HUMAN BEHAVIOUR MODELLING: AN INVESTIGATION USING TRADITIONAL DISCRETE EVENT AND COMBINED DISCRETE EVENT AND AGENT-BASED SIMULATION

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Dedicated to

my beloved husband, Syahnizam Abdullah Sani, for his love and support,
my precious daughter and son, Almira Damia and Almir Daniyal,
the beauties of my life,
my lovely mother, Fatimah Noog Ghani, for your dua and care,and
the memory of my father, Abdul Majid Abdul Kadir. I wish he were alive.

ABSTRACT

This thesis presents a comparison between two simulation methods, namely Discrete Event Simulation (DES) and Agent Based Simulation (ABS). In our literature review we identified a gap in comparing the applicability of these methods to modelling human centric service systems. Hence, we have focused our research on reactive and different level of detail of proactive of human behaviour in service systems.

The aim of the thesis is to establish a comparison for modelling human reactive and different level of detail of proactive behaviour in service systems using DES and ABS. To achieve this we investigate both the similarities and differences between model results performance and the similarities and differences in model difficulty performance.

The comparison of the simulation methods is achieved by using a case study approach. We have conducted three case studies, the choice of our case study systems taking into consideration the number of different key proactive behaviours that can be observed. In the first case study (fitting room services) we consider single proactive staff behaviour, in the second case study (international support services) we consider two proactive staff behaviours and, finally, the third case study (airline check-in services) considers three proactive staff behaviours. The proactive behaviours considered are: taking charge from experience, taking the initiative to fulfil a goal and supervising by learning.

To conduct our case studies we have created two sets of simulation models. The first set consists of one DES model for each of the case studies. As service systems have an organisational structure we could not implement our agent-based simulation models purely as agent-based models. Instead, for the second set we have created combined DES/ABS models (one for each case study), where the DES part represents the system and the ABS part represents the active entities inside the system (i.e. the people).With these models we have carried out two sets of experiments: Set A is concerned with modelling results performance, while set B is related to model difficulty performance. We have then conducted statistical analysis on the results of these experiments.

Evidence from the experiments reveals that DES and combined DES/ABS are found suitable to model the reactive and most levels of proactive behaviour modelled in this thesis. In addition, combined DES/ABS is found more suitable for modelling higher levels of proactive behaviour (complex behaviour). Another finding from the experiments is that it is only worth representing complex proactive behaviour if it occurs frequently in the real system (considering the relation between modelling effort and impact).

The contribution made by this thesis to the body of knowledge is the comparison of DES and combined DES/ABS for modelling human reactive and different level of detail of human proactive behaviour in service systems. This comparison will assist modellers who are new to the field of service systems modelling to make an informed decision on the method they should use for their own modelling, based on the level of proactiveness inherent in the real system and on the levels of difficulties they should expect for each method.

PUBLICATIONS

This section presented a list of publications formed as part of the research work for this thesis.

1. M. A. Majid, P.-O. Siebers and U.Aickelin. Modelling Reactive and Proactive Behaviour in Simulation. Proceedings of Operational Research Society 5th Simulation Workshop (SW10), Worcestershire, England. 2010. 23-31.

2. M.A.Majid, U.Aickelin and P.-O.Siebers. Investigating Output Accuracy for a Discrete Event Simulation Model and an Agent Based Simulation Model. Proceedings of the INFORMS Simulation Society Research Workshop, Warwick, UK. 2009. 101-105.

3. M.A.Majid, U.Aickelin and P.-O.Siebers. Comparing Simulation Output Accuracy of Discrete Event and Agent Based Models: A Quantitative Approach. Proceedings of the Summer Computer Simulation Conference (SCSC 2009), Istanbul, Turkey. 2009. 177-184.

4. M.A.Majid, U.Aickelin and P.-O.Siebers. Modelling and Analysing Human Behaviour in a Department Store using Discrete Event and Agent Based Simulation. Proceedings of the Annual Operational Research Conference 50 (OR 50), York, UK. 2008.153

5. M.A.Majid, U.Aickelin and P.-O.Siebers. Human Behaviour Modelling for Discrete Event and Agent Based Simulation: A Case Study. Proceedings of the Annual Operational Research Conference 49 (OR 49), Edinburgh, UK. 2007. 94

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CHAPTER 1

INTRODUCTION

1.1 Introduction

Chapter 1 introduces the research by first outlining a discussion on the background and motivation for pursuing the study. This is followed by an overview to provide an initial understanding of the research undertaken. A description on how this thesis is organised concludes the chapter.

1.2 Background and Motivation

The evolvement of knowledge has resulted in an increasing number of complex systems in the modern world. In Operation Research (OR), simulation has become a preferred tool for investigating complex systems (Kelton et al. 2007) when an analytical approach prove impossible to use.

Simulation can imitate real world problems by modelling a system's behaviour over a set period of time (Banks 2000). Simulation is considered a decision support tool which has provided solutions to problems in industry since the early 1960s (Shannon 1975).

Historically, simulation is classified into two broad categories, namely continuous and discrete simulation (Raczynski 2006). System Dynamic Simulation (SDS) is the continuous simulation type. SDS models represent real world phenomena using stock and flow diagrams, causal loop diagrams (to represent a number of interacting feedback loops) and differential equations.

The simulation types identified under discrete simulation are Discrete Event Simulation (DES) and Agent Based Simulation (ABS). DES models represent a system based on a series of chronological sequences of events where each event changes the system's state in discrete time. ABS models comprise a number of autonomous, responsive and interactive agents which cooperate, coordinate and negotiate among one another to achieve their objectives. The appearance of ABS as another type of simulation tool helps to gain better simulation results especially when modelling the interaction of people with their environment, or in other words, modelling human behaviour (Dubiel and Tsimhoni 2005).

According to Robinson (2004), studies of human behaviour have received increased attention from simulation researchers in the UK. Human behaviour modelling refers to computer-based models that imitate either the behaviour of a single human or the collective actions of a team of humans (Pew and Mavor 1998).

Nowadays, research on human behaviour is well documented around the world. Throughout this research, simulation seems to be the suitable choice as a model and tool for investigating such behaviour patterns, and DES and ABS are among the most frequently chosen techniques for modelling and simulating human behaviour.

DES and ABS are capable of dealing with individual elements such as individual behaviour which located at low abstraction level (greater detail of the problem under investigation). On the other hand, SDS is more suited to model aggregates located at high abstraction level (less representation of the details of the problem under investigation), including models of strategic decision-making within an organisation. Modelling specific individual behaviour in SDS is difficult to carry out and because of this limitation, SDS is not considered in the present study.

Modelling and simulating human behaviour using the DES and ABS techniques has been applied to various areas such as manufacturing (Siebers 2004), healthcare (Brailsford et al. 2006), military operations (Wray and Laird 2003), crowd behaviour (Shendarkar et al. 2006), retail management (Siebers et al. 2008) and consumer behaviour (Schenk et al. 2007). As the literature indicates, some researchers choose DES as a means to investigate their human behaviour problems; others choose ABS for this purpose. In these cases, the choice of the simulation method relies on the individual judgment of the modeller and their experience with the modelling method. The question, however, remains: For what cases should DES be the simulation method of choice and when should ABS be preferred?

Human behaviour can be categorised into different types, many of which can be found in the service sector. The two most common of these behaviours are reactive and proactive behaviours of the employee (i.e. staff) and customers (i.e. shoppers) of an organisation (Chapter 2: Section 2.6.3).

Reactive behaviour is a response to the environment i.e. an employee's responses to requests from their customer when they are available. Proactive behaviour relates to personal initiative in identifying and solving a problem.

In the service sector, both behaviours play an important role in an organisation's ability to generate income and revenue. However, to understand the potential outcome of reactive and proactive behaviours for the organisation's management within the services sector, it is necessary to study these behavioural performance using the Operational Research (OR) method i.e. simulation. Law and Kelton (2000) suggest using simulation when studying the development of a system over a period of time.

As discussed in the literature review (Chapter 2), DES and ABS techniques appear to be suitable approaches to model reactive and proactive human behaviours. However, the research questions that arise here are:

- Is it worthwhile to put additional effort into modelling proactive human behaviours in an OR simulation study, or do they not have a significant impact on the conclusions to be drawn from the simulation study?
- What are the advantages and disadvantages of DES and ABS in modelling human reactive and proactive behaviours?

Answering both research questions should then help to identify a suitable simulation technique in modelling human behaviour especially proactive behaviour. The choice of an inappropriate simulation technique could lead to an ineffective modelling process (Owen et al. 2008) - for instance, it could take longer to build models.

This thesis describes research work on modelling human reactive and proactive behaviour using two simulation techniques: traditional Discrete Event Simulation (DES) and combined Discrete Event and Agent Based Simulation (combined DES/ABS). The present study is interested in using a combined DES/ABS technique which concerns on modelling a process-oriented system by implementing the actors inside the system (i.e. customers and staff) as agents. Thus, using only the ABS technique will be inappropriate for such investigation.

The rationale behind this study is that, to investigate the different level of detail of proactive behaviour modelled in DES and combined DES/ABS by comparing both simulation techniques in term of simulation result and modelling difficulty. A brief outline of the study is presented in the next section.

1.3 Overview of Research Study

The aim of the research described in this thesis is to explore the capability of DES and combined DES/ABS in modelling the different level of detail of proactive behaviour for service sector systems. In order to accomplish this aim, several measurable objectives must be achieved:

1. To investigate the similarities and differences of the simulation results for DES and combined DES/ABS when modelling reactive and mixed reactive and proactive behaviours.

2. To investigate the similarities and differences of the simulation difficulty with regards to model building time, model execution time and model line of code for DES and combined DES/ABS when modelling reactive and mixed reactive and proactive behaviours.

As stated in the research methodology (Chapter 3), to achieve the research aim and objectives, three case studies from the service sector have been identified. For these, several reactive and mixed reactive and proactive DES and combined DES/ABS models has been build.

With these simulation models (DES and combined DES/ABS), two types of experiments are executed – "model result" experiments and "model difficulty" experiments. The model result experiments are conducted to fulfil the first research objective and the purpose is to understand the similarities and differences of simulation model results using a quantitative method (statistical test).

The model difficulty experiments are conducted to fulfil the second research objective. The model difficulty experiments seek to explore the level of difficulty experienced when modelling the investigated human behaviours. Performance measures for model difficulty experiments are model building time, model execution time and model line of code. Both qualitative (survey) and quantitative (statistical test) methods are used for analysing the results of the model difficulty experiment.

Discussion of the three case studies together with the simulation models (DES and combined DES/ABS) and the experiments (model result and difficulty) are presented in Chapters 4, 5 and 6 for case studies 1, 2 and 3 respectively. Finally, the findings from Chapter 4, 5 and 6 are summarised in Chapter 7 in order to achieve the aim of the research.

1.4 Thesis Contributions

The work carried out in this thesis seeks to produce a key contribution to the body of knowledge in OR and simulation for a number of reasons. The focus is to extrapolate the benefits of adding proactive behaviour in service oriented system. To gain such benefits, the comparisons of modelling reactive and proactive human behaviour through model result and model difficulty experiments are explored in DES and combined DES/ABS.

Furthermore, from the knowledge gained through the empirical studies, a contribution can be made to the literature on the comparative benefits of the two simulation paradigms when modelling different level of proactive behaviour within the service sector systems. As far as we known, there is no other documented work which compares the simulation techniques as presented in this thesis.

1.5 Organisation of Thesis

This thesis consists of seven chapters, structured as follows:

Chapter 2 gives an account of the literature of the two areas relevant to this study: simulation modelling and human behaviour in the service sector. The chapter starts with an exploration of the theory of modelling and simulation. Additionally, the first section explains the three major simulation paradigms (SDS, DES and ABS) in terms of their theory, modelling concept, existing advantages and disadvantages, application areas and lists some of the available simulation software packages. The next section of the literature review discusses the existing comparison of simulation techniques made in the research studies that have compared between SDS vs. DES, SDS vs. ABS, DES vs. ABS and SDS vs. DES vs. ABS in modelling their problem. This is followed by an argument on suitable simulation techniques for modelling human behaviour. Modelling human behaviour using simulation technique is then presented in the next part of the literature review, which describes the definitions of human behaviour modelling and the existing studies of modelling DES and ABS in human behaviour. The chapter closes with an exploration of the literature which describes on human behaviour modelling in the service sector.

Chapter 3 describes the research methodology for each of the case studies. The chapter describes a standard series of processes involved in the case studies; case study description, conceptual modelling, model implementation, verification and validation, the two main experiments (model result and model difficulty) and the comparison between the simulation results. In addition, the main hypotheses are introduced for the two experiments in the case studies.

Chapter 4, 5 and 6 report on case studies 1, 2 and 3 respectively. The structure for each chapter is as described in Chapter 3 and as presented above.

Chapter 7 delineates an overall conclusion of the thesis. This chapter revisits the aims and objectives of this research from the perspective of model result and difficulty investigations in the three case studies. The key contribution to OR and simulation in this study is presented next. Finally, the chapter proposes future work in this area.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

This chapter reviews existing research studies on simulation of human behaviour in the service sector. The review first examines the theory of modelling and simulation and the three well-known simulation paradigms: SDS, DES, and ABS.

Next, existing studies comparing simulation techniques from various areas are presented indicating a gap in research into modelling human behaviour in service-oriented systems using DES and ABS techniques. Then, a discussion of existing literature in modelling human behaviour using simulation techniques (DES and ABS) and human behaviour in service sector are reviewed.

The human behaviours to investigate are then identified; a discussion follows of the comparison measures used for this investigation. The chapter ends with a summary of the literature review.

2.2 Theory of Modelling and Simulation

The first step towards system development is to construct a system model. Researchers offer slightly different definitions of modelling; among them are Fishman (1973), Banks (1998), Zeigler et al.(2000) and Kelton et al. (2007).

Table 2.1 : Definition of modelling

Researchers	Definition
Fishman (1973)	" a formal representation of theory or a formal account of empirical observation "
Banks (1998)	"a model is a representation of an actual system. The model should be complex enough to answer the questions raised, but not too complex"
Zeigler et al.(2000)	" is a set of instructions, rules, equations or constraint for generating I/O behaviour"
Kelton et al. (2007)	Model is just a set of approximations and assumptions, both structural and quantitative about the way the system does or will work.

However, they appear to come to the same conclusion that:

"Modelling is a process of abstracting a real world problem into modelling tools in order to solve problems that occurred in the real world".

There are many diverse types of modelling process; this chapter considers only the analytical and simulation models. Kelton et al. (2007) describe the analytical model as follows: "*Such a model is just a set of approximations and assumptions, both structural and quantitative, about the way the system does or will work.*" In other words, the analytical model is a system of equation that describes the relationships among the variables in predicting the system behaviour

(Maria 1997). Nonetheless, an analytical model is not suitable to solve a complex problem as the solution is very hard to find (Borshchev and Filippov 2004).

A simulation model, however, is preferable to model complex systems as it is more appropriate for modelling dynamic and transient effects (Pidd 1984; Raczynski 2006). McHaney (1991) reports that simulation models have been ranked by the practitioners and academics as the second most important quantitative modelling technique and statistics is the first. A simulation model can be considered as "*a representation of a system that usually takes the form of a set of assumptions concerning the operation of the system. These assumptions are expressed in mathematical, logical and symbolic relationships between the entities, or objects of interest, of the system*." (Banks et al. 2005).

Another definition of a simulation model is provided by Borshchev and Filippov (2004) where they agree that a simulation model is " *a set of rules (i.e. equations, flowcharts, state machines, cellular automata) that define how the system being modelled will change in future given in the present state*." From these definitions, it can be concluded that a simulation model is constructed from a mathematical model that has been computerised in order to provide a better understanding of the investigated system. Simulation models can be classified into three different dimensions as shown in Table 2.1, while Figure 2.1 illustrates the relationship between the analytical and the simulation models with regards to the real world problem.

Table 2.2 : Simulation model classification (Banks et al. 2005; Kelton et al. 2007)

Class of Simulation Models	Definition
Static vs. Dynamic	A static simulation model is a representation of a system at a particular time i.e. Monte Carlo models. A dynamic simulation model is a representation of a system that evolves over time i.e. manufacturing model
Deterministic vs. Stochastic	A deterministic model is a simulation model that does not contain any probabilistic components i.e. all patients arrived at the scheduled appointment time in a hospital. A stochastic model is a simulation model that operates by having at least some random components i.e. simulation of a bank involves random inter-arrival times and random service times.
Continuous vs. Discrete	A continuous model is one in which the state variable(s) change continuously over time i.e. the flow of water into the lake behind a dam. A discrete model is one in which the state variable(s) change only at discrete set of points in time i.e. the check in services at an airport.

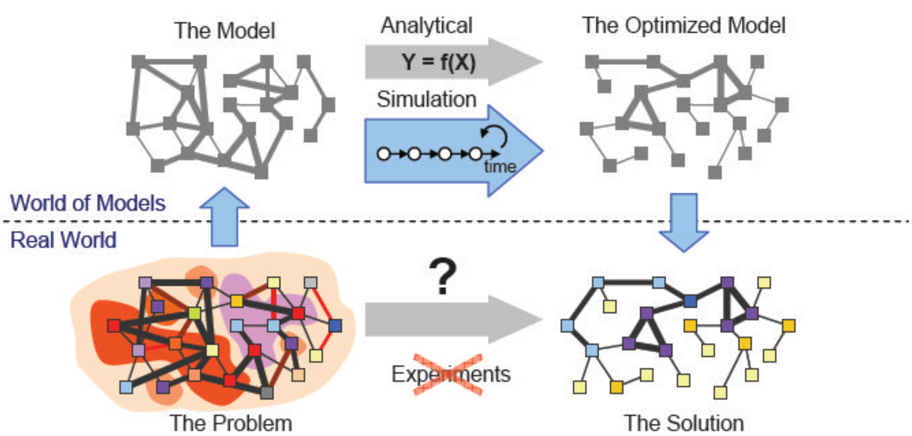


Figure 2.1 : Analytical (static) and simulation (dynamic) modelling (Borshchev and Filippov 2004)

One of the earliest definitions of simulation is from Fishman (1973). He defines simulation as "*the act of representing a system by a symbolic model that can be manipulated easily and that produces numerical results*." Banks (1998; 2000) and Banks et al.(1998; 2000; 2005), follow with a claim that simulation is an imitation process of a real system over time.

However, Robinson (2004) added that simulation is not only an imitation process of a real system over time but also a simplified imitation of an operation system for understanding and improving the system behaviour. Whatever the definition of simulation, there is general agreement that:

"Simulation is a process of imitating the real world system in order to predict the system behaviour by asking "what-if" questions".

Traditionally, there are two types of simulation, namely continuous and discrete simulation (Banks et al. 2005). A representative of continuous simulation is System Dynamic Simulation (SDS). Discrete Event Simulation (DES) and Agent Based Simulation (ABS) conversely are representatives of discrete simulation. A discussion on these three major simulation methods: SDS, DES and ABS are presented in Sections 2.3.1, 2.3.2 and 2.3.3 respectively.

2.3 Major Simulation Methods

This section discusses three common simulation methods known as SDS, DES and ABS. The discussion considers their definition and architecture, the modelling technique, the advantages and disadvantages, the application area and the available simulation software for each of the three approaches.

2.3.1 System Dynamic Simulation

Definition and architecture

System Dynamic Simulation (SDS) is a traditional simulation method which was developed in the mid -1950s (Sterman 2000). Jay Forrester, the founder of SDS, defined it as "*the study of information feedback characteristic of industrial activity to show how organizational structure, amplification (in policies) and time delay (in decision and action) interact to influence the success of enterprise*" (Forrester 1958). In other words, SDS is an approach employed to understand the dynamic behaviour of complex systems over time at aggregate level. SDS gains its understanding of a system by using a holistic approach for modelling the system (Wolstenholme, 1990). It is used as a strategic planning tool which applies for manpower and personnel, population, ecosystems, research and development.

SDS is based on system thinking. In order to build a SDS model, it is essential to understand the cause and effect of the problem. For example, if one potential buyer meets another buyer who has already purchased a product (cause), the interaction of these contacts might result in the purchase of the new product (effect). Thinking about cause and effect is not enough, as changes in a system's performance should also be considered. Therefore in order to understand more about the behaviour of a system, it is necessary to look at the chains of the cause and effect relationships which can form a feedback loop or a causal loop. According to Richardson and Pugh (1981), a feedback loop is *"a closed sequence of causes and effects, that is, a closed path of action and information."*

Modelling technique

A causal loop diagram is a visual representation of the feedback loops in a system. Overall, SDS describes system behaviour as a number of interacting feedback loops in a causal loop diagram, as illustrated in Figure 2.2.

There are two types of feedback loops, shown in the Figure 2.2. The positive reinforcement (labelled R) is the behaviour of growth where it tends to reinforce or amplify the behaviour of a system (Sterman 2000). For example, the more people adopt a new product, the stronger the impact of word-of-mouth. The negative reinforcement or balancing (labelled B) is the behaviour which neutralises and opposes change (Sterman 2000). For example, the more people adopt the new product, the fewer remain as potential adopters. The design of the causal loop diagram is one of the basic process of system dynamic modelling.

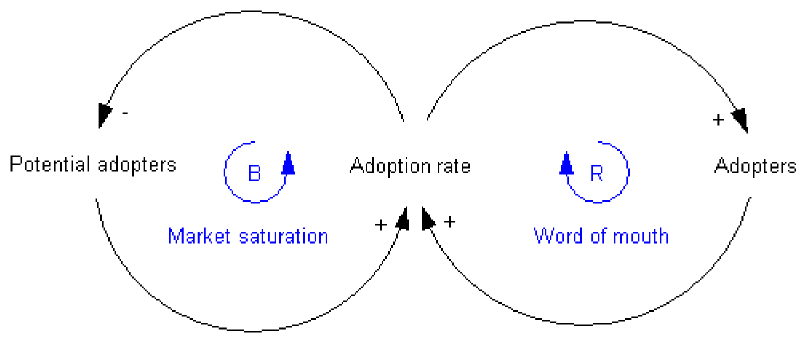


Figure 2.2 : Causal loop diagram of new product adoption model (Sterman 2000)

Other than causal loop diagram, SDS can also be modelled using real phenomena using stock and flow diagrams. The three basic symbols in stock and flow diagrams are: Stock , defined as a quantity that accumulates over time in the form of material (i.e. people) or information (i.e. knowledge) resources. Flow

, which changes the values of stocks; and Auxiliary , which arises when the formulation of a stock's influence on a flow involves one or more intermediate calculations. Figure 2.3 represents the stock and flow diagram for the new product adoption model from Figure 2.2 with some added parameters.

Figure 2.3 describes a stock and flow diagram as a visual representation of the feedback loops for the new product adoption model. There are three feedback loops in this diagram. The first feedback loop on the top left of the picture is a negative reinforcement (or "balancing" and hence labelled B). It indicates the transition between potential adopters to adopters according to a certain rate, determined by innovators. The second feedback loop on the left is also a negative reinforcement. It indicates that with the increase of people becoming adopters, the stock of potential adopters will decrease. The positive reinforcement (labelled R) loop on the right indicates that the more people have already adopted the new product, the stronger the word-of-mouth impact. All feedback loops act simultaneously, but at different times they may have different strengths. Thus, there are growing sales in the initial years, followed by a sales decline with time.

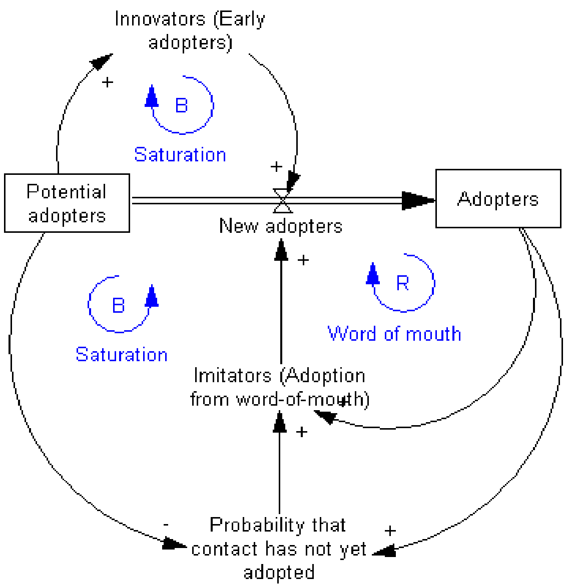


Figure 2.3 : Stock and flow diagram of new product adoption model (Sterman 2000)

Advantages and disadvantages of SDS

Wakeland et al. (2004) have found that SDS is useful in supporting educational learning in terms of increasing conceptual understanding on the investigated problem. Brailsford and Hilton (2000) claim that SDS it is capable of modelling very large complex systems and dealing with a large amount of qualitative and quantitative output measures. In addition, Brailsford and Hilton (2000) also claim that estimating the simulation's parameters and validation process are less difficulty in SDS compared to DES.

The impossibility of modelling a detailed representation of real-life problems at the entity level is one of the limitations of SDS (Wakeland et al. 2004). Besides that, as stated by Brailsford and Hilton (2000), SDS is less capable at modelling detailed resource allocation problems and optimisation or direct prediction. This discussion of the advantages and disadvantages of SDS as presented in this thesis forms only a small part of the debate. For further reading, Chahal and Eldabi (2008) have produced a summary of the existing literature regarding the advantages and disadvantages of SDS.

Application areas and simulation software

SDS has been applied to solve problems in various application areas such as manufacturing (Vlachos et al. 2007), business dynamics (Sterman 2000; Jan and Chen 2005), economic (Barton et al. 2004), biological (Wakeland et al. 2004) and healthcare (Eldabi et al. 2007).

Among the available simulation software for SDS are PowerSim, Vensim, STELLA, and Anylogic.

2.3.2 Discrete Event Simulation

Definition and architecture

DES is one of the better known simulation types as it has been used since the 1950s (Robinson 1994; Hollocks 2004). DES is a dynamic, stochastic and discrete simulation technique (Banks et al. 2005). In DES, simulation time plays an important role (dynamic model) and DES is a stochastic model as it consists of random input components. In addition, DES is discrete because it models a system in which the state of entities in the system change at a discrete time (Carson 2003). Technically, in DES there is only one thread of execution where the system is centralised.

A simple example of this type of simulation is the withdrawal of cash using an ATM service at a bank (Figure 2.4). To complete the withdrawal process at the ATM machine, the state of each customer changes from arrival to waiting to be served and finally to a served customer at a discrete time.

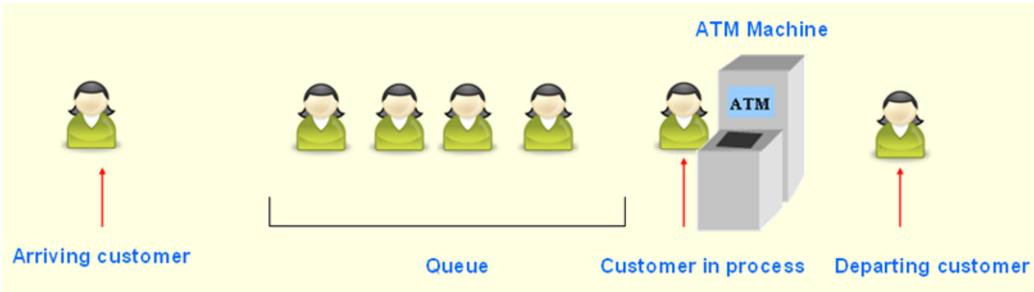


Figure 2.4 : A simple service system : Withdrawal of cash using an ATM service at a bank

In Figure 2.4, customers are represented as entities and the ATM machines as resources in discrete event model (DEM). Both, entities and resources are objects in the system. Entities are the simulated individual elements of the system with behaviours that are being explicitly tracked and can be organised in classes or sets (Pidd 1998). Resources are also individual system elements but they are not modelled individually and treated as countable items (Pidd 1998).

The movement of entities (customers) from one state (arrival state) to another state (waiting state) can be executed in various numbers of mechanisms for modelling DEM. These mechanisms include event-based approaches, activity-based approaches, process-based approaches, and three-phase approaches (Pidd 1984; Robinson 2004). The three-phase approach is used by a number of commercial simulation software packages (Robinson 2004), indicating that this is the preferred mechanism.

Further discussion about three-phase simulation modelling can be found in Michael Pidd's studies (Pidd 1984; Pidd 1998).

Modelling technique

The modelling technique for DES is process flowcharts. Many simulation packages, such as ARENA and Anylogic, have adopted this modelling approach for solving a variety of problems in the manufacturing and service sectors. Process flowcharts illustrate the interaction flow between entities, resources and block charts (i.e. source, process, decision, queue and delay) as shown in Figure 2.5.

Entities (i.e. customers) in Figure 2.5 are created at a source block and then move from one block to another until they leave the system, represented by a sink block. The DES model uses a top-down approach to model system behaviour. This modelling approach has enabled the DES model to be viewed from the perspective of the whole system, which eventually leads to an understanding of the overall system performance.

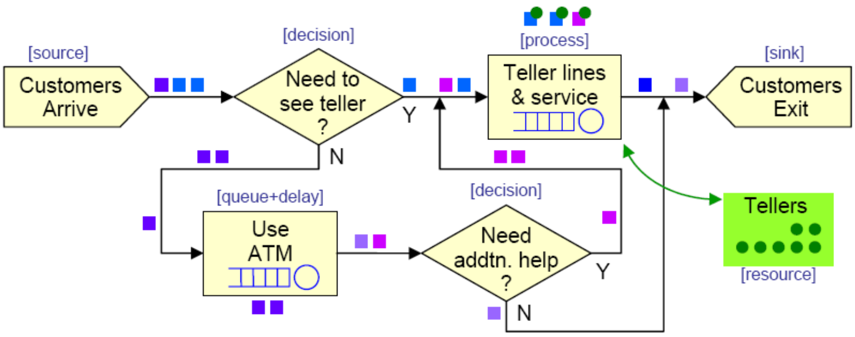


Figure 2.5: Discrete event model : Bank kiosk in Arena ™ (Borshchev and Filippov 2004)

Advantages and disadvantages of DES

The advantages of using DES as a tool to provide decision support in many applications are well documented throughout industry, the military and academia (Dubiel and Tsimhoni 2005).

One of the advantages of using DES compared to other simulation techniques such as SDS or ABS is it models a system in an ordered queue of events which is apart of the processes in manufacturing and service industries. (Siebers et al. 2010)

Another advantage of DES is that it has the ability to be combined with other simulation methods, such as continuous simulation (Zaigler et al. 2000) and agent-based simulation for studying complex systems (Parunak et al. 1998; Darley et al. 2004). A good illustration is an airplane's movement. In the air, the changes in movement of the airplane are continuous over a period of time but when the airplane arrives at the airport, it arrives at a discrete (random) point in time.

However, DES has been found to be difficult to implement in some situations, especially when involving human behaviour (Checkland 1981; Kalpakjian and Schmid 2001; Siebers et al. 2008). As claimed by Dubiel and Tsimhoni (2005) and agreed too by Brailsford and Stubbins (2006), it is not easy to model free or detailed human movement patterns such as crowd behaviour in DES.

Entities in DES are not autonomous and their movements depend on the user's decisions which must be set in the DES's blocks. This issue of autonomy, which relies upon the capability to make independent decisions (Bakken 2006), has made DES a less preferred choice to represent complex human behaviour such as proactive behaviour (Borshchev and Filippov 2004). In DES, people are usually implemented as resources or passive entities. Passive entities are unable to initiate events in order to perform proactive behaviour. Therefore, a proactive event that requires self-initiated behaviour by an individual entity is difficult to implement in DES (Borshchev and Filippov 2004).

In summary, DES is more suited to model operation systems (i.e. in supply chain management) which involve statistical analysis based on time. However, when it comes to modelling complex human behaviour i.e. proactive decision making, it is not easy to implement this kind of behaviour in DES. Therefore, DES has become less preferable as the modelling tool for simulating human behaviour (Bakken 2006) in various application areas.

Application areas and simulation software

According to Law and McComas (1997), the potential of DES is first discovered in the field of manufacturing, where it is used especially when a large amount of investment is involved, or to simulate complex manufacturing processes. For instance, if a company wishes to build a new production line, the line should first be simulated in order to assess whether the line is practical and efficient enough to be implemented. The simulation of the new production line can be considered a reliable way to predict results without having to conduct real experiments.

Since its introduction, the usage of DES has spread to various applications. Common types of DES applications include the design and operation of queuing systems (Komashie and Mousavi 2005), manufacturing and distribution systems (Semini et al. 2006), managing inventory systems (Brailsford and Katsaliaki 2007), health care (Werker and Shechter 2009), business strategic (Hlupic and Vreede 2005), banking (Banks 2000), transportation (Cheng and Duran 2004), disaster planning (Mahoney et al. 2005), and military(Nehme et al. 2008) uses. Well-known examples of simulation packages include Arena, Anylogic, AutoMOD, Extend, ProModel, Quest, Simul8 and Witness.

2.3.3 Agent Based Simulation

Definition and architecture

Agent Based Simulation (ABS) is a new paradigm among simulation techniques and has been used for a number of applications in the last few years, including applications to real-world business problems (Bonabeau 2001). ABS is known under various names as Agent-Based Systems, Agent-Based Modelling and Simulation or Individual-Based Modelling (Macal and North 2005).

The design of ABS is based on artificial intelligence using the concept of robotics and multi-agent systems (MAS)(Macal and North 2005). A MAS consists of a number of agents which interact with one another in the same environment (Wooldridge 2002); each of the agents has its own strategy in order to achieve its objective.

Due to the MAS structure, ABS has the ability to be autonomous, responsive, proactive and social (Jennings et al. 1998). These characteristics help ABS to perceive the agent's environment and take advantage of the opportunities; and possibly to provide initiative, independence and the ability to interact with other agents. For example, a computer game is a computer system that best describes the agent's characteristic. The player (an agent) in the game's environment searches for the best solution and provides a possible solution in order to win the game within a time constraint.

ABS models are essentially decentralised, which means there is no place where the global system behaviour (global dynamics) is defined. Technically, every agent has its own thread of execution; hence, the system is decentralised. ABS uses a bottom-up approach where the modeller defines the behaviour of the agent at the micro level (individual level) and the macro behaviour (system behaviour) emerges from the many interactions between the individual entities

(Macy and Willer 2002). The use of a bottom-up approach is the main difference between DES and ABS modelling techniques.

Modelling technique

One way of modelling ABS is to use a statechart (Figure 2.6), one of the diagrams in The Unified Modelling Language (Samek 2009). According to Borshchev and Filippov (2004), the different states of agents, the transitions between them, the events that trigger those transitions, and the timing and actions that the agent makes during its lifetime can all be visualised graphically using statechart.

Further explanation on modelling using statechart can be found in XJ Technologies(2010). Among the researchers using this modelling method are Buxton (Buxton et al. 2006), Siebers (Siebers et al. 2008), Emrich (Emrich et al. 2007) and Majid (Majid et al. 2010).

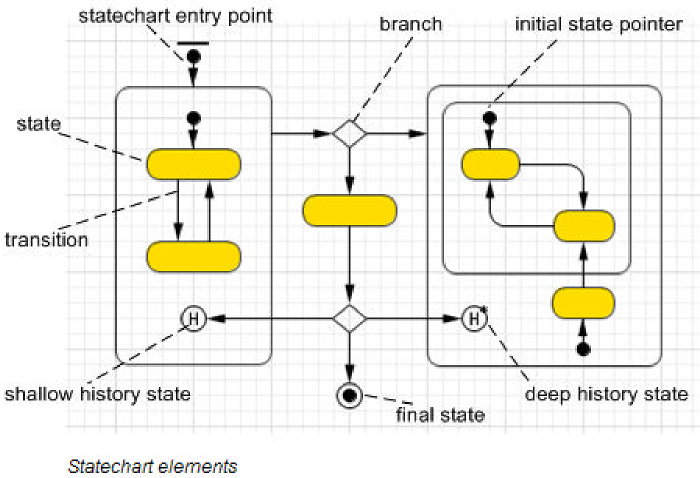


Figure 2.6 : Statechart for Agent Based Modelling (Borshchev and Filippov 2004; XJTechnologies 2010)

Advantages and disadvantages of ABS

According to Bonabeau (2001) the advantages of ABS can be captured in three statements: (i) emergent phenomena (ii) natural representation of system and (iii) flexibility. Emergent phenomena in ABS refers to the movement pattern that occurs from the unpredictable behaviour of a group of people (Bonabeau 2001). For instance, in a fire incident in a shopping complex, people can decide to go to the nearest door to save themselves. The movement of people creates one movement pattern that emerges from the independent decision (autonomous behaviour) of a number of individuals.

Bonabeau argues that the ability to produce emergent phenomena can be considered as the key advantage that makes the ABS more powerful than other simulation techniques. Most of the research studies involving emergent behaviour agree that ABS should be used i.e. in crowd evacuation (Shendarkar et al. 2006) and traffic simulation (Shah et al. 2005). The advantage of ABS over other simulation paradigms is that it can easily model this behaviour of movement, also known as free movement pattern (Dubiel and Tsimhoni 2005; Becker et al. 2006).

The second advantage of ABS is that it can provide a natural description of a system (Bonabeau 2001). ABS can imitate a system close to reality by modelling the behaviour of entities as naturally as possible. For example, it is more realistic to model the way a person behaves while working by adding natural human behaviours, such as being proactive.

Agents are autonomous: they can initiate events independently and are not guided by some central authority or process (Bakken 2006). Additionally, the capability of being autonomous has allowed the agents to model proactive behaviour. ABS also supports communication among the agents (Twomey and Cadman 2002; Scerri et al. 2010) i.e. through message-passing: agents can talk to one another and disseminate information among the population. This is a valuable asset for modelling human behaviour more naturally.

Like DES, ABS is also flexible, albeit in different ways. Bonabeau (2001) claims that ABM provides "*a natural framework for tuning the complexity of the agents: behaviour, degree of rationality, ability to learn and evolve, and rules of interactions*".

However, there are some disadvantages with ABS. It is not widely used, especially in industry; it seems to be of more interest to academics within their research studies than to industries which could implement it within practical applications (Siebers et al. 2010). It is possible that the limitations of ABS account for the lack of interest on the part of the software vendor in producing it, which in turn may be both a cause and a consequence of its lack of uptake and use in many areas.

Another disadvantages of ABS is this simulation method is computationally intensive (Twomey and Cadman 2002; Scerri et al. 2010): ABS plays with multiples of agents which try to find the solution by themselves; this agent's modelling process requires time to generate and eventually demands a large capacity of computer power to support it.

In addition to the disadvantages of ABS is the lack of adequate empirical data. This issues is arisen as there has been questioned whether ABS model can be considered as scientific representation of a system as it has not been built with 100% measurable data (Siebers et al. 2010).

Application areas and simulation software

ABS has been used in many aspects of science, including economics, sociology, and political, physical and biological sciences. Table 2.3 shows the areas and sub-areas where ABS can be applied. Regarding the simulation software for ABS, the best known packages include RePast, Swarm and Anylogic.

Table 2.3 Agent-based modelling applications (Macal and North 2005)

Areas	Sub-Areas
Business and Organizations	• Manufacturing • Consumer markets • Supply chains • Insurance
Economics	• Artificial financial markets • Trade networks
Infrastructure	• Electric power markets • Hydrogen economy • Transportation
Crowds	• Human movement • Evacuation modelling
Society and Culture	• Ancient civilizations • Civil disobedience
Terrorism	• Social determinants • Organizational networks
Military	• Command & control • Force-on-force
Biology	• Ecology • Animal group behaviour • Cell behaviour • Sub-cellular molecular behaviour

2.3.4 Conclusions

The three simulation techniques can be summarised as follows: SDS and DES are the two traditional simulation techniques which have been used for almost six decades. SDS is used for modelling at high abstraction level. This is because SDS is concerned with how a collection of parts operates as a whole, overtime and it is applied when individuals within the system do not have to be highly differentiated and knowledge on the aggregate level is available.

On the contrary, DES is the most suitable and the most frequently used to model a queuing system, as the DES model is originally based on queuing theory. Furthermore, nowadays there are many simulation packages that provide straightforward solutions for modelling process-oriented systems such as queuing systems in DES. DES is used for modelling at a medium and low abstraction levels.

ABS is another simulation technique but more powerful than SDS and DES in terms of its modelling capability. It is based on a multi-agent system and therefore incorporates the capability of agents, such as being autonomous to provide independent decisions. ABS is suitable for modelling emergent phenomena and for presenting real-life systems as naturally as possible. In addition, it can model a system at any abstraction level.

2.4 Comparisons of SDS, DES and ABS

In the literature there are a number of papers which compare SDS, DES and ABS models. Some relevant papers comparing simulation techniques are listed in Table 2.4.

Table 2.4: Some relevant papers comparing simulation techniques

Techniques	Research Area	Findings
SDS and ABS	Biomedical	Wakeland et al.(2004) have found that the understanding of the aggregate behaviour in the SDS model and state changes in individual entities in the ABS model is relevant to the biomedical study.
SDS and DES	Fisheries	Morecroft and Robinson (2006) have found that SDS and DES implement different approaches for modelling but that both are suitable for modelling systems over time.
DES and ABS	Transportation	Becker et al. (2006) have found that DES is less flexible than ABS; it is difficult to model different behaviours of shoppers in DES.
SDS, DES and ABS	General view	Borshchev and Filippov (2004) have found that in general ABS is more capable of capturing real-life phenomena, although in some cases SDS and DES solve a problem more efficiently.

Further comparison studies include research undertaken by Marin et al. (2006), who have built a mixed SDS and ABS for workforce climate. The purpose of mixing the modelling approaches is to produce a decision-making tool which encompasses the strategic and tactical levels of decision-making in the organisation's planning. They have found that SDS models are able to capture the different patterns of employees' behaviour using a large number of differential equations. However, in the case of detailed and complex behaviour of any individual employee, they found that ABS is more suitable for modelling this kind of behaviour.

Reviews of existing comparisons between SDS and DES is undertaken by Tako and Robinson (2006) , Chahal and Eldabi (2008) and Sweetser (1999). Tako and Robinson (2006) have reviewed sixty-five journal articles from 1996-2006 which compare model building, philosophies and model use of SDS and DES models. They conclude that in most areas (for example, manufacturing and supply chain management) SDS has been used for the strategic planning while DES has been used for the operational planning.

Meanwhile, Chahal and Eldabi (2008) have produced a meta-comparison between the two approaches based on a literature survey. They emphasise that it is important to understand from system, problem and methodology perspectives in order to choose a suitable simulation techniques for the system under investigation. Sweetser (1999), on the other hand, has devised a summary and comparison between the two modelling approaches on a production process. His investigation reveals that many problems can be solved by both simulation approaches and probably produce similar results.

Another current comparison of DES and ABS is presented by Pugh (2006) and Yu et al. (2007). Pugh observes that by looking into the model characteristics, DES and ABS models both represent M/M/1 queuing systems well. However, he has found that ABS models are much more difficult to construct compared with DES models. Yu et al. (2007) conducted a quantitative comparison between DES and ABS model characteristics in the field of transportation, and have found that the DES model appears to have greater value in the internal properties of the simulation software: for instance, building DES models in their simulation software requires more model blocks, whereas ABS models require fewer classes. This suggests that even though DES and ABS can both model the system under investigation, their modelling process are different (Becker et al. 2006).

A comparison of the three modelling techniques is also presented by Lorenz and Jost (2006) and Owen et al. (2008), adding further discussion to that raised by Borshchev and Filippov in their study (2004). The studies by Lorenz and Jost (2006) and Owen et al. (2008) have sought to establish a framework to assist the new simulation user in choosing the right modelling techniques. Loren and Jost (2006) focus on developing a framework for multi-paradigm modelling within the social science, while Owen focuses on developing a framework for supply-chain practitioners. These two papers have agreed that each simulation technique has its own strengths and weakness in modelling similar problems.

