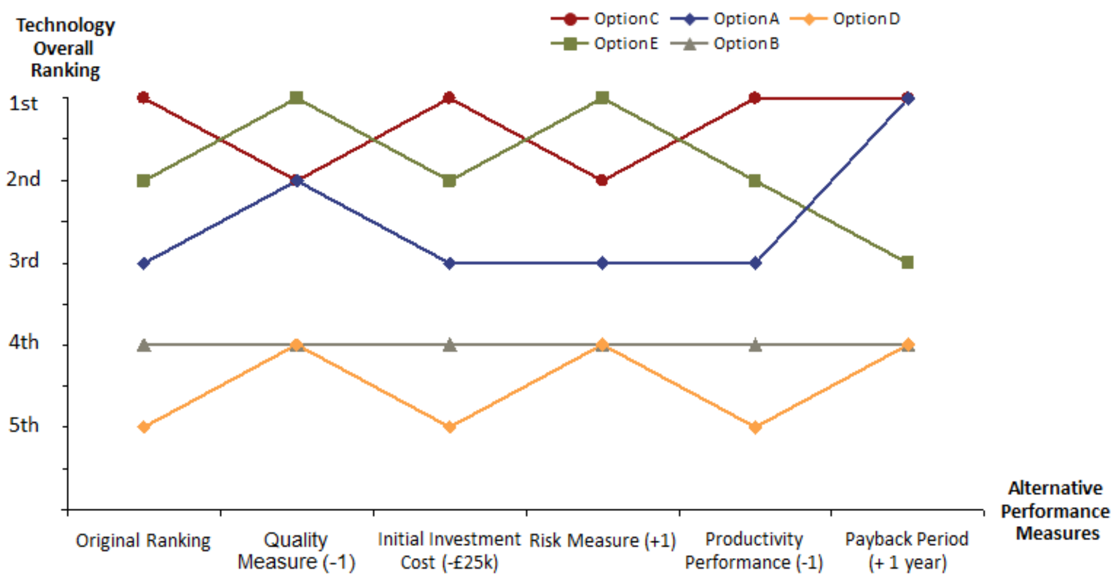

Table 8.9 Sensitivity change per technology for performance measures

It is apparent that Option B remained the most stable throughout the analysis by retaining 4th position within the ranking for all five changes in performance measures. Option E and Option A were the most unstable. However, they did remain ranked between 1st and 3rd place. Option C performed well achieving 1st ranking for 4 out of 6 instances. Upon further analysis, Option E achieved a rating score between 2.125 - 2.49 for all six evaluations. This range of 0.365 was the lowest alteration. The highest change appeared for Option A which was 1.6875 – 3. Option A was the most unstable technology together with Option E, however, Option E's rating score between 2.125 – 2.61was the least range at 0.49.

Overall, the sensitivity analysis demonstrated the stability of the decision algorithm. The performance of each technology for slight changes in measures of each decision factor is promising. The inference algorithm was found to be robust considering the limited number of rules which were fired. The performance would typically decrease for a lower number of rules within a decision tree. During most instances, only a single or two rules were fired which lead to many options receiving the same score.

The final verification method of the model is analysed by pruning the tree. The overall size of the tree can be reduced further by reducing the nodes that provide minor support in further classifying cases. The approach requires a confidence threshold to be specified. Due to the limited number of cases a threshold of 5% was originally specified within Section 8.2.6. However, the goal of pruning is to reduce the complexity of the final classifier as a better predictive accuracy of over fitting. The number of samples in the end node is specified based on a percentage of the number of cases available. A threshold is selected to partition those classes into several groups. To determine if a higher threshold value should be selected, a decision tree was created for a 10% and 15% decision tree.

In order to evaluate the alternative decision tree threshold values, the most suitable tree that provides the highest degree in output confidence is based on the ranking distance between the highest and lowest technology score. A higher confidence level is based on the larger separation of the technology ranking. Technology scores that are similar or closely ranked are difficult to evaluate and provide a low degree of confidence.

Decision trees were created for 10% and 15% thresholds (see appendix A4). The tree builder and inference was reapplied as described within Chapter 7 and the results of each technology show in Table 8.10 and 8.11. For the 10% threshold, options C and E were both highly ranked. Option B and D received identical scores and ranked higher in 3rd place compared with the 15% analysis. The 10% threshold decision tree created 23 rules, 5 less than the 5% threshold; 3 less attributes appeared in the tree. Many of the fired rules were the same as the 5% threshold.

Rank	Technology	*Y*
1	Option C	2.5625
2	Option E	2.49
3	Option B	2.3625
3	Option D	2.3625
4	Option A	1.6875

Table 8.10 10% threshold

Rank	Technology	*Y*
1	Option A	2.573
1	Option C	2.573
1	Option E	2.573
4	Option B	1.69775
4	Option D	1.69775

Table 8.11 15% threshold

Upon reviewing the results from the 15% analysis, option A, C and E each received the same score of 2.573, option B and D both scored identical at 1.69775. It is therefore difficult to make an appropriate judgement of the most suitable technology. The same score and range between the highest and lowest ranked technology were calculated for 10% and 15% thresholds at 0.875. Upon reviewing the original ranking, the range between the highest and lowest performance score was higher at 1.06. Therefore, it is apparent that the 5% threshold is most appropriate as the classification of each technology is sufficient for a decision to be made. In addition, the separation between the higher ranked technologies was more apparent.

To summarise, the three verification methods have demonstrated the ability of the FDT algorithm and inference mechanism to perform well and adapt in times of uncertainty. The FDT algorithm was originally developed for evaluating large data sets but has shown its ability to evaluate a manufacturing technology selection case base and provided sufficient analysis based on past cases to support unknown decision problems.

Whilst a numerical analysis is one form of validation, the following section describes the validation of the decision methodology within a practical environment by industrial experts.

8.3.2 Model Applicability

This sub-section discusses the feedback obtained from the conducted case study pertaining to the application of the developed methodology. A 5-point likert scale was used to assess the degree to which potential users are satisfied with the overall model and framework. A series of open-ended questions were included to further elaborate the opinion of the industrialists. Each participant was notified that the focus of the evaluation was on the overall approach and technique to manufacturing technology selection as a new form of solving the complex problem. The prototype of acquiring the case information for the decision was also introduced.

To assess the methodology, the three criteria proposed by Platts (1990) were adopted: feasibility, usability and utility. Feasibility asks if the methodology could be followed, usability refers to how easily it could be followed, and utility relates to the output. In the case of identifying a manufacturing technology acquisition process, a high utility would suggest the output be useful by experts in the acquisition of a manufacturing technology (Baines and Darlow, 2000).

The following questionnaire (Table 8.12) was developed to assess the applicability of the model. The questionnaire contained 18 questions using the 3 criteria of applicability: feasibility, usability and utility. Industrialists within Airbus took part in the study of evaluating the framework and model. Some participants had been involved in the original application of the previously described case study, whilst the remaining participants had a good knowledge of the technology selection practices. To validate the approach, the methodology was introduced and illustrated. Numerous validation sessions were held and 7 persons involved in the study. The job positions of the participants varied, they included a senior manager within the research department, a number of research engineers and personnel within the quality control. Each had good knowledge of the technology selection practices and investment process.

Assessment Criteria	1	2	3	4	5
1. Feasibility					
1.1 The input requirements is representative of the information used in the decision process					
1.2 The structure and use of historical cases is representative of how a decision maker would learn from a historical case					
1.3 The time taken to use the model was appropriate					
1.4 The required participation level is appropriate for the decision process					
2. Usability					
2.1 The objective and purpose of using the decision model was clearly defined					
2.2 The required input information of the model was understandable					
2.3 The stages of the decision process were clear and well defined					
2.4 The stages of the model were easy to follow					
2.5 All required participants were able to use the model					
2.6 The expected output of the model was appropriate for the type of problem					
3. Utility					
3.1 The structure of the case information and key technical performance indicators were relevant to be considered for the technology selection process					
3.2 Representing the criteria as fuzzy membership sets was relevant to the problem					
3.3 The output of the model was useful for supporting the evaluation and selection of an optimal manufacturing technology					
3.4 The technology selection model facilitated current practices and was worthwhile					
3.5 The output of the model provided confidence to the decision makers/ participants					
4. Suggestions					
4.1 Strengths of the model					
4.2 Weaknesses of the model					
4.3 Areas for improvement					

1 = strongly disagree, 2 = disagree, 3 = neutral, 4 = agree, 5 = strongly agree

Table 8.12 Assessment questionnaire

The results of feasibility, usability and utility are shown in Figure 8.13 and discussed as follows. The question numbers along the *x*-axis related to the question number in Figure 8.13 and the ranking on the *y*-axis relates to the average answer given by each industrialist. During each session, the participants were asked to select a value on the scale provided (1 = strongly disagree, 5 = strongly agree) related to the question. The sessions were open and informal where the strengths and weaknesses of the model were discussed. The researcher recorded all conversations.

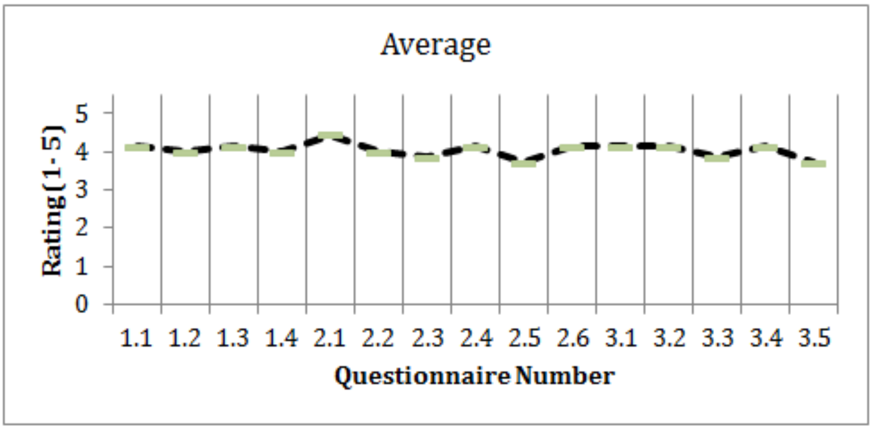

Figure 8.13 Average assessment results from industrialists

Overall, the opinions of experts were that they agreed the model was representative of the decision practices and logic to which an expert would make a decision. The responses given by each participated related to feasibility; usability and utility are now discussed in further detail.

Feasibility

In terms of feasibility, four questions were asked related to the structure of the information within the model and how capable the methodology would be in a practical environment. The answers ranged between *agree* and *strongly agree* and an average of 4.07 out of 5 was recorded. Overall, the participant's felt that the structure and use of historical decision cases and information required to use the model reflected well the decision practices. Several participants felt that it provided a level of structure and logic to their thought. They felt it represented the unconscious recalling of cases when conducting the technology selection process. Many were also impressed with the time taken to use the model. They felt that not having to determine weights for attributes and by providing the exact measurement values (e.g. initial investment cost) for the quantitative attributes, the model was easy to use as they could input the technical performance information of a potential investment.

Each participant agreed that the level of input by each were acceptable and open to the idea of the model being used by a number of personnel within a project. They felt the process provided a good level of coherence and transparency that appears to lack in existing decision approaches. They felt the information helps to overcome the bias in current technology selection due to the openness surrounding the use of the model by multiple participants.

Usability

In terms of usability, 6 questions were asked which related to how easy the model would be to use in practice and how the interpretation of the data would be representative of the output expected to support the investment in a particular technology. The average score given by the usability questions of the 7 participants were slightly lower than feasibility at 4.05. Upon further analysis, question 2.3 and 2.5 received the lowest average score of 3.86 and 3.71 respectively. Comments related to these questions were that each stage of the decision process was not completely clear. Concern was raised about the level of involvement during the tree building and inference application. The participants suggested that some level of involvement should be allowed in order for the knowledge and patterns to be recognised by each decision maker. Questions were raised if all required participants were able to use the model. During the validation study, only half of the participants were familiar with fuzzy logic and those that were not, felt appropriate information be included.

The model was rated well for questions 2.1 and 2.4. Many participants felt that the purpose of using the model was easy to understand and well defined. It was clear how the case-based information would be used to support the selection process and how the relationship of information supports the inference calculation. Feedback from the case acquisition toolset was that the stages are easy to follow and a similar interface for inputting a new problem case would be most appropriate.

Utility

The utility questions of the model received a similar score to the two previous categories and an average score of 4 out of 5 was given. Overall, the participants agreed with each of the questions within the questionnaire. The utility questions related to how relevant and useful the model were. Much discussion was conducted on how representing certain criteria were relevant to the problem. As some persons were unfamiliar with fuzzy logic, the theory was explained. Upon an appropriate explanation, most agreed that the theory appeared to well represent the logic of a decision maker. Discussions included the different opinions of a high and low investment cost. The lack of defined boundary between multiple subjective opinions was found to be apparent during both validation discussions. The structure of the case information and key performance indicators included in each case were agreed to well represent the problem. Defining the level of success was also found to be appropriate and many noted on the appropriateness of using ‘unsuccessful, neutral, successful’ compared to using a scale bar such as 1–10 for defining a project success value. Comments were made about how the output figures were single values and that a decision would have to be made solely on the numerical value, although multiple participants noted how this type of output was similar to a weighted matrix approach. Many commented that the developed model would be better as it eliminated the biased that can be included in weighted toolsets that exist today, whilst giving a single value indication of the best solution.

Overall, each participant believed the model facilitated current practices as it provided a more objective and improved approach to the problem. Many believed it worthwhile to capture historical case information and the ease at which the decision tree is created to be extremely beneficial by creating new, previously unknown knowledge.

Strengths of the model

The main noted strengths of the model were that it helps to overcome the bias that exists in current decision practices. Many experts agreed that they often had a particular bias towards a technology to which they were familiar. This is turn influences their view on certain technologies and can subsequently lead to optimal technologies being disregarded. In addition, the philosophy of capturing decision information without losing knowledge is often lost as people move organisations. A number of participants noted that capturing the information of failed cases was attractive. Employees often ignore failed cases, as they were embarrassed about the failure of a previous investment case. The approach was found to have much potential and support complex decision-making practices. The criteria selected in the model were found to be valid and representative of the problem.

Some participants noted how the use of a single database for a business would be extremely beneficial for organisations that are based across multiple sites. Often decisions are made within similar areas and this type of case-based approach and sharing of structured information worthy to collate.

Weaknesses of the model

Although the algorithm generates the output decision tree automatically, comments suggested that this automation of information may reduce the confidence a decision maker has in the model. During the initial validation, some participants were sceptical about the use of a data-mining algorithm but upon further clarification, each tended to support the use of the approach for when a large database exists. In order for the model to remain accurate, it would have to be constantly updated to reflect any project changes. Although such changes may be minor or not needed, two participants mentioned that personnel might forget to update project information. As such, they suggested the implementation of the model would have to be integrated into the mind-set of industrial decision-makers.

In addition, it must also be noted that in order to use the decision-making tool it requires decisions to have already been made. The information of previous decisions would be collated and used to support future decision problems. The decision model is not a standalone toolset such as AHP but is reliant upon accurate information of past cases. Consideration for the cost and resource of accumulating such information prior to gaining any benefit from the tool needs to be considered. The tool however is well suited to the environment discussed within this chapter where technology decisions are regularly being conducted.

Areas of improvement

Overall, two main areas for improvement were identified. Firstly, it was suggested that some later validation stages of inputting the data would be required. A decision from the model could be based on how a new problem is input or how historical cases have been included; validation by an expert should be considered. Secondly, several participants noted that in practice, a large dataset would be needed and the possibility of making the model more generic for wider portfolio assessment is worthy of investigation.

8.4 Chapter Summary

This chapter described the proposed technology selection toolset applied to an industrial decision case problem within Airbus. It provided an understanding of the mechanisms involved related to the problem domain. The initial sections focused on the intended system architecture that would assist in the development of a prototype model. In addition, the requirement of the user and their interaction with the toolset was described.

The empirical study used 51 decision cases to rank 5 metrology technologies. The initial ranking provided a sound foundation of two appropriate technologies that were similar, although one was rated slightly higher. Upon further analysis, a single optimal technology became apparent. The validation conducted in Section 8.4 firstly justified the stability of the model before focusing on validation from industrial experts. The majority of persons involved in the study favoured the model and some recommendations were made. Overall, all participants felt that the model was an improvement on current practices and that the use of historical case-based information be better than relying solely on an expert. Many believed the justification process to be easier based on known past information.

Chapter 9

Conclusions

In this chapter, the conclusion of the research presented is discussed. This research led to the development of a systematic framework to support decision-making that takes all critical aspects of the process into consideration. A key challenge for the development of such framework were that current practices are based on people's subjective opinion and possibly limited by the collection of past cases. Whilst the developed methodology consists of the experience of experts, the collation of such cases in a single framework has not been developed. Industrial managers make manufacturing investment decisions using their judgement acquired from their involvement in past cases. They consider a complex set of tangible and intangible elements against a set of project objectives. Therefore, this research attempts to make the approach more objective and rational. This research fills the gap in the existing body of literature by exploring how the mining of case-based information can be used to assist technology selection based on a form of classification. An initial study of industrial practices led to an investigation to understand in detail, the technology selection process with particular focus on the structure and characterisation of case-based experience recalled by an expert. This assisted in the development of an experience-based approach through data-mining that uses case information for supporting new decision problems. The methodology focuses on the key relationships among the dataset by identifying patterns of previously implemented technology performance information against the original project requirements. The concluded outcome of each project assists in optimally-selecting the most appropriate technology whilst reducing the overall risk.

9.1 Summary of Research Findings

The initial findings from this research were an investigation of the nature and support of data, information and knowledge within the manufacturing technology selection process. The method was driven by data and information, and directed by the knowledge of an expert. Yet, the type of information and use of such knowledge was not defined. The transformation of information throughout the decision process was apparent and the development of expertise was defined through past technology information. The investigation highlighted the lack of structured inter-enterprise communication and how the transfer of information was not appropriately conducted. Within the process, three definitive supporting categories were identified: 1) content information is prepared at the start of the project for defining the problem and potential technology, 2) the support for evaluation and selection is based on the information available to define the project and guided by the knowledge of the expert within the process to form a decision, and 3) a series of post implementation learning is conducted in the form of expertise that a human expert would capture.

The research led to defining key decision variables for representing historical manufacturing technology implementation cases. Expertise is developed based on the involvement of historical decision-making cases. An expert would recall previous implementation cases they have been involved in and relate key attributes and the performance of the project with a new problem. Chapter 6 set out to define an appropriate structure and set of variables for defining the logic of representing a historical decision case. A series of variables were defined in three categories: the objectives of the project, the technical performance of the selected technology, and a defined level of project success. The form of representing experience was subsequently defined. The results from the study were able to quantify both tangible and intangible attributes in the decision process. A form of developing fuzzy membership functions suited to the problem was also defined and demonstrated.

By incorporating the literature and empirical findings from the survey and focus group, a manufacturing technology selection framework using the FDT data-mining approach was employed. Through information-based historical decision cases, the relationship between different information items stored in a case repository assisted in the classification of new decision problems. The approach is an iteration in which new decision cases are captured and re-used to support future decision problems. The learning approach is constant and generic attributes enable the information to be applied to numerous decision problems. The approach is similar to how an expert would develop expertise through the experience of previous implementation projects. The merging of multiple parts of information in a tree form is simple to understand by a decision maker whilst being highly knowledgeable. The suitability of a manufacturing technology for a new project is subsequently defined from a repository of decision cases. The validation proved good feasibility, usability and utility of the methodology. The sensitivity analysis demonstrated the overall stability of the algorithm.

9.2 Contribution to Knowledge

This research contributes to the field of manufacturing technology management in which most existing literature has focused on multi-criteria and knowledge-based techniques. The research explores how the experience acquired by an expert can be defined in a case-based format of technology implementation. The ability of a data-mining algorithm to identify decision patterns in a technology selection dataset of collaborated experience has shown some promising results. Each knowledge contribution is defined as follows:

The first reported use of fuzzy-decision tree mining for technology selection

- The model replicates the logic of multiple decision experts in a single methodology, reducing the subjective influence
- Development and application of data mining model for technology selection
- Use of structured decision case information to create a knowledge sharing platform through the analysis of relationship information of historical cases

A novel decision-making methodology for manufacturing technology selection was developed that acquires structured information of historical decision cases to form a knowledge sharing platform for evaluating technology investment projects. The approach considers representative decision cases of the information recalled by an expert in existing practices. A tree-like knowledge representation presents analytical patterns and relationships through previous technology selections against a set of project objectives. The relationship of selected technologies and project requirements provides support for new decision problems based on the success/failure of previous implemented solutions. The methodology merges the expertise of multiple cases to reduce the subjective influence in the decision process.

The developed model advances the current literature by exploring the knowledge defined from the analysis of case-based information. An iterative approach ensures the acquisition of cases support new technology selection problems. The model captures the learning of decision cases in a similar format to which an expert would develop expertise. The model reduces the influence of expert bias by providing an objective methodology of acquiring the technical performance information of alternative manufacturing technologies. The approach reduces individual personal influence and nominally supports future technology recommendations.

In-depth study characterising decision cases that support and represent the knowledge development of an expert

- Historical decision cases appropriately defined through structure and decision variables

- Method of analytically representing tangible and intangible decision attribute for technology selection

The research defined an arrangement that represented the structure of past technology projects recalled by an expert to make new decisions. The study identified the original project objectives, performance attributes of selected technology and success/failure of a project; three phases by which previous decision cases are recalled.

The study defined the factors that represented each of the stages. Five alternative project objectives were defined and a measure for each shown. The review identified 27 decision parameters and through a further analysis the factors redefined through ten technology performance attributes. Factors were represented in nominal terms and their values defined. Criteria with ranging values and no clear boundary were represented in a fuzzy format. The inductive reasoning approach developed the appropriate membership functions through industrial experts.

The study advanced the current literature through the representation of previous manufacturing technology decisions. Information recalled by a decision expert and evaluation for experience-based decision-making was demonstrated. A form of acquiring structure decision case information was concluded for completion by experts and non-experts.