It would appear that researchers, when comparing simulation techniques, are in general agreement that it is essential to choose the appropriate modelling technique to ensure an accurate representation of the selected problem in the different areas. However, an exploration of the literature reveals one gap in research. There appears to be a disparity between the high volume of work comparing SDS and ABS, SDS and DES or SDS, DES and ABS, mostly in the area of manufacturing, supply-chain, transportation, fisheries or biomedical industries and no studies which compare SDS, DES and ABS regarding their suitability for human behaviour modelling in the service systems.

The aim of the thesis is to close this gap for service systems models at the tactical and operational level. Therefore, we have chosen to compare DES and ABS rather than all three simulation methods. For the remainder of this thesis, we will focus on these two simulation methods.

2.5 Human Behaviour Modelling

2.5.1 Modelling Human Behaviour using Simulation

As explained by Pew and Mavor (1998), Human Behaviour Representation (HBR), also known as human behaviour modelling, refers to computer-based models which imitate either the behaviour of a single person or the collective actions of a team of people. Nowadays, research into human behaviour modelling is well documented globally and discussed in a variety of application areas. Simulation appears to be the preferred choice as a modelling and simulating tool for investigating human behaviour (ProModel 2010). This is because the diversity of human behaviours is more accurately depicted by the use of simulation (ProModel 2010).

Throughout the literature, the best-known simulation techniques for modelling and simulating human behaviour are DES and ABS. Among existing studies on modelling human behaviour, the use of DES is presented by Brailsford et al. (2006), Nehme et al. (2008) and Baysan et al.(2009). On the other hand, Schenk et al. (2007), Siebers et al. (2007) and Korhonen et al. (2008a; 2008b) recommend ABS for modelling human behaviour.

Brailsford et al. (2006) claim that, based on their experiments of modelling the emergency evacuation of a public building, it is possible to model human movement patterns in DES. However, the complex nature of DES structures where entities in the DES model are not independent and self-directed makes the DES model inappropriate for modelling large-scale systems. This characteristic of entities in DES is agreed by Baysan et al.(2009), who have used DES in planning the pedestrian movements of the visitor to the Istanbul Technical University Science Center. However, due to the dependent entities in the DES model, the pedestrian movement pattern in their simulation model is restricted to pre-determined routes.

By contrast, Korhonen (2008a; 2008b) has developed an agent-based fire evacuation model which models people-flow in free movement patterns. He states that the decision to use ABS is due to the fact that agent-based models can provide a realistic representation of the human body with the help of autonomous agents.

In addition to modelling human behaviour using DES, Nehme et al (2008) have investigated methods of estimating the impact of imperfect situational awareness of military vehicle operators. They claim that it is possible to use the DES model to understand human behaviour by matching the results from the DES model with human subjects.

Schenk et al. (2007) comment that modelling consumer behaviour when grocery shopping is easier using ABS because this model has the ability to integrate communication among individuals or consumers.

Siebers et al. (2007) assert that their research in applying the ABS model to simulate management practices in a department store appears to be the first research study of its kind. They argue that ABS is more suitable than DES for modelling human behaviour due to the characteristics of the ABS model; specifically, it contains pro-activeness and autonomous agents that can behave similar to humans in a real world system.

Instead of choosing only one simulation technique to model human behaviour, some researchers tend to combine DES and ABS in order to model a system which cannot be modelled by either method independently. Such researches have been carried out by Page et al. (1999), Kadar et al. (2005), Dubiel and Tsimhoni (2005) and Robinson (2010) into the operation of courier services in logistics, manufacturing systems, human travel systems and the operation of coffee shop services respectively. They agree that the DES and ABS models can complement each other in achieving their systems' objectives. The combination of

ABS and DES is used when human behaviour has to be modelled for representing communication and autonomous decision-making.

In conclusion, the research into human behaviour using DES and ABS that has been carried out so far suggests that DES and ABS are able to model human behaviour but take different approaches (dependent entities vs. independent agents). The studies outlined above indicate that DES is suitable for capturing simple human behaviour, but is problematic when applied to more complex behaviours as the next event to occur in DES has to be determined. In contrast, ABS offers straightforward solutions to modelling complex human behaviour, i.e. free movement patterns or employee proactive behaviour, as agents can initiate an event themselves.

2.5.2 Human Behaviours in the Service-Oriented System

There are many customer service-based processes which are related to the way the company employs staff to provide support to the customers. A customer service-based process, also called a people-centred system, (Siebers et al. 2010) is where both entities and resources are human (Tumay 1996): examples include the retail sector, call centres, airport check-in services and hospital registration processes.

Good customer service is crucial to any business: it increases sales by encouraging both returning and new customers to make purchase (Ward 2010). Numerous human behaviours involved in customer services have been recognised; this thesis focuses on the reactive and proactive human behaviour of employees and customers within a service system.

Ferber and Drogoul (1991) refer to reactive behaviour as response-type behaviour. Kendall et al. (1998) agree that reactive behaviour can include responses to the changes in the environment. Halpin and Wagner (2003) assert that: "*reactive behaviour may be viewed as a set of reaction patterns that determine how the system reacts to events*". To summarise, the reactive behaviour can be defined as responses to the environment.

Additionally, Kendall et al. (1998) defines proactive behaviour as acts which achieve goals, while Crant (2000) refers to proactive behaviour as "*taking initiative in improving current circumstances; it involves challenging the status quo rather than passively adapting present conditions*." Grant and Ashford (2007) defined proactive behaviour as "*anticipatory action that employees take to impact themselves and/or their environments*".

Furthermore, Parker et al. (2006) have provided a complete definition of proactive behaviour in their review of a wide selection of papers and journals on proactive behaviours in service systems. They describe it as "*self-initiated and future-oriented action that aims to change and improve the situation or oneself*", and identify three main types of proactive behaviours: Type 1 - taking charge to bring about change; Type 2 - using one's initiative to carry out one's job in an innovative way; and Type 3 - scanning the environment to anticipate and prevent future problems.

The various definitions of proactive behaviour from the literature appear to come to the same conclusion that: "*Proactive behaviour is self-initiated behaviour*".

In the daily life of a human being, behaving proactively produces many benefits compared with simply behaving reactively. Being a proactive customer is an effective way to achieve a goal which leads promptly to individual success (Rank et al. 2007). Similarly, proactive behaviour among staff has been seen as a factor in career success (Crant 2000) in a service organisation, where it plays an important role in an organisation's ability to generate income and revenue.

Research into modelling and simulation of reactive and proactive behaviour is presented by Bazzan et al. (1999) and Davidsson (2001). Bazzan et al.(1999) use ABS to study driver behaviour, focusing on reactive and social behaviour. They suggest that it is essential to model the real behaviour of human beings, which contains both reactive and proactive behaviour, in order to predict accurate traffic flow. Davidsson (2001) investigates the benefits of ABS in modelling the proactive human behaviours for designing a control system in an intelligent building. He found that it is a straightforward process to use ABS for modelling proactive behaviour.

Overall, having reactive and proactive human behaviour in an organisation is essential to its success. However, there is still very little research on the subject of modelling reactive and proactive human behaviour, especially in the service sector. Due to this specific gap, our research focuses on the comparison between two simulation techniques (DES and combined DES/ABS) in modelling the increasing level of detail of human behaviour for service systems.

2.5.3 Comparison Measures to Investigate Human Behaviours

Choosing the best simulation model is a challenging task (Law and Kelton 2000), especially when it is possible to use more than one technique, and when choice would have a major effect on the success of the project (Tilanus 1985; Ward 1989; Salt 1993). Morecroft and Robinson (2006) raise an interesting question: "*How to choose which method to use*?". One solution is to understand the similarities and differences between the simulation techniques by conducting an empirical comparison for the problem under investigation (Morecroft and Robinson 2006; Owen et al. 2008; A.Tako and Robinson 2009). This evaluation should be based on model performance elements (Brooks 1996) which are basically comparison measures.

Table 2.5 lists a number of comparison measures that have been used in the literature to compare different simulation techniques. The category "model result" represents the examination of the simulation results based on the chosen performance measures.

The category "model difficulty" represents the level of modelling the investigated problem from the perspective of model building time (time spent to develop a simulation model), model line of codes (line of programming code to develop a simulation model), model execution time (processing time to run a simulation model) and model size (the scope and the level of detail models in a simulation model).

The category "model architecture" represents the investigation into the model structure (i.e. classes vs. blocks, methods vs. procedures), the ability to replicate results, model representation and interpretation (i.e. queues and activities of DES vs. stock and flow of SDS) and the theory of simulation techniques. Finally, the category "model use" represents the perception of the user that the simulation model is useful for the purpose it has been developed for.

According to the researches in Table 2.5, model results and some parts of model difficulty (i.e. model lines of code) are demonstrated by using a quantitative approach. In contrast, model architecture and model use are mainly demonstrated using a qualitative approach.

For our study, we have chosen model result and model difficulty as measures for comparing simulation techniques as we want to conduct a quantitative comparison.

Table 2.5 : Comparison measures from literature

Comparison measures	Division in the comparison measures
Model result	The accuracy of model's results (Brooks 1996) (Becker et al. 2006)
Model difficulty	Model building process (Yu et al. 2007) (A.Tako and Robinson 2008) Model line of code (Wakeland et al. 2005) (Yu et al. 2007) Model execution time (Becker et al. 2006) (Yu et al. 2007) (Wakeland et al. 2005) Model size (Wang and J.Brooks 2007) (Yu et al. 2007)
Model architecture	Model structure (Becker et al. 2006) (Yu et al. 2007) Ability to replicate results (Wakeland et al. 2005) Model representation & interpretation (Morecroft and Robinson 2006) Theory and modelling (Borshchev and Filippov 2004)
Model use	User's perception (A.Tako and Robinson 2009)

2.6 Conclusions

The knowledge gathered through this literature review suggests that it is possible to use both DES and ABS models in modelling reactive and proactive human behaviour. However, no research appears to exist which compares simulation models of such behaviour in the service-oriented systems, an issue which has led to the aims and objectives of this thesis (Chapter 1: Section 1.3).

The present study seeks to investigate a service-oriented system which involves queuing for different services. As in ABS models, the system itself is not explicitly modelled but emerges from the interaction of the many individual entities that make up the system; using ABS alone would not therefore be appropriate to this investigation. However, as ABS seems to be a suitable concept for representing human behaviour, it has been decided to try a combined DES and ABS (combined DES/ABS) approach where the system is modelled in a process-oriented manner with the actors inside the system (i.e. customers and staff) modelled as agents.

This study therefore seeks to compare the capability of combined DES/ABS approach with a more traditional DES approach when modelling reactive and the difference level of proactive behaviours. Chapter 3 presents further discussion of the research approach taken for comparing both simulation models.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Introduction

The previous chapter has emphasised the importance of knowledge of modelling and simulation for human behaviour in service-oriented systems. This knowledge provides an initial awareness for simulation users to allow them to make a careful choice between DES and DES/ABS for modelling human behaviour problems in service-oriented systems. In order to build on this knowledge, three different types of case studies have been undertaken on service-oriented systems. In this chapter, the research methodology used for each of the case studies is briefly discussed in the following sequence: case study description, conceptual model development, model implementation, verification and validation, experimentation and result analysis. The conclusion that can be made as a result of using this research methodology is discussed at the end of the chapter.

3.2 Case Study Description

In order to compare the capability of DES and DES/ABS to model human behaviour in human centric systems (i.e. airport check-in services system), it is necessary to carry out case studies which offer a sufficient amount of data containing human behaviour. Thus, the service sector is targeted, focusing on customer-service processes which are rich in human behaviour, with both entities and resources being human (Tumay 1996).

A key aim of this thesis is to produce a practice for simulation in modelling human behaviour in service-oriented systems. Three case studies have been undertaken to achieve a better generalisation of research output (Flyvbjerg 2006), using information-oriented sampling (Yin 2009).

Flyvbjerg (2006), identifies four types of cases associated with information-oriented sampling: extreme cases, maximum variation cases, critical cases and paradigmatic cases, all of which share similar characteristics in relation to the general problem as shown in Table 3.1.

The present case studies are classified as critical case studies, as the human behaviours models in the three case studies are similar to those found in most service-oriented systems. It is therefore argued that these case studies can serve as an illustrative guideline for modelling human behaviour in other similar service-oriented systems (Siggelkow 2007).

Three different types of service environment are identified on which to model the research problem: a department store (case study 1), a university (case study 2) and an airport (case study 3). Real-life systems are used to model case studies 1 and 2 while a hypothetical system is used for case study 3.

Table 3.1 : Types of information oriented sampling for case study selection (Flyvbjerg 2006)

Information Oriented Sampling	Purpose
Extreme/deviant Cases	To obtain information on unusual cases, which can be especially problematic or especially good in a more closely defined sense.
Maximum variation cases	To obtain information about the significance of various circumstances for case process and outcome (e.g., three to four cases that are very different on one dimension: size, form of organization, location, budget).
Critical cases	To achieve information that permits logical deductions of the type, "If this is (not) valid for this case, then it applies to all (no) cases."
Paradigmatic Cases	To develop a metaphor or establish a school for the domain that the case concerns

A variety of research techniques are used to collect data for case studies 1 and 2: quantitative methods are used to gather data which has been counted (for example, the number of customers, recording customer arrival time, staff service time) and conducting the statistical analysis for reporting real data; qualitative methods such as interviewing and observation are involved in the data gathering process. Qualitative data are used for conceptual model development (discussed in Section 3.5) while quantitative data are used as input data to our simulation models.

Several stages are necessary prior to the collection of real data. The first stage is to determine the data require, such as the arrival rates and cycle times. The second stage is to decide on the performance measures (outputs) of the real system, which form the key indicators for measuring the system's performance. The final stage is to identify the human behaviour to be investigated in the real system. Case study 3, selected from "Simulation with Arena" (Kelton et al. (2007), differs in that the modelling of human behaviour imitates the real world behaviour of humans at an airport using information gathered from secondary data sources such as books and academic papers.

All three case studies investigate reactive and proactive behaviour demonstrated by employees (i.e. sale staff, receptionist etc) and customers (i.e. students, shoppers, etc). Reactive behaviour is defined as a set of responses to the environment (Kendall et al. 1998). In the three case studies, reactive behaviour is the responses made to people's requests such as the response of an employee to a request from a customer (Chapter 2: Section 2.6.3). Proactive behaviour is defined as self-initiated behaviour (Chapter 2: Section 2.6.3) demonstrated, for example, when an employee acts on their own initiative to identify and solve a problem in the work environment.

According to Parker (Parker et al. 2006), in this study, proactive behaviour is categorised into three different types of underlying sub-proactive behaviour, as follows:

Type 1 : Taking action based on previous experience as shown when employees make their own decision to tackle the situation in the investigated environment based on their working experience.

Type 2 : Taking the initiative to fulfil goals, a behaviour that occurs as the result of knowledge gained from observing the investigated environment by the customers.

Type 3 : Supervising by learning, a behaviour that occurs among the employees observed in the investigated environment. Type 3 is the combination of Type 1 and Type 2 proactive behaviours. Based on their knowledge of their working environment and current observation, employees make their own decisions in order to control situations in the case studies environments.

Each of the three case studies is differentiated by modelling different types of behaviour. Each case study models the general idea of reactive behaviour (response to environment) and a specific type of proactive behaviour (Type 1, Type 2, Type 3 or combination). The number of proactive behaviours modelled in each case study is increased by adding one type at each time. In case study 1, reactive and Type 1 proactive behaviour are modelled. Reactive and Type 1 and 2 proactive behaviours are modelled in case study 2. Finally in case study 3, reactive behaviour and all three types of proactive behaviours are modelled. Table 3.2 below shows the human behaviours model in the three case studies.

Table 3.2: The human behaviours in case studies 1, 2 and 3

Case study	Reactive Behaviour	Proactive Behaviour
1	General	Type 1
2	General	Type 1 and 2
3	General	Type 1, 2 and 3

Following the data collection process, data is analysed for use in the conceptual model and model building. Part of the data analysis process is to determine the arrival pattern of the customer in each of the case studies, by selecting suitable statistical distributions and parameters. Chapters 4, 5 and 6 provide a detailed discussion of each case study.

3.3 Conceptual Model Development

Based on the three case studies, three same basic conceptual models are developed for both DES and combined DES/ABS, representing the scope and level (Robinson 1994) of the system under investigation. The concept for a DES model is developed, representing the basic process flow (process-oriented approach) of the three case studies operation (a complex queuing system) using a flow chart.

In the basic process flow, the human behaviours (reactive and proactive) are added in order to show where the behaviours occurred. Flow charts are used to represent DES conceptual models because DES focuses on process flows. The same flow charts are used in combined DES/ABS to represent the DES model inside the combined model.

In addition, an individual-centric approach is used to represent every individual type of agent and their interaction in the implementation of combined DES/ABS model. The individual-centric approach is developed using state chart. State charts show the possible different states of an entity and define the events that cause a transition from one state to another. Chapters 4, 5 and 6 discuss further details of conceptual models for each case study.

3.4 Model Implementation, Verification and Validation

Simulation models are built once the scope and level of DES and combined DES/ABS models have been determined. Figure 3.1 illustrates the steps undertaken for model implementation and validation process. To build simulation models, AnyLogic™ 6.5 Educational version (XJTechnologies 2010) is used, due to the capability of the software to develop DES and combined DES/ABS models in one tool. Once the simulation software has been selected, the next stage is to build and program the simulation model.

For each case study it was essential to design several set-ups for modelling human reactive and proactive behaviours in DES and combined DES/ABS models. The purpose of difference setup is to gain better understanding on the capability of both simulation models in modelling human behaviours.

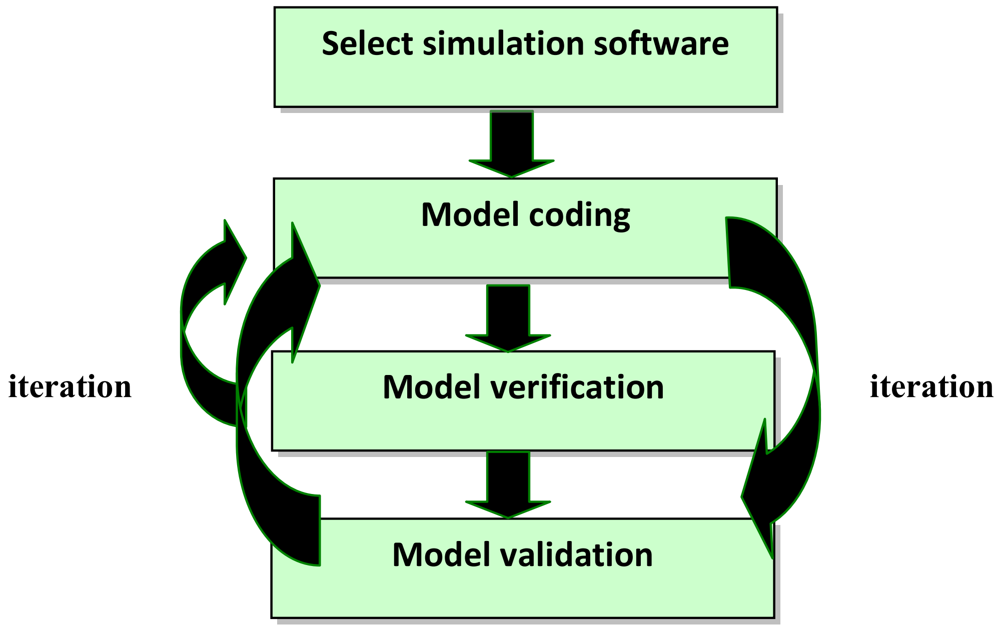


Figure 3.1 : The model implementation, verification and validation process flow

For case studies 1, 2 and 3, the same proactive behaviours with the same logic decision to model the proactive behaviours are implemented in both DES and combined DES/ABS. Additionally, for case study 2 and 3, the different logic decision is used for modelling some proactive behaviour in DES and combined DES/ABS. The difficulty of imitating the natural representation of real-life proactive behaviour in DES models has been seen to be problematic from literature (Chapter 2: Section 2.3.2). This explains the different logic decision adopted for DES and DES/ABS models demonstrating some proactive behaviour in case studies 2 and 3. Both decision trees and probabilistic distributions are used to model proactive behaviours in the simulation models.

Along with the development of the DES and combined DES/ABS models, the verification and validation processes are performed in order to produce good representation of real world service systems. Two verification methods are conducted: checking the code with a simulation expert and visual checks by the modeller. These processes are iteratively conducted during the model building for both DES and combined DES/ABS. A specialist in the chosen simulation software (Anylogic) has been selected as a consultant, who reads through the simulation code focusing on the complex decision logic. Any mistakes on the simulation code are noted and modifications on the code are carried out.

In undertaking the visual checks, the modeller runs both DES and combined DES/ABS models separately and monitors the element behaviours in the simulation models. Both the verification by the expert and the modeller's visual checks are continuously conducted until the correct expected behaviour of the simulation model is achieved.

Two validation processes are chosen - black-box and sensitivity analysis validations. Black box validation is used for case studies 1 and 2 due to data from the real system is available to compare with the simulation results. Sensitivity analysis validation is employed for case studies 1, 2 and 3 in order to examine the sensitivity of the simulation results when the simulation input (i.e. arrival rates) is varied.

The black-box validation compares the simulation outputs from both simulation models with real system outputs, using a quantitative approach. It is not possible to perform black-box validation for case study 3 as there is no information available for the real system. Thus, only sensitivity analysis is performed. In the sensitivity analysis validation, the arrival rates of both simulation models (DES and combined DES/ABS) are varied by producing three types of arrival patterns.

Based on a random choice of increment percentage, the arrival pattern is decided to increase by 30% each time, starting from the first arrival pattern. It must be remembered that the main purpose of the validation process is to investigate the sensitivity of the simulation results in both simulation models to one another. It is therefore agreed that the percentage of increment for the arrival pattern is not crucial.

After the development of DES and combined DES/ABS models in all three case studies (Chapter 4, 5 and 6), experimental conditions such as the run length and number of runs of the simulation models are determined. The operation time of the real system, finishing at the end of a day, is mirrored as the run length in the simulation models.

The number of runs is decided by adopting a graphical approach (Robinson 2004). A graph is plotted from the cumulative mean average of one performance measure i.e. customer waiting times – refer Chapter 4. Then, the graph is inspected in order to find the point where the results (i.e. customer waiting time) in DES and combined DES/ABS converge sufficiently, such that continuing the run will not significantly improve convergence. It is not necessary to consider a warm-up period for all case studies, as the real system operation is a terminating system where the three case studies start from empty systems.

A more detailed discussion on these model implementation and validation processes is provided in Chapters 4, 5 and 6.

3.5 Experimentation

3.5.1 Introduction

Two sets of experiments are carried out in each case study in order to achieve the research objectives (Chapter 1: Section 1.3). Set A, which is concerned with simulation model results, seeks to fulfil the first objective of the study, while Set B, in determining simulation model difficulty, aims to fulfil the second objective of the study (see Chapter 1: Section 1.3).

The purpose behind the model result and model difficulty experiments is to investigate the performance of the simulation results and level of difficulty when modelling human behaviour in both DES and combined DES/ABS models. Each set of experiments is divided into two sub-experiments where Set A consists of Experiments A1 and A2, and Set B consists of Experiments B1 and B2 (Figure

3.2). Experiments A1 and B1 are for investigating reactive modelling while Experiments A2 and B2 are for investigating mixed reactive and proactive modelling in DES and combined DES/ABS. Based on both set of experiments (A and B) in the three case studies, the following main hypotheses are tested.

Ho_1 : DES shows no significant difference in the simulation results when modelling reactive behaviour/ compared with combined DES/ABS.

Ho_2 : DES shows no significant difference in the simulation results when modelling mixed reactive and proactive behaviour compared with combined DES/ABS.

Ho_3 : DES shows less modelling difficulty when modelling reactive behaviour compared with combined DES/ABS.

Ho_4 : DES shows less modelling difficulty when modelling mixed reactive and proactive behaviour compared with combined DES/ABS.

Prior to conducting experiments, it is necessary to identify similar performance measures for DES and combined DES/ABS models. The performance measures are the key indicator of the performance of the simulation models during the experimentation stages. Four main performance measures are identified for all experiments under Set A: waiting time, staff utilisation, the numbers of customers served and not served. These four measures are adopted because they are the most common and among the most important in the service-oriented systems (Robert and Peter 2004).

Moreover, the number of proactive encounters is used as the additional performance measures in the experiments involved with proactive modelling. Meanwhile three main performance measures (known as model difficulty‘s measures) that are used in all experiments under Set B are model building time, model execution time and model line of code (LOC).

These three model difficulty’s measures are adopted as they can be collected straightforward in quantity during the simulation models development (Chapter 2: Section 2.6.3). In addition these three model difficulty’s measures are assumed to be sufficient in presenting the difficulty of one simulation model (Chapter 2: Section 2.6.3).

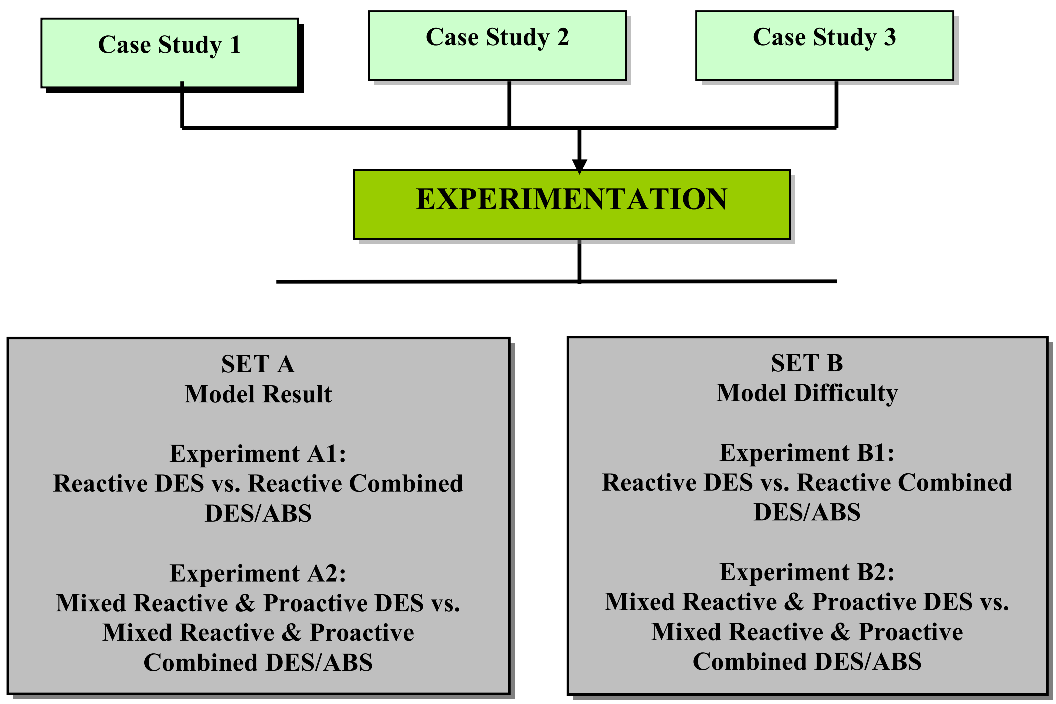


Figure 3.2 : Design of experiment for model result and difficulty investigation

3.5.2 Model Result Experiments

Experimentation starts with Experiment A1: Reactive Human Behaviour, the objective of which is to investigate the performance of simulation results when modelling human reactive behaviour for both DES and combined DES/ABS. The main and sub-hypotheses are first generated, corresponding to a comparison of reactive DES and combined DES/ABS based on the chosen performance measures. The main hypothesis to test in Experiment A1 is same as Ho_1 above (Section 3.5.1).

Next, the results of both performance measures in DES and combined DES/ABS for the reactive experiments are calculated and compared using the same statistical test used in the black box validation (Section 3.4).

This is followed by Experiment A2: Mixed Reactive and Proactive Human Behaviours. In contrast to Experiment A1, the objective of Experiment A2 is to investigate the performance of simulation results in modelling mixed human reactive and proactive behaviour in both DES and combined DES/ABS. In Experiment A2, the main hypothesis to test is same as Ho_2 above (Section 3.5.1).

The same simulation models as used for Experiment A1 are enhanced by adding human proactive behaviour. As discussed in Section 3.2 above, more than one type of proactive behaviour are investigated. Each type of proactive behaviour is divided into different sub-types of proactive behaviours in each case study. In addition, each sub-type of proactive behaviours is performed in difference sub-experiments as shown in Table 3.3.

When the development process is completed, the design of Experiment A2 follows the design of Experiment A1 which includes the development of the hypotheses, a variation of the arrival rates, and statistical testing.

Table 3.3 : The division of type, sub-type and sub-experiments in Experiment A2 for case study 1, 2 and 3

Case Study	Proactive Behaviours		Experiment A2
	Type	Sub-Type	Sub-Experiment
1	1	Sub-Proactive 1 : Speed up service time	Experiment A2_1
		Sub-Proactive 2 : Call for help	Experiment A2_2
		Sub-Proactive 3 : Combination of Sub Proactive 1 and 2	Experiment A2_3
2	1	Sub-Proactive 1 : Request to leave	Experiment A2_1
		Sub-Proactive 2 : Speed up service time	Experiment A2_2
	2	Sub-Proactive 3 : Skipping from queuing	Experiment A2_3
	1 and 2	Sub-Proactive 4 : Combination of Sub-Proactive 1,2 and 3	Experiment A2_4
3	1	Sub-Proactive 1: Request to work faster	Experiment A2_1
	2	Sub-Proactive 2 : Get faster served	Experiment A2_2
	3	Sub-Proactive 3 : Observe suspicious people	Experiment A2_3
	1,2 and 3	Sub-Proactive 4 : Combination of Sub-Proactive 1,2 and 3	Experiment A2_4

3.5.3 Model Difficulty Experiments

Set B experiments begin with conduct of Experiment B1: Reactive DES vs. Reactive Combined DES/ABS model difficulty, the objective of which is to explore model difficulty from the perspective of simulation model building time, model execution time and model line of code (LOC). These measures of model difficulty are essential in contributing to an understanding of the level of difficulty involved in developing a simulation model with the different modelling approaches. In Experiment B1, the main hypothesis to test is same as Ho_3 in Section 3.5.1 above.

The model building time is the time spent to build the simulation model using DES and combined DES/ABS approaches, calculated in units of one hour. The model execution time is the processing time needed to run the simulation model, calculated in seconds. The model line of codes (LOC) refers to the programming code involved in developing the simulation models. To count the number of model LOC, the freeware software Practiline Source Code Counter (PractilineSoftware 2009) is used.

The model difficulty outputs (model building time, model execution time and model line of code) is depend on the simulation software that is used and the experience of the modeller. A scale to represent the standard level of difficulty to compare between both simulation approaches (DES vs. combined DES/ABS) has therefore been applied, as shown in Figure 3.3 below. A scale from 1 to 10 has been used, where a higher value represents a higher degree of difficulty for the developed simulation models.

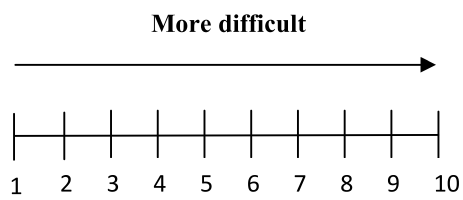


Figure 3.3 : Scale of model difficulty

The first step of Experiment B1 is to convert the results of the model difficulty investigation from DES and combined DES/ABS models into the above scale (Figure 3.3) using a normalisation method (Equation 1). As there are two simulation results (DES vs. combined DES/ABS) to compare with each model difficulty measure, the minimum and maximum results are known. For that reason, the suitable normalisation formula to use is as in Equation 3.1 which follows:

$$\boldsymbol{\delta = \frac{d}{d^{max}} \; x \; R} \qquad \text{(Equation 3.1)}$$

The simulation results ***d*** (either from DES and combined DES/ABS models) i.e. total building time in reactive behaviour, is divided by the maximum value $\boldsymbol{d^{max}}$ either from DES or combined DES/ABS simulation results. Next, the deviation results of $\boldsymbol{d / d^{max}}$ are multiplied by the total number of scale (1 to 10 = 10) **R** in order to convert the deviation results of $\boldsymbol{d / d^{max}}$ into the standard range of model difficulty δ.

Two types of results are gathered for Experiment B1. The first results of the model building time, model execution time and model LOC are obtained from the modeller's work with both DES and combined DES/ABS approaches in case studies 1, 2 and 3.

The second type of results is obtained from a survey conducted among simulation beginners, but only for case study 1. Both results (first and second types) are then converted into the defined scale of difficulty according to the procedure described above.

For all case studies, the first type of results (modeller's results) of DES and combined DES/ABS models are compared using a graphical approach (comparing histograms). A statistical test is not used because the first type of results (modeller's results) contains insufficient data for a valid statistical comparison.

In contrast, the second type of results (survey's results) for DES and combined DES/ABS models is compared using the T-test. Findings from the comparisons of the first (modeller's result) and second (survey's results) types of results are then discussed in order to answer hypothesis B1.

Set B is continued by performing Experiment B2: Mixed Reactive and Proactive DES vs. Mixed Reactive and Proactive Combined DES/ABS models. The objective of Experiment B2 is to explore the simulation model building time, model execution time and model line of code (LOC) in implementing the mixed reactive and proactive behaviours for both simulation models. The simulation data that are used in Set B is the first types of results (modeller' results) as model difficulty's survey is not conducted for case studies 2 and 4. In Experiment B2, the main hypothesis to test is same as Ho_4 in Section 3.5.1 above.

The three performance measures for model difficulty (model building time, model execution time and model LOC) are gathered through the simulation model development during Experiment A2. The three performance measures for the DES and combined DES/ABS models are compared using the same procedure as in Experiment B1.

3.5.4 Comparison of Results

In the experiments above, the impact on modelling reactive and mixed reactive/proactive behaviour in DES and combined DES/ABS is discussed separately. This section seeks to establish the connection in the model results and model difficulty between the two investigated behaviours (reactive vs. mixed reactive and proactive behaviour). First the connection of simulation outputs for DES and combined DES/ABS models is explored by performing the T-test using the following hypothesis:

Ho_5 : Comparing reactive with mixed reactive and proactive behaviour for DES are statistically the same in simulation results.

Ho_6 : Comparing reactive with mixed reactive and proactive behaviour for combined DES/ABS are statistically the same in simulation results.

To answer the hypothesis above, the simulation results from Experiment A1 and A2 are used. As discuses in experiment above, Experiment A2 is divided into a few sub experiments (i.e. Experiment A2-1, A2-2 and A2-3). Experiment A1 is therefore compared with each sub-experiment of Experiment A2 (i.e. Experiment A1 against A2_1, Experiment A1 against A2-2 and Experiment A1 against A2-3) for both DES and combined DES/ABS models.

The customers waiting time and number of customers served are selected as the performance measures because the literature recommends them as important measures to increase productivity in the service-oriented systems (Robert and Peter, 2004). It is assumed that investigating these two measures will provide sufficient evidence in understanding the impact of the simulation outputs in the different behaviours in one simulation technique. The sub-hypotheses are built for each performance measure in DES and combined DES/ABS according to the list of experiments to be compared. Finally, the results of the performance measures in the Experiment A1 against Experiment A2 are gathered and compared for both simulation models.

The comparison work of this study continues with an investigation of the impact of modelling reactive against reactive and proactive behaviour for model difficulty. The first type of result is drawn from the modeller's modelling experience in comparing the model difficulty performance. This data is used in this comparison as it is the only data available for all three case studies. There is only one data point in the modeller data for the measures of each model difficulty, so no statistical tests have been conducted.

A graphical approach is adopted in order to discuss the comparison results between Experiment B1 versus Experiment B2. Histograms are plotted for the three measures in model difficulty (model building time, model execution time and model LOC) for both DES and combined DES/ABS models. There follows a discussion of the differences between Experiment B1 and the sub-experiments of Experiment B2 (B2-1, B2-2 and B2-3) according to the pattern revealed by the histograms.

3.5.5 Survey from Simulation Expert

The objective of the survey is to obtain knowledge from the simulation expert regarding the capability of DES and combined DES/ABS in modelling human behaviours. Results from the survey are important to support the evidence found in the model result and model difficulty investigations in all three case studies (case studies 1, 2 and 3).

The survey was conducted from 23-24 March 2010 at the 5th UK Operational Research Society Simulation Workshop, 2010. Attendees at the conference were approached to participate in the survey by completing a questionnaire during the conference. A total of twenty-eight responses were obtained.

Three main questions were asked in the questionnaire, starting with an initial question regarding the respondent's background and experience of the simulation technique used. The second question sought to ascertain from the experience and the opinions of respondents if the level of proactive behaviour (simple, medium and complex) was easier to model in DES or combined DES/ABS. The aim of the third question was to understand the difficulty of modelling the proactive behaviour from the aspect of model building time, model execution time and model LOC, based on the respondents' experience and opinions. The questionnaire included a combination of closed and open-ended questions. Refer appendix D for an example of survey questions.

The experience of the respondents in DES ranged from one year to forty years, with an average experience of fourteen years, while in combined DES/ABS respondents had between one to ten years' experience, with an average of three years. It is assumed that most respondents had a considerable amount of modelling experience in DES or combined DES/ABS to take part as the simulation expert in this survey.

Results of the survey for questions 2 and 3 are shown in Figures 3.4 and 3.5 respectively. Figure 3.4 shows that 64% of respondents have agreed that modelling simple proactive behaviour can be more easily achieved in DES compared with medium and complex proactive behaviours. In contrast, 75% of respondents have decided that modelling complex behaviour is more suitable for implementing in the combined DES/ABS model. In Figure 3.5, the combined DES/ABS model is found to have a longer model building time (64%,), model execution time (57%) and model LOC (54%), according to the views of respondents.

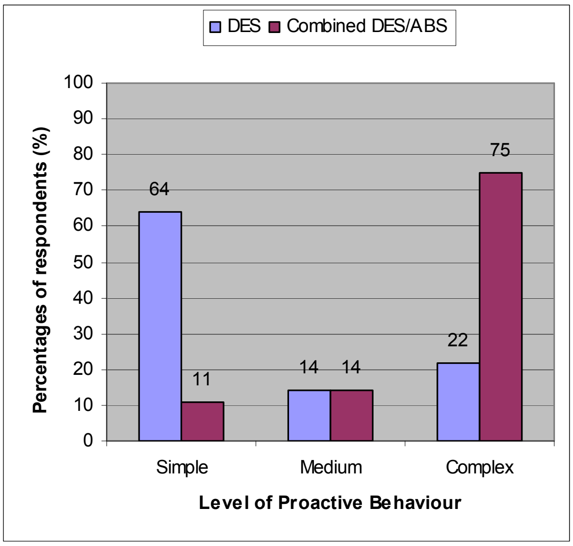


Figure 3.4: Results for question 2 – Respondents' views on the level of proactive behaviour that can be modelled in DES and combined DES/ABS approaches.

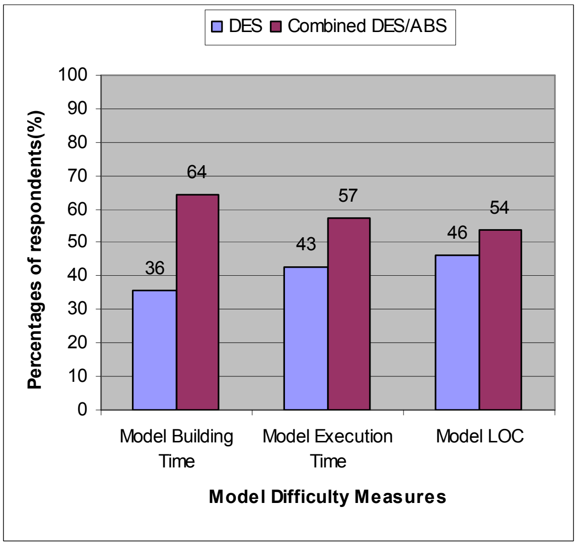


Figure 3.5: Results for question 3 – Respondents' views on the model building time, execution time and LOC for modelling proactive behaviours (simple. medium, complex) using DES and combined DES/ABS approaches.

The result of question 2 in Figure 3.4 is used to support the findings for the correlation in model result for the three case studies (Section 7.2). In addition, the result of question 3 in Figure 3.5 is used to support the finding for the correlation in model difficulty for the three case studies (Section 7.2).

3.6 Chapter Summary

This chapter briefly describes the research methodology used for the case studies. Two types of experiments are conducted: Experiment A for the model result and Experiment B for the model difficulty investigation, both of which are concerned with comparing the simulation results and difficulty (i.e. model building time, model execution time and model LOC) in modelling reactive and mixed reactive/proactive behaviour between DES and combined DES/ABS models.

In addition, a comparison is made of the performance of the model result and difficulty in modelling reactive and mixed reactive/proactive behaviour in one simulation technique; for this purpose a number of hypotheses are tested using the statistical T-test.

Detailed discussion concerning the data collection process, conceptual modelling, model implementation, validation and experimentation for case studies 1, 2 and 3 presented in Chapters 4, 5 and 6 respectively.

CHAPTER 4

CASE STUDY 1: FITTING ROOM OPERATION IN A DEPARTMENT STORE

4.1 Introduction

Case study 1, which examines human behaviour modelling in the fitting room operation in a department store, is presented in this chapter. Real-life reactive and proactive behaviours of staff towards their customers are simplified and an investigation is carried out into how these behaviours affect the simulation models.

The chapter starts with an account of the case study and goes on to describe the development of conceptual modelling based on the case study. A description follows of DES and combined DES/ABS model development and validation. Then the two sets of conducted experiments relating to model output and model difficulty are described and discussed. Finally, the results obtained through the experimentation are presented.

4.2 Case Study

This case study focuses on the operations in the main fitting room in a Womenswear department of one of the top ten department stores in the UK (see Figure 4.1). The case study was selected as a result of the research collaboration between the University of Nottingham and a local department store. To gain insight into the fitting room problem, observation of staff and customers and data collection was conducted for a period of two weeks.

Figure 4.1 illustrates the operation at the fitting room, the numbering and red arrows representing the sequence of operation. The operation in the fitting room starts when the customer arrives. If the sales staff are busy, the customer stays in the waiting line of the fitting room (represented by arrow number 1 in Figure 4.1).

If the member of sales staff is not busy, she counts the number of items of clothing taken in by the customer. Next, the staff member gives the customer a plastic card which identifies the number of items taken in and the room number. The customer then proceeds to the fitting cabin to try on her clothes (represented by arrow number 2 in Figure 4.1). After trying the clothes, she returns the plastic card to the staff member together with the unwanted clothes and leaves the fitting room (represented by arrow numbers 3 and 6 in Figure 4.1).

Those customers who require help join a queue if the staff are busy (represented by arrow number 4 in Figure 4.1). The staff members fulfil the customers' requests for help by assisting them personally or by calling for an available staff member from the department floor. On receiving assistance, the customers follow the steps as presented by the arrow numbers 3 and 6 in Figure 4.1.

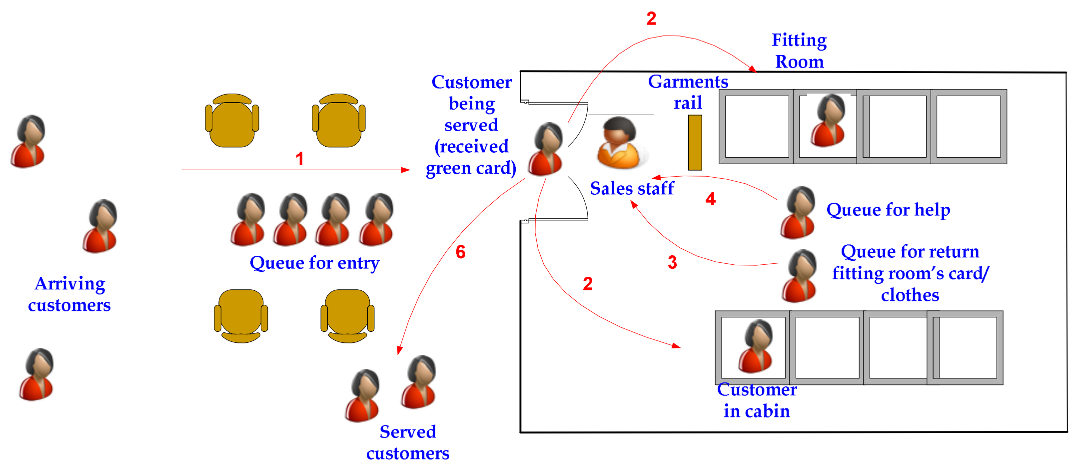


Figure 4.1: The illustration of the fitting room operation from Womenswear department in a department store.