New insight into technology selection in practice and transfer of information and knowledge to support the decision problem

- Decision cycle incorporates vast amounts of information and knowledge through each phase
- Shift from financial-based methodology to risk analysis provides inefficient evaluation

The industrial manufacturing study provided a further and more accurate understanding of the practical approaches to technology selection in industry. Financial-based evaluation tools are well known in technology selection during the initial consideration stages. The study found that although such toolsets are still in use today, the industry is directed towards reducing risk in new technology investment projects as an important evaluation factor. Technology assessments tend to ask questions such as 'what needs careful attention' rather than 'how much will this cost' and 'what is the financial return period'. There is a need to reduce the risk of potential technologies founded on the previous experiences of an expert. Evaluations are conducted by comparing the overall level of risk of multiple technologies before a selection is made. Multiple persons are involved in the evaluation and the process is driven largely by the experience of the decision maker. Depending upon an expert's level of skill, alternative concentrations of attention are conducted. Previous unsuccessful technology projects were found to have great influence on the evaluation of new technologies. Past cases are analysed in detail; the information is rarely shared. Decision makers are aware of past decisions they have been involved in and consider this in new potential solutions.

A further understanding was derived of the information and knowledge that supports the technology selection process. A lack of inter-enterprise communication within organisations was reported during the early stages of the selection process. The dependence on knowledge support by an expert was reported to guide the lack of structured information considered during the technology evaluation phase. Similarly, this was directed by the previous decision knowledge of an expert. An expert supports their decision based on previous engagements and recalls case information in an irrational manner.

In addition, the following secondary contributions have been achieved:

- A comprehensive analysis of the developed decision support tool, based on an industrial case study has been undertaken
- A prototype software application for acquiring historical manufacturing technology decision case information

9.3 Areas of Application

The results from this study are expected to be applicable to a wide range of industrial applications for technology selection. Although the proposed model and methodology has been designed with influence from the practices within the aerospace assembly domain, it will be widely applicable to similar manufacturing technology problems. The key benefit of the approach to technology selection is that multiple decisions are merged in a more objective form than a sole expert and transformed into a classification model. The framework is expected to be particularly applicable to a multitude of manufacturing environments where there is a specific need for selecting an optimal manufacturing technology usually conducted by experts.

While the influence of the sponsoring organisation may be apparent, the approach of using case-based decision information to generate new knowledge and patterns can be applied to other manufacturing industries. Automotive companies constantly consider new, state-of-the-art systems to reduce the overall cost of manufacture. In addition, defence and pharmaceutical manufacturers are aware of maintaining competitive advantage by investing in new equipment. Therefore, the developed approach can be applicable to industries where the selection of a manufacturing technology is required.

9.4 Limitations and Future Work

It is apparent that the reported research has provided a significant step forward to the development of a decision methodology that accurately represents the experience and expertise of human decision makers. The outcome of the research also outlined a series of limitations.

Feedback received from industrial experts highlighted the need to increase their familiarity with the decision model before it received their full support. Potential users expressed their confidence in the system would only become apparent once they were familiar with the classification of information and justification of the decision. They expressed that once this was proven; they would begin to trust the methodology. Some industrialists expressed their scepticism with the case information as their familiarity with such data prior was non-existent. It appeared that to gain the trust of users, they would also have to gain the trust of their colleagues providing accurate information.

Upon reflection of the decision methodology compared with multi-attribute methodology such as QFD, FMEA and AHP, it is apparent that the developed model is not a single, standalone toolset which can be used to support various decisions independently. The ability of QFD to be used haphazardly with little preparation of information is an advantage where decisions are made less regularly. The implementation of the tool developed as part of this research is expected to support decisions across multiple units of a business.

The experience-based technique detailed within Chapter 7 is reliant upon historical case information within the repository to formulate a justification of new decision problems. The methodology is limited by the case information available and as such the benefits gained are likely to be achieved much later. Decisions would be unable to be made immediately upon implementation. The lack of availability of developed software for such a methodology is also apparent. The state-of-the-art study within Chapter 2 highlighted the existing lack of decision support system, particularly within the area of manufacturing technology selection. Whilst the decision tool developed within this thesis was partly modelled in Microsoft Excel, a fully programmed software model would be required for implementation within a manufacturing organisation.

It is expected that the information accumulation for manufacturing technology support will develop over time. Exponentially increasing as further decision opportunities are sought and organisations invest in new, state-of-the-art systems. The resource and time required to capture such information can be intensive and organisations must challenge this to make current data accessible in the future. It would be difficult to convince senior stakeholders to invest in such an approach when benefits will only be gained in the long term.

In addition to the above limitations being recognised, the following future work opportunities were identified:

Investigation of a multi classification approach

The classification approach proposed for the developed model provides a final ranking of each technology as a single unit. The confidence factor is based on previous cases using the multitude of attributes within the decision tree. A single score is provided as an output for defining the most optimal solution. However, the described structure of multiple classes of evaluation attributes could be further extended to the ranking of potential manufacturing technologies. It would therefore be worthy to investigate a multi score system that evaluates technologies based on multiple decision trees for a variety of attributes. For example, numerous rankings could be concluded for all technologies based on cost, technical performance, strategy, *etc*. Each technology would be ranked against multi-attributes through an individually built tree. This would potentially allow for further attributes to be considered in the selection process and a more detailed representation of the suitability to be concluded.

Ability to include weighted criteria within the decision tree classification model

During current technology selection practices, the subjective influence by experts was apparent and weighting towards certain criteria justified for a project. Each parameter considered within the decision tree builder and classification is defined as equal. Therefore, it would be worthy to investigate how a weighing could be applied to different attributes for a decision case and the affect it has on the outcome of the model. Developing a weighted-attribute tree or inclusion within the classification approach may improve the accuracy to the practices of an expert whilst maintaining an objective approach.

Further case studies and long-term deployment

The evaluation findings provided positive evidence of the suitability to the manufacturing technology selection problem. However, the findings can be further verified to understand the reported strengths through the long-term deployment of the decision model. Although the case study described in Chapter 8 showed positive feedback from industrialists, it would be worthy to understand how the decision tool performs and meets the requirements of decision makers during multiple model iterations. An advantage of the model is that it is able to iteratively generate objective information as new cases are acquired; the suitability and adoption of this by managers can further verify the findings. It would permit the feasibility and usability of the methodology in greater detail.

9.5 Concluding Remarks

This work began to achieve an improved methodological approach to the selection of manufacturing technologies. It became obvious that for such a methodological approach to succeed, it would have to be integrated within a manufacturing environment, easy to understand and appropriately justify the results. A crucial factor was to reduce the level of subjectivity in the process whilst representing the logic of an expert. The reported research has introduced an experience-based approach to technology selection that uses the structure of historical decision cases to support new technology classification. The benefits and concerns of technology investment are addressed by supporting the selection process based on previous manufacturing decisions.

This research has provided the future basis for supporting technology selection through a case-based structure that considers the performance of a technology within a project. The approach combines well the structure of technology evaluation and the information an expert would capture in the development of expertise.

While the developed framework is not claimed to be a complex industrial solution, it presents a significant step towards better representing the logic of a decision maker in manufacturing. It is not so mathematically difficult and complex that decision makers will have difficulty using them in practice. As the work was conducted in close collaboration with industry, it is likely that the research will be accepted and adopted by other manufacturing organisations and industries. However, the success of such an implementation will be largely based on the support offered by a company to implement the methodology into existing procedures.

The developments in the preceding twenty years have shown how the reliance on financial models alone is insufficient. This was apparent as multi-criteria approaches were slowly introduced. This advancing trend was still reliant upon direct expertise and input from industrial experts. The research reported within this thesis explores for the first time how experience-based information can be used to support future decision-making problems. This research is likely to define the starting position for experience-based manufacturing technology support algorithms.

In the future decade there will be an increased focus on acquiring knowledge-information through structured expert know-how. This will be between the boundaries of information and knowledge classification where the structure of information and unstructured knowledge is currently positioned. Data sets will rapidly grow and big data seen as the norm. Web 2.0 and semantic web technology will support web-based enterprises to create a dynamic knowledge sharing platform. Manufacturing organisations that recognise this value now and understand the long term benefits will be global leaders within their domain.

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Appendix – A1 Introduction Letter

Liam Evans
Faculty of Engineering
University of Nottingham
University Park
Nottingham
NG7 2RD
Email: epxle1@nottingham.ac.uk

[DATE]

[RECIPIENT]
[RECICIPENT'S COMPANY]
[RECICIPENT'S ADDRESS]

Manufacturing Technology Research Project

Dear [RECIPIENT]

In reference to our recent telephone conversation, I wish to formally introduce my PhD research project. I am currently conducting a study at various manufacturing organisations within Europe to understand the decision-making practices used in manufacturing technology selection. During the initial stage of the study, I am conducting several interviews with officials who are involved in the operations and manufacturing systems decision-making process. The aim of the study is to gain an overview and understanding of the process and key influential issues related to your organisations investment decision-making.

In order to carry out the study, I would require a maximum of 1 hour of your time to ask a number of pre-selected questions in a semi-structured interview format. I can assure anonymity and the information collected shall be treated strictly confidential. I am interested in your opinion and personal experience, and any tools and techniques that support methodologies used during the process.

Your participation in this study would be much appreciated and would be contributing to the research being conducted at the University of Nottingham. Your kind participation in this research will help to identify and document existing decision practices.

I look forward in hearing from you.

Yours sincerely,

Liam Evans
PhD Student

Appendix A2 – Questionnaire

Attendee Job Position .... Date ....

Section 1: Company Information
This section aims to gather general information about the company

Q1. Industrial Sector
....

Q2. Number of employees
0 – 250 ☐ 251-500 ☐ 500 – 1,000 ☐
1,001 – 2,500 ☐ 2,501 – 5,000 ☐ 5,001 – 10,000 ☐ 10,001+ ☐

Q3. Rate of manufacture
....

Q4. Company Turnover
....

Section 2: Automation / System Design
This section aims to determine the level of automation and system design process

Q5. What level of manufacturing automation is used at your company?
High ☐ Medium ☐ Low ☐

Q6. What type of automation is used at your company? (drilling, assembly etc...)
....
....

Q7. What are the main drivers for automation? Could you rank them in order of importance; 1 = high importance & 5 = low important.

Productivity ☐ Technological Strategy ☐ Growth Strategy ☐
Cost ☐ Health & Safety ☐ Flexibility ☐
Quality ☐ Competitive ☐ Other..............................

Q8. Has your company had to revert from an automated process to a manual one? Did an evaluation of both the automated and manual process take place?
....
....

Q9. Who is responsible for the design of your manufacturing system and do they follow a structured approach? How strong is the link between design and manufacture?
....
....
....
....

Q10. What are the most important factors considered during the design phase?
....
....
....

Section 3: Manufacturing Decision Making
This section aims to understand the manufacturing decision making process

Q11. What methods / techniques does your company use for the selection of a manufacturing system?
....
....
....

Q12. Who is involved in the manufacturing decision making process?
....
....
....
....

Q13. Do they use decision making tools / models such as AHP & decision trees?
....
....
....

Q14a. From the following, what is deemed the key criteria for automated manufacturing system selection?