During the data collection and observation process, the reactive and proactive behaviours of staff are identified in order to model them using the DES and combined DES/ABS approaches. Real life reactive and proactive behaviours of the staff towards their customers are simplified and investigated to learn how their behaviour affects the simulation models.

Reactive behaviour refers to the response of staff to customers' requests when they are available. Typically, a member of staff in the fitting room has to carry out three tasks which demonstrate reactive behaviour: (1) she counts the number of clothes and hands out a plastic card which contained the number of clothes taken in and the room number, (2) she provides help while customers are in the fitting room, (3) she receives back the plastic card and any unwanted clothes when the customer leaves the fitting room area.

On the other hand, proactive behaviour refers to a staff member's self-initiated behaviour, for example in dealing with various demands. The proactive behaviour on which this case study focuses is the Type 1: proactive behaviour - taking charge to bring about change. This behaviour occurs as a result of staff experience in controlling the situation in the fitting room. Two sub-proactive behaviours belonging to this type are investigated. The first is a staff member who speeds up her service as the fitting room is getting busier resulting in time consuming service and delays in serving customers. The second proactive behaviour is a staff request for help from another staff member in dealing with the busy situation in the fitting room.

As well as identifying behaviours to implement in DES and combined DES/ABS models, data have also been obtained for use as the input to the simulation models. These include customer arrival rate, staff utilisation, staff service time and customer testing clothes time.

The input for customer arrival rate in the simulation models are obtained by inspecting the arrival process observed in the real system over the cycle of a typical day (shown in Appendix A.1).

In the simulation models the arrival process has been modelled using an exponential distribution with an hourly changing arrival rate in accordance with the arrival rates in Appendix A.1. The reason for choosing the exponential distribution as the arrival distribution for the simulation models (DES and combined DES/ABS) is that it describes the time period between events in a Poisson stream, the common stream used to represent queuing systems, recommended by Beasley (2010). He states that *"The Poisson stream is important as it is a convenient mathematical model of many real life queuing systems and is described by a single parameter - the average arrival rate"* (Beasley 2010).

The simulation inputs for a sale staff service time and customer testing clothes time (as shown in the basic model in Section 4.4.1.) are obtained by calculating the minimum, average and maximum both times (service time and testing clothes time) of the observation days.

Following an analysis of the data collected, the level of detail to be modelled in the DES and combined DES/ABS models has been considered; this is also known as conceptual modelling.

4.3 Towards the Implementation of the Simulation Models

4.3.1 Process-oriented Approach in DES Model

The development of conceptual models for case study 1 are as described in Chapter 3 (Section 3.3). Both DES and combined DES/ABS uses the same basic conceptual model but the implementation of both simulation models is different.
The process-oriented approach is used to represent the implementation of DES model as shown in Figure 4.2. The development for DES model begins by developing the basic process flow of the fitting room operation (a complex queuing system). Then, the investigated human behaviours (reactive and proactive) are added to the basic process flow in order to show where the behaviours occurred in the fitting room operations operation (see Figure 4.2).

The operation in the fitting room starts when customers arrive at the fitting room entrance. If cabins are not available or if the staff are busy, the arriving customers will wait in the queue until they are served. If there is a cabin, the staff will react to the waiting customers by counting the number of items of clothing they bring in and by giving them a card which displays the room number and the number of items of clothing.

Next, the customers will proceed to the cabins and try on their clothes. If a customer wishes to request any help, she can do so by calling the staff. If a member of staff is available, she will immediately fulfil this request. If the staff member is busy serving another customer, the customer requiring help has to wait.

When the customers have finished trying on the clothes, they will need to return to the staff any unwanted items together with the fitting room card before leaving. The customers will wait in a queue if staff are not available, or will be served if a member of staff is available. After being served, the customers will leave the fitting room.

If the fitting room operation becomes too busy in meeting demands from customers, the staff will proactively speed up her serving time towards all customers or call for help from another available staff member on the department floor (shown by symbol A in Figure 4.2).

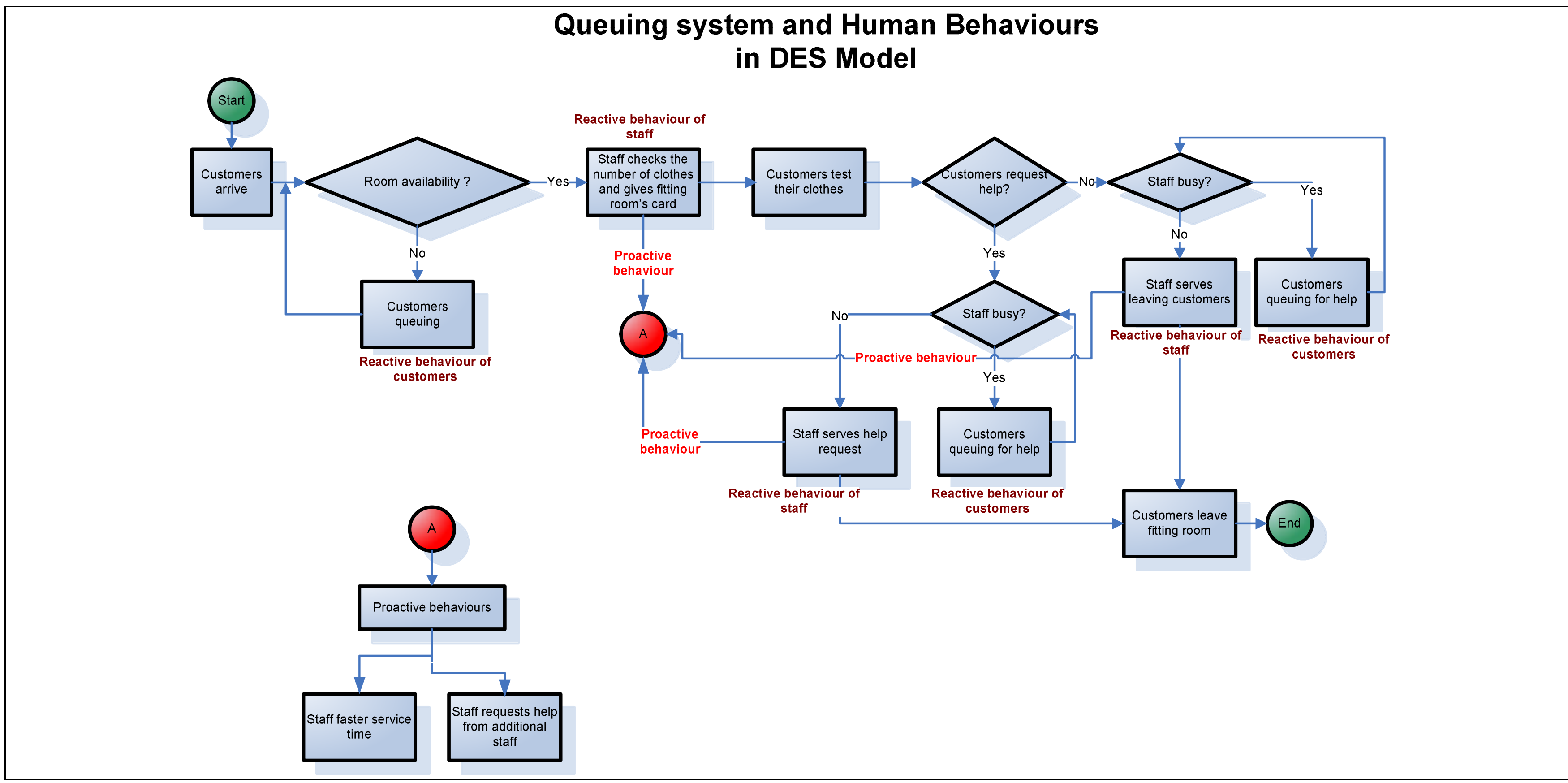


Figure 4.2 : Implementation of DES model

4.3.2 Process-oriented and Individual-oriented Approach in Combined DES/ABS Model

Two approaches are used for developing the combined DES/ABS models: the process-oriented approach (to represent the DES model- same as in Section 4.3.1) and the individual-centric approach (to represent the ABS model- see Figure 4.3). The individual-centric modelling is illustrated by state charts (Figure 4.3) to represent different types of agents (customers, staff, and fitting rooms).

As shown in Figure 4.3 below, the customer's agent consists of various states (i.e. *being idle*) while the staff's agent consists of *idle* and *busy* states. Some of the state changes of agents (customers or staff) are connected by passing messages, the purpose of which is to show the communication between the agents.

For example, if a customer arrives at the fitting room entrance, she will be in the *idle* state for a while, and then change to the *queuing for entry* state if the staff member is busy and all the fitting room cabins are occupied. Otherwise, if both staff and one of the cabins are in the *idle* state, the customer will communicate with the staff by sending a "*serve*" message.

Once the staff member receives the message "*serve*", she changes from the *idle* to the *busy* state, while the customer changes from the *queuing for entry* to the *being served* state. After the member of staff finishes serving the customer (counts the number of items of clothing and gives the fitting room card), the customer will send the staff a "*release*" message and a "*go to cabin*" message to the cabins. The staff member will then change to the *idle* state, the customer will change to the *trying clothes* state and one of the cabins will change to the *busy* state.

While trying on the clothes, the customer can request any help from the fitting room staff by calling them using a "*serve help customer*" message. If the staff member is in the *busy* state, the customer will then change to the *queuing for help* state while still in the cabin. If the staff are in the *idle* state, the customer will then send them another message known as "*serve*". Once the staff member receives the "*serve*" message from the customer, the staff will change to the *busy* state and the customer will change to the *being served help* state. Again, after the member of staff finishes serving the customer, the customer will send her a "*release*" message and the state of the staff member will change from *busy* to *idle*.

After trying on the clothes, the customer will proceed to the staff member to return any unwanted clothes and the fitting room card. To check her availability, the customer will send a "*serve return customer*" message. If the staff member is in the *busy* state, the customer will then change to the *queuing for return* state. If the staff member is in the *idle* state, the customer will then send her another message known as "*serve*". Once the member of staff receives the "*serve*" message from the customer, she will change to the *busy* state and the customer will change to the *being served return* state. Again, after the member of staff finishes serving the customer, the customer will send her a "*release*" message and the state of the staff member will change from *busy* to *idle*. In addition, the customer will change to the *being idle* state and leave the fitting room.

The additional staff member is the one who helps the fitting room staff when there is a request for assistance from the customer. The call for additional staff is part of the proactive behaviour investigated in this case study. Further processes of calling for help by the fitting room staff to additional staff are therefore described in the experimentation section (Section 4.5.1- Experiment A2-3). The additional staff also has two states same with the fitting room's staff states: *idle* and *busy*.

Following the understanding of the DES and combined DES/ABS modelling approaches, the development of their simulation models is now implemented.

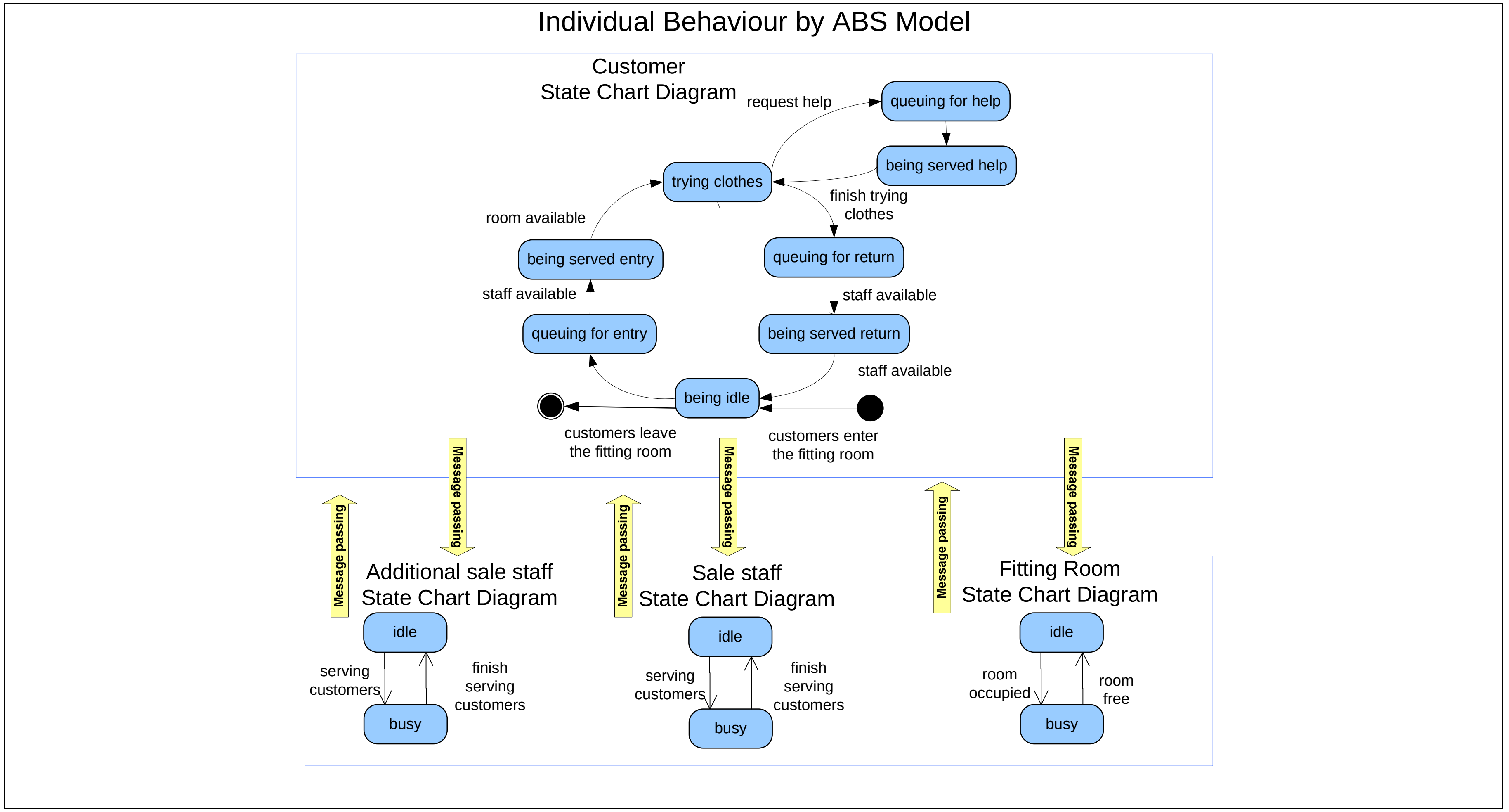


Figure 4.3 : Implementation of individual-centric modelling for combined DES/ABS model

4.4 Model Implementation, Verification and Validation

4.4.1 Basic Model Setup

Two simulation models are developed, based on both conceptual models presented in Section 4.3, and are implemented in the multi-paradigm simulation software AnyLogic™ 6.5 (XJTechnologies 2010). Both simulation models consist of an arrival process (customers); three single queues (entry queue, return queue, help queue); and resources (one sales staff member, one fitting room with eight fitting cubicles).

Customers, staff and fitting rooms are all passive objects in the DES model, while in the combined DES/ABS model customers, staff and fitting rooms are all active objects (agents). Passive objects are entities that are affected by the simulation‘s elements as they move through the system, while active objects are the entities acting as agents themselves by initiating actions (Siebers et al. 2010).

Both simulation models make use of same model input parameter values as described as following:-

i. Customer object/agent

Based on the arrival process of customers observed in the real system, illustrated in Appendix A.1 (Section 4.3), the arrival rate of the simulation model is defined. In the simulation model the arrival rate is modelled using an exponential distribution with an hourly changing arrival rate in accordance with the arrival rates shown in Table 4.1. The arrival pattern as in Table 4.1 is used because it matches the real data arrival pattern. Appendix A.2 below shows the comparison of the real data with the simulation input.

In addition to the customer's setup, customers will leave the fitting room's queue after waiting for 15 minutes or refuse to join the queue if the number of customers waiting in the queue is more than 20 customers. The values for customers balking (refusing to join the queue) and reneging (leaving the queue after joining) the fitting room's queue are obtained from the real observation.

Table 4.1 : Customers arrival rate

Time	Rate
9.00 – 10.00am	Approximately 10 people per hour
10.00 – 11.00am	Approximately 40 people per hour
11.00 – 12.00pm	Approximately 40 people per hour
12.00 – 1.00 pm	Approximately 60 people per hour
1.00 – 2.00 pm	Approximately 60 people per hour
2.00 – 3.00 pm	Approximately 43 people per hour
3.00 – 4.00 pm	Approximately 43 people per hour
4.00 – 5.00 pm	Approximately 30 people per hour

ii. Sales staff object/agent

In both simulation models, one member of staff has been modelled performing all three tasks mentioned in section 4.3 above: Task 1 (counting clothes on entry), Task 2 (providing help) and Task 3 (counting clothes on exit).

Task priority is allocated on a first in first out basis. Table 4.2 illustrates the service time used to represent the task execution time of a staff in both DES and combined DES/ABS models. The service times in Table 4.2 are presented in minutes and triangular distributions are used to represent the defined service times in both simulation models. These service times are defined through the data gathered from the real system based on the minimum, mode and maximum service times to serve the related tasks (shown in Table 4.2).

Table 4.2 : Sale staff service time

Service Time Parameters	**Value**
Staff Service Time (for Task 1, 2 and 3)	Minimum: 0.25, Mode : 0.38, Maximum : 0.5

iii. Fitting room object/agent

The fitting room that is modelled contains eight fitting cabins. The trying clothes time in fitting room by customers is based on the triangular probability distribution and is presented in minutes (shown in Table 4.3).

Table 4.3 : Trying clothes time

Delay Time Parameters	**Value**
Trying clothes time	Minimum: 4, Mode : 6.5, Maximum : 10

Prior to conducting the validation experiments, the first step is to determine the experimental condition such as the simulation model run length, the warm up period and the number of runs (see Chapter 3 : Section 3.4). As the simulation models are terminating simulations, a warm-up period has not been considered in this case study. The simulation models are terminated after a standard business day (8 hours), thus the run length is eight hours imitating the real operation time.

Next, the number of runs is determined using graphical representation (Robinson 1994). Customers waiting time is used as the measure of deciding the number of runs. Both simulation models are run for 200 times and the cumulative average of customers waiting time is plotted as shown in Appendix A.3. At 100 runs, the simulation results between DES and combined DES/ABS models are found to have converged sufficiently. Thus, a total of 100 runs is chosen as the number of runs for DES and combined DES/ABS models and is applied throughout the case study experiments. In addition, the basic models setup in this section is applied to all experiments discussed in this case study.

4.4.2 Verification and Validation

The verification and validation process is performed simultaneously with the development of the basic simulation models for DES and combined DES/ABS. The verification processes are discussed in Chapter 3: Section 3.4. Two types of validation process are performed: black-box and sensitivity analysis validations.

Black-Box Validation: Comparison with Real System

Black box validation has been used for the first validation process in which the simulation results from both simulation models are compared with the real system output in terms of quantities. For this validation, statistical tests are used. Standard parametric statistical test - T-test is chosen due to the central limit theorem. Such theorem states that the distribution of the mean of the chosen number of runs (100) is almost certainly normal.

The use of T-test leads to the assumption that all comparative measures (i.e. customers waiting time, staff utilisation, number of customers served, etc) adopted in this study are normally distributed.

If data is normally distributed, the measures of central tendency (e.g. mean, median and mode) are the same once the normal distribution is symmetric. Hence, in order to compare the mean values using T-test, the following hypotheses is examined:

$Ho_{BlackBox\_A}$: The customers waiting time resulting from DES are not significantly different to those observed in the real system.

$Ho_{BlackBox\_B}$: The customers waiting time resulting from combined DES/ABS model are not significantly different to those observed in the real system.

$Ho_{BlackBox\_C}$: The staff serving utilisation resulting from DES model is not significantly different to those observed in the real system.

$Ho_{BlackBox\_D}$: The staff serving utilisation resulting from combined DES/ABS model is not significantly different to those observed in the real system.

In order to perform the T-test, the Minitab ™ (Minitab 2000) statistical software is used. The customers waiting time and staff serving utilisation are selected as the performance measures since the historic data of both measures is available to perform this test. The means and standard deviation (sd) of the customers waiting time and staff serving utilisation from both simulation models and the real system are calculated (as shown in Table 4.4) and the significance level is 0.05. A test result (p-value) higher than 0.05 will allow a null hypothesis fails to be rejected; otherwise it has to be rejected.

Table 4.4 : Data of real system, DES and combined DES/ABS

Performance measures		**Real System**	**DES**	**Combined DES/ABS**
Customers waiting time (minute)	Mean	1.61	1.69	1.61
	SD	1.22	1.4	1.7
Staff serving utilisation (%)	Mean	52	53	54
	SD	7.01	7.43	7.77

Testing the DES model results against the real system measures reveals a p-value of 0.217 for customers waiting time and 0.305 for staff serving utilisation. Meanwhile, a p-value of 0.422 is obtained for customers waiting time and 0.281 for staff serving utilisation when testing DES/ABS model results against the real system. Since both DES and DES/ABS p-values are above the chosen level of significance (0.05), the $Ho_{BlackBox\_A}$, $Ho_{BlackBox\_B}$, $Ho_{BlackBox\_C}$ and $Ho_{BlackBox\_D}$ hypotheses are failed to be rejected.

From the statistical test results, it can be confirmed that the average customers waiting time and staff serving utilisation resulting from both simulation models are not significantly different from the ones observed in the real system. As the overall result of this black-box validation test, the DES and combined DES/ABS models shows a good representation of the real system.

Sensitivity Analysis Validation

The purpose of the sensitivity analysis validation is to examine the sensitivity of the simulation results when customers arrival rate are systematically varied with three differences of arrival patterns as shown in Appendix A.4. Chapter 3 (Section 3.4) explains the setup of the arrival patterns.

The idea behind sensitivity analysis validation is to observe how this validation affected the DES and combined DES/ABS models' performance measures. In addition, in this validation test, all performance measures are expected to increase along with the increment of the number of customers in the simulation models.

The selected comparative measures for this sensitivity analysis validation are customers waiting time, staff serving utilisation, number of customers served and number of customers not served.

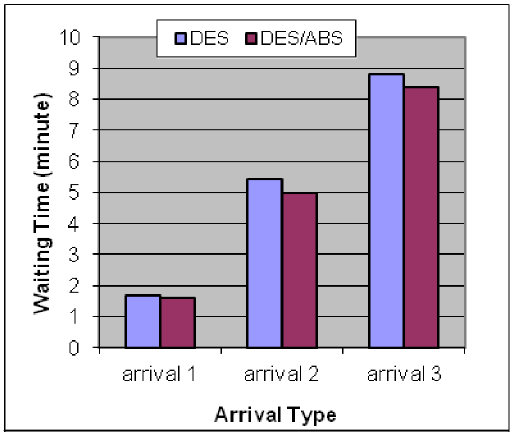
Results for the sensitivity analysis for DES and combined DES/ABS are illustrated in Table 4.5 and Figure 4.4 (a-d). The results in both Tables 4.5 and Figure 4.4 (a-d) reveal similar patterns for all performance measures. Both simulation models (DES and combined DES/ABS) demonstrate an increment for all performance measures when the customer's arrival rate is increased.

All performance measures are found to be increased rationally as shown by the nature of any service–oriented systems; when the number of customers' increases, staff utilisation will also increase and the queue will become longer. This will affect customers' waiting time when customers will have to stay longer in the system. Automatically, when the waiting time gets longer, more customers will not be served because customers leave the queue after waiting so long or because there are fewer members of staff to serve the waiting customers.

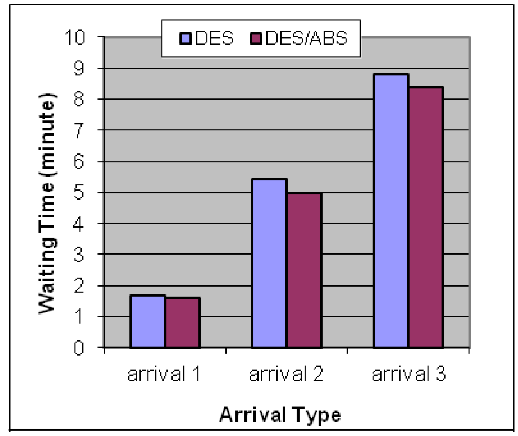
It can be concluded that the sensitivity analysis has made the same impact on both simulation models when varying customer's arrival rates - all performance measures investigated in this validation test are increased, as expected.

Table 4.5 : Results of sensitivity analysis validation

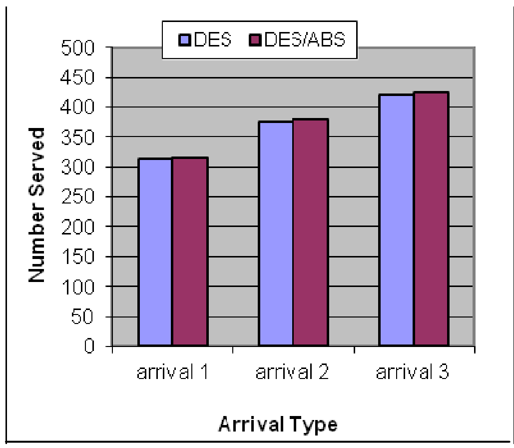
Simulation Models	**Performance measures**		**Arrival Pattern**		
			1	**2**	**3**
DES	Customers waiting time	Mean	1.69	5.41	8.82
		SD	1.4	1.15	0.77
	Staff serving utilisation	Mean	53	60	69
		SD	7.43	7.88	6.96
	Number of customers served	Mean	313	375	420
		SD	16.04	13.82	20.79
	Number of customers not served	Mean	3	31	113
		SD	3.51	14.33	21.41
DES/ABS	Customers waiting time	Mean	1.61	5	8.38
		SD	1.7	2.16	1.82
	Staff serving utilisation	Mean	54	61	70
		SD	7.77	8.52	9.8
	Number of customers served	Mean	315	379	433
		SD	18.7	23.36	31.16
	Number of customers not served	Mean	3	28	96
		SD	3.75	24.21	43.61



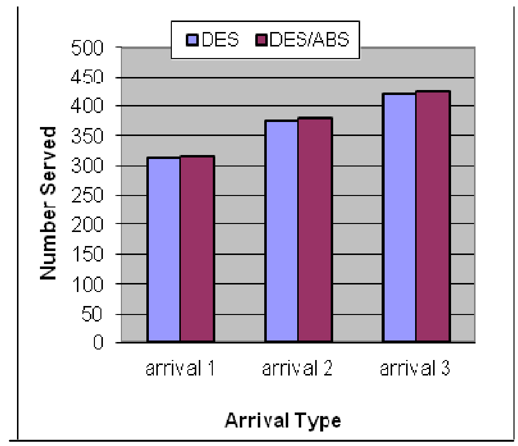
(a) Customers waiting time



(b) Staff serving utilisation



(c) Number of customers served



(d) Number of customers not served

Figure 4.4 : Bar charts of results in the sensitivity analysis validation

Conclusions

The black-box validation process reveals that the DES and combined DES/ABS simulation models are a good representation of the real system (by referring to the customer waiting time and staff serving utilisation results comparison). In the sensitivity analysis validation, both simulation models demonstrate a close correspondence in the median of customers waiting time and the staff serving utilisation. In addition, all the investigated performances measures show, as expected, the increment of the results in both DES and combined DES/ABS models when the number of customers arrival are increased.

These two validation tests provide some level of confidence that the simulation models of this study are sufficiently accurate for predicting the performance of the real system.

4.5 Experimentation

4.5.1 Introduction

As discussed in Chapter 3 Section 3.5, two sets of experiments are conducted: Set A for model result and Set B for model difficulty. These two sets of experiments-Set A and B are to fulfil the research objectives 1 and 2 (Chapter 1: Section 1.3), respectively.

The purpose of both sets of experiments has been to investigate the performance of the simulation results and level of difficulty in DES and combined DES/ABS when modelling the reactive and the increasing level of proactive human behaviours. The main hypotheses to investigate for both set of experiments are as stated in Chapter 3 (Section 3.5.1).

This experimentation section is therefore divided into two sub-sections according to each set in order to answer the hypotheses.

4.5.2 Set A : Model Result Investigation

Experiment A1: Reactive Human Behaviour

The Set A experimentation begin with Experiment A1: Reactive Human Behaviour. Experiment A1 is essential to determine the similarities and dissimilarities of both simulation models (DES and combined DES/ABS) in the results performance when modelling reactive behaviour. In Experiment A1, the main hypothesis is same as in Ho_1 in Chapter 3 (Section 3.5.1).

The selected comparative measures for this reactive experiment are customers waiting time, staff serving utilisation, number of customers served and number of customers not served.

The simulation model setup for modelling reactive behaviour is based on the same design in both DES and DES/ABS models. For the reactive behaviour investigation, one staff member is observed performing all three reactive jobs: Task 1 (counting clothes on entry), Task 2 (providing help) and Task 3 (counting clothes on exit). The staff member served the customers by first come first serve approach.

The level of significance 0.05 is chosen for the test analysis and is used together with the T- test throughout the experiments conducted in this case study. The hypotheses for Experiment A1 are as follows:

Ho_{A1_1} : The customers waiting time resulting from reactive DES model is not significantly different from reactive combined DES/ABS model.

Ho_{A1_2} : The staff serving utilisation resulting from reactive DES model is not significantly different from reactive combined DES/ABS model.

Ho_{A1_3} : The number of customers served resulting from reactive DES model is not significantly different from reactive combined DES/ABS model.

Ho_{A1_4} : The number of customers not served resulting from reactive DES model is not significantly different with reactive combined DES/ABS model.

Results for DES and combined DES/ABS are shown in Table 4.6 and Figure 4.5(a-d). Table 4.7 shows the result of the comparison between both models, using the T- test. The results in both Tables 4.6 and Figure 4.5 (b-d) illustrate that there are similar patterns for all performance measures.

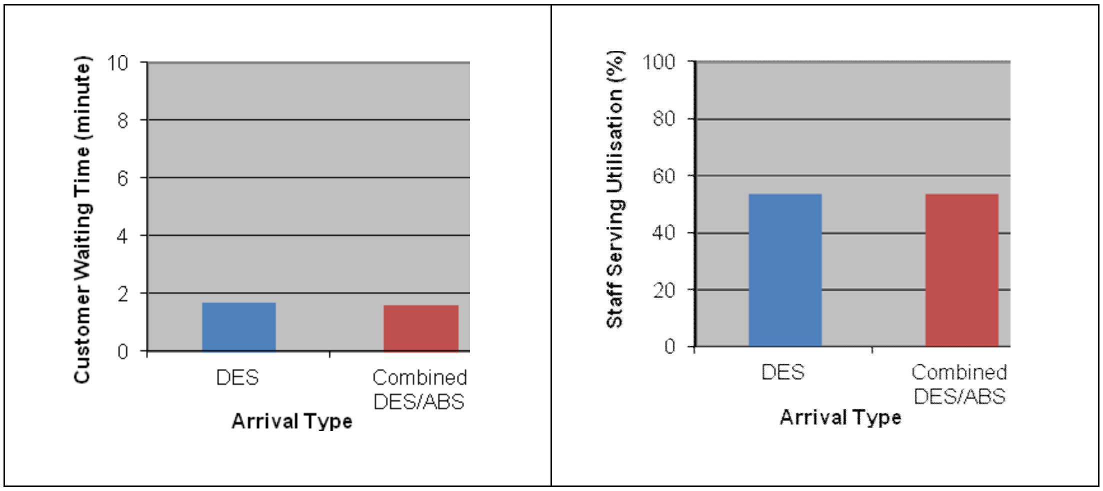
However, the bar charts in Figure 4.5 (a) illustrates a lower customers waiting time in the DES/ABS model compared with the DES model. To confirm the similarity and dissimilarity of the simulation results, the statistical test is conducted. According to the T- test results in Table 4.8, all performance measures show the p-values are higher than the selected level of significant value. Therefore the Ho_{A1_1}, Ho_{A1_2}, Ho_{A1_3}, and Ho_{A1_4} hypotheses are failed to be rejected.

The T-test results confirmed that there is no significant difference between the customers waiting time in both simulation models; this result is also applied to other performance measures. Hence, the Ho_1 hypothesis is failed to reject.

Overall, modelling the same behaviour using a same logic decision in DES and combined DES/ABS models show a similar impact in the performance of their simulation results.

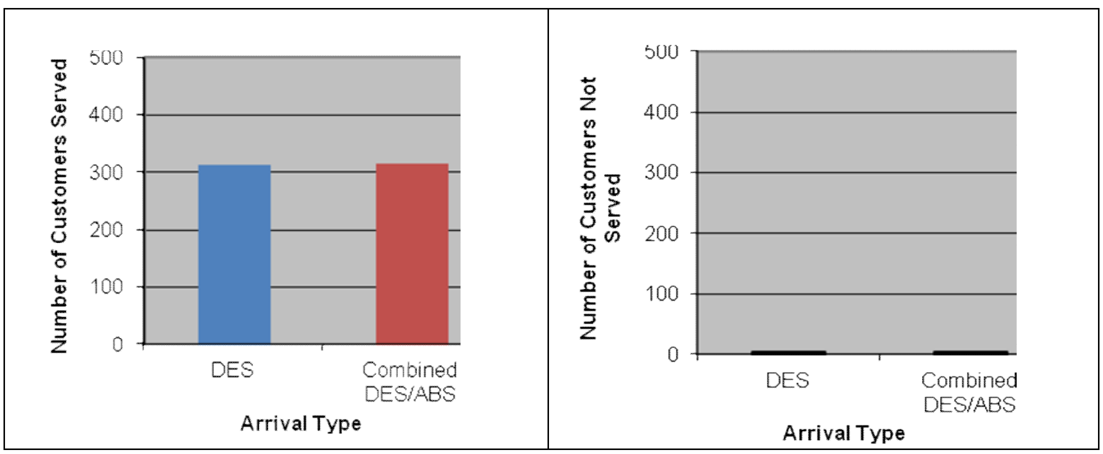
Table 4.6 : Results of Experiment A1

Performance measures		**DES**	**Combined DES/ABS**
Customers waiting time (minute)	Mean	1.69	1.61
	SD	1.4	1.7
Staff serving utilisation (%)	Mean	53	54
	SD	7.43	7.77
Number of customers served (people)	Mean	313	315
	SD	16.04	18.7
Number of customers not served (people)	Mean	3	3
	SD	3.51	3.75



(a) Customers waiting time

(b) Staff serving utilisation



(c) Number of customers served

(d) Number of customers not served

Figure 4.5 : Bar charts of results in Experiment A1

Table 4.7 : Results of T-test in Experiment A1

Performance Measures	**DES vs. Combined DES/ABS**	
	P-value	**Result**
Customers waiting time	P = 0.736	Fail to reject
Staff serving utilisation	P = 0.952	Fail to reject
Number of customers served	P = 0.423	Fail to reject
Number of customers not served	P = 0.534	Fail to reject

Experiment A2: Mixed Reactive and Proactive Human Behaviours

The experimentation is continued with Experiment A2, which is concerned with modelling mixed reactive and proactive human behaviours in both DES and combined DES/ABS models. Experiment A2 is important for the second objective of this research - to determine the similarities and dissimilarities of both DES and combined DES/ABS in the simulation results performance when modelling human mixed reactive and proactive behaviours. Chapter 3 gives details regarding this experiment. The main hypothesis to test in Experiment A2 is same with Ho_2 in Chapter 3 (Section 3.5.1).

The simulation models as discussed in Experiment A1 above are modified by adding the human proactive behaviour. As stated in Chapter 3 Section 3.5, the Type 1 proactive behaviour in case study 1 is investigated. The Type 1 proactive behaviour is related to the behaviour of a member of staff making her own decisions based on her real-life experience.

There are two proactive behaviours to present in both DES and combined DES/ABS models. The first of these is modelled when the sale staff speeds up service time to meet the various demands in the fitting room. The second is modelled when the sale staff requests help from other available staff on the department floor when the situation in the fitting room is beyond the sale staff control.

However, to investigate the impact of reactive behaviour with the two proactive behaviours in the simulation models, Experiment A2 is divided into three sub-experiments (A2_1, A2_2 and A2_3) as described in Chapter 3: Section 3.5

(Table 3.2). These sub-experiments are performed according to the basic model setup described in Section 4.4.1 above, together with some additional individual behaviours.

Experiment A2-1: Mixed Reactive and Sub-Proactive 1 Behaviours

The model setup for reactive behaviour is same to that in Experiment A1. In the proactive behaviour modelling setup, the staff changed their service times from normal to fast when there are customers queuing for available fitting room cubicles or to be served by the staff. The normal service time is reduced by 20% in order to speed up the servicing time following the behaviour of the staff in the real system when the fitting room gets too busy.

The benefit of having staff speeds up the service time proactive behaviour is observed to overcome the problem of one member of staff calling for help from another. The investigated proactive behaviour is implemented using the procedures shown in Appendix A.5 Decisions are made based on a set of selection rules and probabilistic distribution. Each block in Appendix A.5 represents the event as shown in Appendix A.6.

As shown in Appendix A.5, conditions in the fitting room and numbers of waiting customers in the three queues are checked continuously via probability distribution. When the condition is met, the service time is speeded up automatically. After some delay caused by the probability distribution, the new service time is changed to the existing service time.

In Experiment A2-1, the simulation results of five system performance measures is observed; four from Experiment A1; and one is the investigated proactive behaviour (the number of service time changes).

The hypotheses for T-test in Experiment A2-1 use the same four performance measures as in Experiment A1 but these performance measures are tested with a name link to Experiment A2-1 as follows: $Ho_{A2\text{-}1\_1}$, $Ho_{A2\text{-}1\_2}$, $Ho_{A2\text{-}1\_3}$, and $Ho_{A2\text{-}1\_4}$, for (in the same order) the customers waiting time, staff serving utilisation, the number of customers not served and the number of customers served. In addition, the hypothesis for the investigated proactive behaviour in Experiment A2-1 is:

$Ho_{A2\text{-}1\_5}$: The number of service time changes resulting from mixed reactive and proactive DES model is not significantly different from mixed reactive and proactive combined DES/ABS model.

Results for Experiment A2-1 are shown in Table 4.8 and Figure 4.6(a-e). The results of from the T-test are shown in Table 4.9. A similar pattern of results is found in the comparison of performance measures of DES and combined DES/ABS models, as illustrated in Table 4.8 and Figure 4.6 (a-e) including the observed proactive behaviour: number of service time changes. The result from the statistical test also produced similar results for both simulation models.

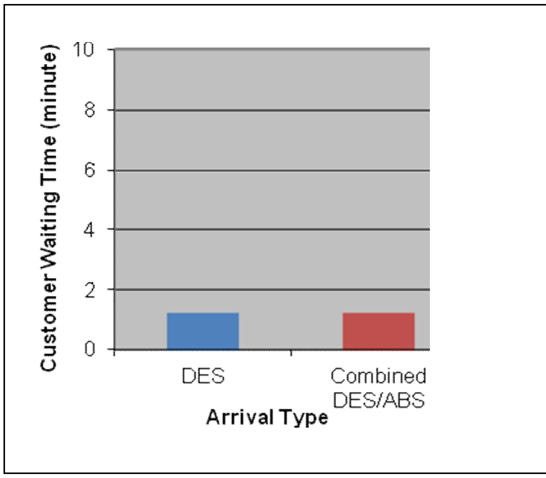
According to the test results presented in Table 4.9, all performance measures show the p-values that are greater than the chosen level of significance value (0.05). Thus, the Ho_{A2-1_1}, Ho_{A2-1_2}, Ho_{A2-1_3}, Ho_{A2-1_4} and Ho_{A2-1_5} hypotheses are failed to be rejected.

Table 4.8 : Results of Experiment A2-1

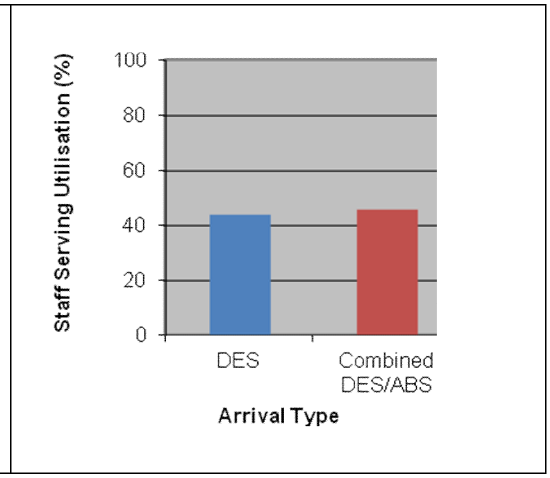
Performance measures		**DES**	**Combined DES/ABS**
Customers waiting time (minute)	Mean	1.24	1.21
	SD	0.89	1.15
Staff serving utilisation (%)	Mean	44	46
	SD	6.3	7.88
Number of customers served (people)	Mean	313	313
	SD	17.72	17.91
Number of customers not served (people)	Mean	4	3
	SD	3.43	3.96
Number of service time changes	Mean	26	24
	SD	14.41	15.54

Table 4.9 : Results of T-test in Experiment A2-1

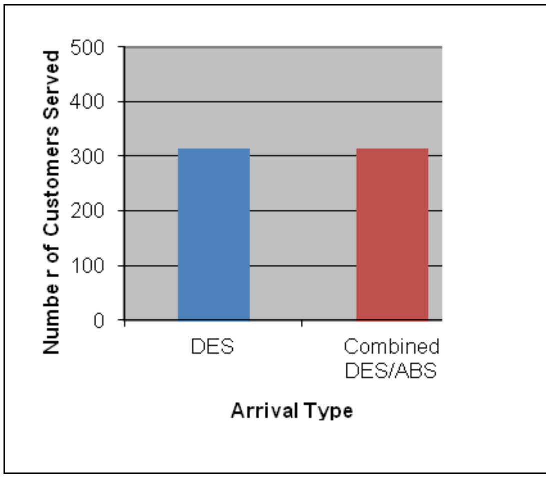
Performance Measures	**DES vs. Combined DES/ABS**	
	P-value	**Result**
Customers waiting time	P = 0.845	Fail to reject
Staff serving utilisation	P = 0.122	Fail to reject
Number of customers served	P = 0.997	Fail to reject
Number of customers not served	P = 0.851	Fail to reject
Number of service time change	P = 0.376	Fail to reject



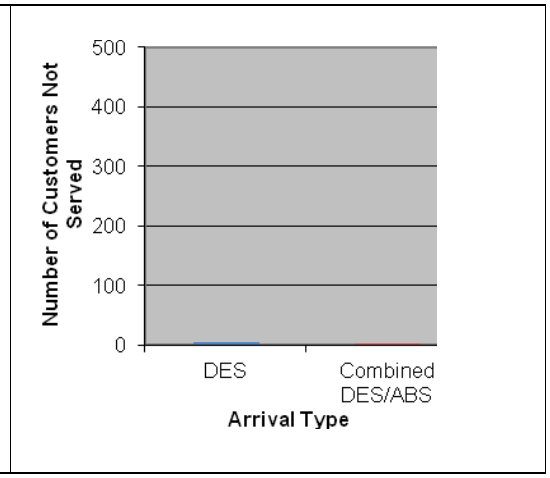
(a) Customers waiting time



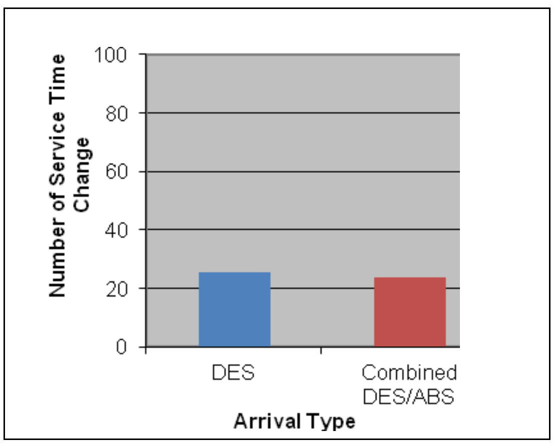
(b) Staff serving utilisation



(c) Number of customers served



(d) Number of customers not served



(e) Number of service time changes

Figure 4.6 : Bar charts of results in Experiment A2-1

It can be concluded that modelling the same proactive behaviour with the similar decision logic has produced a similar impact on the simulation results for both simulation models. In addition, the impact of modelling proactive behaviour is seen in both simulation models when the sales staff speeds up their service time frequently and the number of customers not served decreases.

To confirm our finding in Experiment A2-1, modelling another Type 1 proactive behaviour is presented in Experiment A2-2.

Experiment A2-2: Mixed Reactive and Sub-Proactive 2 Human Behaviours

This experimentation into mixed reactive and proactive behaviours has investigated the requests made by a member of staff for help from another staff member. The purpose of request for help is to deal with the extremely busy situation in the fitting room, when there are many customers queuing for available fitting room cubicles or to get served by the staff. The reactive behaviour modelled for Experiment A2-2 is similar to that in Experiment A1; for the second proactive behaviour i.e. the staff calling for help during a busy period, is imitated. This second proactive behaviour can be seen to overcome the problem of having more than one permanent staff member in the fitting room.

The decision-making process for executing the second proactive behaviour (the staff calling for help) based on a set of selection rules and probabilistic distribution is illustrated in Appendix A.7. The pseudo codes to execute the proactive behaviour in Experiment A2-2 are presented in Appendix A.8. Each block in Appendix A.8 represents the event as shown in Appendix A. 7.

The similar condition observed in Experiment A2-1 above is used to execute the proactive behaviour displayed by the call for help. The availability of the fitting room and the number of waiting customers in the three queues are continuously checked via probability distribution. When the condition is met, one member of staff is added to both simulation models. The newly added staff remained in the fitting room for a period of time according to the probability distribution. When the delay time ended, the new staff is removed from the simulation models in order to present the behaviour of leaving the fitting room.

Six performance measures are used in this Experiment A2-2: four from Experiment A1 plus two others: staff serving utilisation (refers to newly added staff) and number of calls for help.

The hypotheses for T-test in Experiment A2-2 use the same four performance measures as in Experiment A1 but these performance measures are tested with a name link to Experiment A2-2 as follows: Ho_{A2-2_1}, Ho_{A2-2_2}, Ho_{A2-2_3}, and Ho_{A2-2_4}, for (in the same order) the customers waiting time, staff serving utilisation, the number of customers not served and the number of customers served. In addition, the hypotheses for the investigated proactive behaviour in Experiment A2-1 are:

Ho_{A2-2_5} : The new added staff serving utilisation resulting from mixed reactive and proactive DES model is not significantly different from mixed reactive and proactive combined DES/ABS model.

$Ho_{A2\text{-}2\_6}$: The number of calls for help resulting from mixed reactive and proactive DES model is not significantly different from mixed reactive and proactive combined DES/ABS model.

Results for Experiment A2-2 are shown in Table 4.10 and Figure 4.7 (a-f). The results of the T-test are shown in Table 4.11.

Table 4.10 : Results of Experiment A2-2

Performance measures		**DES**	**Combined DES/ABS**
Customers waiting time (minute)	Mean	0.58	0.46
	SD	0.31	0.58
Staff serving utilisation (%)	Mean	45	44
	SD	4.72	5.44
Number of customers served (people)	Mean	7	9
	SD	2.42	6.97
Number of customers not served (people)	Mean	309	309
	SD	13.61	16.82
New added staff serving utilisation (%)	Mean	3	3
	SD	1.45	1.78
Number of calls for help	Mean	4	4
	SD	1.72	2.2

Table 4.10 and Figure 4.7 (a-f) illustrate the slight difference in results between the DES and combined DES/ABS in all performance measures. However, the T-test statistical test has demonstrated the similarities of test results after comparing all performance measures between both simulation models. The test results in Table 4.11 illustrate that the p-values from all performance measures are greater than the chosen level of significant value (0.05). The $Ho_{A2\text{-}2\_1}$, $Ho_{A2\text{-}2\_2}$, $Ho_{A2\text{-}2\_3}$, $Ho_{A2\text{-}2\_4}$ $Ho_{A2\text{-}2\_5}$ and $Ho_{A2\text{-}2\_6}$ hypotheses, therefore failed to be rejected.

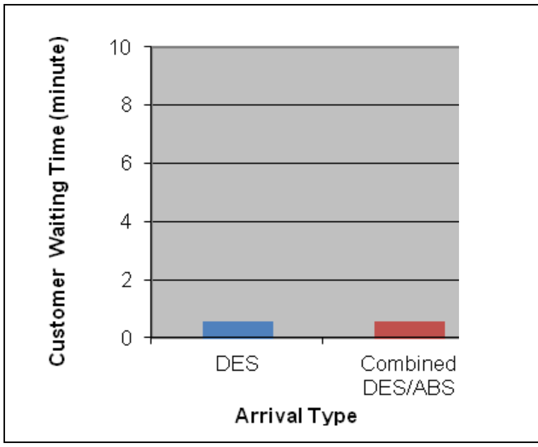
The similarity of results which has found in the T-test has revealed no significant difference in the result performance of both DES and combined DES/ABS models when modelling similar proactive behaviour with similar execution of proactive decision logic.

Modelling calls for help in both simulation models produces the same impact as in Experiment A2-1, when a new staff member is added to the fitting room operation and the number of customers not served is reduced.

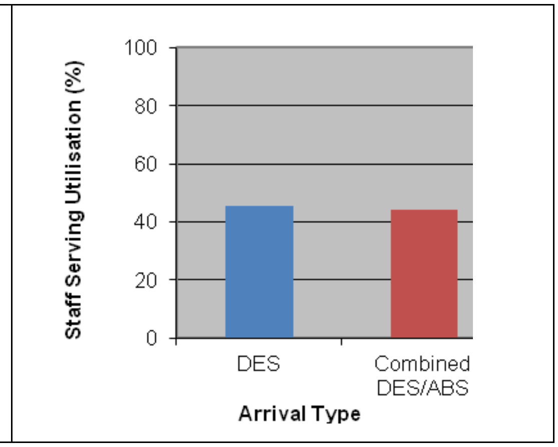
Again, modelling proactive behaviour in Experiment A2-2 has shown a greater impact on the results performance when using either DES or combined DES/ABS. Next, the impact on the simulation results can be observed if the proactive behaviours modelled in Experiment A2-1 and A2-2 are combined. The combined proactive behaviours are investigated in the following Experiment A2-3.

Table 4.11 : Results of T-test in Experiment A2-2

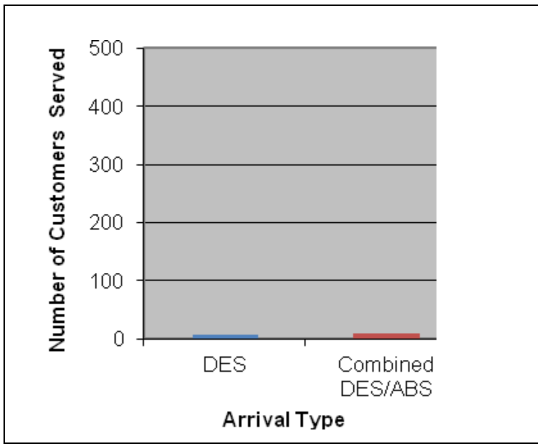
Performance Measures	**DES vs. Combined DES/ABS**	
	P-value	**Result**
Customers waiting time	P= 0.414	Fail to reject
Staff serving utilisation	P= 0.009	Fail to reject
Number of customers served	P= 0.675	Fail to reject
Number of customers not served	P= 0.461	Fail to reject
New added staff serving utilisation	P= 0.176	Fail to reject
Number of calls for help	P= 0.108	Fail to reject



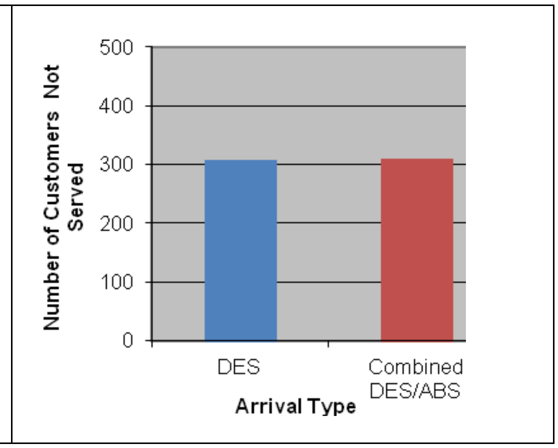
(a) Customers waiting time



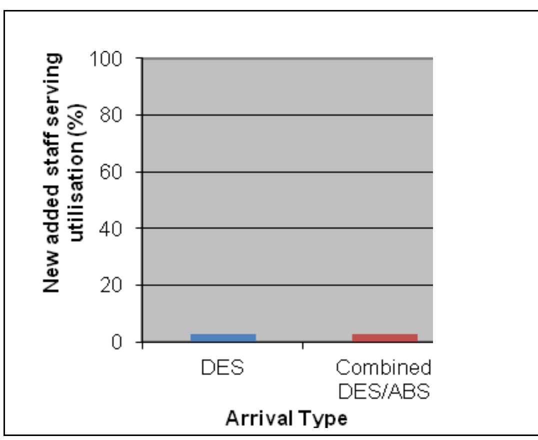
(b) Staff serving utilisation



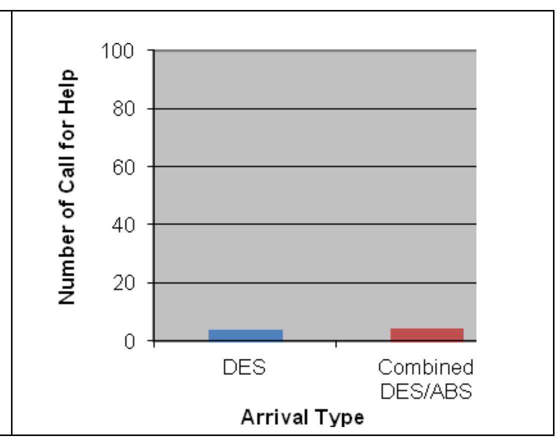
(c) Number of customers served



(d) Number of customers not served



(e) New added staff serving utilisation



(f) Number of calls for help

Figure 4.7 : Bar charts of results in Experiment A2-2

Experiment A2-3: Mixed Reactive and Sub-3 Combined Proactive Behaviours

A same setup of Experiment A1 is employed to model the reactive behaviour in Experiment A2-3. The investigated proactive behaviours in Experiment A2-3 are the combination of service time changes and calls for help. The purpose of combining these two proactive behaviours is to investigate the impact of the simulation results when having more than one proactive behaviour.

The decision-making process for executing these proactive behaviours (service time changes and calls for help) is based on a set of selection rules and probabilistic distribution (shown in Appendix A.9). The pseudo codes to execute the combined proactive behaviours are illustrated in Appendix A.10. Similar to the previous experiments (A2-1 and A2-2), each block in Appendix A.9 represents the event as shown in Appendix A.10.

The availability of the fitting room cubicles and the number of waiting customers on the three queues is continuously checked via probability distribution. When the conditions are met, the service time is speeded up automatically. After a delay caused by the probability distribution, the new service time is changed to the existing service time. If there are customers still queuing even when the fitting room cubicle is available, the event call for help will automatically start. The event call for help will add to the fitting room operation one member of staff who will remain there for a period of time according to the probability distribution. When the delay time is ended, the staff will leave the fitting room.

Seven performance measures are applied in this experiment: four from Experiment A1, plus new added staff serving utilisation, number of service time changes and number of calls for help. To investigate the impact of the simulation models towards their results performance, the T-test is again used.

The hypotheses for T-test in Experiment A2-3 use the same four performance measures as in Experiment A1 but these performance measures are tested with a name link to Experiment A2-3 as follows: $Ho_{A2\text{-}3\_1}$, $Ho_{A2\text{-}3\_2}$, $Ho_{A2\text{-}3\_3}$, and $Ho_{A2\text{-}3\_4}$, for (in the same order) the customers waiting time, staff serving utilisation, the number of customers not served and the number of customers served. In addition, the hypotheses for the investigated proactive behaviour in Experiment A2-3 are:

$Ho_{A2\text{-}3\_5}$: The number of service time changes resulting from mixed reactive and proactive DES model is not significantly different from mixed reactive and proactive combined DES/ABS model.

$Ho_{A2\text{-}3\_6}$: The new added staff serving utilisation resulting from mixed reactive and proactive DES model is not significantly different from mixed reactive and proactive combined DES/ABS model.

$Ho_{A2\text{-}3\_7}$: The number of calls for help resulting from mixed reactive and proactive DES model is not significantly different from mixed reactive and proactive combined DES/ABS model.

Results for Experiment A2-3 are shown in Table 4.12 and Figure 4.8(a-g). The results of the T-test are shown in Table 4.13. This experiment revealed a similar impact of results with Experiments A2-1 and A2-2.

Results of all performance measures presented in Table 4.12 and Figure 4.8 (a-g) indicate that there are no important differences between DES and combined DES/ABS models. In the same way as in Experiment A2-1 and A2-2, the results of two simulation models are compared using the T-test. Table 4.13 also show the results of the T-test are similar in the performance measures of both DES and combined DES/ABS models.

According to the test results in Table 4.13, all performance measures have shown the p-values that are higher than the chosen level of significant value (0.05). Thus, the $Ho_{A2\text{-}3\_1}$, $Ho_{A2\text{-}3\_2}$, $Ho_{A2\text{-}3\_3}$, $Ho_{A2\text{-}3\_4}$, $Ho_{A2\text{-}3\_5}$, $Ho_{A2\text{-}3\_6}$ and $Ho_{A2\text{-}3\_7}$ hypotheses are failed to be rejected.

Similar with Experiment A2-1 and A2-2, modelling the combined proactive behaviours in DES and combined DES/ABS has revealed no significant difference in between their simulation results performance.

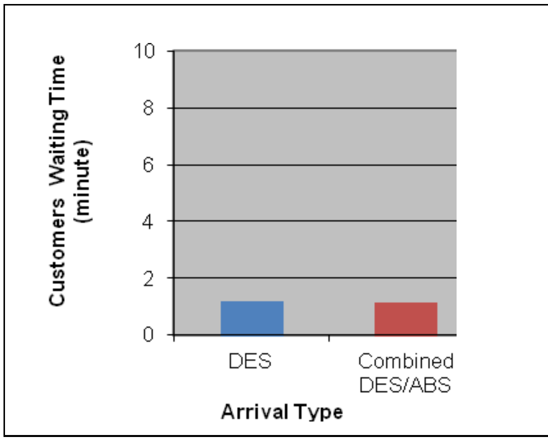
In addition, the same impact on modelling combined proactive behaviours is obtained in both DES and combined DES/ABS models. Modelling combination proactive behaviours as presented in Experiment A2-3 has provided new understanding about the effectiveness of having more than one proactive behaviour in the service-oriented system.

Speeding up the service-time could avoid staff having to request help from other colleagues. This explains why the number of calls for help is very low (as shown in Table 4.12 and Figure 4.8 (g). as the staff member has speeded up her service time and so less help from other staff is required. The reason for such performance by both proactive behaviours (speed up the service time and call for help) is because they are based on the same condition- the queue length.

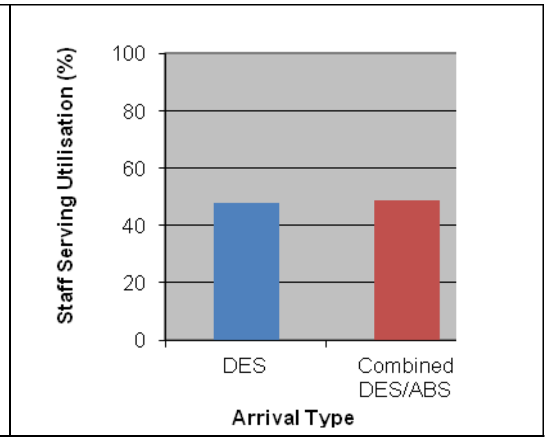
In addition, the same impact of speeding up the service time as presented in Experiment A2-1 can also be seen in Experiment A2-3, where the number of customers not served is reduced. The effect of having more than one proactive behaviour is important, especially for policy management in a service-oriented organisation.

Table 4.12 : Results of Experiment A2-3

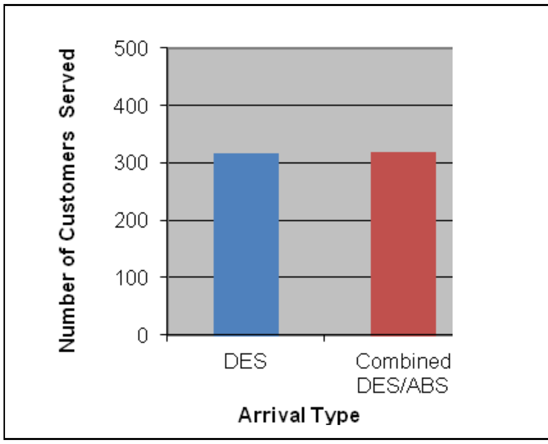
Performance measures		**DES**	**Combined DES/ABS**
Customers waiting time (minute)	Mean	1.19	1.15
	SD	0.47	0.91
Staff serving utilisation (%)	Mean	47	47
	SD	4.98	5.79
Number of customers served (people)	Mean	0	0
	SD	0.47	0.49
Number of customers not served (people)	Mean	316	319
	SD	19.44	21.13
Number of service times changes	Mean	0	0
	SD	1.12	1.3
New added staff serving utilisation (%)	Mean	24	27
	SD	11.86	18.86
Number of calls for help	Mean	0	0
	SD	0.60	0.7



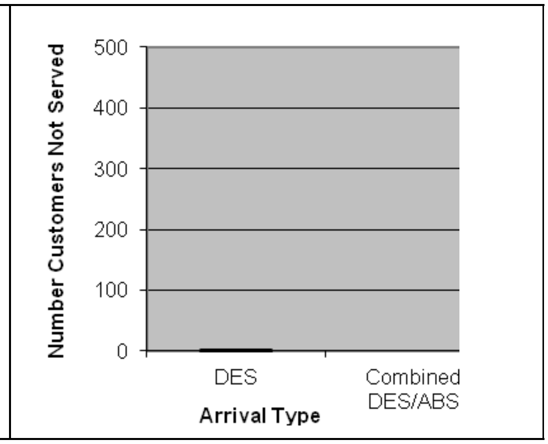
(a) Customers waiting time



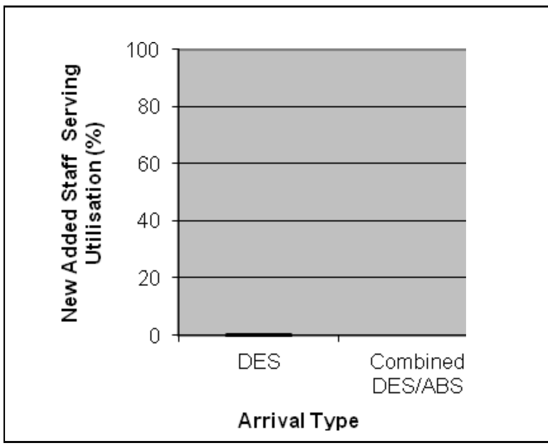
(b) Staff serving utilisation



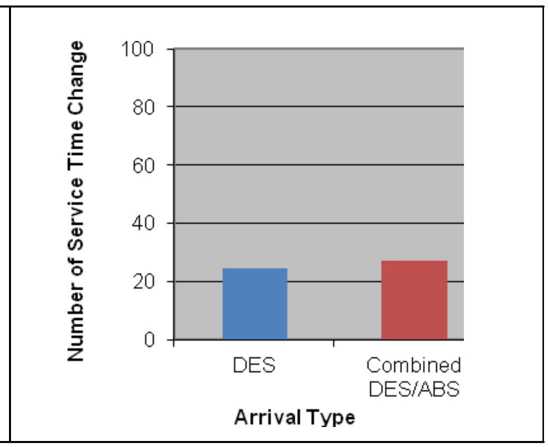
(c) Number of customers served



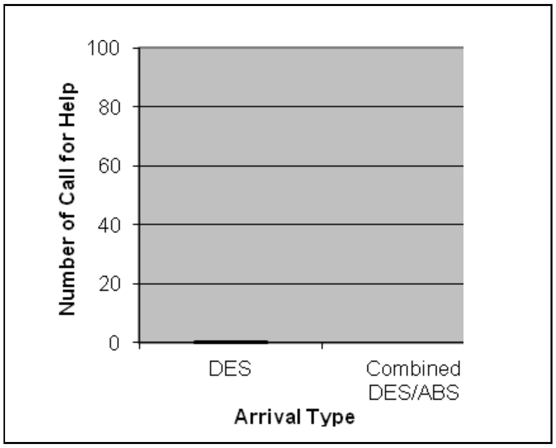
d) Number of customers not served



(e) Number of service time changes



(f) New added staff serving utilisation



(g) Number of calls for help

Figure 4.8 : Bar charts of results in Experiment A2-3

Table 4.13 : Results of T-test in Experiment A2-3

Performance Measures	DES vs. Combined DES/ABS	
	P-value	Result
Customers waiting time	P= 0.695	Fail to reject
Staff serving utilisation	P= 0.520	Fail to reject
Number of customers served	P= 0.397	Fail to reject
Number of customers not served	P= 0.907	Fail to reject
Number of service time changes	P= 0.329	Fail to reject
New added staff serving utilisation	P= 0.073	Fail to reject
Number of calls for help	P= 0.159	Fail to reject

Conclusions Experiment A1 and Experiment A2

Modelling reactive behaviours in DES and combined DES/ABS as presented in Experiment A1 has shown similar simulation results, thus Ho_{A1} is failed to be rejected hypothesis.

Furthermore, modelling mixed reactive and proactive behaviours as presented in Experiment A2-1, Experiment A2-2 and Experiment A2-3 have demonstrated similarities of results in the statistical test and as a result the Ho_{A2} hypothesis is also failed to be rejected.

The model result investigation has therefore proved that modelling the same human behaviours with the same modelling solution in DES to that in combined DES/ABS has shown similarities in simulation results for this case study. In fact, modelling proactive behaviours has produced a greater impact on the simulation results performance in both simulation models by reducing the number of customers not served.

Next, the performance of both simulation models are investigated in model difficulty experiment in order to know which simulation model is the best choice for the current case study operation or other similar-service oriented system operation.

4.5.3 Set B : Model Difficulty Investigation

Experiment B1: Reactive Human Behaviour

Set B of model difficulty investigation begin with Experiment B1: Reactive Human Behaviour, the objective of which is to examine the difficulty of modelling reactive behaviour from the perspective of model building time, model execution time and model line of code (LOC). Hence, the main hypothesis to test is as same as Ho_3 in Chapter 3 (Section 3.5.1).

The model building result is gathered by calculating the time spent (in hours) to build the investigated behaviour in DES and combined DES/ABS models. The model execution time is collected after the simulation run. Appendix A.11 illustrates the current specification of the computer hardware used for the modelling work. The model LOC is gathered from the java code in the simulation software (Anylogic). The freeware software, namely Practiline Source Code Counter (PractilineSoftware 2009), is used for counting the line of code.

The reactive experiment of model difficulty has obtained two types of results for model building time, model execution time and model LOC. The first set of results (as described in Chapter 3: Section 3.5.1) is obtained from the modeller's experience in developing the reactive behaviour using both simulation models; the second set is gathered through the survey conducted among the PhD students.

Both sets of results (first and second) of model building time, model execution time and model LOC from both DES and combined DES/ABS models are converted into the standard scale of model difficulty as discuss in Equation 3.1 (Chapter 3: Section 3.5.1).

The investigation on the model difficulty is started by discussing the first result of the reactive experiment. Each measure of model difficulty has only one data point because the simulation models are developed by one modeller.

The result value (RV) in Table 4.14 presents the simulation results gathered from the modeller's investigation of measures of model difficulty. The difficulty value (DV) in Table 4.14 is the new simulation result resulting from converting the result value into the scale of model difficulty.

For example, the model building time is 26 hours and 76 hours in the DES and combined DES/ABS models respectively. With reference to Equation 3.1 (Chapter 3: Section 3.5.1), the result of model difficulty, i.e. DES model building time (26 hours), is divided by the result of maximum model difficulty, i.e. combined DES/ABS model building time (76 hours). The deviation result of 26 / 76 is then multiplied by the total number of scales of model difficulty (10) - refer Chapter 3: Section 3.5.2 for the scales of model difficulty. From the calculation to convert into the standard scale of model difficulty, scale 3 is obtained for the DES model. Next, the same process of calculation is carried out for the combined DES/ABB model and a scale of 10 is calculated.

Table 4.14 : Results from the modeller's experience for model difficulty measures in Experiment B1

Performance Measures	**DES**		**DES/ABS**	
	RV	**DV**	**RV**	**DV**
Model Building Time	26 hours	3	76 hours	10
Model Execution Time	8.5 seconds	4	20.8 seconds	10
Model LOC	3874 lines	10	3899 lines	10

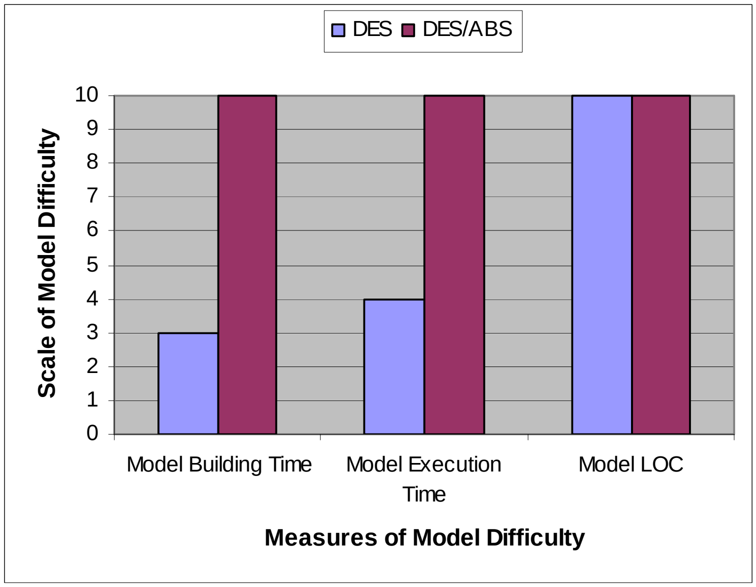


Figure 4.9: Bar charts of the first result of model difficulty measures (modeller's experience) in Experiment B1.

The quantitative approach (comparing the percentages of scale of difficulty) is used to compare the results of model difficulty between DES and combined DES/ABS in Table 4.14 and Figure 4.9, while the qualitative approach is used to answer the Ho_3 hypothesis in Experiment B1. A qualitative approach, as described in Chapter 3: Section 3.5.2, is chosen because the results for all data of model difficulty measures contain insufficient data samples to execute the statistical test (i.e. T-test).

The pattern illustrated by histogram in Figure 4.9 shows a very considerable difference between the model building and model execution time measures of DES compared with combined DES/ABS. The scale of difficulty shows that a higher value represented a greater degree of difficulty in one simulation model. Thus, Figure 4.9 illustrates that model building and execution times are 70% and 60% respectively, faster in the DES model compared to the combined DES/ABS model.

However, the model LOC suggested there is no difference between both simulation models.

The percentages comparison of the scale of difficulty has shown that DES has produced a faster development time and faster model execution time compared to the combined DES/ABS model with approximately the same amount of line of code.

Overall, it can be concluded that, from the perspectives modelling difficulty, DES produces a better performance than combined DES/ABS when modelling human reactive behaviour in fitting room operation. To confirm this conclusion, the performance of the second set of results of the reactive experiment is examined next.

The second result of the model difficulty investigation in modelling the reactive human behaviour is collected from a survey carried out in the computer laboratory at the School of Computer Science, University of Nottingham.

The candidates of the survey are among ten PhD students who are at a beginner-level of expertise in modelling and simulation, their experience averaging one year. Before joining the survey, the selected participants have attended the simulation workshop for five days of theory and practical work, as an underlying preparation for the survey; this level of user is targeted so that they could benefit from the human behaviour modelling practice.

The students are divided into two groups: the first, with five participants, is involved in developing the DES model, while the second, also with five participants, is involved in developing the combined DES/ABS model. Because users are new to the simulation area of study, a complete user manual on developing both simulation models is provided as a guideline; this manual took into account the results of model difficulty measures (model building time, model execution time and model LOC). On the same simulation models, the measures of model difficulty will produce similar results. However, the differences between the results of model difficulties' measures will be obtained when comparing between different simulation techniques.

The survey is conducted over two sessions, group one (DES model development) in the morning and group two (combined DES/ABS model development) in the afternoon. Each session run for 4 hours. The simulation model required for the development of the DES and combined DES/ABS models is the simplified version of the modeller simulation models, to ensure that the model could be developed within the estimated lab time. After developing the simulation models, the students were requested to fill in the questionnaires (Appendix A.12) in order to report their findings on the simulation difficulty.

The performance of DES and combined DES/ABS in model difficulty is investigated using the statistical T-test with level of significant - 0.05. The following hypotheses are tested:

Ho_{B1_1} : The model building time for reactive DES is not significantly different from combined DES/ABS.

Ho $_{B1\_2}$: The model execution time for reactive DES is not significantly different from combined DES/ABS.

Ho $_{B1\_3}$: The model LOC for reactive DES is not significantly different from combined DES/ABS.

The second set of results of Experiment B1 is gathered through the survey is presented in Table 4.15 and Figure 4.10. The same procedure as in first results of model difficulty measures (modeller's experience data) are undertaken to convert the survey results into one standard scale of model difficulty.

Table 4.15 : Results from the survey for model difficulty measures in Experiment B1

Performance Measures	**DES**		**DES/ABS**	
	RV	**DV**	**RV**	**DV**
Model Building Time	0.85 hour	4	2.05 hours	10
Model Execution Time	0.82 second	4	2.16 seconds	10
Model LOC	1678 lines	10	1694 lines	10

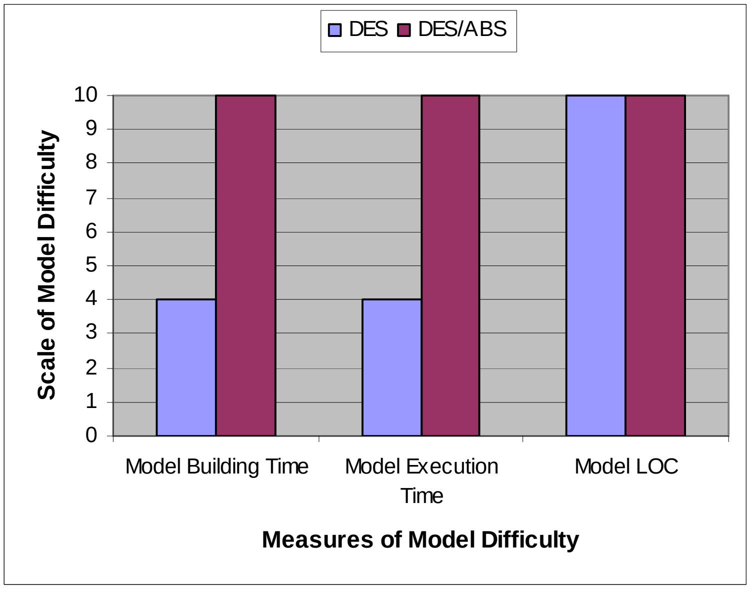


Figure 4.10 : Bar charts of the second result of model difficulty measures (survey) in Experiment B1

The results of the survey from the three perspectives of model difficulty measures demonstrate the dissimilarity of pattern between DES and combined DES/ABS in model building time and model execution time. To confirm these differences, the statistical T-test is conducted. The test has been chosen due to the small amount of data sampled in the survey.

It is found from the statistical test that the p-values of DES compared with those of combined DES/ABS for model building time, model execution time and model LOC are 0.000, 0.000, and 0.216 respectively. The p-values for model building time and execution time is lower than the level of significance; hence the Ho_{B1_1} and Ho_{B1_2} hypotheses are rejected. Meanwhile, the p-values for model LOC is greater than the level of significant (0.05); hence the Ho_{B1_3} hypothesis is therefore failed to be rejected.

The statistical test has proved that there are dissimilarities of results between DES and combined DES/ABS models in model building time and model execution time. In contrast a similarity of results is also found in model LOC between both simulation models.

The statistical test results in second result of model difficulty (survey data) have shown the similar pattern of results found in first result of model difficulty (modeller's experience data). Therefore, the statistical analysis test conducted for second results of model difficulty (survey data) has confirmed the first result of model difficulty as discussed above. Simulation difficulty for reactive DES shows the different performance compared to combined DES/ABS and Ho_3 hypothesis is then rejected.

Overall, it can be concluded that the DES model's results have shown a better performance (faster in building and execution time) in simulation model difficulty than combined DES/ABS model when modelling mixed reactive and proactive behaviours regardless the model LOC.

Experiment B2: Mixed Reactive and Proactive Human Behaviours

Experiment B2 is associated with modelling the mixed reactive and proactive behaviour in DES and combined DES/ABS. The objective of this experiment is to compare the performance of both simulation models in terms of model difficulty.

As in Experiment B1, the model difficulty measures under investigation are model building (in hours), model execution time (in seconds) and model LOC (in lines). Similarly, two sets of results are collected, the first from modeller's experience and the second from a second survey conducted among students. The main hypothesis to test is same as Ho_4 in Chapter 3 (Section 3.5.1).

First, modeller's experience data is discussed based on the results of the model difficulty measures obtained from the modelling work in Experiment A2. In Experiment A2, three sub-experiments (A2_1, A2_2and A2_3) are conducted as discussed in Chapter 3: Section 3.5.1. The model difficulty results from all experiments in Experiment A2 are placed in the sub-experiments in Experiment B2 in order to avoid the confusion in further investigation. Model difficulty results in Experiments A2-1, A2-2 and A2-3 are therefore placed in Experiments B2-1, B2-2, and B2-3 respectively.

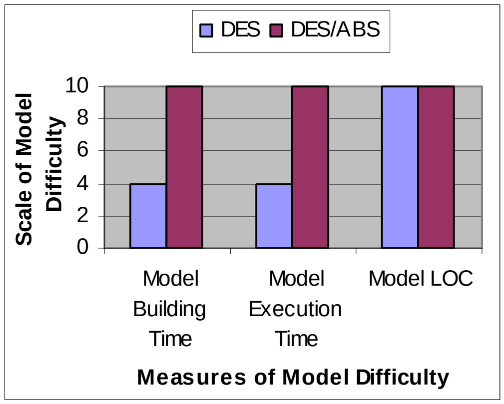
Table 4.16 and Figure 4.11 summarise the results of model difficulty measures for these three sub-experiments (Experiments B2-1, B2-2, and B2-3). The same processes as in Experiment B1 is undertaken to convert both results (modeller's experience and survey) of model difficulty measures in Experiment B2.

Table 4.16 : Results from the modeller's experience for model difficulty measures in Experiment B2

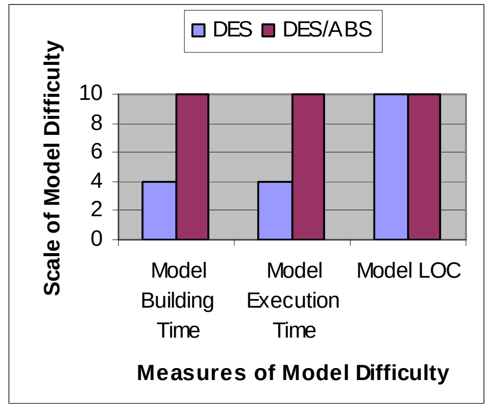
Measures of Model Difficulty	DES					
	Exp B2-1		Exp B2-2		Exp B2-3	
	RV	DV	RV	DV	RV	DV
Model Building Time	30 hours	4	35 hours	4	40 hours	4
Model Execution Time	9 seconds	4	9.3 seconds	4	11.5 seconds	4
Model LOC	3899 lines	10	4155 lines	10	4412 lines	10
Measures of Model Difficulty	**Combined DES/ABS**					
	Exp B2-1		**Exp B2-2**		**Exp B2-3**	
	RV	**DV**	**RV**	**DV**	**RV**	**DV**
Model Building Time	84 hours	10	89 hours	10	93 hours	10
Model Execution Time	21.4 seconds	10	22.8 seconds	10	27.5 seconds	10
Model LOC	4122 lines	10	4344 lines	10	4577 lines	10

As in Experiment B1, there is only one data point of results for model difficulty measures from the viewpoint of the modeller, so percentages comparison of the scale of model difficulty is chosen instead of conducting a statistical test.

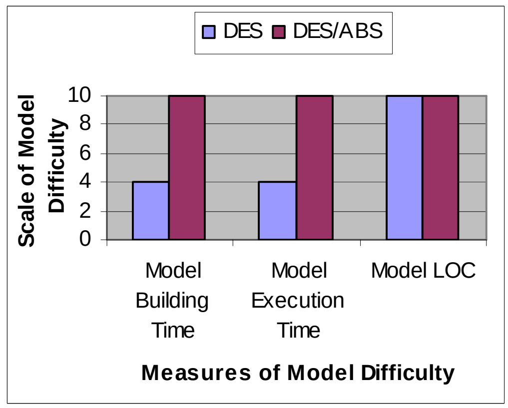
The same performance of results of model difficulty is found in the three experiments (B2-1, B2-2 and B2-3) for both simulation models. In both model building and model execution time, DES model has shown 60% less difficulty than combined DES/ABS model. In model LOC, both simulation models have shown the same level of difficulty.



(a) Results of Experiment B2-1



Results of Experiment B2-2



(c) Results of Experiment B2-3

Figure 4.11 : Bar charts of the first result of model difficulty measures (modellers' experience) in Experiment B2

To verify the first results of model difficulty measures (modellers' experience data), the second set of results of model difficulty is investigated through the survey. The statistical T- test (with level of significant 0.05) is used to compare the results of the second set of model difficulty with the following hypotheses:

Ho_{B2_1} : The model building time for mixed reactive and proactive DES is not significantly different from combined DES/ABS.

Ho $_{B2\_2}$: The model execution time for mixed reactive and proactive DES is not significantly different from combined DES/ABS.

Ho $_{B2\_3}$: The model LOC for mixed reactive and proactive DES is not significantly different from combined DES/ABS

Table 4.17 and Figure 4.12 illustrate these results, while Table 4.18 shows a statistical comparison of results using the T-test.

Table 4.17 : Results from the survey for model difficulty measures in Experiment B2

Measures of Model Difficulty	**DES**					
	Exp B2-1		**Exp B2-2**		**Exp B2-3**	
	RV	**DV**	**RV**	**DV**	**RV**	**DV**
Model Building Time	1 hours	4	1.19 hours	4	1.30 hours	4
ModelExecution Time	0.9 second	4	0.98 seconds	4	1.2 seconds	4
Model LOC	2150 lines	10	2430 lines	10	2491 lines	10
Measures of Model Difficulty	**Combined DES/ABS**					
	Exp B2-1		**Exp B2-2**		**Exp B2-3**	
	RV	**DV**	**RV**	**DV**	**RV**	**DV**
Model Building Time	2.50 hours	10	3 hours	10	3.50 hours	10
ModelExecution Time	2.16 seconds	10	2.5 seconds	10	2.9 seconds	10
Model LOC	2215 lines	10	2557 lines	10	2647 lines	10

The same patterns of survey results from the three experiments (B2_1, B2_2, and B2_3) are found as shown in Table 4.17 and Figure 4.12(a-c). In addition the pattern of survey results are found the same as in modeller's experience results for the three experiments (B2_1, B2_2, and B2_3).

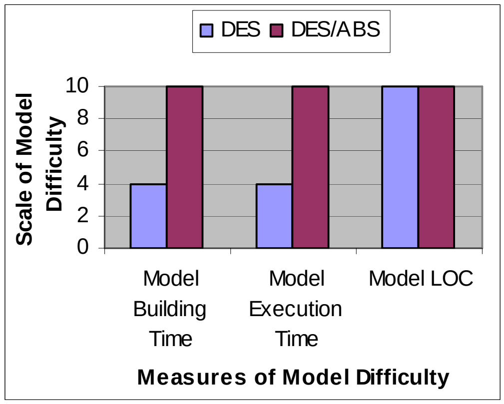
Furthermore, the results from the three experiments in Figure 4.12 (a-c) also illustrates the very considerable differences in the model building time and model execution time between the DES and combined DES/ABS models. The differences of these results are verified by conducting the statistical T-test.

Table 4.18 illustrates that the p-values of DES against combined DES/ABS for model building time and model execution time are lower than the chosen level of significance, thus Ho_{B2_1} and Ho_{B2_2} are rejected. In contrast, the p-values for model LOC is greater than the chosen level of significance, hence Ho_{B2_3} is failed to be rejected.

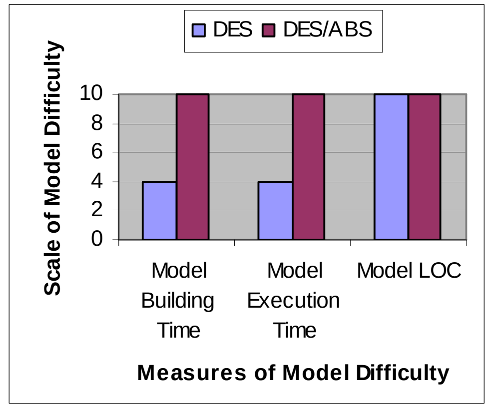
The statistical analysis test shows that dissimilarities of model difficulties measures are found in model building time and model execution time while model LOC has shown the similar results between DES and combined DES/ABS models.

Additionally, the statistical analysis test conducted for second results of model difficulty (survey data) has confirmed the first result of model difficulty (modeller's experience) as discussed above. Simulation difficulty for mixed reactive and proactive DES shows the different performance compared to combined DES/ABS and Ho_{B2_C1} hypothesis is then rejected.

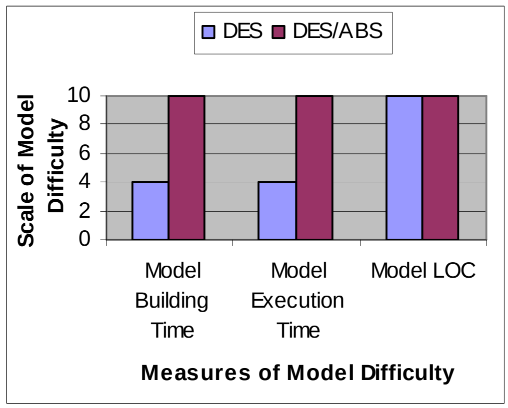
Overall, Experiment B2 has proven that DES model has shown an effective performance (faster in building and execution time) in simulation model difficulty when modelling mixed reactive and proactive behaviour compared to combined DES/ASB model.