Technical Ability ☐ Financial Measures ☐ Laws & Regulations ☐
Production Requirement ☐ Health & Safety ☐ Market Environment ☐
Company Vision ☐ Social Factors ☐ Other...................

Q14b. When selecting a manufacturing system, what criteria are used to evaluate them?
....
....

Q15. What type of financial justification models does your company use?

Project New Cash Flow ☐
Net Present Value (NPV) ☐
Internal Rate of Return (IRR) ☐
Return on Investment (ROI) ☐
Payback Period ☐
Total Cost ☐
Total Capital Cost ☐
Total Operation Cost ☐
Cost per Transaction ☐
Other....................................... ☐

Q17. Does your organisation incorporate any knowledge capture practices in the domain of manufacturing technology selection?
....
....
....
....

Q18. Do you believe your current decision making process to be satisfactory?
....
....
....

Q19. If a formalised decision making methodology which integrated strategic, financial and technical issues was developed, would you use it?
....
....

Appendix – A3 Developed Fuzzy Membership Functions

<u>Company Reputation</u>

To develop the membership function for the company reputation attribute, 5 experts were required to give their opinion of a random set of cost values between the defined ranges. Overall, 3 fuzzy regions were first defined as "poorly regarded", "good" and "well regarded". To develop these functions, each expert was asked to indicate a random number between 0 and 10 (with 0 representing poor and 10 well regarded). The results of the input are shown in Table A3.1(a-e).

Expert 1	
Value	**Category**
1	Poor
2	Poor
3	Poor
6	Well
7	Well
8	Well

Expert 2	
Value	**Category**
4	Poor
5	Poor
6	Poor
7	Well
9	Well
10	Well

Expert 3	
Value	**Category**
0	Poor
2	Poor
4	Well
6	Well
8	Well
10	Well

Expert 4	
Value	**Category**
0	Poor
2	Poor
5	Well
6	Well
7	Well
10	Well

Expert 5	
Value	**Category**
4	Poor
5	Poor
6	Poor
7	Poor
9	Well
10	Well

Table A3.1 a/b/c/d/e Expert opinion input for company reputation

Subsequently, the inductive reasoning approach described by Christensen (1980) was performed (as illustrated within Chapter 6) and fuzzy membership functions shown in Figure A3.1.

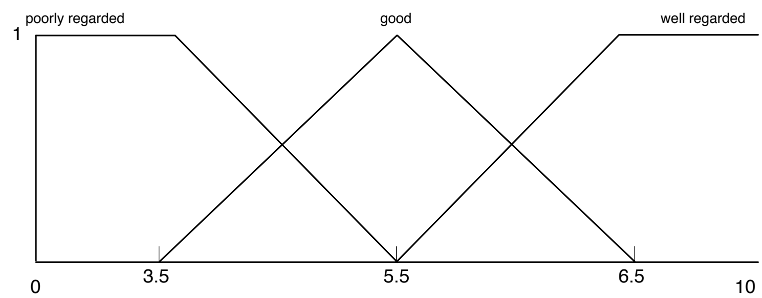

Figure A3.1 Company reputation fuzzy membership function

Payback Period

To develop the membership function for the payback period attribute, 5 experts were required to give their opinion of a random set of duration values between the defined ranges. Overall, 3 fuzzy regions were first defined as "low", "medium" and "high". To develop these functions, each expert was asked to indicate a random duration value between 0 and 5 years (with 0 representing low and 5 high). The results of the input are shown in Table A3.2(a-e).

Expert 1	
Value (yrs)	**Category**
0	Low
0.25	Low
0.5	Low
2	Low
3	High
5	High

Expert 2	
Value (yrs)	**Category**
0.5	Low
1	Low
1.5	Low
2.5	Low
4	High
5	High

Expert 3	
Value (yrs)	**Category**
1.5	High
2	High
2.5	High
3	High
3.5	High
4	High

Expert 4	
Value (yrs)	**Category**
0.5	Low
1	Low
1.5	Low
2	Low
2.5	Low
3	Low

Expert 5	
Value (yrs)	**Category**
0.25	Low
0.5	Low
1	Low
1.5	Low
2	High
2.5	High

Table A3.2 a/b/c/d/e Expert opinion input for payback period

Subsequently, the inductive reasoning approach described by Christensen (1980) was performed (as illustrated within Chapter 6) and fuzzy membership functions shown in Figure A3.2.

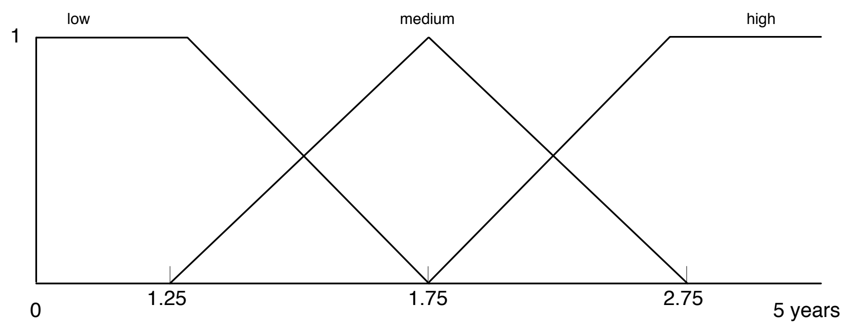

Figure A3.2 Payback period fuzzy membership function

Productivity

To develop the membership function for the productivity attribute, 5 experts were required to give their opinion of a random set of values between the defined ranges. Overall, 3 fuzzy regions were first defined as "low performance", "good" and "high efficiency". To develop these functions, each expert was asked to indicate a random number between 0 and 10 (with 0 representing low performance and 10 high efficiency). The results of the input are shown in Table A3.3(a-e).

Expert 1	
Value	**Category**
2	Low
4	Low
5	Low
6	High
9	High
10	High

Expert 2	
Value	**Category**
4	Low
5	High
6	High
7	High
9	High
10	High

Expert 3	
Value	**Category**
0	Low
2	Low
3	Low
4	Low
5	Low
6	Low

Expert 4	
Value	**Category**
3	Low
4	Low
5	Low
8	High
9	High
10	High

Expert 5	
Value	**Category**
1	Low
2	Low
6	Low
7	Low
9	High
10	High

Table A3.3 a/b/c/d/e Expert opinion input for company reputation

Subsequently, the inductive reasoning approach described by Christensen (1980) was performed (as illustrated within Chapter 6) and fuzzy membership functions shown in Figure A3.3.

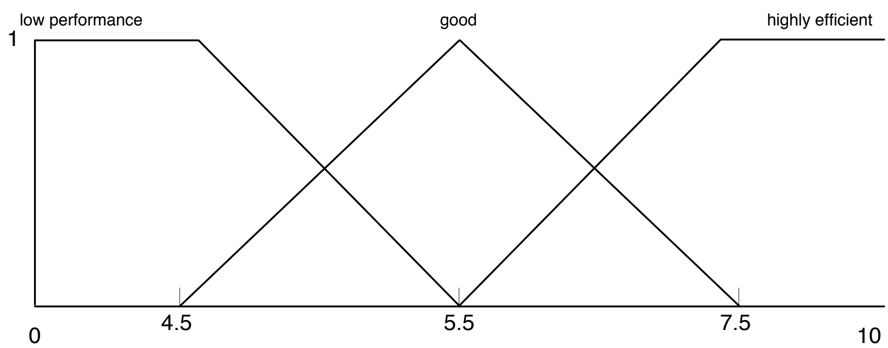

Figure A3.3 Productivity fuzzy membership function

Risk

To develop the membership function for the risk attribute, 5 experts were required to give their opinion of a random set of duration values between the defined ranges. Overall, 3 fuzzy regions were first defined as “low”, “medium” and “high”. To develop these functions, each expert was asked to indicate a random value between 0 and 10 (with 0 representing low and 10 high). The results of the input are shown in Table A3.4(a-e).

Expert 1	
Value	**Category**
0	Low
1	Low
3	Low
4	Low
6	High
7	High

Expert 2	
Value	**Category**
2	Low
3	Low
4	Low
5	Low
6	High
8	High

Expert 3	
Value	**Category**
4	Low
5	High
7	High
8	High
9	High
10	High

Expert 4	
Value	**Category**
1	Low
3	Low
5	High
7	High
8	High
9	High

Expert 5	
Value	**Category**
1	Low
2	Low
5	Low
6	Low
9	High
10	High

Table A3.4 a/b/c/d/e Expert opinion input for risk

Subsequently, the inductive reasoning approach described by Christensen (1980) was performed (as illustrated within Chapter 6) and fuzzy membership functions shown in Figure A3.4.

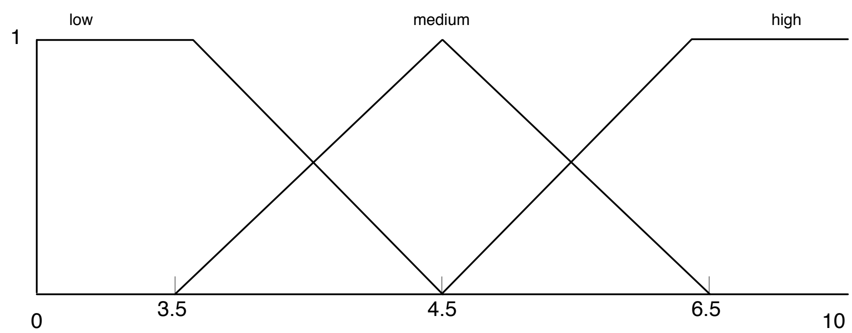

Figure A3.4 Risk fuzzy membership function

Quality

To develop the membership function for the quality attribute, 5 experts were required to give their opinion of a random set of duration values between the defined ranges. Overall, 3 fuzzy regions were first defined as "low", "medium" and "high". To develop these functions, each expert was asked to indicate a random value between 0 and 10 (with 0 representing low and 10 high). The results of the input are shown in Table A3.5(a-e).

Expert 1	
Value	**Category**
0	Low
1	Low
3	Low
4	Low
6	Low
7	High

Expert 2	
Value	**Category**
2	Low
3	Low
4	Low
5	Low
6	High
8	High

Expert 3	
Value	**Category**
4	Low
5	Low
7	Low
8	High
9	High
10	High

Expert 4	
Value	**Category**
1	Low
3	Low
5	Low
7	High
8	High
9	High

Expert 5	
Value	**Category**
1	Low
2	Low
5	Low
6	High
9	High
10	High

Table A3.5 a/b/c/d/e Expert opinion input for risk

Subsequently, the inductive reasoning approach described by Christensen (1980) was performed (as illustrated within Chapter 6) and fuzzy membership functions shown in Figure A3.5.

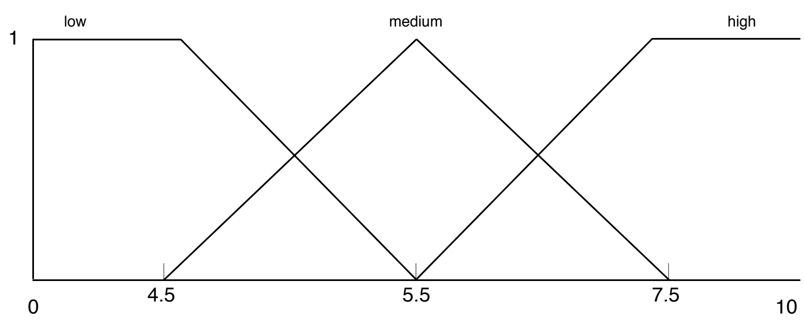

Figure A3.5 Quality fuzzy membership function

Longevity

To develop the membership function for the longevity attribute, 5 experts were required to give their opinion of a random set of duration values between the defined ranges. Overall, 3 fuzzy regions were first defined as “short”, “average” and “long”. Firstly, a number of experts were consulted on the typical longevity period of a technology. The product lifecycle would likely be 25 years and a range of 0 – 25 years was specified. To develop these functions, each expert was asked to indicate a random duration between 0 and 25 years (with 0 representing short and 25 long). The results of the input are shown in Table A3.6(a-e).

Expert 1	
Value (yrs)	**Category**
0.5	Short
1	Short
5	Short
7	Short
10	Long
15	Long

Expert 2	
Value (yrs)	**Category**
2	Short
5	Short
8	Long
15	Long
20	Long
25	Long

Expert 3	
Value (yrs)	**Category**
1	Short
5	Short
10	Short
15	Long
20	Long
23	Long

Expert 4	
Value (yrs)	**Category**
5	Short
7	Short
12	Short
17	Long
22	Long
25	Long

Expert 5	
Value (yrs)	**Category**
2	Short
4	Short
6	Short
12	Long
18	Long
24	Long

Table A3.6 a/b/c/d/e Expert opinion input for risk

Subsequently, the inductive reasoning approach described by Christensen (1980) was performed (as illustrated within Chapter 6) and fuzzy membership functions shown in Figure A3.6.

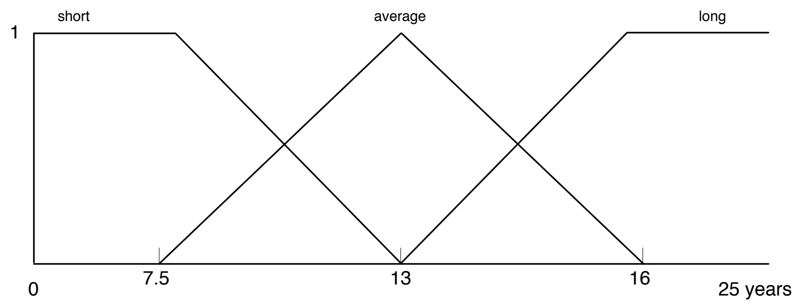

Figure A3.6 Longevity fuzzy membership function

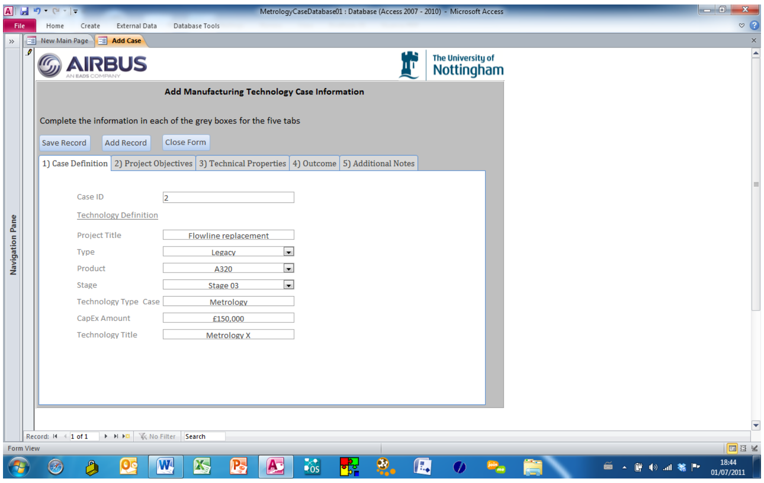

Figure A4.1 Add technology case example (1)

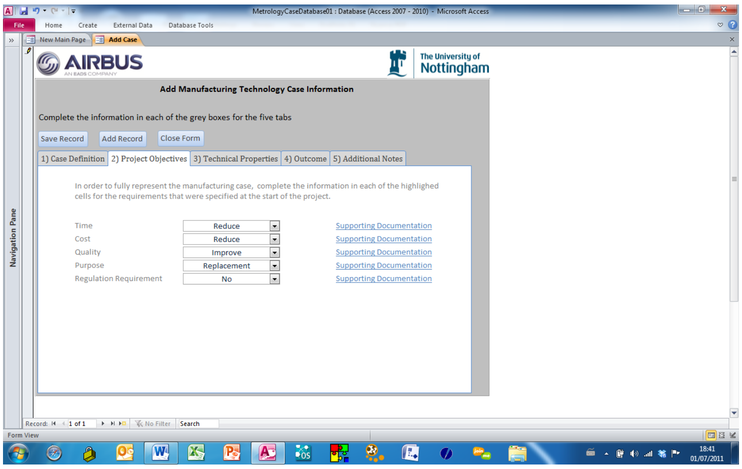

Figure A4.2 Add technology case example (2)

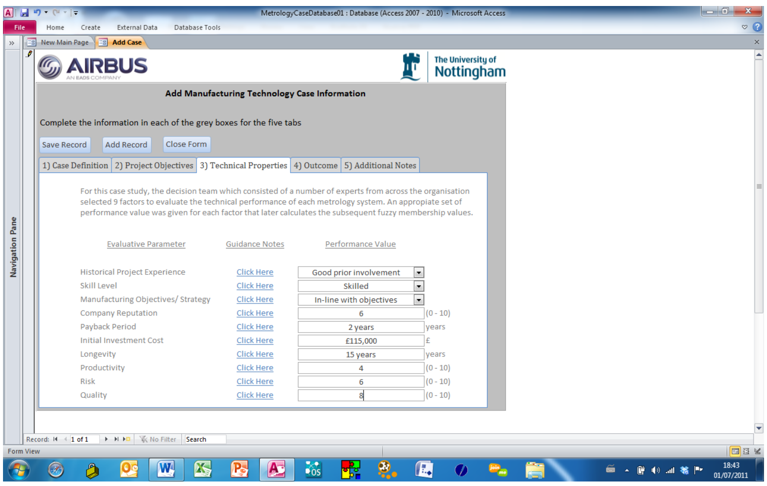

Figure A4.3 Add technology case example (3)

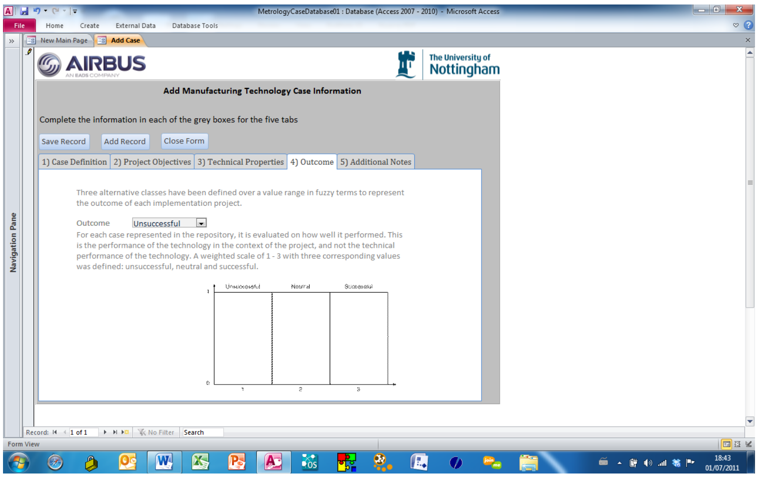

Figure A4.4 Add technology case example (4)

Case Definition	Project Requirements								
Case ID	**Time**	Reduce	Non-Applicable	**Cost**	Reduce	Non-Applicable	**Quality**	Improve	Non-Applicable
1	Reduce	1	0	Reduce	1	0	Improve	1	0
2	Reduce	1	0	Reduce	1	0	Improve	1	0
3	Reduce	1	0	Reduce	1	0	Improve	1	0
4	Reduce	1	0	Reduce	1	0	Non-Applicable	0	1
5	Reduce	1	0	Reduce	1	0	Non-Applicable	0	1
6	Reduce	1	0	Reduce	1	0	Non-Applicable	0	1
7	Reduce	1	0	Reduce	1	0	Non-Applicable	0	1
8	Non-Applicable	0	1	Reduce	1	0	Non-Applicable	0	1
9	Reduce	1	0	Reduce	1	0	Improve	1	0
10	Reduce	1	0	Non-Applicable	0	1	Non-Applicable	0	1
11	Reduce	1	0	Non-Applicable	0	1	Non-Applicable	0	1
12	Reduce	1	0	Non-Applicable	0	1	Non-Applicable	0	1
13	Reduce	1	0	Non-Applicable	0	1	Non-Applicable	0	1
14	Non-Applicable	0	1	Non-Applicable	0	1	Improve	1	0
15	Non-Applicable	0	1	Non-Applicable	0	1	Improve	1	0
16	Non-Applicable	0	1	Non-Applicable	0	1	Improve	1	0
17	Non-Applicable	0	1	Non-Applicable	0	1	Improve	1	0
18	Non-Applicable	0	1	Non-Applicable	0	1	Improve	1	0
19	Non-Applicable	0	1	Non-Applicable	0	1	Improve	1	0
20	Non-Applicable	0	1	Non-Applicable	0	1	Improve	1	0
21	Reduce	1	0	Reduce	1	0	Improve	1	0
22	Non-Applicable	0	1	Non-Applicable	0	1	Improve	1	0
23	Reduce	1	0	Reduce	1	0	Non-Applicable	0	1
24	Reduce	1	0	Non-Applicable	0	1	Non-Applicable	0	1
25	Reduce	1	0	Reduce	1	0	Non-Applicable	0	1
26	Reduce	1	0	Reduce	1	0	Non-Applicable	0	1
27	Non-Applicable	0	1	Non-Applicable	0	1	Non-Applicable	0	1
28	Non-Applicable	0	1	Non-Applicable	0	1	Non-Applicable	0	1
29	Reduce	1	0	Reduce	1	0	Non-Applicable	0	1
30	Non-Applicable	0	1	Reduce	1	0	Non-Applicable	0	1
31	Reduce	1	0	Non-Applicable	0	1	Non-Applicable	0	1
32	Non-Applicable	0	1	Non-Applicable	0	1	Improve	1	0
33	Reduce	1	0	Non-Applicable	0	1	Improve	1	0
34	Non-Applicable	0	1	Non-Applicable	0	1	Improve	1	0
35	Non-Applicable	0	1	Non-Applicable	0	1	Improve	1	0
36	Non-Applicable	0	1	Non-Applicable	0	1	Improve	1	0
37	Reduce	1	0	Reduce	1	0	Non-Applicable	0	1
38	Non-Applicable	0	1	Non-Applicable	0	1	Improve	1	0
39	Reduce	1	0	Reduce	1	0	Improve	1	0
40	Reduce	1	0	Reduce	1	0	Improve	1	0
41	Reduce	1	0	Reduce	1	0	Improve	1	0
42	Reduce	1	0	Reduce	1	0	Non-Applicable	0	1
43	Reduce	1	0	Reduce	1	0	Improve	1	0
44	Reduce	1	0	Reduce	1	0	Improve	1	0
45	Reduce	1	0	Reduce	1	0	Improve	1	0
46	Reduce	1	0	Reduce	1	0	Improve	1	0
47	Reduce	1	0	Reduce	1	0	Improve	1	0
48	Reduce	1	0	Reduce	1	0	Non-Applicable	0	1
49	Reduce	1	0	Reduce	1	0	Non-Applicable	0	1
50	Reduce	1	0	Reduce	1	0	Improve	1	0
51	Reduce	1	0	Reduce	1	0	Improve	1	0