(a) Results of Experiment B2-1



Results of Experiment B2-2



(c) Results of Experiment B2-3

Figure 4.12 : Bar charts of the second result of model difficulty measures (survey) in Experiment B2

Table 4.18: Results of T-test in Experiment B2

Model Difficulties' Measures	**DES vs combined DES/ABS**					
	Exp B2-1		**Exp B2-2**		**Exp B2-3**	
	P-value	**Status**	**P-value**	**Status**	**P-Value**	**Status**
Model Building Time	0.000	Reject	0.000	Reject	0.000	Reject
Model Execution Time	0.000	Reject	0.000	Reject	0.000	Reject
Mode LOC	0.195	Fail to reject	0.121	Fail to reject	0.253	Fail to reject

Conclusions of Experiment B1 and Experiment B2

Experiment B1 and B2 have revealed dissimilarities in the results of model building time and model execution time measures between DES and combined DES/ABS from the modeller's point of view (first result) and survey (second result). In contrast, the model LOC give a similar result in both simulation models.

It can be concluded that modelling reactive and mixed reactive and proactive behaviours has a better performance (faster in development and execution time) in DES model compare to the combined DES/ABS model, when investigating model difficulty.

4.5.4 Comparison of Results

The experiment section reports in turn on the investigations of the impact of reactive and mixed reactive and proactive behaviours towards the model result (Experiments A1 and A2) and model difficulty (Experiments B1 and B2) for DES and combined DES/ABS models. In this Section 4.5.4, therefore, discussion about the correlation between similar sets of experiments (A1 vs. A2 and B1 vs. B2) is presented for each simulation approach.

In Experiment A1, similarities of simulation results have been found between DES and combined DES/ABS models when modelling the reactive behaviour of sales staff towards customers. In addition, modelling mixed reactive and proactive behaviours in Experiment A2 has also shown a similar match between both simulation models. However, the impact on model results when modelling reactive behaviour (Experiment A1) against mixed reactive and proactive behaviour (Experiment A2) in one simulation approach is still unknown.

Therefore, in order to examine the relationship between Experiments A1 and A2 in both simulation models, a statistical test has been performed in order to answer the Ho_5 hypotheses stated in Chapter 3 (Section 3.5.4).

As there are three sub-experiments (A2-1, A2-2 and A2-3) within Experiment A2, Experiment A1 is therefore compared with each of these sub-experiments as follows: A1 vs. A2.1, A1 vs. A2-2, and A1 vs. A2.3. Two identical performance measures are used in Experiments A1 against A2 – customers waiting time and number of customers not served - have been chosen for the statistical test(T-test). The first hypothesis to test is as follow:

Ho_{A3_1} : The customers waiting time resulting from the DES model is not significantly different in Experiments A1 and A2-1.

Next, the customers waiting time resulting from the DES model in Experiment A1 is compared with Experiment A2-2 and A2-3 using the following hypotheses : Ho_{A3_2} and Ho_{A3_3} (in the same order). Same with combined DES/ABS model, the result from Experiment A1 is also compared with Experiment A2-1, A2-2 and A2-3 with the following hypotheses: Ho_{A3_4} , Ho_{A3_5} and Ho_{A3_6} (in the same order).

To compare the staff serving utilisation in the three experiments of DES and combined DES/ABS, the following hypotheses are tested: Ho_{A3_7}, Ho_{A3_8},

Ho_{A3_9} for DES - Experiment A1 vs. Experiment A2-1, A2-2 and A2-3 and Ho_{A3_10}, Ho_{A3_11}, Ho_{A3_12} for combined DES/ABS - Experiment A1 vs. Experiment A2-1, A2-2 and A2-3.

To test the above hypotheses, the T-test is used again. Table 4.19 shows the two performance measures data from each experiment for the correlation comparison while Table 4.20 shows the results of p-values from the T-test (the chosen significant value: 0.05) comparing Experiment A1 with A2-1, A2-2 and A2-3.

Table 4.19 shows the two performance measures data from each experiment for the correlation comparison while Table 4.20 shows the results of p-values from the Mann-Whitney test (the chosen significant value: 0.05) comparing Experiment A1 with A2-1, A2-2 and A2-3.

Table 4.19 : The data of the chosen performance measures for the correlation comparison

Experiment	**DES**		**Combined DES/ABS**	
	Customers waiting time (minutes)	**Number of customers not served**	**Customers waiting time (minutes)**	**Number of customers not served**
A1	1.33	0.97	3	2
A2-1	0.94	0.70	0	0
A2-2	0.58	0.42	0	0
A2-3	0.91	0.87	0	0

Table 4.20: Results of T- test comparing Experiment A1 with A2-1, A2-2 and A2-3.

Experiments	Performance measures	DES	DES/ABS
		P-Value	P-Value
A1 vs. A2-1	Customer waiting times	0.012	0.02
	Number of customers not served	0.000	0.000
A1 vs. A2-2	Customer waiting times	0.000	0.000
	Number of customers not served	0.000	0.000
A1 vs. A2-3	Customer waiting times	0.012	0.013
	Number of customers not served	0.000	0.000

According to Table 4.20 above, the comparison of Experiment A1 against all experiments (A2-1, A2-2 and A3-3) demonstrates that the DES and combined DES/ABS p-values for customers waiting time and number of customers not served are smaller than the chosen significance level (0.05), therefore the all hypotheses (from Ho_{A3_1} to Ho_{A3_13} hypotheses$_{)}$ for this comparison test are rejected.

The statistical test for Experiment A1 against A2 has confirmed there are significant differences between the customers waiting time and number of customers not served in Experiment A1 compared with Experiment A2-1, A2-2 and A2-3 for both DES and combined DES/ABS models. The Ho_5 hypothesis therefore is rejected.

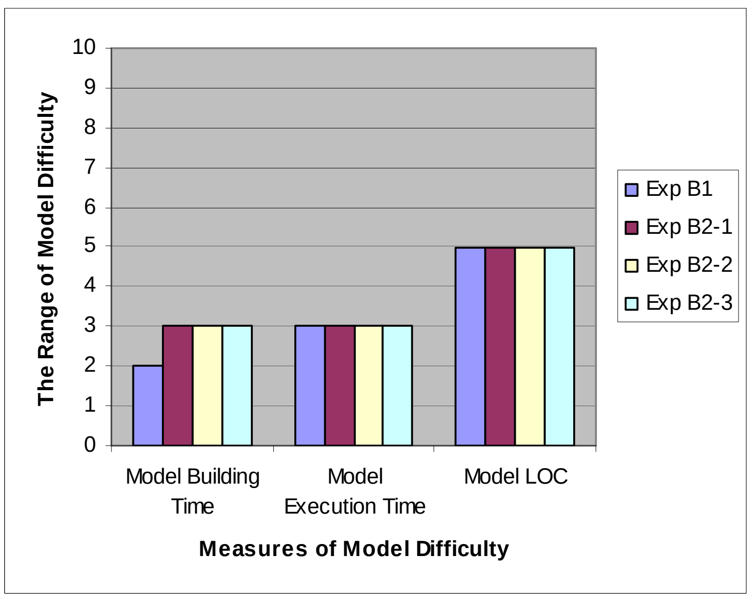
In case study 1, having proactive behaviours are capable to provide a greater impact to the customers waiting time and the number of customers not served in both simulation models. In addition, another new understanding is found when modelling more than one member of staff as presented in Experiment A2-2 where it provides a bigger impact in reducing the customers waiting time and number of customers not served more efficiently than using more than one proactive behaviour as demonstrated in Experiment A2-3.

Overall, the correlation investigation of the simulation results has revealed that both DES and combined DES/ABS have produced the similar greater impact when modelling proactive behaviour in the fitting room operation rather. The results of the investigation into model difficulty are considered next in order to answer the Ho_6 hypothesis as stated in Chapter 3 (Section 3.5.4).

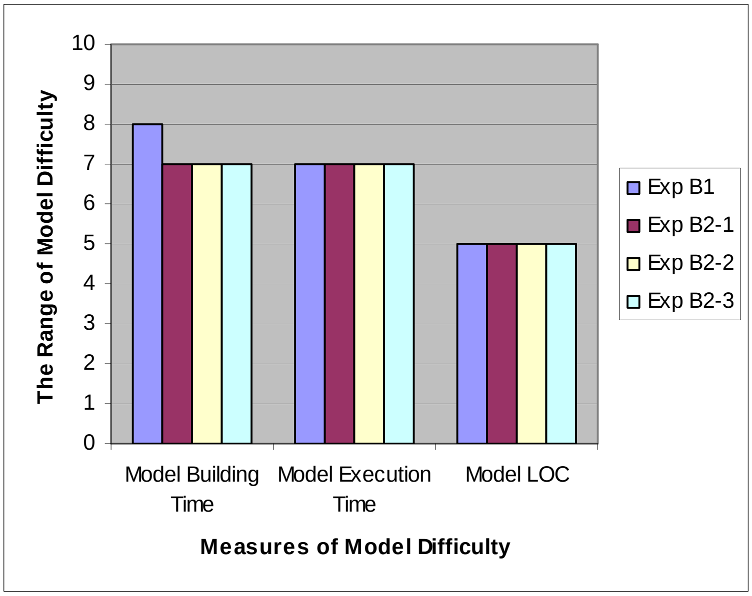
Experiment B1 and B2 suggests a dissimilarity in results between DES and combined DES/ABS in the three measures of model difficulty (model building time, model execution time and model LOC). However, there is some uncertainty about the impact of the results of model difficulty in one simulation approach when modelling reactive (Experiment B1) against mixed reactive and proactive behaviour (Experiment B2). Further comparison work has therefore been conducted in order to make clear the relationship between Experiments B1 and B2 in both simulation models.

The comparison investigation between Experiment B1 against Experiment B2 has yielded results based on both first results (modeller experience) and second results (survey). In this correlation investigation for model difficulty, the survey results of model building time, model execution time and model LOC are used because no significant difference has been found between the survey results and those of the modeller experience (Section 4.5.2). It has therefore been proposed that the same results will be produced if either modeller results or survey results are used for the correlation investigation between Experiment B1 and B2.

Since there is only one data point in the modeller result for each measure of model difficulty, no statistical test has been conducted. The graphical approach is used to represent the results of the comparison between Experiments B1 and B2. Experiment B2 has three sub-experiments (B2-1, B2-2 and B2-3); Experiment B1 has been compared with each of the sub-experiments of B2. Figure 4.13 illustrates the histograms of Experiments B1 and B2 (B2-1, B2-2 and B2-2) for DES and combined DES/ABS models:



(a) Model difficulty results in DES model for Experiments B1 and B2



(b) Model difficulty results in combined DES/ABS model for Experiments B1 and B2

Figure 4.13 : Histogram of Model Difficulty in Experiments B1 and B2

In Experiment B1 and B2, the average scales of model difficulty for model building time and model execution time for the DES model are at 3 and for the combined DES/ABS model they are at 7. This indicated that the average scale of both measures (model building and model execution time) for the DES model are approximately 57% less difficult than for the combined DES/ABS model. In contrast, the model LOC between DES and combined DES/ABS models have shown a similarity in term of their scale of difficulty.

The comparison that is made between reactive and mixed reactive and proactive experiments in model difficulty leads to the overall conclusion that there is a higher level of difficulty when modelling human behaviour in combined DES/ABS than in DES models.

4.6 Conclusions

The investigation on the model result and model difficulty for reactive behaviour modelling has revealed that DES shows no significant difference in the simulation results compared with the combined DES/ABS model. In addition, DES has also shown less modelling difficulty compared with the combined DES/ABS model when modelling simple human behaviour (reactive behaviour).

Furthermore, modelling mixed reactive and proactive behaviour or complex human behaviours has also revealed that DES shows no significant difference in the simulation results with less modelling difficulty compared with combined DES/ABS model.

Additionally, from the evidence of the model result investigations, modelling mixed reactive and proactive behaviours compared with modelling reactive behaviours does have a greater impact on the simulation results performance in both DES and combined DES/ABS models.

This case study exploration has produced the following recommendation: First: modelling proactive behaviour does have an important impact to the fitting room performance or any other similar service-oriented system. Second: if modelling difficulty (model building time, model execution time and model LOC) is the main concern for developing a simulation model with reactive or mixed behaviours than DES is the suitable modelling approach for presenting the investigated or similar service-oriented systems**.** Otherwise, combined DES/ABS is also suitable for presenting such service-oriented systems with higher level of modelling difficulty.

However, some questions remain: what can be understood if more complex human behaviours are implemented in combined DES/ABS model for solving a similar problem as in DES model? Does such modelling effort have a significant impact on the conclusion to be drawn? Chapter 5 therefore presents a second case study based on the public sector, which explores these questions further.

CHAPTER 5

CASE STUDY 2: INTERNATIONAL SUPPORT SERVICES IN THE UNIVERSITY

5.1 Introduction

This chapter presents case study 2 which explores the modelling of international support services in one university. As in case study 1, the real world reactive and proactive behaviours of staff (receptionist and advisors) and students are simplified and an investigation is carried out to inspect the performance of DES and combined DES/ABS in modelling both behaviours (reactive and proactive). Case study 2 is presented in this chapter the in same sequence as that outlined in Chapter 3 and Case Study 1 (Chapter 4).

5.2 Case Study

The subject of the second case study is the delivery of international support services at the University of Nottingham which is one of the world's most prominent universities in the world. One of the main reasons for this choice is that there is frequent interaction between students and support services staff, and interaction behaviour is an important part of the present study into human behaviour.

The international support services are located in the International Support Services Team (ISST) in the International Office, offering a wide range of support for the International and European Union students; the office is open from 9.00 am to 5.00 pm every weekday. The present research focuses on the international support operation based at the reception area and within the advisory service. To get an insight into the ISST, observation of staff and students and data collection are conducted for a period of one week. Figure 5.1 illustrates the delivery of support services by the ISST in the University’s International Office, the numbers and red arrows representing the sequence of operation.

In ISST, there is one member of staff (receptionist) who works at the reception area and two staff for the advisory service (advisories) who give support over the telephone and also offer a one to one support service.

First, the arriving students or incoming phone calls at ISST are served by the receptionist (represented by arrow number 1 in Figure 5.1). At the reception area, the receptionist has to deliver two types of service support tasks: (1) serve the incoming students at the reception desk and (2) respond to incoming phone calls. General enquiries and support requests from a student (i.e. enquiry on a visa presentation schedule) made either in person or on the phone are handled by the receptionist, whose support is available for the whole day. Second, students leave the reception area or the phone calls end after being served by the receptionist (represented by flow number 2 in Figure 5.1).

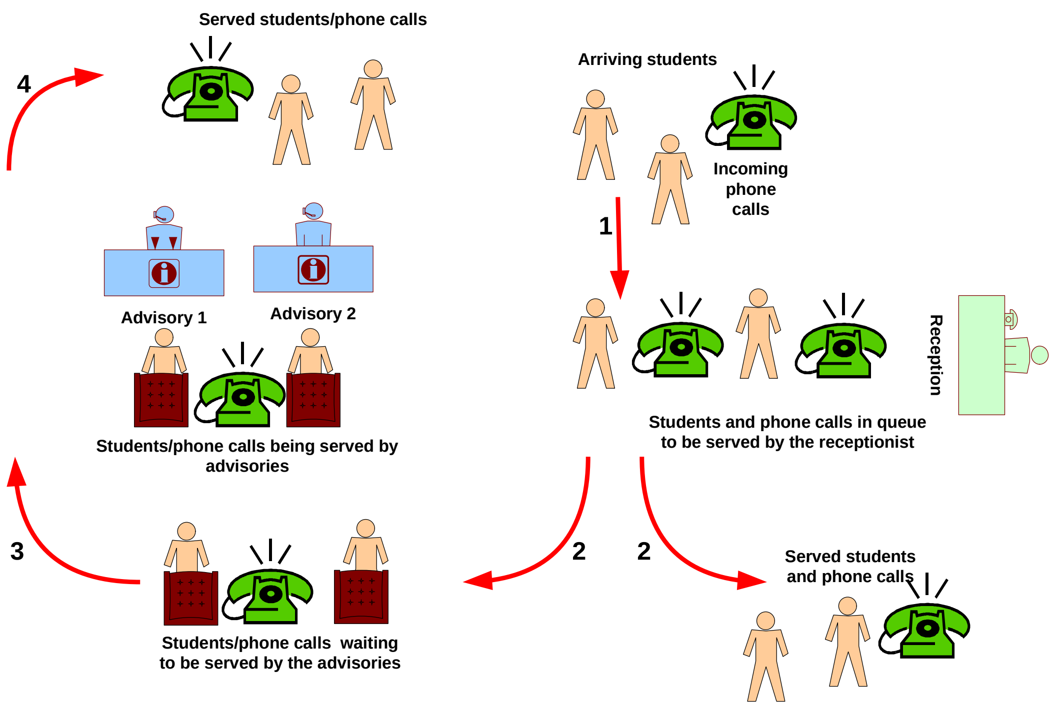


Figure 5.1: Delivery of the support services in the ISST at the University's International Office

The student can also get help from the advisory service via the walk-in section which is accessible from 1.00 pm to 4.00 pm (represented by flow number 1 again in Figure 5.1). A student who wishes to meet with the advisor in the afternoon is required to complete a request form at the receptionist area. The receptionist then gives the student a waiting number and the advisor calls the student when it is his/her turn (represented by the other arrow number 2 in Figure 5.1). The number and the form that is completed earlier are collected by the advisor on duty before serving the students (represented by the arrow number 3 in Figure

5.1). The student leaves the advisory section after obtaining the required support (represented by the arrow number 4 in Figure 5.1).

The observation of staff and students in the ISST has identified the reactive and proactive behaviours needed for the present study. Chapter 3: Section 3.2 provides a definition of reactive and proactive behaviours. The receptionist has demonstrated four reactive behaviours tasks: 1) accepting requests from students in person or on the phone 2) providing general support to students face to face and during incoming calls 3) searching for information and 4) giving waiting numbers to students. The reactive behaviour observed in the advisors is to provide detailed support to students in person while reactive behaviour of students or phone calls is to wait in the queue if the staffs (receptionist/advisors) are no available.

With regard to proactive behaviour, on the other hand, the receptionist is observed to cease handing out waiting numbers if, in their view, there are too many students waiting in the remaining time to be served by the advisors. Their decision to stop handing out waiting numbers is based on monitoring experience at the ISST operation. The advisors demonstrate proactive behaviour in speeding up their service time to ensure that all students who are waiting are served in the remaining operation time, a decision that is also based on the experience in serving students. The proactive behaviour observed in the students is skipping the queue in order to ask the receptionist a question. The decision to skip the queue is initiated from observing the queue at reception.

During the data collection process, some data are obtained to be used as the input to both DES and combined DES/ABS models. These include students' arrival rate, the receptionist's service time and the advisors' service time. The students' arrival rate in the simulation models is obtained by inspecting the arrival process observed in the real system over the cycle of one day (shown in Figure 5.2 below).

Similar to case study 1 (Chapter 4: Section 4.2), the arrival rate in case study 2 has been modelled using exponential distribution with an hourly changing rate in accordance with the arrival pattern shown in Appendix B.1. Refer case study 1 (Chapter 4: Section 4.2) for the reason of choosing exponential distribution for the students' arrival rate in both simulation models (DES and combined DES/ABS).

The simulation inputs for receptionist service time and advisors service time (as shown in the basic model in Section 5.4.1.) are obtained by calculating the minimum, average and maximum service time of the observation days.

After analysing the data collection, the level of detail to be modelled in the DES and combined DES/ABS models is considered; this is also known as conceptual modelling.

5.3 Towards the Implementation of the Simulation Models

5.3.1 Process-oriented Approach in DES Model

Both DES and combined DES/ABS uses the same basic conceptual model but the implementation of both simulation models is different. As described in Chapter 3 (Section 3.3), DES uses the process-oriented approach and the development of DES model begins by developing the basic process flow of the ISST operations (a complex queuing system).Then, the investigated human behaviours (reactive and proactive) are added to the basic process flow in order to show where the behaviours occurred in the ISST operation (see Figure 5.2).

In the DES model shown in Figure 5.2, there are three arrival sources at the ISST: students arrive for general enquiries; students arrive to meet with an advisory; or students make incoming phone calls. For the first arrival source (students arrive for general enquiries), if the receptionist is busy, the students will react to the receptionist by staying in the queue. If the student is impatient or needs to ask the receptionist a question, they will proactively skip from queuing to meet the receptionist upon arrival or while queuing (represents by the symbol C in Figure 5.2). On the other hand, if the receptionist is not busy, he/she will serve the students immediately. If the receptionist does not know the answer to the student's enquiry, he/she will display reactive behaviour to answer the question by searching the information. Otherwise, if he/she knows the answer, he/she will respond to the question and afterwards the students will leave the ISST.

The flow chart for the second arrival source (students arrive to meet with an advisory) is the same as the first arrival source when the receptionist is busy. If the receptionist is not busy, he/she will respond to the students by requesting them to fill in a form to meet with the advisors and then give them (the students) a card with a waiting number. The receptionist, however, will proactively stop the students meeting with the advisors if he/she has found that there are many students waiting. (represents by symbol A in Figure 5.2). If the advisors are busy, the students will respond by waiting to be called. Otherwise, the advisors will provide support to the students and the served students will leave the ISST. If the advisors have noticed there is a long queue of waiting students, the advisors will speed up the support time in order to deal with the waiting students in the available operation time (represents by symbol B in Figure 5.2).

For the third arrival source (incoming phone calls), the flow chart is similar to the first and second arrival sources, but the incoming phone calls only demonstrate reactive behaviour when the receptionist is busy. The receptionist otherwise will serve the phone calls if he/she is not busy. The receptionist will provide support if he/she knows the answer to the enquiries, otherwise he/she will transfer the calls to the available advisors. If the advisors are busy, the caller will respond to the advisors by waiting, otherwise if the advisors are not busy, the phone calls will be served. Again, if the queue of students waiting is too long, the advisors will speed up the support time in order to serve all waiting students in the available operation time (represents by symbol B in Figure 5.2).

5.3.2 Process-oriented and Individual-oriented Approach in Combined DES/ABS Model

Two approaches are used for developing the combined DES/ABS model: the process-oriented approach (to represent the DES model – used the same conceptual model as in Figure 5.2) and the individual-centric approach (to represent the ABS model - see Figure 5.3). The individual-centric modelling is illustrated by state charts in Figure 5.3 to represent different types of agents (students/phone calls, receptionist and advisories).

The students/phone calls agent consists of the various states for students/phone calls at three different arrival sources (students arrive for general enquiries, students arrive to meet with an advisory and students make incoming phone calls). Receptionist and advisory are in *idle* and *busy* states.

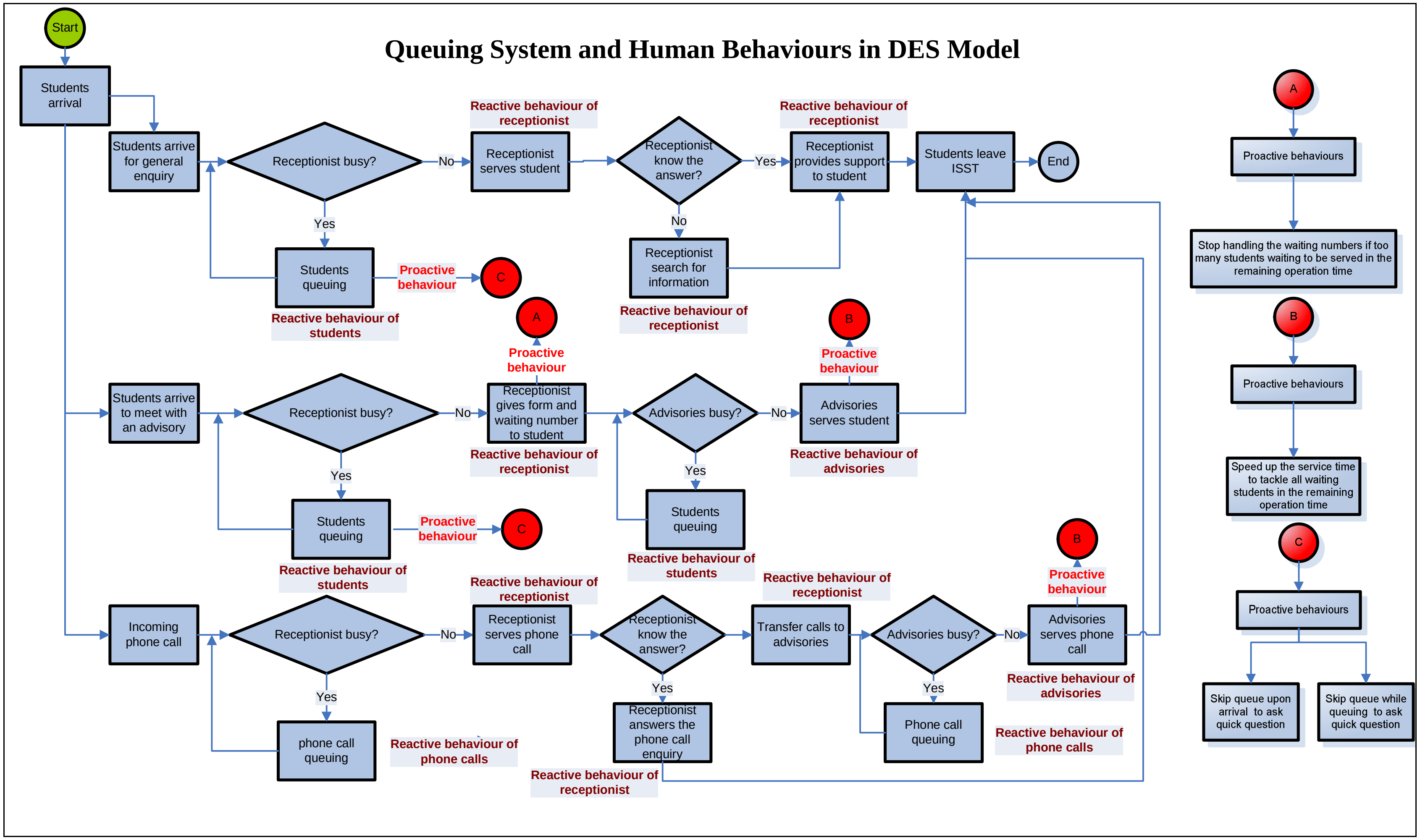


Figure 5.2 : The implementation of DES model

Some of the states change for students/phone calls in that receptionist and advisory agents are connected to each other by passing messages. For example, if a student for general enquiries enters the ISST, the student will be in *idle* state for a while.

Then, the student changes to *waiting to be served* state and immediately checks the availability of the receptionist. If the receptionist is in *busy* state, the student will change him/her state from *idle* to *waiting to be served*. If the receptionist is in *idle* state, the receptionist will communicate with the student by sending a "*receptionist call student*" message and the student will respond by sending a "*serve*" message.

Once the receptionist receives the message "*serve*", the receptionist will change his/her state from *idle* to *busy*, while the student will change his/her state from *waiting to be served* to *being served.* After the receptionist has finished serving the student, the student will send a "*release*" message to the receptionist. The student will change to state *idle* and leave the ISST while the receptionist will change to state *idle*.

A similar process is also executed for the other two arrival sources (students arrive to meet with an advisory and incoming phone calls) as they are based with the same student/phone calls agent. The communication between the advisor agent and the students/phone calls agent is also the same as the students/phone calls agent and the receptionist agent.

After considered on the DES and combined DES/ABS conceptual models, the development of both simulation models is then implemented.

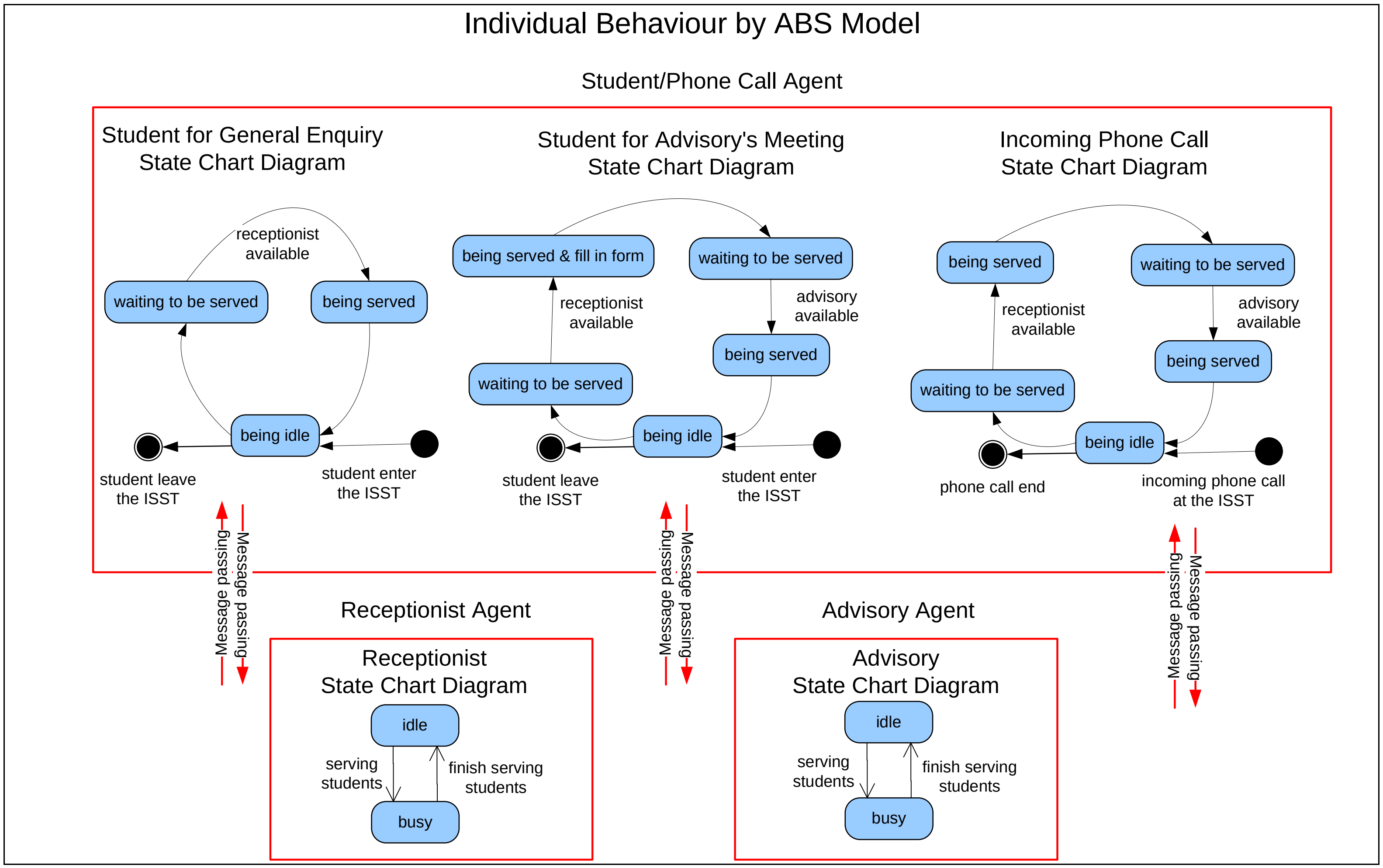


Figure 5.3 : The implementation of Combined DES/ABS model

5.4 Model Implementation and Validation

5.4.1 Basic Model Setup

From the development of the conceptual models, two simulation models are built using Anylogic TM 6.5 Educational version (XJTechnologies, 2010). Both simulation models consist of three arrival processes (students' arrival for general enquiry, students' arrival for advisory meeting, and incoming phone calls); one single queue for each arrival, and three resources (one receptionist and two advisors). In the DES model, student/phone call, receptionist and advisors are all passive objects while in the combined DES/ABS model, all are active objects (agents). Refer Chapter 4 (Section 4.4.1) for the definition of passive and active objects. Both simulation models make use of same model input parameter values.

This study next considers how objects or agents in both simulation models are set up:

i. Student/phone call object/agent

The arrival rates of students and incoming phone calls are defined according to the real system arrival data in Appendix B.1 (Section 5.2). In one day, there are five arrival patterns: 9.00-10.00am, 10.00-12.00pm, 12.00-2.00pm, 2.00-4.00pm and 4.00-5.00pm. They are modelled in both DES and combined DES/ABS models. This arrival pattern is used because it matches the real data arrival pattern. Appendix B.2 shows the comparison of the real data with the simulation input. The arrival pattern for all arrival sources (students' arrival for general enquiry, students' arrival for advisory meeting, and students' making incoming phone calls) in both DES and combined DES/ABS models are depicted in Table 5.1.

Table 5.1 : Students and phone calls arrival rates

Arrival Type	Time	Rate
Students for general enquiry	9.00 – 10.00 am	Approximately 8 people per hour
	10.00 – 11.00pm	Approximately 12 people per hour
	11.00 – 12.00pm	Approximately 12 people per hour
	12.00 – 1.00 pm	Approximately 15 people per hour
	1.00 – 2.00 pm	Approximately 15 people per hour
	2.00 – 3.00 pm	Approximately 14 people per hour
	3.00 – 4.00 pm	Approximately 14 people per hour
	4.00 – 5.00 pm	Approximately 10 people per hour
Students for advisory meeting	9.00 – 10.00am	Approximately 0 people per hour
	10.00 – 11.00pm	Approximately 0 people per hour
	11.00 – 12.00pm	Approximately 0 people per hour
	12.00 – 1.00 pm	Approximately 9 people per hour
	1.00 – 2.00 pm	Approximately 9 people per hour
	2.00 – 3.00 pm	Approximately 7 people per hour
	3.00 – 4.00 pm	Approximately 7 people per hour
	4.00 – 5.00 pm	Approximately 6 people per hour
Incoming phone calls	9.00 – 10.00am	Approximately 2 people per hour
	10.00 – 11.00pm	Approximately 4 people per hour
	11.00 – 12.00pm	Approximately 4 people per hour
	12.00 – 1.00 pm	Approximately 5 people per hour
	1.00 – 2.00 pm	Approximately 5 people per hour
	2.00 – 3.00 pm	Approximately 3 people per hour
	3.00 – 4.00 pm	Approximately 3 people per hour
	4.00 – 5.00 pm	Approximately 2 people per hour

ii. Receptionist object/agent

In both simulation models, there is one receptionist who is responsible for task 1 (accepting requests from students in person or on the phone), task 2 (providing support), task 3 (searching for information) and task 4 (giving waiting numbers to students). The priority of these tasks is based on a first in first out principle. Table 5.2 illustrates the service time used to represent the task execution time of a receptionist in both simulation models. The service times in Table 5.2 are presented in minutes and triangular distributions are used to represent the defined service times in both DES and combined DES/ABS models. These service times are defined through the data gathered from the real system based on the minimum, mode and maximum service times to serve the related tasks (shown in Table 5.2).

Table 5.2 : Receptionist service time

Service Time Parameters	Value
Receptionist Serve Service Time	Minimum: 0.17, Mode : 0.25, Maximum : 0.33
Receptionist Search Info Time	Minimum: 0.50, Mode : 1.00, Maximum : 1.50
Receptionist Support Time	Minimum: 0.50, Mode : 1.00, Maximum : 2.00
Receptionist Transfer Call Time	Minimum: 0.25, Mode : 0.25, Maximum : 0.50

iii. Advisor object/Agent

Two advisors are modelled in both DES and DES/ABS models. The task for an advisor is the provision of support services to students face to face and during incoming phone calls. The advisors provide support on a first in first out basis. Table 5.3 illustrates the service time used to represent the task execution time of an advisor. The description of advisor service time is similar to that of receptionist service time.

Table 5.3 : Advisors service time

Service Time Parameters	Value
Advisor Student Service Time	Minimum : 2, Mode : 4, Maximum : 10
Advisor Call Service Time	Minimum : 2, Mode : 6, Maximum : 8

The experimental conditions such as the number of runs for this case study are based on a simulation models' setup same to that in case study 1 (Chapter 4:

Section 4.4.1). The run length for this case study is 8 hours, imitating the normal operation of the real-life system in ISST while there is no warm up period in this case study as stated in Chapter 3: Section 3.4.

Next, the verification and validation processes are conducted in order to ensure the basic models for both DES and combined DES/ABS are valid.

5.4.2 Verification and Validation

The verification and validation process are performed simultaneously during the development of the basic simulation models (DES and combined DES/ABS). Two verification methods are conducted: checking the code with simulation expert and visual checks by modeller (refer Chapter 3: Section 3.4) while two validation methods are chosen: black–box and sensitivity analysis test.

Black-box validation: Comparison with real system

The black box validation is employed as the first validation process in which the simulation results from both simulation models (DES and combined DES/ABS) are compared in terms of quantities with the real system results. For this validation, a same statistical test as in Case Study 2 (Chapter 4) with the same explanation as in Chapter 4: Section 4.4.2 is used.

Thus, the use of T-test leads to the assumption that all comparative measures (i.e. students waiting time, receptionist utilisation, number of students served, etc) adopted in this study are normally distributed. To compare the mean values using T-test, the same hypotheses as in Chapter 4: Section 4.4.2 is examined. To link the hypotheses in Chapter 4 with Chapter 5, the performance measures used for $H_{BlackBox\_A}$ and $H_{BlackBox\_B}$ are changed to students waiting time and $H_{BlackBox\_C}$ and $H_{BlackBox\_D}$ are changed to receptionist utilisation. The students waiting time at reception and receptionist utilisation are used as the performance measures as the historic data of both measures is available.

The Minitab ™ (Minitab, 2000) statistical software is used to perform the T-test. The means and the standard deviation (SD) of the students waiting time at reception and receptionist utilisation from both simulation models and the real system are calculated for this test (Table 5.4). The same rules of statistic applied in the Chapter 4 are used in order to reject or fail to reject the hypotheses.

Table 5.4 : Data of real system, DES and combined DES/ABS

Performance measures		**Real System**	**DES**	**Combined DES/ABS**
Waiting time (minute) for receptionist	Mean	1.43	1.54	1.51
	SD	0.85	1.00	1.09
Receptionist utilisation (%)	Mean	52	54	54
	SD	10.13	14.7	14.9

Testing the DES model results against the real system measures reveals a p-value of 0.466 for waiting time and 0.886 for receptionist utilisation. Similar p-values are also obtained for both performance measures in the combined DES/ABS model. Since both DES and combined DES/ABS p-values are above the chosen level of significance (0.05), the hypotheses $Ho_{BlackBox\_A}$, $Ho_{BlackBox\_B,}$ $Ho_{BlackBox\_C,}$ and $Ho_{BlackBox\_D}$ are failed to be rejected.

From the statistical test results, it can be confirmed that the average student waiting times at reception and the receptionist utilisation resulting from both simulation models are not significantly different to those observed in the real system. As the overall result of this black-box validation test, the DES and combined DES/ABS models show a satisfactory representation of the real system.

Sensitivity Analysis Validation

The purpose of this sensitivity analysis validation is to examine the sensitivity of the simulation results when students/phone calls arrival rates are systematically varied with three differences of arrival patterns as shown in Table 5.5. Chapter 3 (Section 3.4) explains the setup of the arrival patterns.

The idea behind sensitivity analysis validation is to observe how this validation affected the DES and combined DES/ABS models' performance measures. In addition, in this validation test, all performance measures are expected to increase along with the increment of the number of students/phone calls in the simulation models.

The selected comparative measures for sensitivity analysis validation are waiting times at reception (from the three queues: students' arrival for general enquiry, students' arrival for advisory meeting and incoming phone calls), waiting times at advisors (from two queues: student's arrival for advisory meeting and incoming phone calls), receptionist utilisation, advisor utilisation, number of students served, and number of students not served.

Table 5.5 : The arrival patterns from three difference arrival sources in ISST

Students' arrival for general enquiry			
Arrival Time	Arrival Pattern 1 (people per hour)	Arrival Pattern 2 (people per hour)	Arrival Pattern 3 (people per hour)
9.00 – 10.00 am	8	10	13
10.00 – 12.00pm	24	31	40
12.00 – 2.00 pm	30	39	51
2.00 – 4.00 pm	27	35	46
4.00 – 5.00 pm	10	13	17
Students' arrival for advisor meeting			
Arrival Time	Arrival Pattern 1 (people per hour)	Arrival Pattern 2 (people per hour)	Arrival Pattern 3 (people per hour)
9.00 – 10.00 am	0	0	0
10.00 – 12.00pm	0	0	0
12.00 – 2.00 pm	18	23	30
2.00 – 4.00 pm	14	18	23
4.00 – 5.00 pm	6	8	10
Incoming phone calls			
Arrival Time	Arrival Pattern 1 (people per hour)	Arrival Pattern 2 (people per hour)	Arrival Pattern 3 (people per hour)
9.00 – 10.00 am	2	3	4
10.00 – 12.00pm	8	10	13
12.00 – 2.00 pm	10	13	17
2.00 – 4.00 pm	7	9	12
4.00 – 5.00 pm	4	5	7

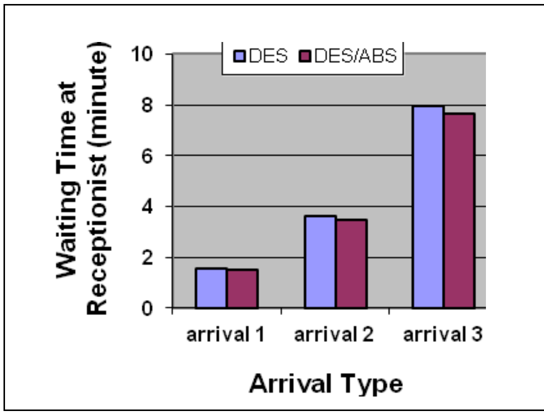
Results for the sensitivity analysis for DES and combined DES/ABS are illustrated in Table 5.6 and Figure 5.4(a-f). The results in both Table 5.6 and Figure 5.4 (a-f) reveal similar patterns for all performance measures. Both simulation models (DES and combined DES/ABS) demonstrate an increment for all performance measures when the students/phone calls arrival rate is increased.

It can be concluded that the sensitivity analysis has made the same impact on both simulation models when varying the students/phone calls arrival rates. This sensitivity analysis validation also shows the sensitivity of all performance measures - when the number of students/phone calls are increased, all performance measures investigated in this validation test also increase, as expected.

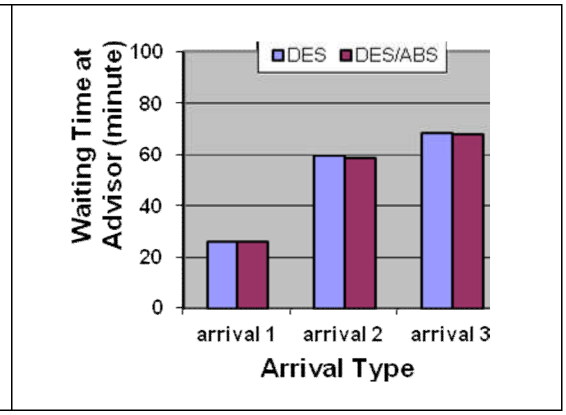
Table 5.6 : Results of sensitivity analysis validation

Simulation Models	Performance measures		Arrival Pattern 1	Arrival Pattern 2	Arrival Pattern 3
DES	Waiting times for receptionist (minute)	Mean	1.54	3.64	7.97
		SD	1.00	1.97	3.37
	Waiting time for advisors (minute)	Mean	25.92	59.38	68.50
		SD	2.70	12.06	10.40
	Receptionist utilisation (%)	Mean	54	63	75
		SD	14.71	13.39	9.91
	Advisor utilisation (%)	Mean	68	67	68
		SD	3.62	2.73	3.04
	Number of students served (people)	Mean	188	210	247
		SD	16.25	20.36	20.58
	Number of students not served (people)	Mean	0	0	36
		SD	0.10	1.75	31.63
Combined DES/ABS	Waiting time for receptionist (minute)	Mean	1.51	3.49	7.66
		SD	1.09	1.99	3.49
	Waiting time for advisors (minute)	Mean	25.99	58.77	67.84
		SD	2.77	12.26	11.05
	Receptionist utilisation (%)	Mean	54	64	75
		SD	14.90	13.40	10.37
	Advisor utilisation (%)	Mean	68	66	68
		SD	3.65	2.90	3.21
	Number of students served (people)	Mean	189	208	244
		SD	16.43	20.58	21.16
	Number of students not served (people)	Mean	0	1	35
		SD	0.14	1.80	32.25

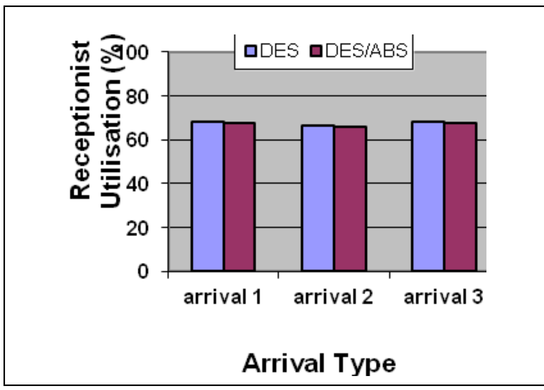
Similar with case study 1 (Chapter 4 : Section 4.4.2), all performance measures are found to be increased rationally as shown by the nature of any service–oriented systems; when the number of customers increases, staff utilisation will also increase and the queue will become longer.