Table A4.1 Metrology database (numerically represented) – section 1

Purpose	Productivity	Capacity	Replacement	Modification	New Product	**Regulation Requirement**	Yes	No
Replacement	0	0	1	0	0	No	0	1
Replacement	0	0	1	0	0	No	0	1
Replacement	0	0	1	0	0	No	0	1
Capacity	0	1	0	0	0	No	0	1
Capacity	0	1	0	0	0	No	0	1
Capacity	0	1	0	0	0	No	0	1
New Product	0	0	0	0	1	No	0	1
New Product	0	0	0	0	1	No	0	1
Modification	0	0	0	1	0	Yes	1	0
New Product	0	0	0	0	1	No	0	1
New Product	0	0	0	0	1	No	0	1
New Product	0	0	0	0	1	No	0	1
New Product	0	0	0	0	1	No	0	1
New Product	0	0	0	0	1	No	0	1
New Product	0	0	0	0	1	No	0	1
New Product	0	0	0	0	1	No	0	1
New Product	0	0	0	0	1	No	0	1
New Product	0	0	0	0	1	No	0	1
New Product	0	0	0	0	1	No	0	1
New Product	0	0	0	0	1	No	0	1
Productivity	1	0	0	0	0	No	0	1
Replacement	0	0	1	0	0	No	0	1
Replacement	0	0	1	0	0	No	0	1
New Product	0	0	0	0	1	No	0	1
New Product	0	0	0	0	1	No	0	1
New Product	0	0	0	0	1	No	0	1
Replacement	0	0	1	0	0	No	0	1
New Product	0	0	0	0	1	No	0	1
Productivity	1	0	0	0	0	No	0	1
New Product	0	0	0	0	1	No	0	1
Replacement	0	0	1	0	0	No	0	1
Capacity	0	1	0	0	0	No	0	1
Productivity	1	0	0	0	0	No	0	1
New Product	0	0	0	0	1	No	0	1
New Product	0	0	0	0	1	No	0	1
New Product	0	0	0	0	1	No	0	1
Replacement	0	0	1	0	0	No	0	1
New Product	0	0	0	0	1	No	0	1
New Product	0	0	0	0	1	No	0	1
Replacement	0	0	1	0	0	No	0	1
Replacement	0	0	1	0	0	No	0	1
New Product	0	0	0	0	1	No	0	1
Replacement	0	0	1	0	0	No	0	1
Replacement	0	0	1	0	0	No	0	1
Replacement	0	0	1	0	0	No	0	1
Replacement	0	0	1	0	0	No	0	1
Replacement	0	0	1	0	0	No	0	1
New Product	0	0	0	0	1	No	0	1
New Product	0	0	0	0	1	No	0	1
Replacement	0	0	1	0	0	No	0	1
Replacement	0	0	1	0	0	No	0	1

Table A4.2 Metrology database (numerically represented) – section 2

Technology Technical Attributes											
Historical Project Experience	Good	No Prev	Diss App	**Skill Level**	Skilled	Semi-Skilled	Unskilled	**Manufacturing Objectives/ Strategy**	In-line with objective	Partial	Non-related
Good prior involvement	1	0	0	Skilled	1	0	0	In-line with objective	1	0	0
Good prior involvement	1	0	0	Skilled	1	0	0	In-line with objective	1	0	0
Good prior involvement	1	0	0	Skilled	1	0	0	In-line with objective	1	0	0
Good prior involvement	1	0	0	Skilled	1	0	0	In-line with objective	1	0	0
Good prior involvement	1	0	0	Skilled	1	0	0	In-line with objective	1	0	0
Good prior involvement	1	0	0	Skilled	1	0	0	In-line with objective	1	0	0
Good prior involvement	1	0	0	Skilled	1	0	0	In-line with objective	1	0	0
Good prior involvement	1	0	0	Skilled	1	0	0	In-line with objective	1	0	0
No previous dealings	0	1	0	Semi-Skilled	0	1	0	Partial	0	1	0
Good prior involvement	1	0	0	Skilled	1	0	0	Partial	0	1	0
Good prior involvement	1	0	0	Skilled	1	0	0	Partial	0	1	0
Good prior involvement	1	0	0	Skilled	1	0	0	Partial	0	1	0
Good prior involvement	1	0	0	Skilled	1	0	0	Partial	0	1	0
Good prior involvement	1	0	0	Skilled	1	0	0	In-line with objective	1	0	0
Good prior involvement	1	0	0	Skilled	1	0	0	In-line with objective	1	0	0
Good prior involvement	1	0	0	Skilled	1	0	0	In-line with objective	1	0	0
Good prior involvement	1	0	0	Skilled	1	0	0	In-line with objective	1	0	0
Good prior involvement	1	0	0	Skilled	1	0	0	In-line with objective	1	0	0
Good prior involvement	1	0	0	Skilled	1	0	0	In-line with objective	1	0	0
Good prior involvement	1	0	0	Skilled	1	0	0	In-line with objective	1	0	0
Good prior involvement	1	0	0	Semi-Skilled	0	1	0	Partial	0	1	0
No previous dealings	0	1	0	Unskilled	0	0	1	Non-related	0	0	1
No previous dealings	0	1	0	Semi-Skilled	0	1	0	Partial	0	1	0
Good prior involvement	1	0	0	Skilled	1	0	0	In-line with objective	1	0	0
No previous dealings	0	1	0	Semi-Skilled	0	1	0	Partial	0	1	0
No previous dealings	0	1	0	Semi-Skilled	0	1	0	Partial	0	1	0
Good prior involvement	1	0	0	Skilled	1	0	0	In-line with objective	1	0	0
Good prior involvement	1	0	0	Skilled	1	0	0	In-line with objective	1	0	0
Good prior involvement	1	0	0	Skilled	1	0	0	In-line with objective	1	0	0
Good prior involvement	1	0	0	Skilled	1	0	0	In-line with objective	1	0	0
Good prior involvement	1	0	0	Skilled	1	0	0	In-line with objective	1	0	0
Good prior involvement	1	0	0	Skilled	1	0	0	In-line with objective	1	0	0
Good prior involvement	1	0	0	Skilled	1	0	0	Partial	0	1	0
No previous dealings	0	1	0	Skilled	1	0	0	Partial	0	1	0
No previous dealings	0	1	0	Skilled	1	0	0	Partial	0	1	0
No previous dealings	0	1	0	Skilled	1	0	0	Partial	0	1	0
Good prior involvement	1	0	0	Skilled	1	0	0	In-line with objective	1	0	0
Good prior involvement	1	0	0	Skilled	1	0	0	In-line with objective	1	0	0
No previous dealings	0	1	0	Semi-Skilled	0	1	0	Partial	0	1	0
Good prior involvement	1	0	0	Skilled	1	0	0	In-line with objective	1	0	0
No previous dealings	0	1	0	Semi-Skilled	0	1	0	Non-related	0	0	1
No previous dealings	0	1	0	Semi-Skilled	0	1	0	Non-related	0	0	1
No previous dealings	0	1	0	Skilled	1	0	0	Partial	0	1	0
Good prior involvement	1	0	0	Skilled	1	0	0	In-line with objective	1	0	0
Good prior involvement	1	0	0	Skilled	1	0	0	In-line with objective	1	0	0
Good prior involvement	1	0	0	Skilled	1	0	0	In-line with objective	1	0	0
Good prior involvement	1	0	0	Skilled	1	0	0	In-line with objective	1	0	0
Good prior involvement	1	0	0	Skilled	1	0	0	In-line with objective	1	0	0
No previous dealings	0	1	0	Skilled	1	0	0	Partial	0	1	0
Good prior involvement	1	0	0	Skilled	1	0	0	In-line with objective	1	0	0
Good prior involvement	1	0	0	Skilled	1	0	0	Partial	0	1	0

Table A4.3 Metrology database (numerically represented) – section 3

Company Reputation	Poor (MF)	Good (MF)	Well reg (MF)	**Payback Period**	Low (MF)	Med (MF)	High (MF)
6	0.00	0.50	0.50	2	0.00	0.75	0.25
6	0.00	0.50	0.50	1	1.00	0.00	0.00
6	0.00	0.50	0.50	1	1.00	0.00	0.00
6	0.00	0.50	0.50	1.5	0.50	0.50	0.00
6	0.00	0.50	0.50	1.5	0.50	0.50	0.00
6	0.00	0.50	0.50	1.5	0.50	0.50	0.00
8	0.00	0.00	1.00	2	0.00	0.75	0.25
8	0.00	0.00	1.00	2	0.00	0.75	0.25
5	0.17	0.83	0.00	5	0.00	0.00	1.00
8	0.00	0.00	1.00	2.5	0.00	0.25	0.75
8	0.00	0.00	1.00	2	0.00	0.75	0.25
8	0.00	0.00	1.00	2	0.00	0.75	0.25
7	0.00	0.00	1.00	3	0.00	0.00	1.00
8	0.00	0.00	1.00	2	0.00	0.75	0.25
8	0.00	0.00	1.00	2	0.00	0.75	0.25
8	0.00	0.00	1.00	2	0.00	0.75	0.25
8	0.00	0.00	1.00	2	0.00	0.75	0.25
8	0.00	0.00	1.00	2	0.00	0.75	0.25
8	0.00	0.00	1.00	2	0.00	0.75	0.25
8	0.00	0.00	1.00	2.5	0.00	0.25	0.75
7	0.00	0.00	1.00	1.5	0.50	0.50	0.00
5	0.17	0.83	0.00	1	1.00	0.00	0.00
8	0.00	0.00	1.00	2	0.00	0.75	0.25
8	0.00	0.00	1.00	2	0.00	0.75	0.25
6	0.00	0.50	0.50	1	1.00	0.00	0.00
6	0.00	0.50	0.50	1	1.00	0.00	0.00
8	0.00	0.00	1.00	1.5	0.50	0.50	0.00
8	0.00	0.00	1.00	2	0.00	0.75	0.25
8	0.00	0.00	1.00	1.5	0.50	0.50	0.00
8	0.00	0.00	1.00	3	0.00	0.00	1.00
8	0.00	0.00	1.00	2.5	0.00	0.25	0.75
8	0.00	0.00	1.00	2.5	0.00	0.25	0.75
8	0.00	0.00	1.00	2	0.00	0.75	0.25
6	0.00	0.50	0.50	3.5	0.00	0.00	1.00
6	0.00	0.50	0.50	3	0.00	0.00	1.00
6	0.00	0.50	0.50	3	0.00	0.00	1.00
7	0.00	0.00	1.00	3	0.00	0.00	1.00
7	0.00	0.00	1.00	4	0.00	0.00	1.00
7	0.00	0.00	1.00	3.5	0.00	0.00	1.00
8	0.00	0.00	1.00	2	0.00	0.75	0.25
6	0.00	0.50	0.50	5	0.00	0.00	1.00
6	0.00	0.50	0.50	5	0.00	0.00	1.00
7	0.00	0.00	1.00	3	0.00	0.00	1.00
8	0.00	0.00	1.00	5	0.00	0.00	1.00
8	0.00	0.00	1.00	3	0.00	0.00	1.00
8	0.00	0.00	1.00	3	0.00	0.00	1.00
8	0.00	0.00	1.00	3	0.00	0.00	1.00
6	0.00	0.50	0.50	3	0.00	0.00	1.00
7	0.00	0.00	1.00	3	0.00	0.00	1.00
8	0.00	0.00	1.00	3.5	0.00	0.00	1.00
8	0.00	0.00	1.00	3.5	0.00	0.00	1.00

Table A4.4 Metrology database (numerically represented) – section 4

Initial Investment Cost	Low (MF)	Med (MF)	High (MF)	**Longevity**	Short (MF)	Avg (MF)	Long (MF)	**Productivity**	Low (MF)	Good (MF)	High (MF)
£115,000	0.00	0.76	0.24	15	0.00	0.33	0.67	4	1.00	0.00	0.00
£185,000	0.00	0.00	1.00	15	0.00	0.33	0.67	7	0.00	0.25	0.75
£150,000	0.00	0.35	0.65	15	0.00	0.33	0.67	7	0.00	0.25	0.75
£75,000	0.27	0.73	0.00	15	0.00	0.33	0.67	8	0.00	0.00	1.00
£75,000	0.27	0.73	0.00	15	0.00	0.33	0.67	8	0.00	0.00	1.00
£75,000	0.27	0.73	0.00	15	0.00	0.33	0.67	8	0.00	0.00	1.00
£150,000	0.00	0.35	0.65	20	0.00	0.00	1.00	9	0.00	0.00	1.00
£100,000	0.00	0.94	0.06	20	0.00	0.00	1.00	8	0.00	0.00	1.00
£250,000	0.00	0.00	1.00	10	0.55	0.45	0.00	5	0.50	0.50	0.00
£150,000	0.00	0.35	0.65	15	0.00	0.33	0.67	8	0.00	0.00	1.00
£150,000	0.00	0.35	0.65	15	0.00	0.33	0.67	8	0.00	0.00	1.00
£150,000	0.00	0.35	0.65	15	0.00	0.33	0.67	8	0.00	0.00	1.00
£150,000	0.00	0.35	0.65	10	0.55	0.45	0.00	6	0.00	0.75	0.25
£100,000	0.00	0.94	0.06	15	0.00	0.33	0.67	7	0.00	0.25	0.75
£100,000	0.00	0.94	0.06	15	0.00	0.33	0.67	7	0.00	0.25	0.75
£100,000	0.00	0.94	0.06	15	0.00	0.33	0.67	7	0.00	0.25	0.75
£100,000	0.00	0.94	0.06	15	0.00	0.33	0.67	9	0.00	0.00	1.00
£100,000	0.00	0.94	0.06	15	0.00	0.33	0.67	6	0.00	0.75	0.25
£100,000	0.00	0.94	0.06	15	0.00	0.33	0.67	6	0.00	0.75	0.25
£100,000	0.00	0.94	0.06	15	0.00	0.33	0.67	8	0.00	0.00	1.00
£60,000	0.47	0.53	0.00	20	0.00	0.00	1.00	8	0.00	0.00	1.00
£50,000	0.60	0.40	0.00	10	0.55	0.45	0.00	3	1.00	0.00	0.00
£125,000	0.00	0.65	0.35	10	0.55	0.45	0.00	5	0.50	0.50	0.00
£150,000	0.00	0.35	0.65	15	0.00	0.33	0.67	8	0.00	0.00	1.00
£25,000	0.93	0.07	0.00	10	0.55	0.45	0.00	7	0.00	0.25	0.75
£25,000	0.93	0.07	0.00	15	0.00	0.33	0.67	7	0.00	0.25	0.75
£125,000	0.00	0.65	0.35	15	0.00	0.33	0.67	8	0.00	0.00	1.00
£125,000	0.00	0.65	0.35	15	0.00	0.33	0.67	9	0.00	0.00	1.00
£100,000	0.00	0.94	0.06	15	0.00	0.33	0.67	9	0.00	0.00	1.00
£125,000	0.00	0.65	0.35	20	0.00	0.00	1.00	6	0.00	0.75	0.25
£125,000	0.00	0.65	0.35	15	0.00	0.33	0.67	8	0.00	0.00	1.00
£125,000	0.00	0.65	0.35	15	0.00	0.33	0.67	7	0.00	0.25	0.75
£150,000	0.00	0.35	0.65	15	0.00	0.33	0.67	8	0.00	0.00	1.00
£150,000	0.00	0.35	0.65	10	0.55	0.45	0.00	7	0.00	0.25	0.75
£125,000	0.00	0.65	0.35	10	0.55	0.45	0.00	7	0.00	0.25	0.75
£125,000	0.00	0.65	0.35	10	0.55	0.45	0.00	7	0.00	0.25	0.75
£250,000	0.00	0.00	1.00	15	0.00	0.33	0.67	7	0.00	0.25	0.75
£250,000	0.00	0.00	1.00	15	0.00	0.33	0.67	4	1.00	0.00	0.00
£125,000	0.00	0.65	0.35	15	0.00	0.33	0.67	7	0.00	0.25	0.75
£125,000	0.00	0.65	0.35	15	0.00	0.33	0.67	6	0.00	0.75	0.25
£250,000	0.00	0.00	1.00	25	0.00	0.00	1.00	3	1.00	0.00	0.00
£250,000	0.00	0.00	1.00	25	0.00	0.00	1.00	7	0.00	0.25	0.75
£125,000	0.00	0.65	0.35	15	0.00	0.33	0.67	7	0.00	0.25	0.75
£250,000	0.00	0.00	1.00	15	0.00	0.33	0.67	6	0.00	0.75	0.25
£150,000	0.00	0.35	0.65	15	0.00	0.33	0.67	6	0.00	0.75	0.25
£150,000	0.00	0.35	0.65	15	0.00	0.33	0.67	5	0.50	0.50	0.00
£150,000	0.00	0.35	0.65	15	0.00	0.33	0.67	5	0.50	0.50	0.00
£150,000	0.00	0.35	0.65	20	0.00	0.00	1.00	7	0.00	0.25	0.75
£125,000	0.00	0.65	0.35	15	0.00	0.33	0.67	7	0.00	0.25	0.75
£125,000	0.00	0.65	0.35	10	0.55	0.45	0.00	8	0.00	0.00	1.00
£125,000	0.00	0.65	0.35	20	0.00	0.00	1.00	8	0.00	0.00	1.00

Table A4.5 Metrology database (numerically represented) – section 5

Risk	Low (MF)	Med (MF)	High (MF)	Quality	Low (MF)	Med (MF)	High (MF)	Project Outcome
6	0.00	0.25	0.75	8	0.00	0.00	1.00	Unsuccessful
3	1.00	0.00	0.00	9	0.00	0.00	1.00	Successful
3	1.00	0.00	0.00	9	0.00	0.00	1.00	Successful
5	0.00	0.75	0.25	8	0.00	0.00	1.00	Successful
3	1.00	0.00	0.00	8	0.00	0.00	1.00	Successful
3	1.00	0.00	0.00	8	0.00	0.00	1.00	Successful
2	1.00	0.00	0.00	8	0.00	0.00	1.00	Successful
3	1.00	0.00	0.00	7	0.00	0.25	0.75	Successful
8	0.00	0.00	1.00	5	0.50	0.50	0.00	Unsuccessful
2	1.00	0.00	0.00	9	0.00	0.00	1.00	Successful
2	1.00	0.00	0.00	9	0.00	0.00	1.00	Successful
2	1.00	0.00	0.00	9	0.00	0.00	1.00	Successful
5	0.00	0.75	0.25	7	0.00	0.25	0.75	Neutral
3	1.00	0.00	0.00	8	0.00	0.00	1.00	Successful
3	1.00	0.00	0.00	8	0.00	0.00	1.00	Successful
3	1.00	0.00	0.00	8	0.00	0.00	1.00	Successful
3	1.00	0.00	0.00	8	0.00	0.00	1.00	Successful
3	1.00	0.00	0.00	8	0.00	0.00	1.00	Successful
3	1.00	0.00	0.00	8	0.00	0.00	1.00	Successful
3	1.00	0.00	0.00	8	0.00	0.00	1.00	Successful
1	1.00	0.00	0.00	8	0.00	0.00	1.00	Successful
5	0.00	0.75	0.25	2	1.00	0.00	0.00	Neutral
5	0.00	0.75	0.25	6	0.00	0.75	0.25	Neutral
4	0.50	0.50	0.00	8	0.00	0.00	1.00	Neutral
1	1.00	0.00	0.00	6	0.00	0.75	0.25	Successful
1	1.00	0.00	0.00	6	0.00	0.75	0.25	Successful
3	1.00	0.00	0.00	8	0.00	0.00	1.00	Successful
3	1.00	0.00	0.00	9	0.00	0.00	1.00	Successful
3	1.00	0.00	0.00	8	0.00	0.00	1.00	Neutral
4	0.50	0.50	0.00	4	1.00	0.00	0.00	Unsuccessful
3	1.00	0.00	0.00	8	0.00	0.00	1.00	Successful
1	1.00	0.00	0.00	8	0.00	0.00	1.00	Successful
3	1.00	0.00	0.00	6	0.00	0.75	0.25	Unsuccessful
1	1.00	0.00	0.00	7	0.00	0.25	0.75	Successful
4	0.50	0.50	0.00	5	0.50	0.50	0.00	Neutral
4	0.50	0.50	0.00	5	0.50	0.50	0.00	Neutral
3	1.00	0.00	0.00	9	0.00	0.00	1.00	Successful
4	0.50	0.50	0.00	7	0.00	0.25	0.75	Neutral
5	0.00	0.75	0.25	6	0.00	0.75	0.25	Successful
4	0.50	0.50	0.00	7	0.00	0.25	0.75	Unsuccessful
10	0.00	0.00	1.00	10	0.00	0.00	1.00	Unsuccessful
10	0.00	0.00	1.00	10	0.00	0.00	1.00	Neutral
7	0.00	0.00	1.00	8	0.00	0.00	1.00	Unsuccessful
6	0.00	0.25	0.75	7	0.00	0.25	0.75	Unsuccessful
6	0.00	0.25	0.75	7	0.00	0.25	0.75	Unsuccessful
6	0.00	0.25	0.75	8	0.00	0.00	1.00	Unsuccessful
6	0.00	0.25	0.75	8	0.00	0.00	1.00	Unsuccessful
4	0.50	0.50	0.00	8	0.00	0.00	1.00	Neutral
7	0.00	0.00	1.00	9	0.00	0.00	1.00	Neutral
6	0.00	0.25	0.75	6	0.00	0.75	0.25	Neutral
4	0.50	0.50	0.00	6	0.00	0.75	0.25	Unsuccessful