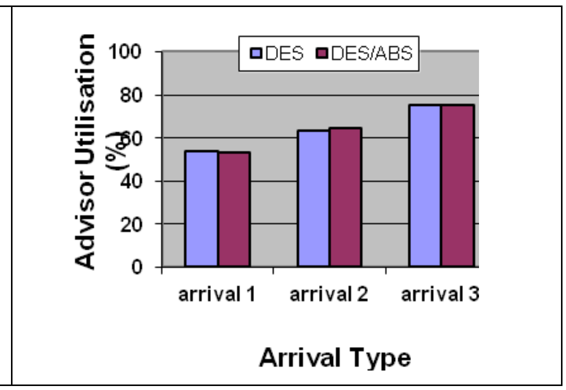
(a) Waiting time for receptionist



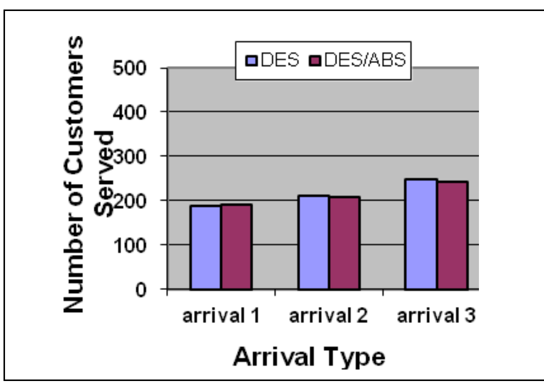
(b) Waiting time for advisors



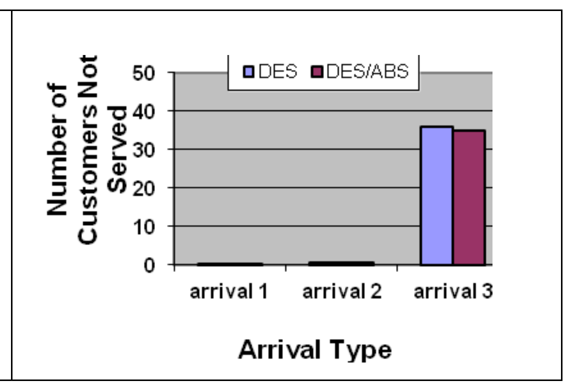
(c) Receptionist utilisation



(d) Advisors utilisation



(e) Number of students served



(f) Number of students not served

Figure 5.4 : Bar charts of results in the sensitivity analysis validation

Conclusions

In the black-box validation, a comparison of the full simulation models with the real system demonstrates a close correspondence in the mean student waiting time at reception and the percentage of receptionist utilisation. In the sensitivity analysis validation, all the investigated performances measures show, as expected, the increment of the results in both DES and combined DES/ABS models when the number of arrivals (students/phone calls) are increased. These two validation tests provide some level of confidence that both simulation models are sufficiently accurate for predicting the performance of the real system.

5.5 Experiments

5.5.1 Introduction

As discussed in Chapter 3 (Section 3.5), two sets of experiments, namely, Set A for the model result and Set B for the model difficulty, have been carried out in this case study to fulfil research objectives 1 and 2 respectively. The purpose of both sets of experiments has been to investigate the performance of the simulation results and level of difficulty of model building time, model execution time and model LOC in DES and combined DES/ABS when modelling the reactive and proactive human behaviours. The main hypothesis to investigate for both set of experiments is same as in Chapter 3 (Section 3.5.1).

Therefore, to answer the above hypotheses, this section is therefore divided into two sub-sections according to each set of experiment.

5.5.2 Set A : Model Result Investigation

Experiment A1: Reactive Behaviour

Set A experiments begin by performing Experiment A1: Reactive Behaviour. Experiment A1 is vital to determine the similarities and dissimilarities of both DES and combined DES/ABS models in the simulation result performance when modelling human reactive behaviour, the first objective of this research. Statistical testing is used as the method to compare modelling reactive behaviour in DES with combined DES/ABS. In this experiment, the main hypothesis to test is Ho_1 same as in Chapter 4 (Section 4.5.2).

The selected comparative measures for this reactive experiment are the same with the sensitivity analysis validation in Section 5.4.2 above (waiting times at reception - from the three queues: students' arrival for general enquiry, students' arrival for advisory meeting and incoming phone calls, waiting times at advisors - from two queues: student's arrival for advisory meeting and incoming phone calls; receptionist utilisation, advisors utilisation, number of students served, and number of students not served).

The basic model setup described in Section 5.4.1 is again used to model the reactive behaviour in DES and combine DES/ABS models. In both reactive simulation models, one receptionist reacted to requests from students on their arrival and from incoming calls. The reactive behaviours performed by the receptionist are i) accepting requests from students or incoming calls ii) providing support to students and incoming calls iii) searching for information regarding the students' requests iv) giving waiting number to students. In addition to this experiment, two advisors have provided related support to students in person or by phone. Students are served by the receptionist and advisors both in person and over the phone, using the first come first serve approach. If receptionist and advisors are busy, the students have reacted in person/on the phone by waiting in the queue. The hypotheses for Experiment A1 are as follows:

Ho_{A1_1} : The students waiting time for reception resulting from reactive DES model is not significantly different in the reactive combined DES/ABS model.

Ho_{A1_2} : The students waiting time for advisors resulting from reactive DES model is not significantly different in the reactive combined DES/ABS model.

Ho_{A1_3} : The receptionist utilisation resulting from reactive DES model is not significantly different in the combined reactive DES/ABS model.

Ho_{A1_4} : The advisors utilisation resulting from reactive DES model is not significantly different in the reactive combined DES/ABS model.

Ho_{A1_5} : The number of customers served resulting from reactive DES model is not significantly different in the reactive combined DES/ABS model.

Ho_{A1_6} : The number of customers not served resulting from reactive DES model is not significantly different in the reactive combined DES/ABS model.

Results for DES and combined DES/ABS models are illustrated in Table 5.7 and Figure 5.5(a-f). Table 5.8 also shows the result of the comparison of both models using a T-test. The results in both Tables 5.7 and Figure 5.5(a-f) reveal similar patterns for all performance measures.

In addition, Table 5.8 also depicts similar results of the T-test for all performance measures in both DES and DES/ABS models. According to the test results given in Table 5.8, all performance measures show p-values that are higher than the chosen level of significant value (0.05). Thus, the $Ho_{A1\_C2\_1}$, $Ho_{A1\_C2\_2}$, $Ho_{A1\_C2\_3}$, $Ho_{A1\_C2\_4}$, $Ho_{A1\_C2\_5}$ and $Ho_{A1\_C2\_6}$ hypotheses are failed to be rejected.

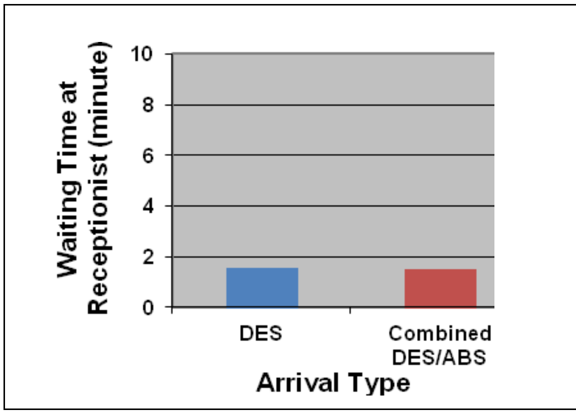
It can be concluded that modelling similar reactive behaviour with the same logic decisions has made the same impact on both simulation models. Hence, the simulation result for reactive DES and combined DES/ABS models is not statistically different.

Table 5.7 : Results of Experiment A1

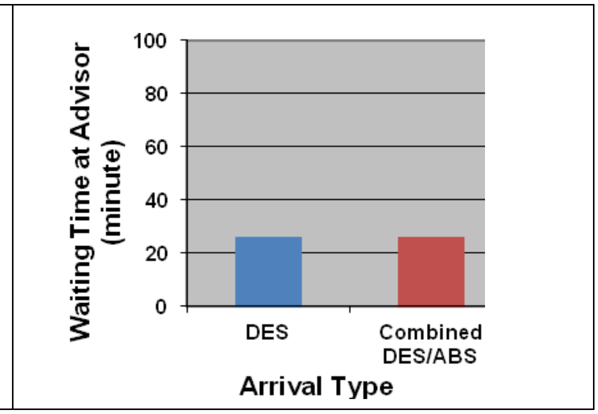
Performance measures		DES	Combined DES/ABS
Waiting times for receptionist (minute)	Mean	1.54	1.51
	SD	1.00	1.09
Waiting times for advisors (minute)	Mean	25.92	25.99
	SD	2.70	2.77
Receptionist utilisation (%)	Mean	54	54
	SD	14.71	14.90
Advisor utilisation (%)	Mean	68	68
	SD	3.62	3.65
Number of students served (people)	Mean	188	189
	SD	16.25	16.43
Number of students not served (people)	Mean	0	0
	SD	0.10	0.14

Table 5.8 : Results of T-test in Experiment A1

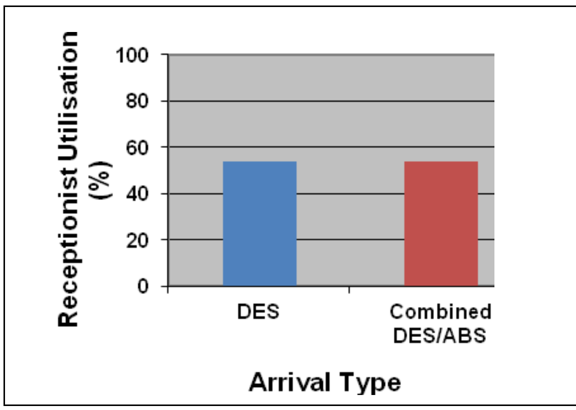
Performance Measures	DES vs. Combined DES/ABS	
	P-value	Result
Waiting times for receptionist	P = 0.824	Fail to reject
Waiting times for advisors	P = 0.856	Fail to reject
Receptionist utilisation	P = 0.819	Fail to reject
Advisors utilisation	P = 0.140	Fail to reject
Number of students served	P = 0.685	Fail to reject
Number of students not served	P = 0.563	Fail to reject



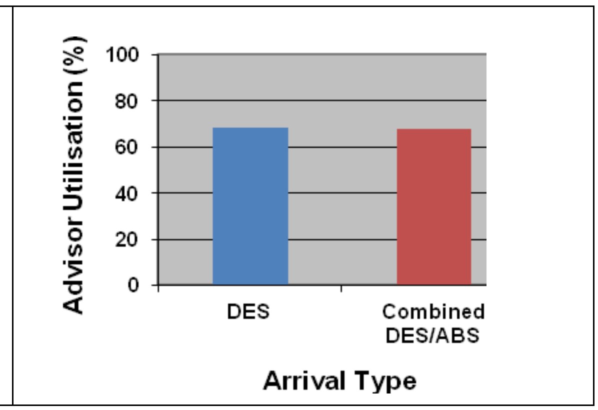
(a) Waiting times for receptionist



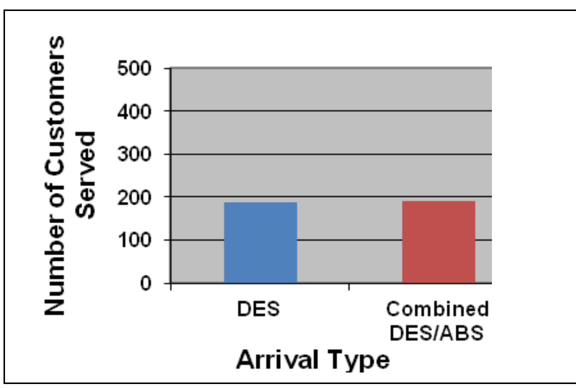
(b) Waiting times for advisors



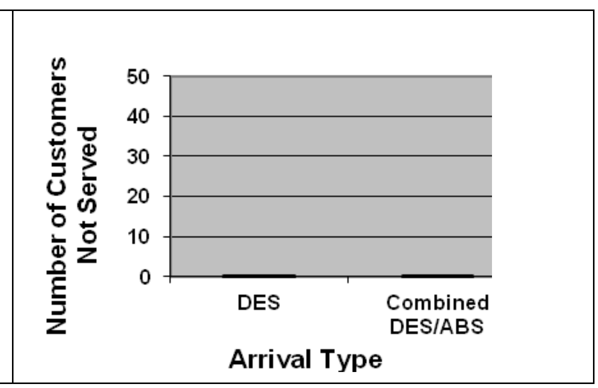
(c) Receptionist utilisation



(d) Advisors utilisation



(e) Number of students served



(f) Number of students not served

Figure 5.5 : Bar charts of results in Experiment A1

Experiment A2 : Mixed Reactive and Proactive Human Behaviours

The next experiment to perform is Experiment A2 – modelling mixed reactive and proactive behaviours. Experiment A2 is important for the second objective of this research - to determine the similarities and dissimilarities of both DES and combined DES/ABS in the simulation results performance when modelling human mixed reactive and proactive behaviours. Chapter 3 gives details regarding this experiment. The main hypothesis to test is as same as Ho_2 in Chapter 3 (Section 3.5.1).

In this experiment, the human proactive behaviours identified in Section 5.2 are modelled in both DES and combined DES/ABS models. The simulation models used in Experiment A1 are modified in order to model the Type 1 and Type 2 proactive behaviours (Chapter 3: Section 3.5.1).

The Type 1 proactive behaviour models in Experiment A2 is related to the behaviour of receptionist and advisors when making their own decisions, based on their experience, to deal with the hectic situation in ISST. Two proactive behaviours under Type 1 are investigated in both simulation models: firstly, the receptionist stops handing out waiting numbers when there are too many students to be served by the advisors in the remaining time; secondly, advisors speed up their service time to ensure that all students waiting to be served are supported in the remaining operation time.

The Type 2 proactive behaviour models in Experiment A2 refer to the observed behaviour of students in achieving their aim. The students skip queues in order to ask the receptionist a question. This type of behaviour is the third proactive behaviour to investigate in Experiment A2.

As the simulation models use in this experiment are the enhancement models from Experiment A1, an investigation of reactive behaviour also formed part of the current experiment. To examine the impact of including reactive and Type 1 and Type 2 proactive behaviours in the simulation models, Experiment A2 is divided into four sub-experiments (A2-1, A2-2, A2-3 and A2-4) as described in Chapter 3: Section 3.5 (Table 3.2). These sub-experiments are performed according to the basic model setup described in Section 5.4.1 above, together with some additional individual behaviours.

Experiment A2-1: Mixed Reactive and Sub-Proactive 1 Behaviours

The model setup for reactive behaviour is the same as that in Experiment A1. The proactive behaviour in ceasing to hand out waiting cards is initiated by the receptionist once there is no available time slot to meet with advisors, identified by dividing the remaining simulation time with the advisors' student service time. The benefit of this proactive behaviour is seen to overcome the problem of students waiting too long or advisors working beyond the operation time.

Appendix B.3 and Appendix B.4 represent the decision-making flow chart and pseudo codes for modelling the receptionist's proactive behaviour in both simulation models, respectively. Both DES and combined DES/ABS models are implemented with a same logic decision, as shown in Appendix B.3. The advisors' slots are checked continuously during the simulation time: if the queue for the advisors is smaller than the number of available slots, the students are given waiting cards, otherwise they are requested to leave the ISST.

However, both DES and combined DES/ABS models have applied a different model design in executing a same logic decision, as shown by the pseudo codes in Appendix B.4. In the real system, the decision of ceasing to hand out waiting cards to students is made by the receptionist. In combined DES/ABS model, such proactive behaviour is executed similar to as it occurred in real-life, where the communication between receptionist and staff is visible. On the other hand, such proactive behaviour is executed at one block according to conditions in another block in DES model.

Experiment A2-1 has observed the simulation results from seven performance measures: six from Experiment A1, together with the number of students requested to leave (the investigated proactive behaviour).

The hypotheses to test in Experiment A2-1 use the same six performance measures as in Experiment A1, but these performance measures are tested with a name link to Experiment A2-1 as follows : $Ho_{A2\text{-}1\_1}$, $Ho_{A2\text{-}1\_2}$, $Ho_{A2\text{-}1\_3}$, $Ho_{A2\text{-}1\_4}$, $Ho_{A2\text{-}1\_5}$ and $Ho_{A2\text{-}1\_6}$ for (in the same order) the student waiting times for receptionist, the student waiting times for advisors, the receptionist utilisation, the advisors' utilisation, the number of students not served and the number of students served. In addition, the hypothesis for the investigated proactive behaviour in Experiment A2-1 is:

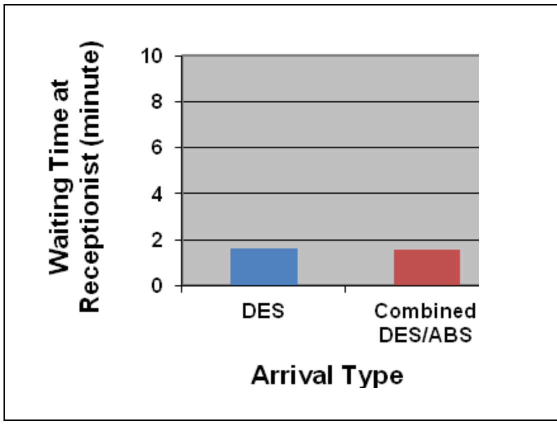
$Ho_{A2\text{-}1\_7}$: The number of students requested to leave resulting from mixed reactive and proactive DES model is not significantly different in the mixed reactive and proactive combined DES/ABS model.

Results for Experiment A2-1 are shown in Table 5.9 and Figure 5.6 while results of the T-test are shown in Table 5.10 below. Similar patterns of simulation results of the investigated performance measures for both the DES and the combined DES/ABS models are illustrated in Table 5.9 and Figure 5.6 (a-g). The T-test in Table 5.10 also has produced similar results for both simulation models, revealing p-values that are greater than the chosen level of significant (0.05) in all performance measures. Thus, the $Ho_{A2\text{-}1\_1}$, $Ho_{A2\text{-}1\_2}$, $Ho_{A2\text{-}1\_3}$, $Ho_{A2\text{-}1\_4}$, $Ho_{A2\text{-}1\_5}$, $Ho_{A2\text{-}1\_6}$, and $Ho_{A2\text{-}1\_7}$ hypotheses are failed to be rejected.

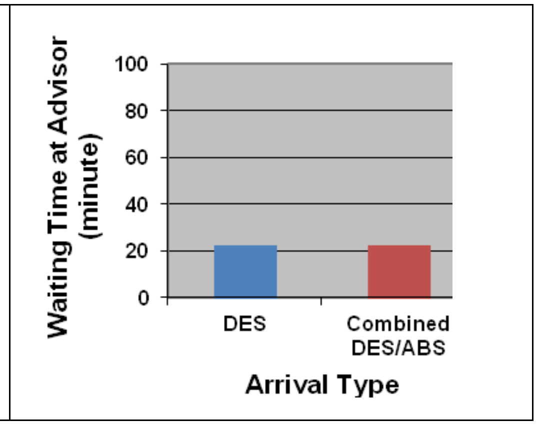
As in Experiment A1, Experiment A2-1 has also proved that modelling using a same logic decision for investigating comparable human behaviour has produced a similar impact on both simulation models. The impact on the results of the performance measures is seen when a receptionist stops handling the waiting cards and the students who seek to meet the advisors are requested to leave. The departing students from the ISST operation have reduced the number of students not served.

Table 5.9 : Results of Experiment A2-1

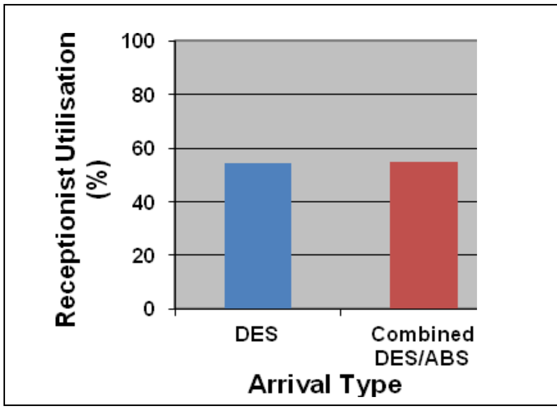
Performance measures		**DES**	**Combined DES/ABS**
Waiting times for receptionist (minute)	Mean	1.61	1.55
	SD	0.98	7.33
Waiting time for advisors (minute)	Mean	22.29	22.24
	SD	16.44	17.08
Receptionist utilisation (%)	Mean	55	55
	SD	14.34	14.70
Advisor utilisation (%)	Mean	56	57
	SD	8.74	8.83
Number of students served (people)	Mean	221	221
	SD	18.90	20.17
Number of students not served (people)	Mean	0	0
	SD	1.20	1.39
Number of students requested to leave (people)	Mean	11	12
	SD	14.73	15.09



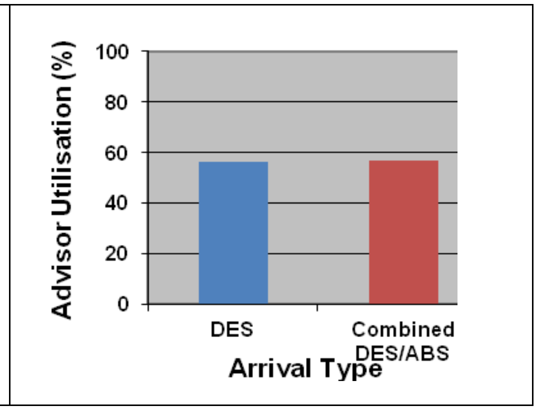
(a) Waiting times for receptionist



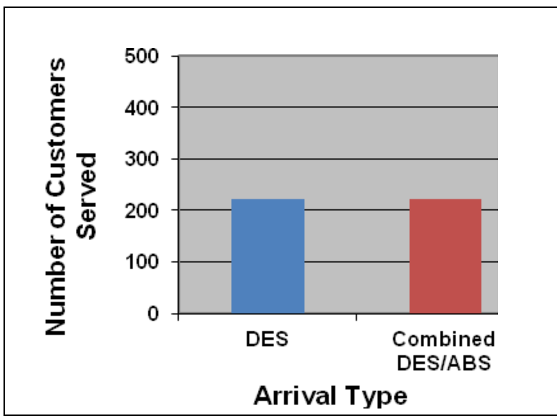
(b) Waiting times for advisors



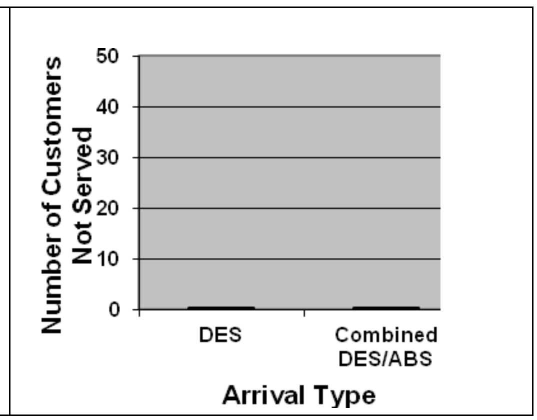
(c) Receptionist utilisation



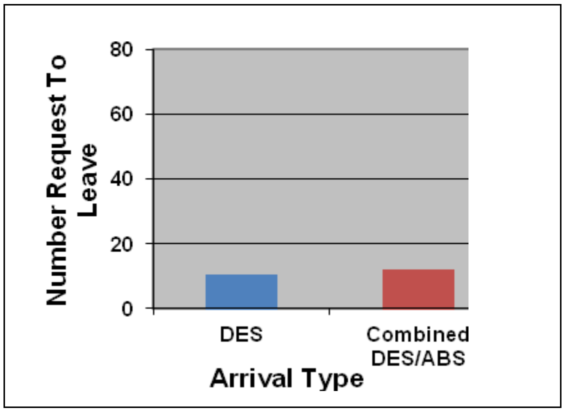
(d) Advisors utilisation



(e) Number of students served



(f) Number of students not served



(g)Number of students requested to leave

Figure 5.6 : Bar charts of results in Experiment A2-1

Table 5.10 : Results of T-test in Experiment A2-1

Performance Measures	DES vs. Combined DES/ABS	
	P-value	Result
Waiting times for receptionist	P = 0.664	Fail to reject
Waiting times for advisors	P = 0.984	Fail to reject
Receptionist utilisation	P = 0.907	Fail to reject
Advisors utilisation	P = 0.664	Fail to reject
Number of students served	P = 0.948	Fail to reject
Number of students not served	P = 0.515	Fail to reject
Number of students requests to leave	P = 0.446	Fail to reject

Experiment A2-2: Mixed Reactive and Sub-Proactive 2 Behaviours

In Experiment A2-2, the proactive behaviour under investigation is the behaviour of advisors speeding up the service time in order to deal with all students who are waiting during the ISST operation time.

The simulation models' setup for the reactive behaviour in DES and combined DES/ABS are similar those in Experiment A1. In the proactive behaviour model setup, the advisors' service time is speeded up by 20%, overcoming the problem of serving students beyond the operation time. The service time is speeded up by 20 % following the real system observation on the staff behaviour, when the staff have served the customers more quickly than in normal service time in order to deal with the hectic situation in the fitting room operation.

The proactive behaviours in Experiments A2-1 and A2-2 are capable of solving the same problem, but the decision to initiate such behaviour came from other people (in Experiment A2-1 by receptionist and in Experiment A2-2 by advisors).

Appendix B.5 illustrates the decision-making flow chart to execute the investigated proactive behaviour, while Figure Appendix B.6 shows the implementation of such proactive behaviour in pseudo codes for both DES and combined DES/ASB models. The advisors' slots are checked continuously during the simulation time. If the queue length at the advisors is greater than the number of available time slots, the advisors will speed up the service time by 20% more than the normal service time; otherwise the normal service time is executed.

In this experiment, seven performance measures are used, including six from Experiment A1 together with the number of service time changes (the investigated proactive behaviour in this case study). The T-test is used to investigate the impact of the simulation models on the current experiment.

The hypotheses to test in Experiment A2-2 use the same with the six performance measures as in Experiment A1 but these performance measures are tested with a name link to Experiment A2-2 as follows : $Ho_{A2\text{-}2\_1}$, $Ho_{A2\text{-}2\_2}$, $Ho_{A2\text{-}2\_3}$, $Ho_{A2\text{-}2\_4}$, $Ho_{A2\text{-}2\_5}$ and $Ho_{A2\text{-}2\_6}$ for (in the same order) the student waiting times for receptionist, the student waiting times for advisors, the receptionist utilisation, the advisors utilisation, the number of students not served and the number of students served, respectively. In addition, the hypothesis for the investigated proactive behaviour in Experiment A2-2 is:

$Ho_{A2\text{-}2\_7}$: The number of service time changes resulting from mixed reactive and proactive DES model is not significantly different in the mixed reactive and proactive combined DES/ABS model

Results for Experiment A2-2 are shown in Table 5.11 and Figure 5.7 (a-g) and results of the T-test are shown in Table 5.12 below. Table 5.10 and Figure 5.7 (a-g) show the similarities in pattern between the simulation results of the two simulation models (DES and combined DES/ABS models). The statistical test confirmed these similarities.

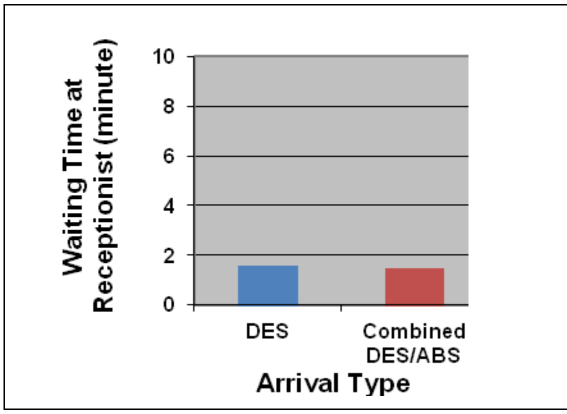
The test results presented in Table 5.12 demonstrate that the p-values from all performance measures are greater than the chosen level of significant (0.05). Therefore, the $Ho_{A2\text{-}2\_1}$, $Ho_{A2\text{-}2\_2}$, $Ho_{A2\text{-}2\_3}$, $Ho_{A2\text{-}2\_4}$, $Ho_{A2\text{-}2\_5}$, $Ho_{A2\text{-}2\_6}$ and $Ho_{A2\text{-}2\_7}$ hypotheses are failed to be rejected.

Again, no significant differences between the DES and combined DES/ABS are identified when modelling similar mixed reactive and proactive human behaviour using a same logic decision in both models. The statistical test has confirmed that the DES model is capable of producing a similar impact with combined DES/ABS when modelling human reactive and proactive behaviour in the service-oriented system with regards to the investigated proactive behaviour.

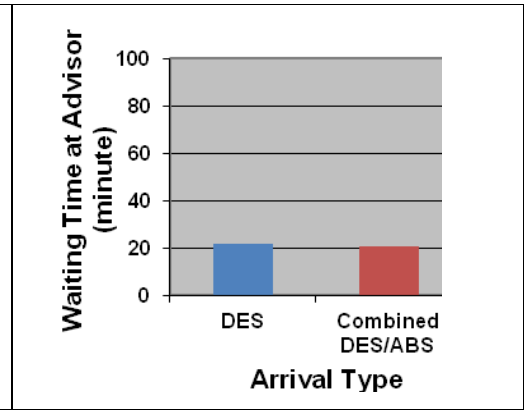
The greatest impact of modelling proactive behaviour in both simulation models is also seen on the number of students not served, where it has been reduced to zero, as in Experiment A2-1. The impact on the simulation results for both DES and combined DES/ABS when modelling another type of proactive behaviour (skipping the queue) is then investigated in Experiment A2-3.

Table 5.11 : Results of Experiment A2-2

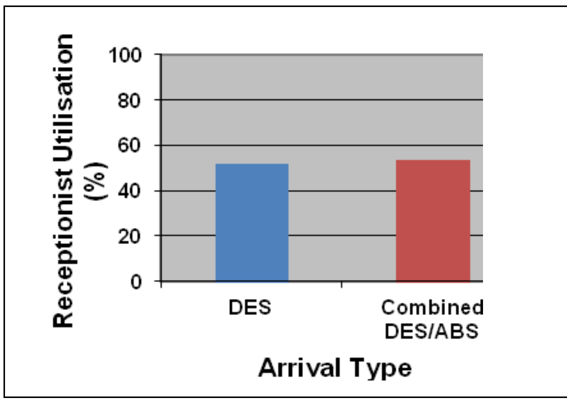
Performance measures		**DES**	**Combined DES/ABS**
Waiting times for receptionist (minute)	Mean	1.55	1.46
	SD	1.07	0.97
Waiting time for advisors (minute)	Mean	21.87	20.80
	SD	20.25	20.78
Receptionist utilisation (%)	Mean	52	54
	SD	13.18	15.11
Advisor utilisation (%)	Mean	55	55
	SD	9.71	10.60
Number of students served (people)	Mean	224	224
	SD	17.13	18.38
Number of students not served (people)	Mean	0	0
	SD	0.00	0.00
Number of service time changes	Mean	19	23
	SD	24.99	28.65



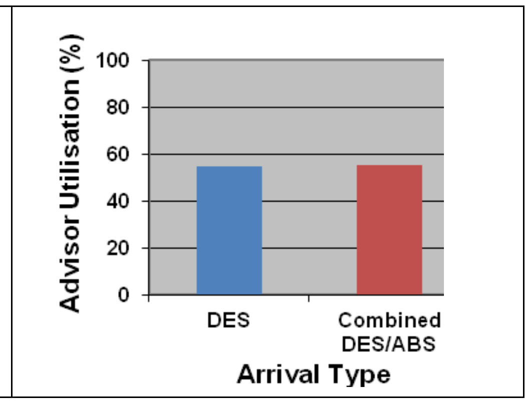
(a) Waiting times for receptionist



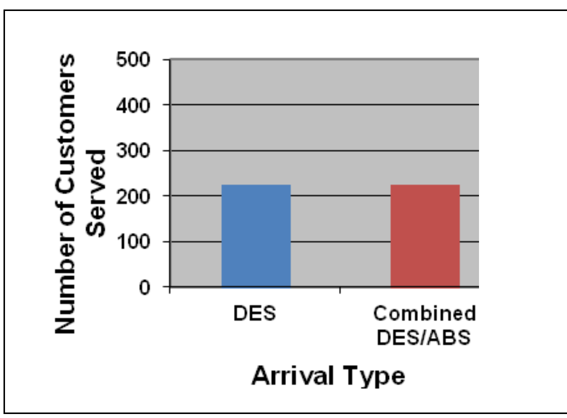
(b) Waiting times for advisors



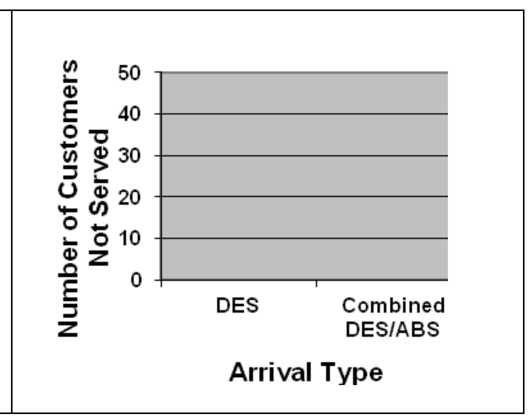
(c) Receptionist utilisation



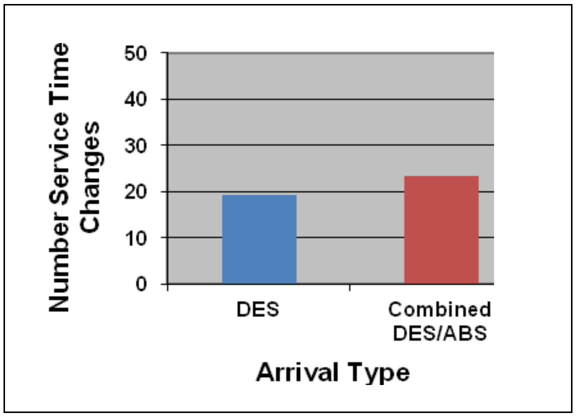
(d) Advisors utilisation



(e) Number of students served



(f) Number of students not served



(g) Number of service time changes

Figure 5.7 : Bar charts of results in Experiment A2-2

Table 5.12 : Results of T-test in Experiment A2-2

Performance Measures	DES vs. Combined DES/ABS	
	P-value	Result
Waiting times for receptionist	P = 0.524	Fail to reject
Waiting times for advisors	P = 0.714	Fail to reject
Receptionist utilisation	P = 0.327	Fail to reject
Advisors utilisation	P = 0.741	Fail to reject
Number of students served	P = 0.924	Fail to reject
Number of students not served	P = 0.871	Fail to reject
Number of service time changes	P = 0.283	Fail to reject

Experiment A2-3: Mixed Reactive and Sub-Proactive 3 Behaviours

The investigated proactive behaviour in Experiment A2-3 is the queue skipping among students in order to meet the receptionist, thus avoiding too long a wait if their request could be settled quickly. Appendix B.7 illustrates the decision-making flow chart to execute the third proactive behaviour while Appendix B.8

shows the pseudo code for the decision-making process for both DES and combined DES/ABS models.

As shown in Appendix B.7(a), in DES model, 5% of the arriving students at the ISST (the 5% value is gained through the real observation) are having the skip from queue behaviour. Those students who skip the queue on arrival are added to the front of the queue; if they do not show this behaviour they are added to the end of the queue.

To model the real situation in ISST, 5% of students in combined DES/ABS model as shown in Appendix B.7 (b), demonstrate skipping the queue behaviour on arrival and also show this behaviour while queuing. The same process as in DES is model for the students who skip the queue on arrival. If the students have decided to skip the queue while queuing, the behaviour of the receptionist is checked. If the receptionist can be easily interrupted, then the students skip the queue by being allocated a place at the front of the queue. On the hand, if it is difficult to interrupt the receptionist, the students remain in the same position in the queue.

The different solution is applied to both DES and combined DES/ABS to solve the same queuing behaviour is because the behaviour of skipping the queue while queuing by students is difficult to implement using DES approach as entities in DES model are passive objects. Passive objects are unable to initiate events as it follows a restricted process-oriented order in the DES modelling. Modelling skipping the queue while queuing would require a significant amount of programming logic to be inserted in several DES blocks, as modelling such behaviour is complicated for process-flow modelling; this is therefore not attempted.

In this experiment, eight performance measures are used, including six from Experiment A1 together plus two the investigated behaviours - the number of students skipping the queue (upon arrival) and the number of students skips the queue (while waiting).

The hypotheses to test in Experiment A2-3 use the same with the six performance measures as in Experiment A1 but these performance measures are tested with a name link to Experiment A2-3 as follows : $Ho_{A2\text{-}3\_1}$, $Ho_{A2\text{-}3\_2}$, $Ho_{A2\text{-}3\_3}$, $Ho_{A2\text{-}3\_4}$, $Ho_{A2\text{-}3\_5}$ and $Ho_{A2\text{-}3\_6}$ for (in the same order) the student waiting times for receptionist, the student waiting times for advisors, the receptionist utilisation, the advisors utilisation, the number of students not served and the number of students served, respectively. In addition, the hypotheses for the investigated proactive behaviour in Experiment A2-3 are:

$Ho_{A2\text{-}3\_7}$: The number of students skipping queue (upon arrival) resulting from mixed reactive and proactive DES model is not significantly different in the mixed reactive and proactive combined DES/ABS model.

$Ho_{A2\text{-}3\_8}$: The number of students skipping queue (while queuing) resulting from mixed reactive and proactive DES model is not significantly different in the mixed reactive and proactive combined DES/ABS model.

Results for Experiment A2-3 are shown in Table 5.13 and Figure 5.8 (a-h) while the results of the T-test are shown in Table 5.14 below. Unexpectedly, the results illustrated in Table 5.13 and Figure 5.8(a-g) of the Experiment A2-3 show a similar pattern between the simulation results of the DES and combined DES/ABS models even though an extra individual behaviour is added in combined DES/ABS model except in Figure 5.8(h).

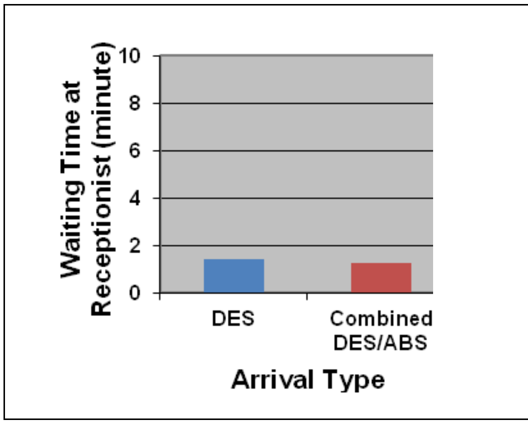
To confirm the similarities and dissimilarities in the simulation results, T-test is conducted. Table 5.14 reveals similar results for the T-test, where the p-values from all performance measures are greater than the chosen level of significant (0.05) expect for the number of students skipping queue (while queuing). Therefore, the hypotheses $Ho_{A3\text{-}2\_1}$, $Ho_{A3\text{-}2\_2}$, $Ho_{A2\text{-}2\_3}$, $Ho_{A3\text{-}2\_4}$, $Ho_{A3\text{-}2\_5}$, $Ho_{A3\text{-}2\_6}$ and $Ho_{A3\text{-}2\_7}$ are failed to be rejected while $Ho_{A3\text{-}2\_8}$ is rejected.

The statistical test has confirmed that there are similarities in results in both simulations even though individual behaviour (skipping the queue while queuing) is added to the combined DES/ABS model. The simulation results have proved that adding skipping the queue behaviour while queuing in the combined DES/ABS model does not affect the overall results.

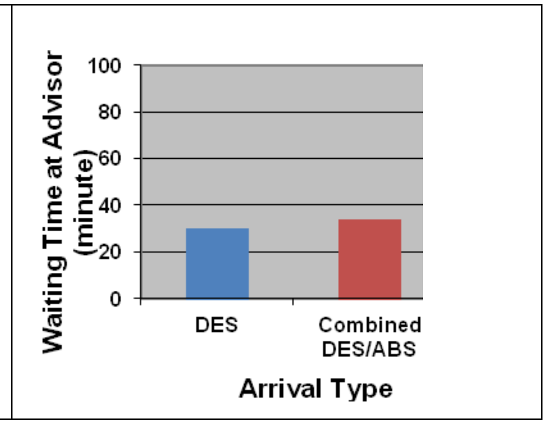
Modelling queue skipping does not habitually occur in the investigated case study and, for that reason, the number of students not served is decreased less than in other investigated proactive behaviours in Experiments A2-1 and A2-2. Modelling human behaviours which do not occur frequently does not have a great impact on the performance of a simulation model and it may therefore be considered unimportant for the service-oriented system study.