Table A4.6 Metrology database (numerically represented) – section 6

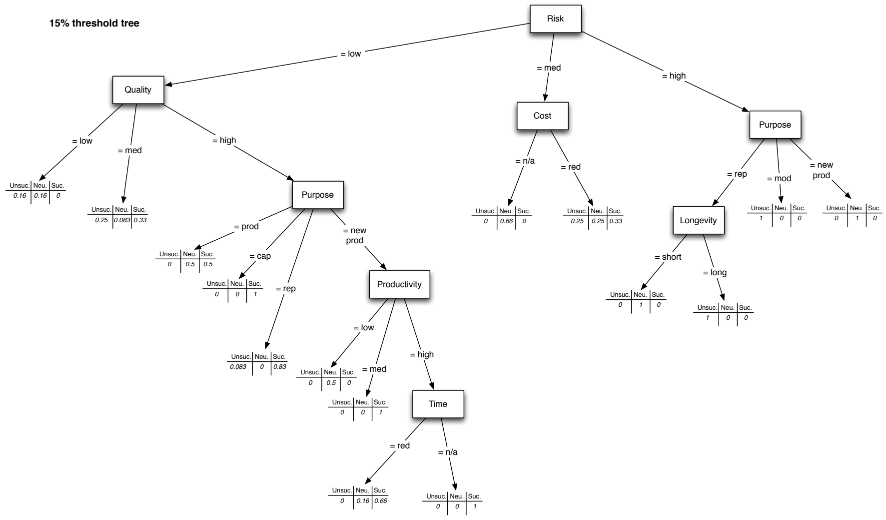

Figure A4.5 Decision tree using 15% threshold

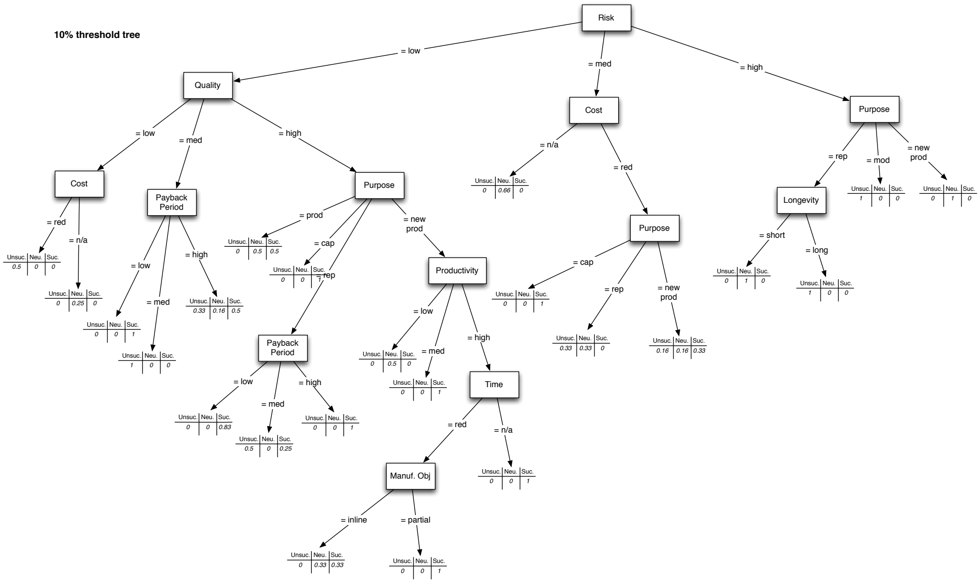

Figure A4.6 Decision tree using 10% threshold

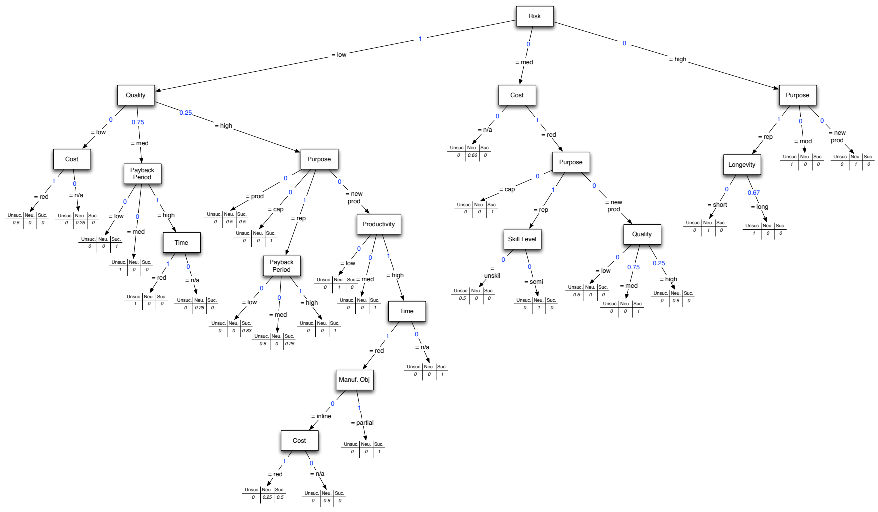

Figure A4.7 Decision tree with applied option B

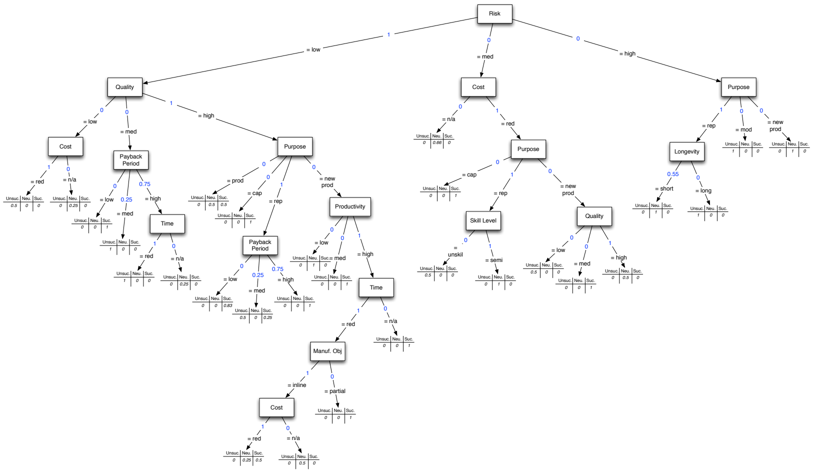

Figure A4.8 Decision tree with applied option C

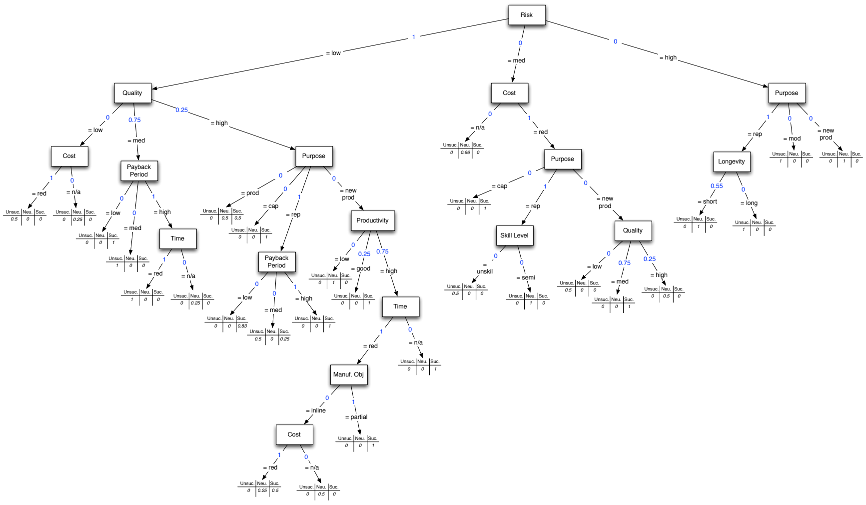

Figure A4.9 Decision tree with applied option D

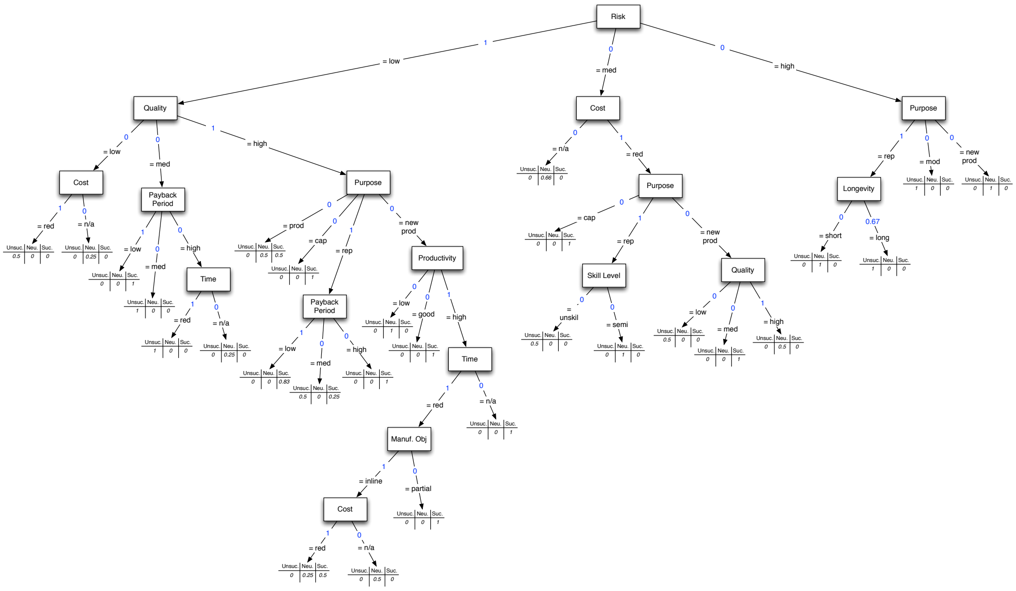

Figure A4.9 Decision tree with applied option E

Questionnaire Results (Validation)

Question Number	Ind. 1	Ind. 2	Ind. 3	Ind. 4	Ind. 5	Ind. 6	Ind. 7	Average	Group Avg.
1.1	3	4	4	5	4	4	5	4.14	4.07
1.2	4	4	3	4	4	4	5	4.00	
1.3	4	4	4	4	5	4	4	4.14	
1.4	4	4	4	3	5	3	5	4.00	
2.1	4	4	4	5	5	4	5	4.43	4.05
2.2	3	4	3	4	5	5	4	4.00	
2.3	3	4	4	3	4	5	4	3.86	
2.4	3	4	4	4	5	4	5	4.14	
2.5	4	4	3	4	4	3	4	3.71	
2.6	4	4	5	4	4	4	4	4.14	
3.1	4	5	4	4	5	4	3	4.14	4.00
3.2	3	3	5	5	5	4	4	4.14	
3.3	4	4	4	4	4	4	3	3.86	
3.4	5	3	5	4	4	4	4	4.14	
3.5	3	3	5	4	4	3	4	3.71	

Table A4.7 Questionnaire results (case study)