Table 5.13 : Results of Experiment A2-3

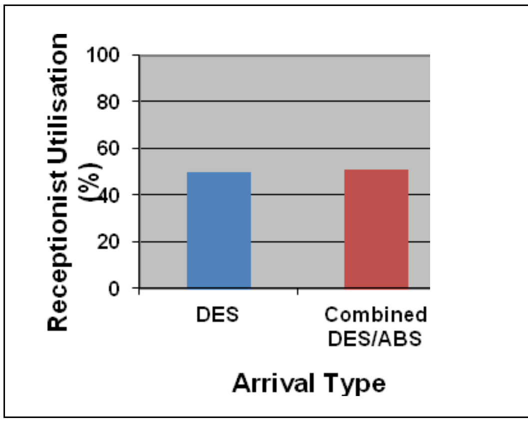
Performance measures		**DES**	**Combined DES/ABS**
Waiting times for receptionist (minute)	Mean	1.14	1.26
	SD	0.77	1.15
Waiting time for advisors (minute)	Mean	30.13	34.00
	SD	23.00	26.82
Receptionist utilisation (%)	Mean	50	51
	SD	13.39	14.37
Advisor utilisation (%)	Mean	58	58
	SD	9.56	10.39
Number of students served (people)	Mean	223	222
	SD	20.42	21.87
Number of students not served (people)	Mean	0	0
	SD	0.98	1.00
Number of students skipping queue- upon arrival (people)	Mean	5	5
	SD	2.37	2.42
Number of students skipping queue-while queuing (people)	Mean	-	2
	SD	-	1



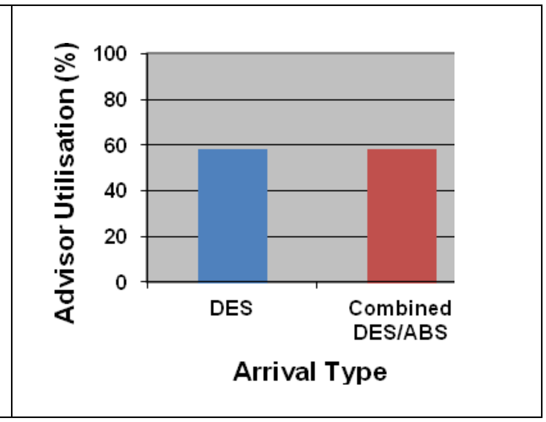
(a) Waiting time for receptionist



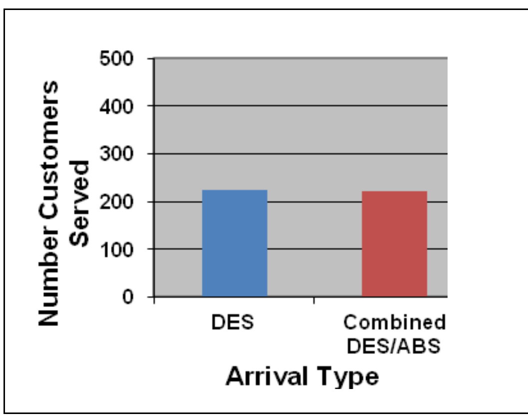
(b) Waiting time for advisors



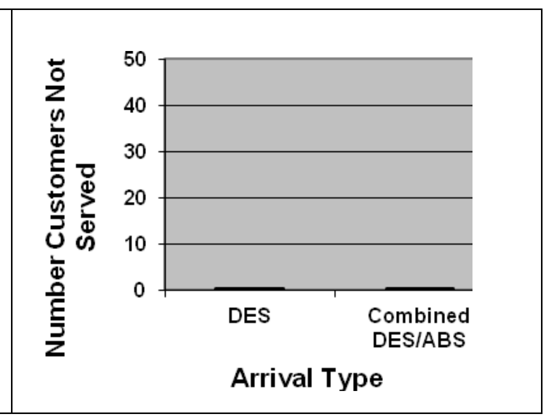
(c) Receptionist utilisation



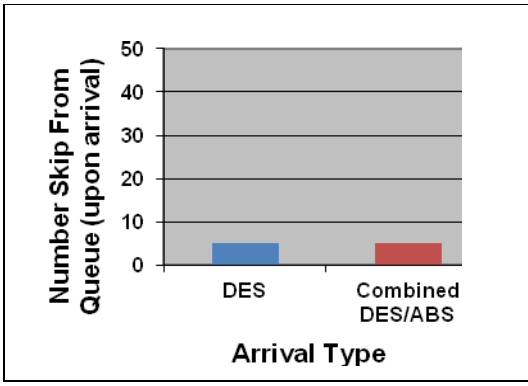
(d) Advisors utilisation



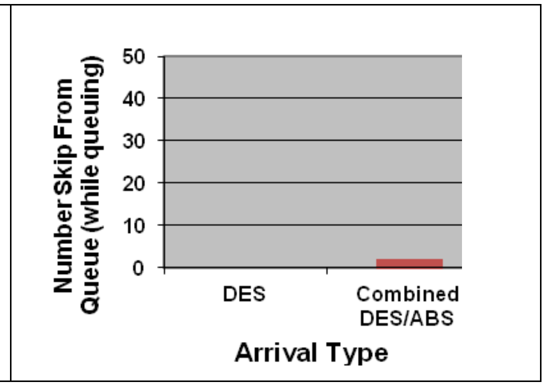
(e) Number of students served



(f) Number of students not served



g) Number of students skipping queue (upon arrival)



(h) Number of students skipping queue (while queuing)

Figure 5.8 : Bar charts of results in Experiment A2-3

Table 5.14 : Results of T-test in Experiment A2-3

Performance Measures	DES vs. Combined DES/ABS	
	P-value	**Result**
Waiting time for receptionist	P = 0.294	Fail to reject
Waiting time for advisors	P = 0.274	Fail to reject
Receptionist utilisation	P = 0.646	Fail to reject
Advisors utilisation	P = 0.843	Fail to reject
Number of students served	P = 0.624	Fail to reject
Number of students not served	P = 0.760	Fail to reject
Number of students skipping queue (upon arrival)	P = 0.556	Fail to reject
Number of students skipping queue (while queuing)	Statistical test not available	

Next the proactive behaviours in Experiments A2-1, A2-2 and A2-3 are combined in Experiment A2-4 in order to examine the performance of the DES and combined DES/ABS models when modelling various proactive behaviours simultaneously.

Experiment A2-4: Mixed Reactive and Sub-4 Proactive Behaviours

Experiment A2-4 sought to investigate the modelling of mixed reactive and combined proactive behaviours in both DES and combined DES/ABS models. The combined proactive behaviours consisted of the sub-1, sub-2 and sub-3 proactive behaviours that are the subject of the previous experiments (Experiments A2-1, A2-2 and A2-3).

The purpose of this combination is to examine the impact of the simulation results for both simulation models when modelling similar reactive and proactive behaviours. In addition, the experiment sought to discover what could be learnt from the performance of the simulation results when adding more complex proactive behaviours in order to create realistic simulation models using the combined DES/ABS approach.

To execute the proactive behaviours in the current experiment, similar rules or logic decisions and the pseudo codes to that of Experiment A2-1(sub-1 proactive), Experiment A2-2 (sub-2 proactive) and Experiment A2-2 (sub-3 proactive) are used.

Nine performance measures are used in this experiment, including six from Experiment A1 together with an additional four from the investigated proactive behaviours: the number of students requested to leave, the number of service changes and the number of students skipping the queue(upon arrival) and the number of students skipping the queue(while queuing).

The hypotheses to test in Experiment A2-4 are the same with the six performance measures in Experiment A1 but these performance measures are tested with a name link to Experiment A2-4 as follows : $Ho_{A2\text{-}4\ \_1}$, $Ho_{A2\text{-}4\ \_2}$, $Ho_{A2\text{-}4\ \_3}$,

$Ho_{A2\text{-}4\_4}$, $Ho_{A2\text{-}4\_5}$ and $Ho_{A2\text{-}4\_6}$ for the student waiting times for receptionist, the student waiting times for advisors, the receptionist utilisation, the advisors utilisation, the number of students not served and the number of students served, respectively. In addition, the hypotheses for the investigated proactive behaviour in Experiment A2-4 are:

$Ho_{A2\text{-}4\_7}$: The number of students requested to leave resulting from mixed reactive and proactive DES model is not significantly different from mixed reactive and proactive combined DES/ABS model.

$Ho_{A2\text{-}4\_8}$: The number of service time changes resulting from mixed reactive and proactive DES model is not significantly different from mixed reactive and proactive combined DES/ABS model.

$Ho_{A2\text{-}4\_9}$: The number of students skipping queue (upon arrival) resulting from mixed reactive and proactive DES model is not significantly different from mixed reactive and proactive combined DES/ABS model.

$Ho_{A2\text{-}4\_10}$: The number of students skipping queue (while queuing) resulting from mixed reactive and proactive DES model is not significantly different from mixed reactive and proactive combined DES/ABS model.

Results for Experiment A2-4 are shown in Table 5.15 and Figure 5.9(a-j), and the results of the T- test are shown in Table 5.16 below. The similarities in results between DES and combined DES/ABS are again found in the combined proactive experiment, as shown in Table 5.15 and Figure 5.9(a-i) except Figure 5.9 (j).

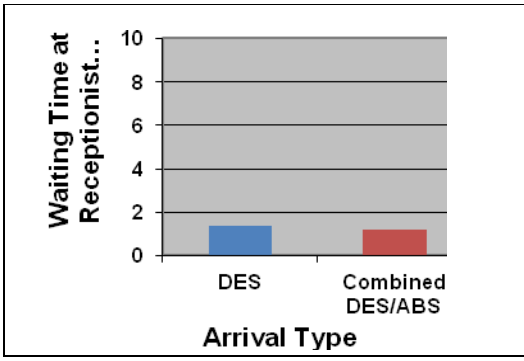
The similarities and dissimilarities of results found in the Experiment A2-4 are then confirmed by the statistical test (Table 5.16) in which the p-values from all performance measures are greater than the chosen level of significant (0.05) except for the number of students skipping queue (while queuing). Therefore, the hypotheses Ho_{A2-4_1}, Ho_{A2-4_2}, Ho_{A2-4_3}, Ho_{A2-4_4}, Ho_{A2-4_5}, Ho_{A2-4_6}, Ho_{A2-4_7}, Ho_{A2-4_8} and Ho_{A2-4_9} are failed to be rejected while Ho_{A2-4_10} is rejected.

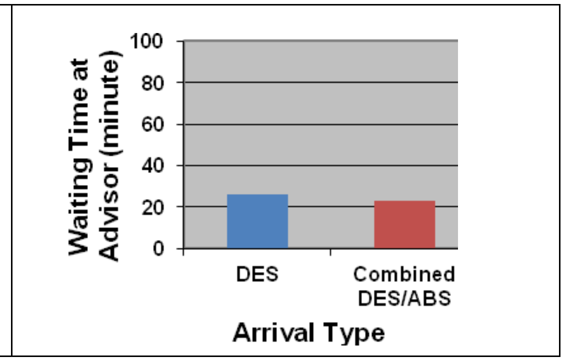
From the results of the statistical test, it is confirmed that there is no significant difference between the results in the DES and combined DES/ABS models for all performance measures except for the added extra individual (students skipping while queuing) which does not modelled in DES. For a second time the test has proved modelling an extra individual behaviour does not gives a big impact to the simulation results if it does not habitually occur in the investigated case study.

Table 5.15 : Results of Experiment A2-4

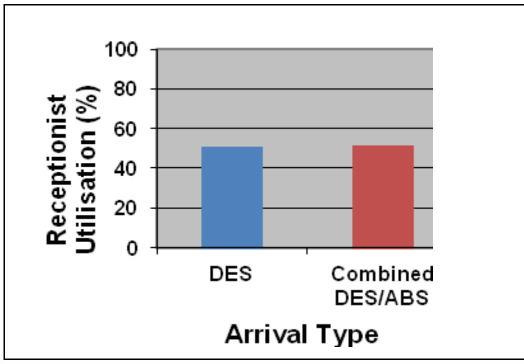
Performance measures		**DES**	**Combined DES/ABS**
Waiting times for receptionist (minute)	Mean	1.37	1.22
	SD	1.18	0.74
Waiting time for advisors (minute)	Mean	26.39	23.10
	SD	21.19	17.21
Receptionist utilisation (%)	Mean	51	51
	SD	15.04	15.93
Advisor utilisation (%)	Mean	57	57
	SD	9.31	10.50
Number of students served (people)	Mean	219	214
	SD	16.29	19.07
Number of students not served (people)	Mean	0	0
	SD	0.00	10.50
Number of students requested to leave (people)	Mean	6	5
	SD	16.29	19.07
Number of service time changes	Mean	1	1
	SD	0.00	2.66
Number of students skipping queue-upon arrival (people)	Mean	5	6
	SD	2.06	0.35
Number of students skipping queue-while queuing (people)	Mean	-	2
	SD	-	0.15

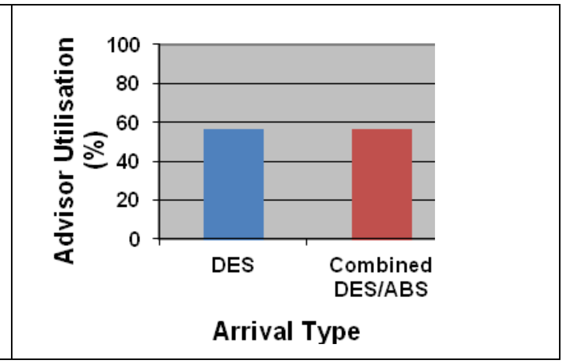
It has been observed that modelling various proactive behaviours in a service-oriented system do provide a big impact to the number of customer not served. The receptionist who is proactive (by ceasing to give out waiting cards if too many students are waiting for an advisor) is effective in avoiding a build-up of queues in the ISST. This explains why the proactive behaviour of the advisors (speeding up their service time) makes less impact since the students who are waiting can be served in the remaining operation time.



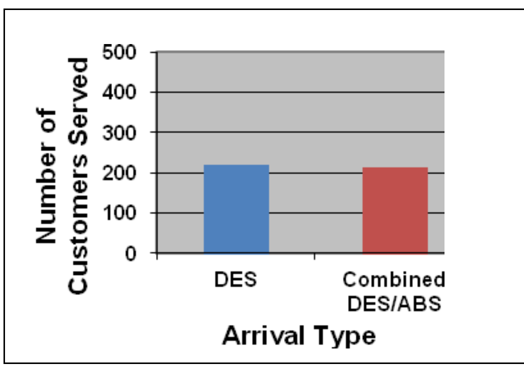


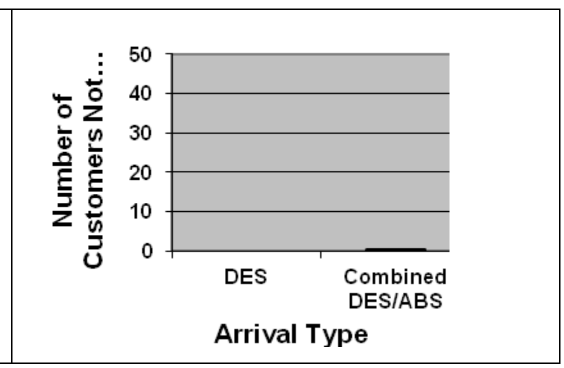
(a) Waiting times for receptionist (b) Waiting times for advisors



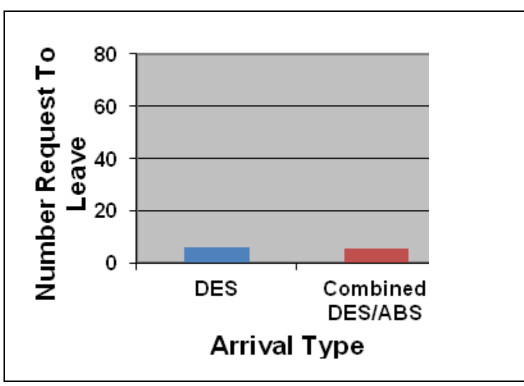


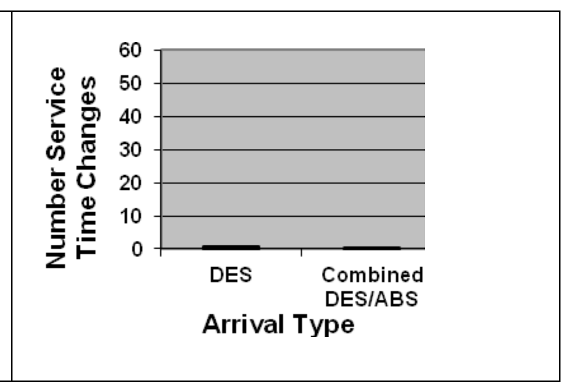
(c) Receptionist utilisation (d) Advisors utilisation



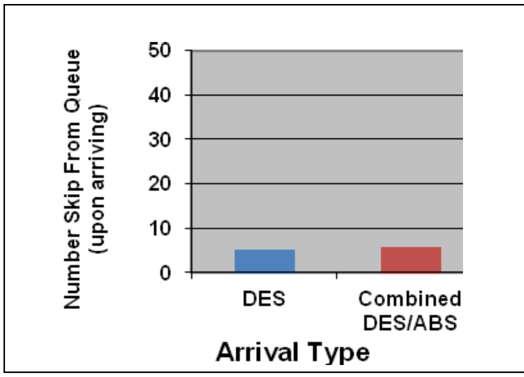


(e) Number of students served (f) Number of students not served

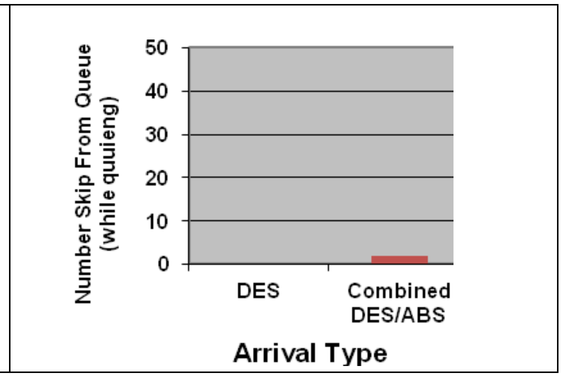




(g) Number of students request to leave (h) Number of service time changes



(i) Number of students skipping queue (upon arrival)



(i) Number of students skipping queue (while queuing)

Figure 5.9 : Bar charts of results in Experiment A2-4

Table 5.16 : Results of T-test in Experiment A2-4

Performance Measures	DES vs. Combined DES/ABS	
	P-value	Result
Waiting times for receptionist	P = 0.279	Fail to reject
Waiting times for advisors	P = 0.229	Fail to reject
Receptionist utilisation	P = 0.753	Fail to reject
Advisors utilisation	P = 0.889	Fail to reject
Number of students served	P = 0.075	Fail to reject
Number of students not served	P = 0. 891	Fail to reject
Number of students requested to leave	P = 0.510	Fail to reject
Number of service changes	P = 0.039	Fail to reject
Number of students skipping queue (upon arrival)	P = 0.218	Fail to reject
Number of students skipping queue (while queuing)	Statistical test is not available	

Conclusions of Experiment A1 and Experiment A2

Experiments A1 and A2 have identified similarities in results between DES and combined DES/ABS models and as a result the main hypotheses for these experiments – Ho_1 and Ho_2 (Chapter 3: Section 3.5.1) - are failed to be rejected.

The model result investigation has proved that DES model is capable of producing results similar to those of combined DES/ABS model when modelling the similar human reactive and proactive behaviours using the similar solution.

In order to answer the main hypothesis Ho_3 and Ho_4 (Chapter 3:Section 3.5.1) while establish the best choice of simulation models for the current case study problem, or for a similar service-oriented problem, the DES and combined DES/ABS models' performance in the model difficulty investigation is next explored.

5.5.3 Set B: Model Difficulty Investigation

Experiment B1: Reactive Human Behaviour

The Set B investigation into model difficulty begin with Experiment B1: Reactive Human Behaviour, which adopted a similar objective and process of data collection as those used in Experiment B1 of case study 1 (Chapter 4: section 5.5.3) and also described in Chapter 3 : Section 3.5.1.

However, in contrast with case study 1, only one type of model difficulty result is obtained for case study 2 and that is from the modeller's modelling experience in developing the simulation models. All experiments in Set B: Model Difficulty Investigation (Experiments B1 and B2) are therefore based on modeller's modelling experience view point. Hence, the main hypothesis to test in this Experiment B1 is as same as Ho_3 in Chapter 1: Section 3.5.1.

The results from the modeller's modelling experience of model building time, model execution time and model line of code (LOC) are converted into the standard scale of model difficulty as in Equation 3.1 and discussed in Chapter 3: Section 3.5.2.

For example, the model building time is 32 hours and 92 hours in the DES and combined DES/ABS models respectively. With reference to Equation 3.1, the result of model difficulty, i.e. DES model building time (32 hours), is divided by the result of maximum model difficulty, i.e. combined DES/ABS model building time (92 hours). The deviation result of 32 / 92 is then multiplied by the total number of scales of model difficulty (10) (refer Chapter 3: Section 3.5.3). From the calculation to convert into the standard scale of model difficulty, scale 3 is obtained for the DES model.

Next, the same process of calculation is carried out for the combined DES/ABB model and a scale of 10 is calculated. Table 5.17 presents the results for measures model of difficulty in Experiment B1. RV (Result Value) represents the results of measures of difficulty from Experiment A1, while DV (Difficulty Value) represents the RV results that are converted into the scale of difficulty.

Table 5.17 : Results from modeller's modelling experience for measures of model difficulty in Experiment B1

Performance Measures	**DES**		**Combined DES/ABS**	
	RV	**DV**	**RV**	**DV**
Model Building Time	32 hours	3	92 hours	10
Model Execution Time	9 seconds	4	21.3 seconds	10
Model LOC	5690 lines	10	5637 lines	10

The quantitative approach is used to compare the results of model difficulty between DES and combined DES/ABS in Table 5.17, as shown in Figure 5.10, while the qualitative approach is used to answer the Ho_3 hypothesis in Experiment B1. A qualitative approach, as described in Chapter 3: Section 3.5.3, is chosen because the results for all data of model difficulty measures contain insufficient data samples to execute the statistical test.

The scale of difficulty showed that a higher value represented a greater degree of difficulty in one simulation model. Figure 5.10 illustrates that model building and execution times are 70% and 60% respectively, faster in the DES model compared to the combined DES/ABS model. However, the model LOC suggested there is no difference between both simulation models.

The graphical comparison showed that DES has produced a better model difficulty performance than combined DES/ABS when modelling human reactive behaviour. The model difficulty performance of DES in modelling reactive behaviour for case study 2 is found to be similar with the result obtained in case study 1 (Chapter 4: Section 4.5.3). Thus, to answer the hypothesis in Experiment B1 of case study 2, the result of the Ho_3 hypothesis in case study 1, which is based on statistical testing, is referred. According to this result, the Ho_3 hypothesis is understandably failed to be rejected. The similar understanding of DES and combined DES/ABS performance in this model difficulty experiment can be assumed for modelling a complex queuing system in another similar service-oriented problem.

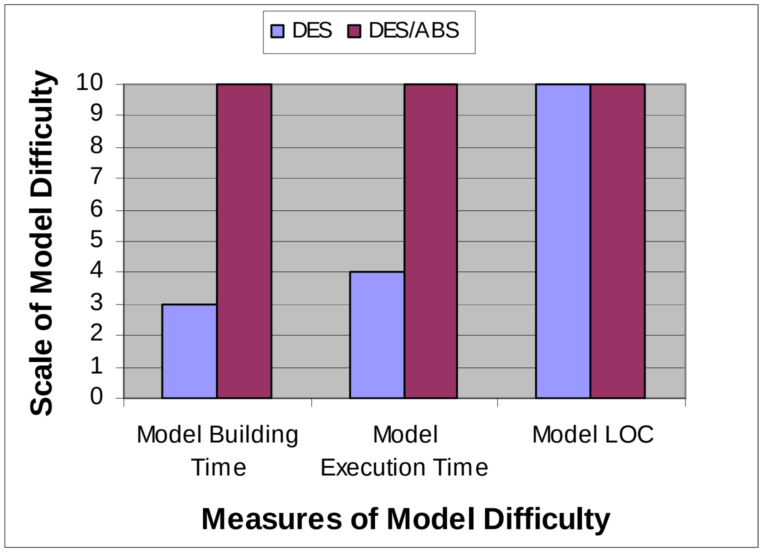


Figure 5.10 : Bar charts of the first result of model difficulty measures (modeller's experience) in Experiment B1

Experiment B2: Mixed Reactive and Proactive Human Behaviours

Experiment B2 is related to investigate the performance of modelling mixed reactive and proactive behaviour in DES and DES/ABS in terms of model difficulty. As in Experiment B1, model building (in hours), model execution time (in seconds) and model LOC (in lines) are the comparison measures for the current experiment.

Results for the measures of model difficulty are gained from the modelling work in Experiment A2. As in Experiment A2, four sub-experiments are conducted: A2-1, A2-2, A2-3 and A2-4. The model difficulty results from all experiments in Experiment A2 are placed in the sub-experiments in Experiment B2 in order to avoid the confusion in further investigation. Model difficulty results in Experiments A2-1, A2-2, A2-3 and A2-4 are therefore placed in Experiments B2-1, B2-2, B2-3 and B3-4 respectively. Hence, the main hypothesis to test in this Experiment B2 is as same as Ho_4 in Chapter 1: Section 3.5.1.

Table 5.18 and Figure 5.11 summarises the results of these four-sub-experiments (B2-1, B2-2, B2-3 and B3-4). Processes similar to those carried out previously in Experiment B1 (based on Equation 3.1 in Chapter 3: Section 3.5.3) are undertaken to convert the results of Experiment B2 into one standard scale of model difficulty.

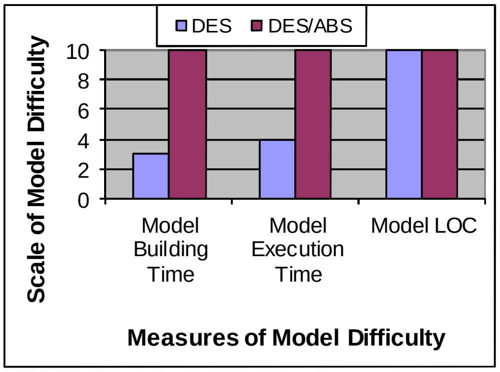
The results of the measures of model difficulty for all four sub-experiments, presented in Figure 5.11, suggested a similarity of pattern. As in Experiment B1, the greatest impact in this investigation is seen in the model building and model execution time of DES model, where the scale of difficulty are at 3 and 4 in Experiment B2-1, B2-2 and B2-3 and both (model building and model execution time) at 4 in Experiment B2-4.

Meanwhile, in the combined DES/ABS model is at 10 in all experiments of Experiment B2. This scale result has showed that the DES model has presented more than two times less difficult than the DES/ABS model. Even though dissimilar results are found in model building and execution measures, the result of model LOC has revealed the same match between DES and combined DES/ABS in Experiments B2-1, B2-2, B2-3 and B2-4. As shown in Table 5.18, combined DES/ABS model in Experiment B2-4 has demonstrated a slightly higher of line of code compared with DES models, due to the extra logic decisions have used to model extra proactive behaviour. Nevertheless, the difference in model LOC is not too critical as both (DES and combined DES/ABS models) have showed a same scale of difficulty for Experiment B2-4.

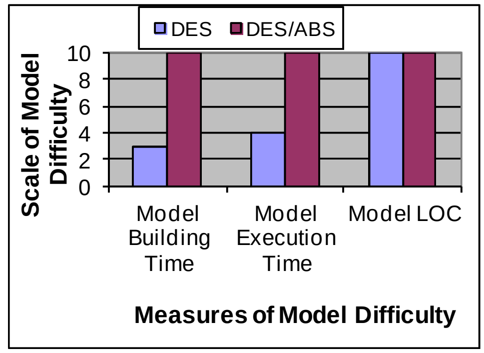
Table 5.18 : Results from modeller's experience for model difficulty measures in Experiment B2

Measures of Model Difficulty	DES							
	Exp B2-1		Exp B2-2		Exp B2-3		Exp B2-4	
	RV	DV	RV	DV	RV	DV	RV	DV
Model Building Time	34 hours	3	36 hours	3	40 hours	3	42 hours	4
Model Execution Time	9.2 seconds	4	9.8 seconds	4	10.2 seconds	5	10.5 seconds	4
Model LOC	5851 lines	10	5714 lines	10	6021 lines	10	6204 lines	10
Measures of Model Difficulty	**Combined DES/ABS**							
	Exp B2-1		**Exp B2-2**		**Exp B2-3**		**Exp B2-4**	
	RV	**DV**	**RV**	**DV**	**RV**	**DV**	**RV**	**DV**
Model Building Time	98 hours	10	104 hours	10	110 hours	10	115 hours	10
Model Execution Time	21.4 seconds	10	21.9 seconds	10	22.1 seconds	10	23.5 seconds	10
Model LOC	5940 lines	10	5754 lines	10	6049 lines	10	6499 lines	10

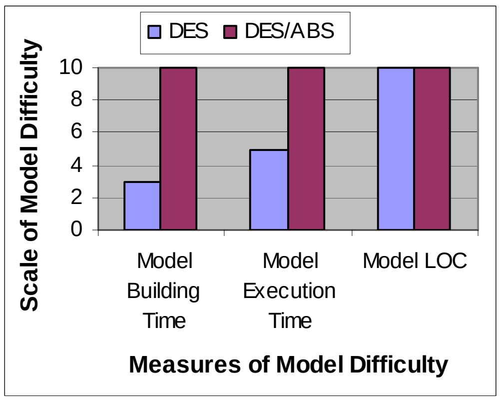
To summarise, with regard to model difficulty, the DES model has performed more effectively in modelling human mixed reactive and proactive behaviour in the investigated service-oriented system compared to the combined DES/ABS model. Again the same result has found between case study 1 and case study 2 with regards to the DES model difficulty performance in Experiment B2. Thus, based on the same reason as discussed in Experiment B1 above, Ho_4 hypothesis is failed to be rejected. The result of Ho_4 hypothesis has confirmed that simulation difficulty for mixed reactive and proactive DES and combined DES/ABS are statistically difference.



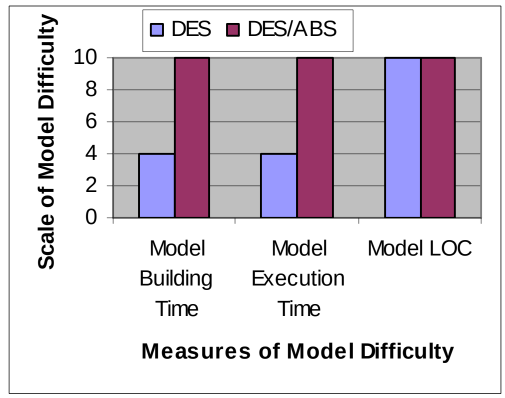
(a) Experiment B2-1



(b) Experiment B2-2



(c) Experiment B2-3



(d) Experiment B2-4

Figure 5.11 : Bar charts of the first result of model difficulty measures (modeller's experience) in Experiment B2

Conclusions of Experiment B1 and Experiment B2

The impact of modelling reactive and mixed reactive and proactive behaviour has been observed in the DES model where the results of model building and execution time are overall more than two times faster than in the combined DES/ABS model. On the other hand, model LOC has not shown any important difference between these simulation models (DES and combined DES/ABS). Overall, the investigations into model difficulty conducted in Experiments B1 and

B2 have revealed a more satisfactory performance for the DES model compared with the combined DES/ABS models.

5.5.4 Comparison of Results

In the above experimentation, the impact of modelling reactive and mixed reactive and proactive behaviours on model result and model difficulty are investigated separately for the DES and combined DES/ABS models. In this Section 5.5.4, therefore, discussion about the correlation between similar sets of experiments (A1 vs. A2 and B1 vs. B2) is presented for each simulation approach.

The discussion of results comparison among the conducted experiments (A1 A2, B1 and B2) begins with the model result experiments (Experiment A1 vs. A2). Experiment A1 has identified the similarities of model result between DES and a combined DES/ABS model when modelling the reactive behaviour. In addition, modelling mixed reactive and proactive behaviour in Experiment A2 has indicated a similar match between both simulation models. In order to see the relationship between Experiments A1 and A2, a statistical test is performed according to the Ho_5 hypothesis in Chapter 3 (Section 3.5.4).

Experiment A2 has consisted of four sub-experiments (A2-1, A2-2, A2-3 and A2-4), so Experiment A1 is compared with each of the sub-experiments of A2. The two identical performance measures (waiting time at receptionist and number of students not served) are used in this comparison. The first hypothesis to test is as follow:

Ho_{A3_1} : The waiting time at receptionist resulting from the DES model is not significantly different in Experiments A1 and A2-1.

Next, similar to the Chapter 4 (Section 4.5.4) the waiting time at receptionist resulting from the DES model in Experiment A1 is compared with Experiment A2-2, A2-3 and A2-4 using the following hypotheses : Ho_{A3_2}, Ho_{A3_3} and Ho_{A3_4} (in the same order). Same with combined DES/ABS model, the result from Experiment A1 is also compared with Experiment A2-1, A2-2, A2-3 and A2-4 with the following hypotheses: Ho_{A3_5}, Ho_{A3_6}, Ho_{A3_7} and Ho_{A3_8} (in the same order).

To compare the number of students not served in the four experiments of DES and combined DES/ABS, the following hypotheses are tested: Ho_{A3_9}, Ho_{A3_10}, Ho_{A3_11} and Ho_{A3_12} for DES - Experiment A1 vs. Experiment A2-1, A2-2, A2-3 A2-4, A2-5 and Ho_{A3_13}, Ho_{A3_14}, Ho_{A3_15} and Ho_{A3_16} for combined DES/ABS - Experiment A1 vs. Experiment A2-1, A2-2 and A2-3.

To test the above sub-hypotheses, a test similar to that in the Experiment Section 5.5.2 and 5.5.3 above - the T- test - is conducted and the significant level used is 0.05. Table 5.19 shows the data of the chosen performance measures for the correlation comparison while Table 5.20 shows the results of p-values from the T-test comparing Experiment A1 with A2-1, A2-2, A2-3 and A2-4.

Table 5.19 : The data of the chosen performance measures for the correlation comparison

Experiment	DES		Combined DES/ABS	
	Customers waiting time (minutes)	Number of customers not served	Customers waiting time (minutes)	Number of customers not served
A1	1.43	6	1.41	5
A2-1	1.29	0	1.25	0
A2-2	1.30	0	1.24	0
A2-3	1.24	0	1.22	0
A2-4	1.22	0	1.21	0

Table 5.19 below shows that all p-values for waiting times and number of customers not served in all four experiments are smaller than the chosen significance level (0.05). Thus, the hypotheses from Ho_{A3_1} to Ho_{A3_16} above are rejected.

The statistical test results reveals the significant difference between the reactive behaviour results in Experiment A1 compared to Experiments A2-1 to A2-4 which consisted of proactive behaviour modelling. Hence, Ho_5 hypothesis is rejected.

From the correlation investigation of model result, a new knowledge is obtained. Modelling mixed reactive and proactive behaviours in DES and combined DES/ABS models does give a big impact to the system performance in this case study. In addition, both DES and combined DES/ABS models produce the similar performance in the correlation investigation of model result as both models produce the similar simulation results in this case study.

Table 5.20: Results for T- test comparing Experiment A1 with A2-1, A2-2, A2-3 and A2-4.

Experiments	Performance measures	DES	DES/ABS
		P-Value	P-Value
A1 vs. A2-1	Waiting times	0.0041	0.0022
	Number of customers not served	0.0000	0.0000
A1 vs. A2-2	Waiting times	0.0105	0.0141
	Number of customers not served	0.0000	0.0000
A1 vs. A2-3	Waiting times	0.0033	0.0104
	Number of customers not served	0.0000	0.0000
A1 vs. A2-4	Waiting times	0.0042	0.0014
	Number of customers not served	0.0000	0.0000

In Experiment B1 and B2, it is found that the DES model has produced a better performance (less difficult) than in the combined DES/ABS models in model difficulty investigation. In order to perceive the relationship between Experiments B1 and B2 when using a similar simulation approach, the Ho_6 hypothesis as stated in Chapter 3 (Section 3.5.4) is tested.

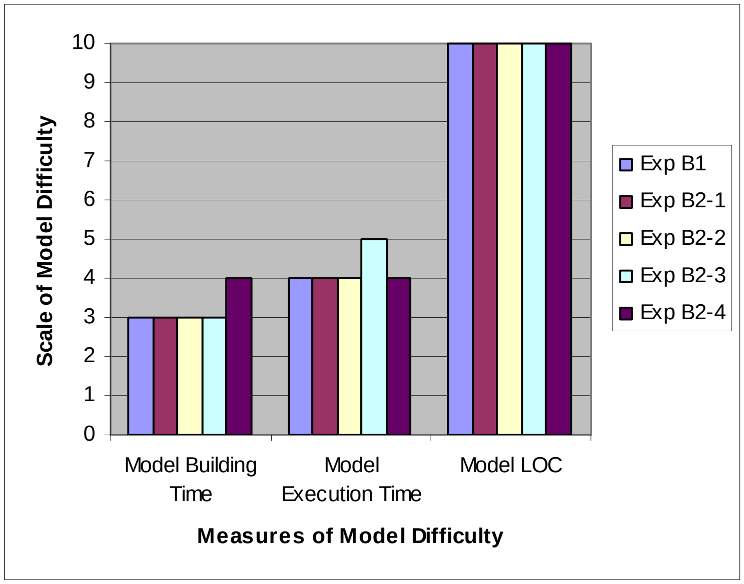
In investigating the correction of results for Experiment B1 against B2, a graphical comparison is conducted, chosen because the available data in model difficulty investigation (based on the modeller's modelling experience) is insufficient to perform the standard parametric test (i.e. T- test).

As in Experiment A1, there are also four sub-experiments in Experiment B2: B2-1, B2-2, B2-3 and B2-4. Each of these sub-experiments is compared with

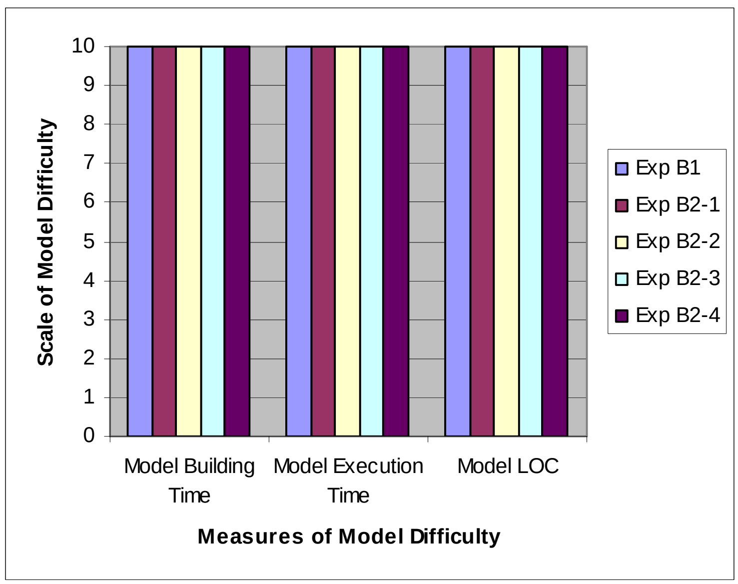
Experiment B1. The histogram in Figure 5.20 illustrates the results of Experiment B1 and B2 (B2-1, B2-2, B2-2 and B2-4) for the DES and combined DES/ABS models.

Refer to Figure 5.12, the average scale of difficulty for all experiments for the DES (Figure 5.12-a) model in model building and execution time is at scale 3 and 4, respectively while the combined DES/ABS model (Figure 5.12-b) is at scale 10 for both difficulty measures. The model LOC for all experiments, however, have showed the scale of difficulty at scale 10, which are same for both simulation models. The scale results indicate that model building and model execution time for reactive and mixed reactive and proactive behaviour modelling using DES model are at average 70% and 60% respectively less difficult compared to combined DES/ABS approach regardless of the model LOC result.

The model difficulty results in case study 2 have again shown a similarity in model difficulty results with case study 1 (Chapter 4: Section 4.5.3) - the DES model is less difficult than the combined DES/ABS model. As in case study 1, T-test is used to answer the hypothesis for Ho_6; thus, this result is taken for answering the Ho_6 hypothesis in case study 2. The Ho_6 hypothesis is therefore rejected. The Ho_6 hypothesis has confirmed that simulation difficulty for reactive compare to mixed reactive and proactive behaviour is statistically the not same for DES and combined DES/ABS.



(a) Model difficulty results in DES model for Experiment B1 and B2



(b) Model difficulty results in combined DES/ABS model for Experiment B1 and B2

Figure 5.12 : Histograms of model difficulty in Experiment B1 and B2

5.6 Conclusions

From the evidences of model result and model difficulty investigation above, modelling reactive behaviour (simple human behaviour) and mixed reactive and proactive behaviour(complex behaviour) in DES model produces the similar simulation results with less modelling difficulty compared to combined DES/ABS model.

Furthermore, the simulation results of the reactive behaviour compare to mixed reactive and proactive behaviours modelling do show important differences between the two simulation models (DES and combined DES/ABS). Therefore, in the model result correlation, modelling mixed reactive and proactive behaviour does give a big impact to the performance of the service-oriented system in case study 2.

Overall, from the evidences of two investigations (model result and model difficulty), same conclusion as in Chapter 4 (Section 4.5.5) can be made: Modelling reactive and proactive behaviour using the DES approach has found to be the suitable modelling solution for case study 2 or for any other similar service-oriented problem if model building time, model execution time and model LOC is the main concern. This is because, the DES model has shown no significant difference in the simulation results and performed better in model difficulty (faster in model building and execution time) than the combined DES/ABS model.

In addition, modelling the real system problem as realistically as possible is less feasible in case study 2 if the human behaviour to be modelled does not occur frequently in real-life.

However, the questions remain: what can be understood if the human behaviours to model often occur in a real situation; and does this have a significant impact on the conclusion to be drawn? To answer these questions, investigating more real complex human behaviours is presented in Chapter 6.

CHAPTER 6

CASE STUDY 3: CHECK-IN SERVICES IN AN AIRPORT

6.1 Introduction

This chapter presents a case study on modelling human behaviour at the check-in services in an airport. In this study, the simplified real world reactive and proactive behaviours of staff and travellers are investigated in DES and combined DES/ABS for understanding the performance of both simulations in modelling human behaviours. The purpose and the research methodology undertaken in this case study is as described in Chapter 3 and also in case study 1 (Chapter 4) and case study 2 (Chapter 5).

6.2 Case Study

The operation at the check-in counters in an airport has been chosen as the third case study because it demonstrates a diversity of contact between counter staff and travellers, which is essential to this study of human behaviour. Information on this third case study is chosen from "Simulation with Arena" by Kelton (2007).

Figure 6.1 illustrates the operation at the airport check-in service, the numbering and red arrows representing the sequence of operation. The operation at the airport check-in service of this case study starts from the point at which travellers enter the main entrance door of the airport and progress to the one from the five check-in counters of an airline company (represented by arrow number 1 in Figure 6.1).

The operation at the five check-in counters is from 8.00 am to 12.00 am every day. If members of staff at the related check-in counters are busy, the travellers have to wait in the counter queue (represented by arrow number 2 in Figure 6.1). If counter staff are available, then travellers will move to the check-in counter (represented by arrow number 3 in Figure 6.1). Once their check-in is completed, the travellers are free to go to their boarding gates (represented by arrow number 3 in Figure 6.1).

To model the human reactive and proactive behaviours, information on real human behaviours at the airport is gathered through secondary data sources such as books and academic papers. The reactive behaviour that has been investigated relates to counter staff reactions to travellers in processing their check-in requests and their response to travellers waiting in queues during busy periods.

The proactive behaviours have been modelled are the behaviours of another member of staff (supervisor) who is responsible for observing and controlling the check-in services. The first proactive behaviour of a supervisor is a request to the counter staff to work faster in order to reduce the number of travellers waiting in queues. The decision to execute such proactive behaviour is based on their working experience.

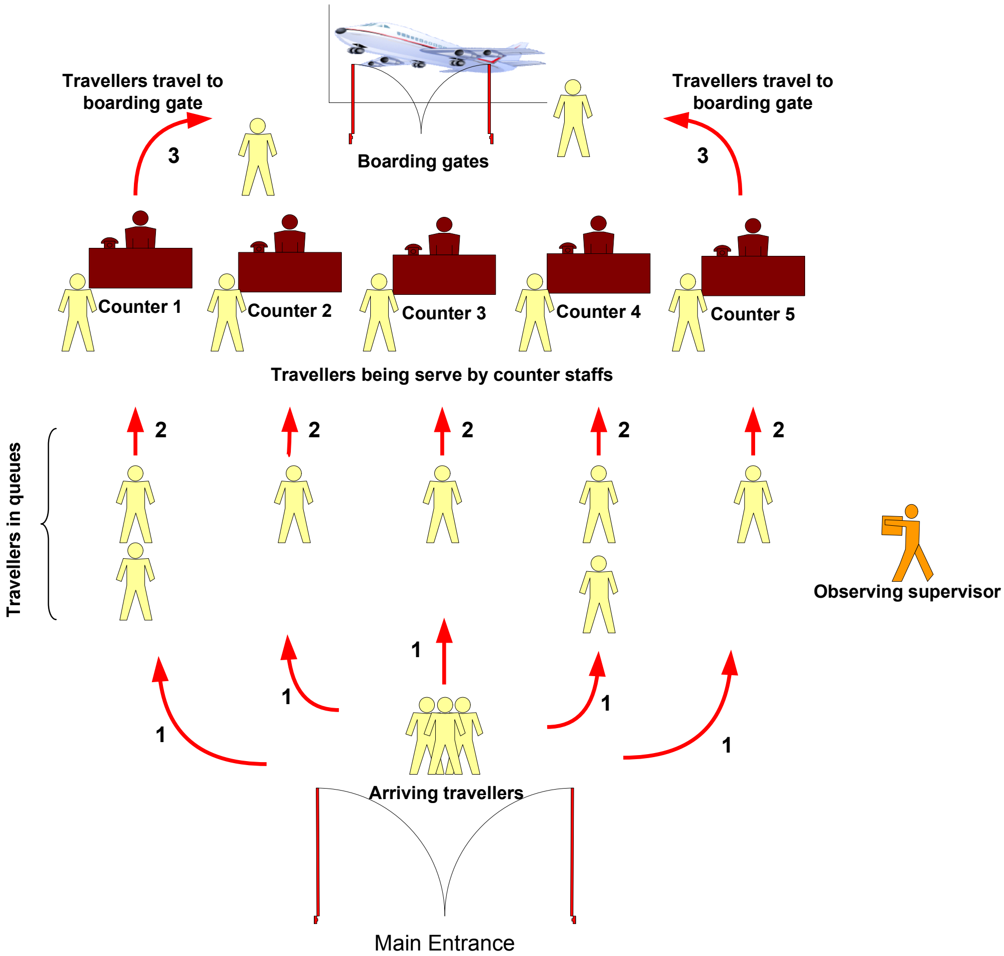


Figure 6.1: The illustration of the check-in services in an airport

Identifying and removing any suspicious travellers from queues is the supervisor's second proactive behaviour to be modelled, their decision again based on observation and working experience. Suspicious travellers include those with overweight hand or cabin luggage, drunken travellers and unauthorised pregnant women. The proactive behaviour of travellers is related to their search for the shortest queue in order to be served more quickly. The decision by travellers to execute such proactive behaviour is generated from knowledge that they gather through observing other queues while checking-in.

After analysing the operation at the check-in counter, the level of detail to be modelled in the DES and combined DES/ABS models, also known as conceptual modelling, is then considered.

6.3 Towards the Implementation of the Simulation Models

6.3.1 Process-oriented Approach in DES Model

The development of conceptual modelling for case study 3 is as same as that described in Chapter 3 (Section 3.3). Both DES and combined DES/ABS uses slightly different conceptual model and different model implementation approach. Figure 6.2 shows the implementation of DES model using process-oriented approach beginning by developing the basic process flow of the airport's check-in services operation.

As in case studies 1 and 2, the investigated human behaviours (reactive and proactive behaviours) are added to the DES model in order to show where the behaviours have occurred in the check-in services system.

In the DES model below, travellers are the single arrival source at the check-in services system. When travellers arrive at the airport's main entrance, they will go to particular airline company check-in services. On arrival at the check-in services, if the counter staff are busy then the travellers will wait for their turn in the counter's waiting line. Before joining any counters' waiting line, the travellers will proactively search for the shortest queue in order to be served more quickly (represented by symbol A1 in Figure 6.2).

While queuing to be served, the travellers still aim to be served more quickly, so will proactively move to a shorter queue (represented by symbol A2 in Figure 6.2). Next, if the counter staff are available, they will respond to the travellers' requests by serving them. Finally, after being served, the travellers will progress to the boarding gate to catch their flight. In the airport's check-in services system, there is a supervisor who is responsible for observing the check-in areas for suspicious travellers. Once identified, the supervisor will proactively remove these travellers from the queues (represented by symbol B1 in Figure 6.2); they will also request the counter staff with long queues to work faster (represented by symbol B2 in Figure 6.2).

6.3.2 Process-oriented and Individual-oriented Approach in Combined DES/ABS Model

As with case studies 1 and 2, two approaches are used for developing the combined DES/ABS models: the process-oriented approach (to represent the DES model, the same DES model as in Figure 6.2 is used) and the individual-centric approach. Figure 6.3 represents an individual-centric approach, a part of the model for the combined DES/ABS model. The individual-centric modelling is illustrated by state charts (Figure 6.3) to represent different types of agents (travellers, counter staff and supervisor).

As shown in Figure 6.3, the travellers' agent consists of various states (i.e. *being idle*) while counter staff consist of *idle* and *busy* states and supervisor will always in an *observing* state. As in case studies 1 and 2, some of the state changes of agents (travellers, counter staff and supervisor) are connected through passing messages, the purpose of which is to show the communication between the agents.

For example, if a traveller arrives at the airport's main entrance, they will be in the *idle* state for a while, and then they changes to the *travel to the check-in counter* state in order to be served. The traveller exits the *travel to the check-in counter* state after some delay (uniform distribution) and next changes to the *waiting to be served* state. The availability of the counter staff is immediately checked. If one of the counter staff is in a state *idle*, they will communicate with the traveller by sending a "*staff call traveller*" message and the traveller will respond by sending a "*serve*" message. Once the staff member receives the message "*serve*", their state changes from *idle* to *busy,* while the traveller's state changes from *waiting to be served* to *being served*. After the member of staff finishes serving the traveller, the traveller will send them a "*release*" message. The traveller will then change to the *idle* state and leave for the boarding gate, while the staff will change to the *idle* state. The supervisor agent is always in the *observing* state as they are responsible for monitoring the process in the check-in service during the operation time.

After this consideration of the DES and combined DES/ABS conceptual models, the development of their simulation models is now implemented.

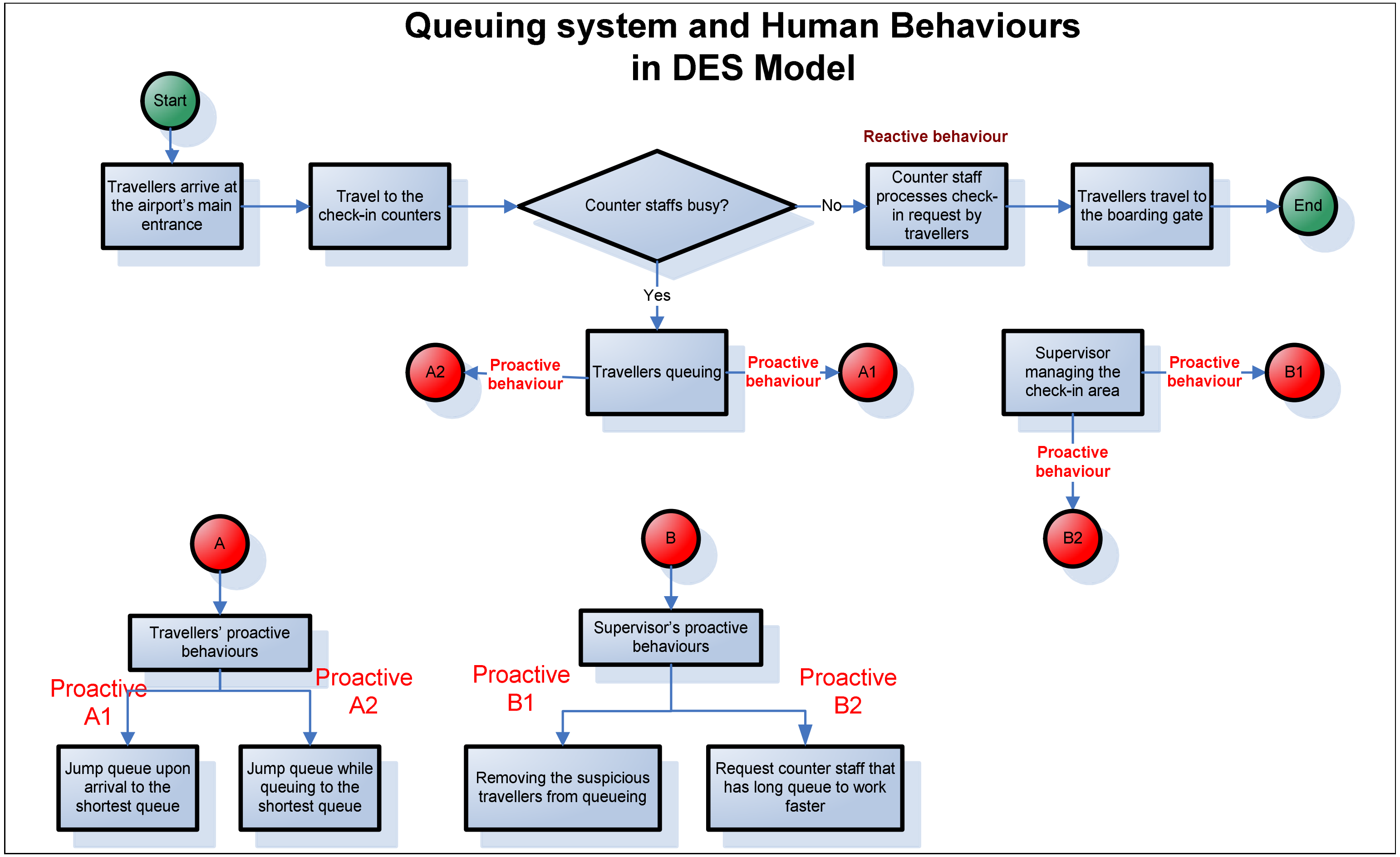


Figure 6.2 : The implementation of DES model

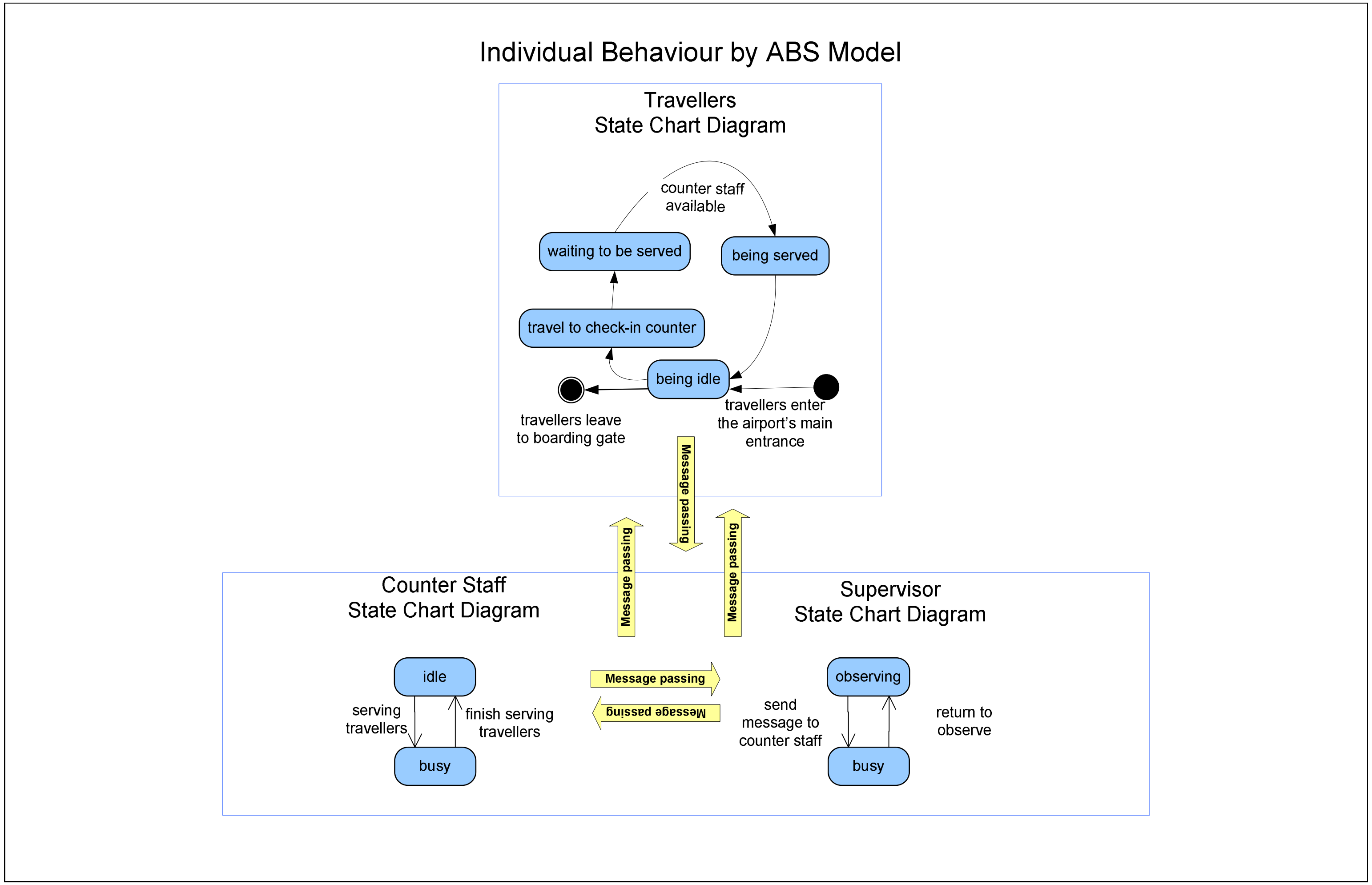


Figure 6.3 : The implementation of Combined DES/ABS model

6.4 Model Implementation and Validation

6.4.1 Basic Model Setup

Two simulation models have been developed from the conceptual models and have been implemented in the multi-paradigm simulation software AnyLogic™ (XJTechnologies, 2010). Both simulation models consist of one arrival process (travellers), five single queues, and resources (five counters staff). Travellers, counter staff and supervisor are all passive objects in the DES model while in the combined DES/ABS all of them are active objects. Refer Chapter 4: Section 6.4.1 for the definition of passive and active objects.

A discussion follows on how objects in DES model or agents in combined DES/ABS model are set up:

i. Travellers object/agent

The arrival rate of the simulation model is gathered from "Simulation with Arena" by Kelton (2007). In both DES and combined DES/ABS models, the arrival process is modelled using an exponential distribution with the arrival rate shown in Table 6.1. The arrival rate is equivalent to an exponentially distributed inter-arrival time with mean = 1/rate. The travel time as stated in Table 6.1 is the delay time for travellers moving from the airport entrance to the check-in counters.

Table 6.1 : Travellers arrival rates

Arrival Type	Time	Rate
Travellers arrival time	8.00 – 24.00 am	Approximately 30 people per hour
Travellers travel time	upon arriving	Uniform (1,2)- minimum 1 minute , maximum 2 minutes

ii. Counter staff object/Agent

In both simulation models, five members of counter staff have been modelled performing the task of processing travellers' check-in requests. Task priority is allocated on a first in first out basis according to the service time stated in Table 6.2 below:

Table 6.2 : Counter staff service time

Service Time Parameters	Value
Counter staff service time	Weibull (7.78,3.91)

iii. Supervisor Agent (only in combined DES/ABS model)

The supervisor agent is modelled in the combined DES/ABS model while in DES model the supervisor is imitated by a set of selection rules (programming function). This is because in the DES model the communication between the entities is not capable of being modelled. In both simulation models, the supervisor is not directly involved with the check-in process. He/she is there only to observe the situation at the check-in counter, so no service time is defined for the supervisor for both simulation models (DES and combined DES/ABS).

The experimental conditions such as the number of runs for this case study are based on a simulation models' setup similar to that in case study 1 (Chapter 4: Section 4.4.1). The run length for this case study is 16 hours, imitating the normal operation of the check-in counter at an airport while there is no warm up period in this case study as stated in Chapter 3: Section 3.4.

Next, the verification and validation processes are conducted in order to ensure the basic models for both DES and combined DES/ABS are valid.

6.4.2 Verification and Validation

The verification and validation process are performed simultaneously during the development of the DES and combined DES/ABS models. Similar with case studies 1 and 2, checking the code with simulation expert and visual checks by modeller are the conducted verification processes (refer Chapter 3: Section 3.4). A sensitivity analysis test is chosen for the validation, but black-box validation is not executed as in other case studies because no real data has been gathered for case study 3.

Sensitivity Analysis Validation

The purpose of this sensitivity analysis validation is to examine the sensitivity of the simulation results when travellers' arrival rate is systemically varied with three differences of arrival patterns as shown in Table 6.3. Chapter 3 (Section 3.4) explains the setup of the arrival patterns and the objective of the sensitivity analysis validation.

Table 6.3 : The arrival patterns for three different arrival sources at airport check-in services

Travellers arrival patterns			
Arrival time	Arrival Pattern 1 (in people)	Arrival Pattern 2 (in people)	Arrival Pattern 3 (in people)
8.00 am – 24.00 am	30 per hour	39 per hour	51 per hour

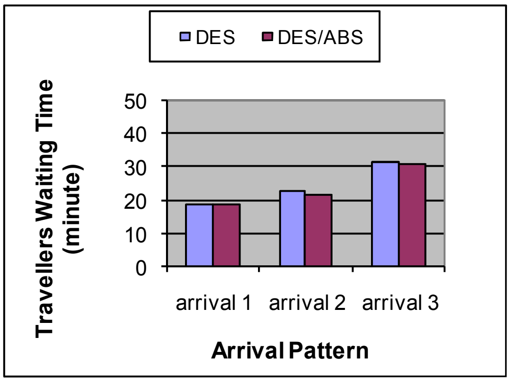
For this validation test, all performance measures are expected to increase along with the increment of the number of travellers in both simulation models (DES and combined DES/ABS models).

The chosen comparative measures for sensitivity analysis validation are travellers waiting time, counter staff utilisation, number of travellers served and number of travellers not served. Both DES and combined DES/ABS models used in this experiment are the basic models as described in Section 6.4.1 above.

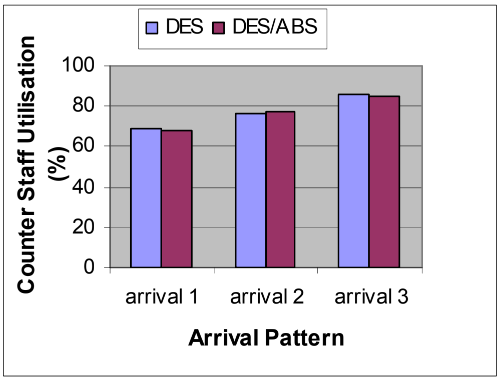
Results for the sensitivity analysis for DES and combined DES/ABS are shown in Table 6.4 and Figure 6.4 (a-d). The patterns of results for all performance measures in this case study, illustrated by the histograms in Figure 6.4 (a-d), are found similar when the travellers' arrival rate is increased. All performance measures demonstrate an increment when more travellers arrive at the airport check-in services. Again, as discussed in the previous case studies, the sensitivity analysis in case study 3 has revealed a similar impact (all performance measures are increased as expected) on both simulation models when varying the travellers arrival rates. As a conclusion, the sensitivity analysis test provides some level of confidence that both simulation models are adequately valid for use in the experimentation section (Section 6.5).

Table 6.4 : Results of sensitivity analysis validation

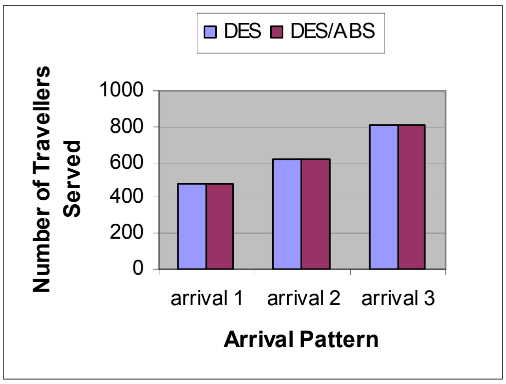
Simulation Models	Performance measures		Arrival Pattern 1	Arrival Pattern 2	Arrival Pattern 3
DES	Travellers waiting times (minute)	Mean	18.64	22.78	31.15
		SD	23.91	21.60	27.08
	Counter staff utilisation (%)	Mean	64	74	83
		SD	18.58	16.77	16.68
	Number of travellers served (people)	Mean	473	618	804
		SD	22.35	49.49	113.24
	Number of travellers not served (people)(people)	Mean	4	6	11
		SD	2.25	6.78	4.11
Combined DES/ABS	Travellers waiting times (minute)	Mean	18.46	21.40	30.66
		SD	24.84	25.18	29.48
	Counter staff utilisation (%)	Mean	65	74	82
		SD	20.59	17.75	15.21
	Number of travellers served (people)	Mean	473	618	806
		SD	22.81	52.11	115.24
	Number of travellers not served (people)(people)	Mean	4	5	9
		SD	4.71	6.99	4.89



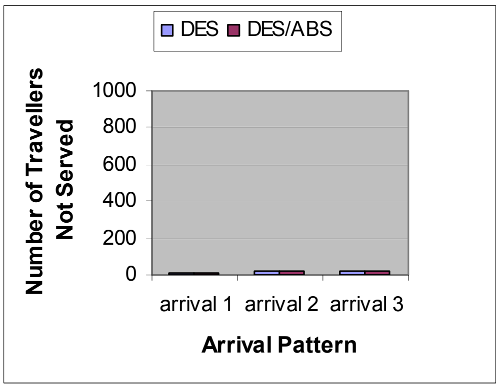
(a) Travellers waiting time



(b) Counter staff utilisation



(c) Number of travellers served



(d) Number of travellers not served

Figure 6.4 : Bar charts of results in the sensitivity analysis validation

6.5 Experimentation

6.5.1 Introduction

As described in Chapter 3 (Section 3.5), two sets of experiments are conducted in this case study: Set A - model result and Set B - model difficulty investigation. Chapter 3 gives a detailed description of each experiment under both sets in this section. The same statistical tests as in Chapter 4 and Chapter 5 are used for all experiments conducted in this case study.

The implementation of the Set A - model result and Set B - model difficulty experiments for the current case study is next discussed. The main hypotheses to investigate for both set of experiments (Set A and B) are same as Ho_1, Ho_2 Ho_3 and Ho_4 as in Chapter 3 (Section 3.5.1).

6.5.4 Set A : Model Result Investigation

Experiment A1: Reactive Proactive Behaviour

As described in Chapter 3, the model result experimentation begins with Experiment A1: Reactive Proactive Behaviour. This experiment is important for the first objective of this research – to determine the similarities and dissimilarities of both DES and combined DES/ABS in the simulation results performance when modelling human reactive behaviours. The main hypothesis to test in Experiment A1 is Ho_1 as in Chapter 3 (Section 3.5.1).

The chosen comparative measures for this reactive experiment are the same with the sensitivity analysis validation in Section 6.4.2 above (travellers waiting time, counter staff utilisation, number of travellers served and number of travellers not served.

The DES and combined DES/ABS basic models developed in Section 6.4.1 above are used in this experiment. For both simulation models, the similar solutions to model the reactive behaviours are used for the current experiment. The reactive behaviour of the counter staff is demonstrated in processing the travellers' check-in requests on a first come first serve basis, while the reactive behaviour for travellers is to stay in the queue if the counter staff are busy. The hypotheses for Experiment A1 for the T-test are as follows:

Ho_{A1_1} : The travellers waiting time resulting from the reactive DES model is not significantly different from the reactive combined DES/ABS model.

Ho_{A1_2} : The counter staff utilisation resulting from the reactive DES model is not significantly different from the combined reactive DES/ABS model.

Ho_{A1_3} : The number of travellers served resulting from the reactive DES model is not significantly different from the reactive combined DES/ABS model.

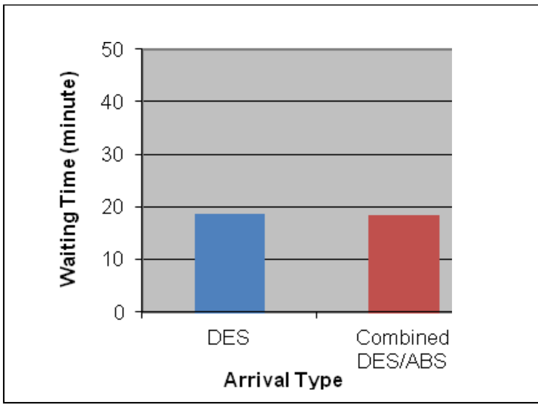
Ho_{A1_4} : The number of travellers not served resulting from the reactive DES model is not significantly different from the reactive combined DES/ABS model.

Results for DES and combined DES/ABS models are shown in Table 6.5 and Figure 6.5 (a-d). Table 6.6 shows the results of comparing both models using the T-test. The patterns of results for all performance measures in this case study, illustrated in Figure 6.5 (a-d) in the histograms, are found to be similar between both simulation models and also to those in the reactive behaviour experiments in previous case studies 1 and 2. The test results in Table 6.6 show that the p-values for each performance measure are higher than the chosen level of significant value (0.05). Thus the Ho_{A1_1}, Ho_{A1_2}, Ho_{A1_3}, and Ho_{A1_4}, hypotheses are failed to be rejected.

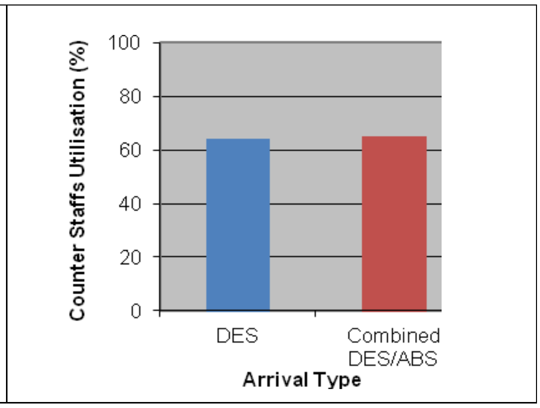
Again, as in the previous case studies, results in the case study 3 has revealed a similar impact on both simulation models when modelling similar reactive behaviour using similar logic solution. Hence, the simulation result for the reactive DES and combined DES/ABS models is statistically show no differences and the Ho_1 hypothesis is failed to be rejected.

Table 6.5 : Results of Experiment A1

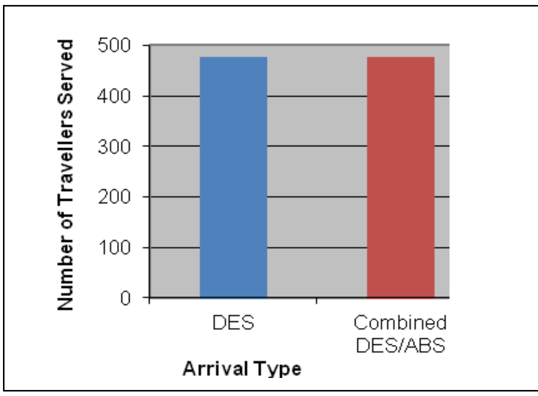
Performance measures		DES	Combined DES/ABS
Travellers waiting times (minute)	Mean	18.64	18.46
	SD	23.91	24.84
Counter staff utilisation (%)	Mean	64	65
	SD	18.58	20.59
Number of travellers served (people)	Mean	473	473
	SD	22.35	22.81
Number of travellers not served (people)	Mean	4	4
	SD	2.25	4.71



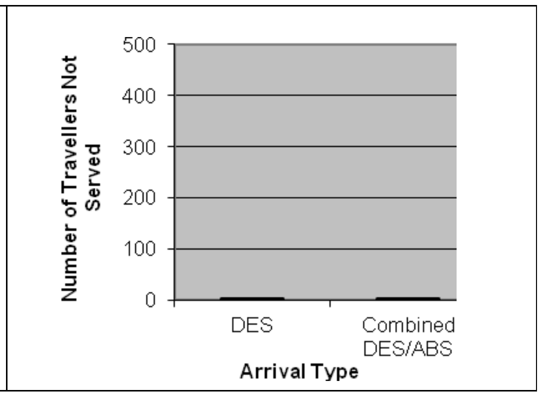
(a) Travellers waiting time



(b) Counter staff utilisation



(c) Number of travellers served



(d) Number of travellers not served

Figure 6.5 : Bar charts of results in Experiment A1

Table 6.6 : Results of T-test in Experiment A1

Performance Measures	DES vs. Combined DES/ABS	
	P-value	Result
Travellers waiting time	P = 0.801	Fail to reject
Counter staff utilisation	P = 0.422	Fail to reject
Number of travellers served	P = 0.763	Fail to reject
Number of travellers not served	P = 0.851	Fail to reject

Experiment A2: Mixed Reactive and Proactive Behaviours

After completing the reactive experiment, the next experiment has involved the mixed reactive and proactive behaviours for both DES and combined DES/ABS models. Experiment A2 is important for the second objective of this research - to determine the similarities and dissimilarities of both DES and combined DES/ABS in the simulation results performance when modelling human mixed reactive and proactive behaviours. Chapter 3 gives details regarding this experiment. The main hypothesis to test in Experiment A2 is Ho_2 as stated in Chapter 3(Section 3.5.1).

The identified human proactive behaviours as discussed in Section 6.2 above are modelled in both the DES and combined DES/ABS models. The simulation models in Experiment A1 are improved in order to model the mixed reactive and proactive behaviours categorised under Type 1, 2 and 3 (Chapter 3: Section 3.5).

Type 1 proactive behaviour has modelled in Experiment A2 is related to the behaviour of the supervisor, who is responsible for ensuring that the check-in process is under control. The supervisor's proactive behaviour is demonstrated by requesting counter staff to work faster in order to serve travellers who have been waiting a long time. The decision of requesting counter staff to work faster is based on the supervisor's awareness that some travellers would not move to another shorter queue.

Type 2 proactive behaviour is demonstrated by the behaviours of travellers who require faster service. Finding the shortest queue on arrival at the check-in services and moving from one queue to another shorter queue while queuing have exemplifies the proactive behaviours of travellers.

The supervisor's Type 3 proactive behaviour is exhibited in identifying suspicious travellers, based on their own experience and observation at the check-in counters.

To investigate the impact of Type 1, Type 2 and Type 3 proactive behaviours for both DES and combined DES/ABS models, Experiment A2 is divided into four sub-experiments, as described in Chapter 3 (Section 3.5.1).

Experiment A2-1: Mixed Reactive and Sub-Proactive 1 Behaviours

The model setup for reactive behaviour followed a similar setup to that in Experiment A1. For both simulation models, implementation of the Type 1 proactive behaviour is based on a slightly different solution. Figure 6.6 and Figure 6.7 represent the decision-making flow chart and pseudo code for modelling the supervisor's proactive behaviour in both simulation models respectively.

In the DES model, there is no communication between the supervisor and the counter staff since entities in DES are centralised and the communication behaviour is impossible to implement. To imitate supervisor behaviour - Appendix C.1 (a), therefore, a set of rules (a programming function) is used in order to check continuously if the queue length is greater than the average queue length. If it is greater, then the normal service time for counter staff is reduced by 10%. After some delay performed by probability distribution, the service time for counter staff is returned to normal service time.

In contrast, the situation in the real-life system is imitated in the combined DES/ABS model – Appendix C.1 (b). During the observation time performed by probability distribution, the supervisor has noticed the queue length at one of the counters is greater than the average queue length, so quickly sends a message to the appropriate member of counter staff to work faster. The counter staff member will receive the message and meet this request by reducing 10 per cent of their normal service time. Speeding up the service time by 10% is found sufficient for the airport check-in counter staff faced with long check-in processing times when dealing with various types of travellers.

Then the counter staff will return to the normal service time after the delay performed by probability distribution. The pseudo codes for both DES and combined DES/ABS to model proactive behaviours are shown in Appendix C.2 (a-b).

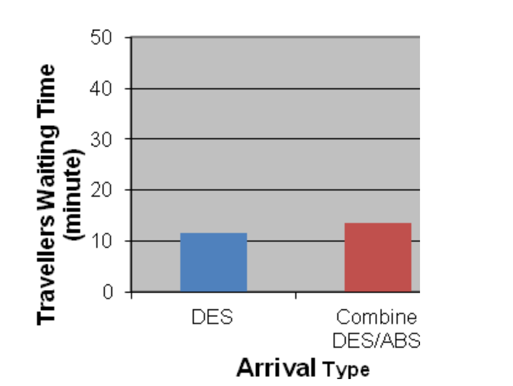
In Experiment A2-1, the simulation results from five performance measures are observed. There are four performance measures from Experiment A1, plus the number of requests to counter staff to work faster (the investigated proactive behaviour). The hypotheses for T-test in Experiment A2-1 use the same four performance measures as in Experiment A1 but these performance measures are tested with a name link to Experiment A2-1 as follows: $Ho_{A2\text{-}1\_1}$, $Ho_{A2\text{-}1\_2}$, $Ho_{A2\text{-}1\_3}$, and $Ho_{A2\text{-}1\_4}$, for (in the same order) the travellers waiting time, the counter staff utilisation, the number of travellers not served and the number of travellers served. In addition, the hypothesis for the investigated proactive behaviour in Experiment A2-1 is:

$Ho_{A2\text{-}1\_5}$: The number of requests to counter staff to work faster resulting from the mixed reactive and proactive DES model is not significantly different from the mixed reactive and proactive combined DES/ABS model.

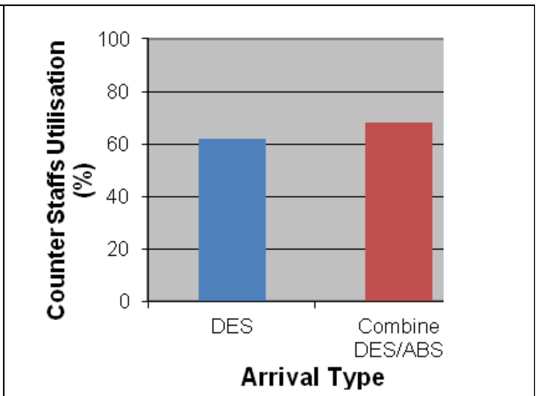
Results for Experiment A2-1 are shown in Table 6.7 and Figure 6.6(a-e) and the results of the T-test are shown in Table 6.8. In Experiment A2-1, different patterns of results are found between the DES and combined DES/ABS models, as illustrated in Table 6.7 and Figure 6.6(a-e). The T-test in Table 6.8 has revealed that the p-values for all the investigated performance measures except the number of travellers served and not served in this Experiment A2-1 are lower than the chosen level of significant value (0.05). Thus, the $Ho_{A2\text{-}1\_1,}$ $Ho_{A2\text{-}1\_2,}$ and $Ho_{A2\text{-}1\_5}$ hypotheses are rejected while $Ho_{A2\text{-}1\_3,}$ $Ho_{A2\text{-}1\ 4}$ hypotheses are failed to reject.

Table 6.7 : Results of Experiment A2-1

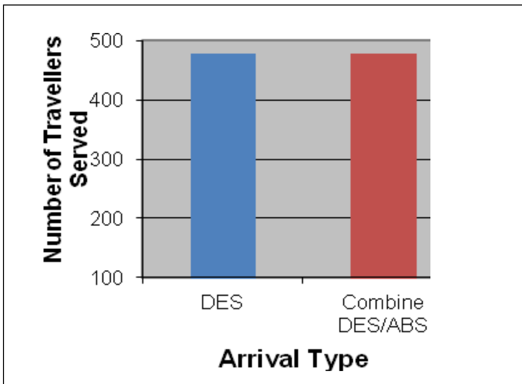
Performance measures		DES	Combined DES/ABS
Travellers waiting time (minute)	Mean	11.56	13.57
	SD	18.81	24.84
Counter staff utilisation (%)	Mean	62	68
	SD	18.58	24.84
Number of travellers served (people)	Mean	478	477
	SD	27.95	29.11
Number of travellers not served (people)	Mean	0	0
	SD	1.22	1.45
Number of requests to counter staff to work faster	Mean	77	43
	SD	27.57	24.84



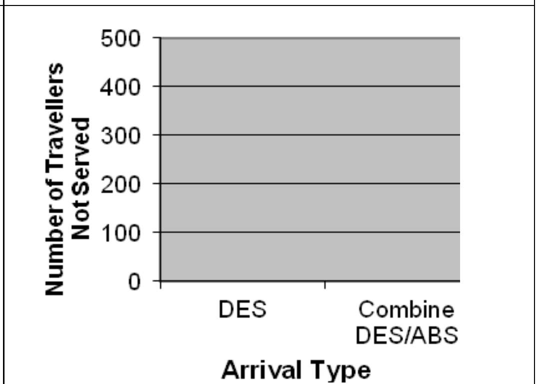
(a) Travellers waiting times



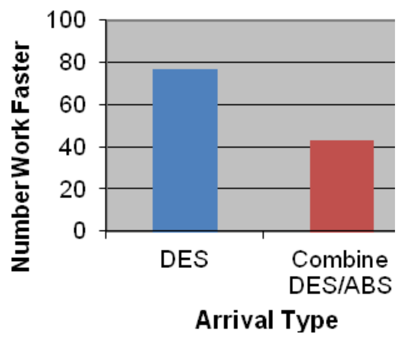
(b) Counter staff utilisation



(c) Number of travellers served



(d) Number of travellers not served



(e) Number of requests to counter staff to work faster

Figure 6.6 : Bar charts of the results in Experiment A2-1

Table 6.8 : Results of T-test in Experiment A2-1

Performance Measures	DES vs. Combined DES/ABS	
	P-value	Result
Travellers waiting time	P = 0.000	Reject
Counter staff utilisation	P = 0.015	Reject
Number of travellers served	P = 0.877	Fail to reject
Number of travellers not served	P = 0.669	Fail to reject
Number of requests to counter staff to work faster	P = 0.012	Reject

Modelling proactive behaviour in Experiment A2-1 has revealed differences in the impact on the simulation results when modelling the airport check-in services using DES and combined DES/ABS approaches. These differences can be explained by the fact that both models have used different logic decisions to solve a similar problem. The DES model has applied a set of rules to model the behaviour of a supervisor when observing the check-in operation continuously.

On the other hand, the actual behaviour of the real-life system has presented in the combined DES/ABS model imitated the supervisor's observation behaviour with some time delay, and the communication between the supervisor and the counter staff is visible. Continuous observation of queue length at the check-in counters has explained why, based on a specific observation time period, the number of requests made to the counter staff to work faster is higher in the DES model than in the combined DES/ABS model. When more staff work faster, the travellers are served more quickly, explaining why the DES model waiting time is lower than the combined DES/ABS model.

Experiment A2-1 has revealed that it was possible to model the behaviour exhibited in requesting the counter staff to work faster in both simulation models, using diverse solutions to achieve different types of understanding.

Experiment A2-2: Mixed Reactive and Sub-Proactive 2 Behaviours

Experiment A2-2 has investigated the mixed reactive and second proactive behaviours for this case study. The reactive behaviour and the simulation models' setup for DES and combined DES/ABS are same to that of Experiment A1. The Type 2 proactive behaviours in this experiment are displayed by travellers seeking the shortest queue on arrival at the check-in services, and moving from one queue to another while waiting, in order to obtain faster service. Both simulation models are modelled using different solutions to solve a similar problem. Appendix C.3 (a-b) and Appendix C.4 (a-b) illustrate the decision-making process for dealing with the problem to obtain faster service, in the context of decision flow and pseudo code, respectively.

As shown in Appendix C.2 (a) upon arrival, the travellers in DES model have searched for the shortest queue. If one queue is shorter than all the other queues, the travellers will move to the shortest queue, or will continue looking for the shortest queue before joining it.

Similar to DES model, upon arrival, the travellers have searched for the shortest queue as shown in Appendix C.2 (b). The same decision logic for finding the shortest queue on arrival in the DES model is applied in the combined DES/ABS model. In addition, to imitate the situation in the real-life system more naturally, the behaviour of moving to another queue while queuing is implemented only in the combined DES/ABS model. The travellers will continue to search for the shortest queue while remaining in their original queue. Such behaviour is difficult to model using the DES and refer Experiment A2-3 in case study 2 (Chapter 5: Section 5.5.1) for further explanation.

In Experiment A2-2, six performance measures are used, including four from Experiment A1 plus two the investigated proactive behaviours- the number of travellers searching for the shortest queue (upon arrival) and the number of travellers searching for the shortest queue (while queuing).

The hypotheses for T-test in Experiment A2-2 use the same four performance measures as in Experiment A1 but these performance measures are tested with a name link to Experiment A2-2 as follows: $Ho_{A2\text{-}2\_1}$, $Ho_{A2\text{-}2\_2}$, $Ho_{A2\text{-}2\_3}$, and $Ho_{A2\text{-}2\_4}$, for (in the same order) the travellers waiting time, the counter staff utilisation, the number of travellers not served and the number of travellers served, respectively. In addition, the hypotheses for the two investigated proactive behaviours in Experiment A2-2 are:

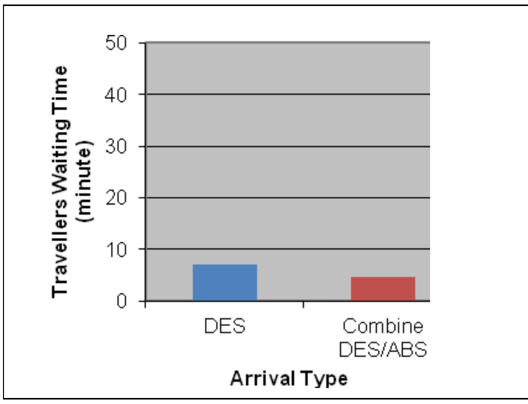
$Ho_{A2\text{-}2\_C3\_5}$: The number of travellers searching for the shortest queue (upon arriving) resulting from the mixed reactive and proactive DES model is not significantly different from the mixed reactive and proactive combined DES/ABS model.

$Ho_{A2\text{-}2\_C3\_6}$: The number of travellers searching for the shortest queue (while queuing) resulting from the mixed reactive and proactive DES model is not significantly different from the mixed reactive and proactive combined DES/ABS model.

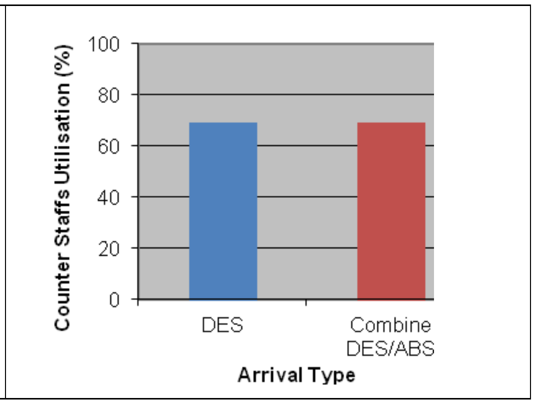
Results for Experiment A2-2 are shown in Table 6.9 and Figure 6.7, and the results of the T-test are shown in Table 6.10 below.

Table 6.9 : Results in Experiment A2-2

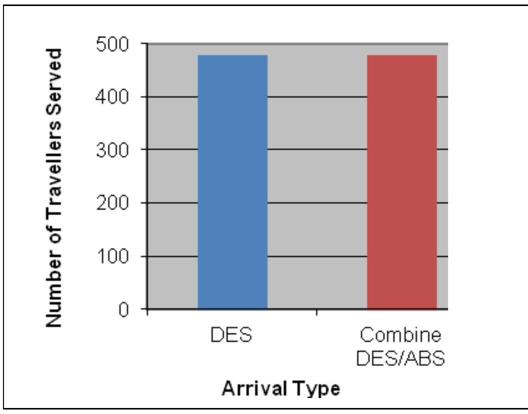
Performance measures		**DES**	**Combined DES/ABS**
Travellers waiting times (minute)	Mean	7.15	4.56
	SD	3.77	2.74
Counter staff utilisation (%)	Mean	69	69
	SD	12.35	15.24
Number of travellers served (people)	Mean	478	478
	SD	19.84	22.78
Number of travellers not served (people)	Mean	0	0
	SD	0.00	0.00
Number of travellers searching for shortest queue (upon arrival)	Mean	472	479
	SD	45.88	41.22
Number of travellers searching for shortest queue (while queuing)	Mean	n/a	255
	SD	n/a	28.13



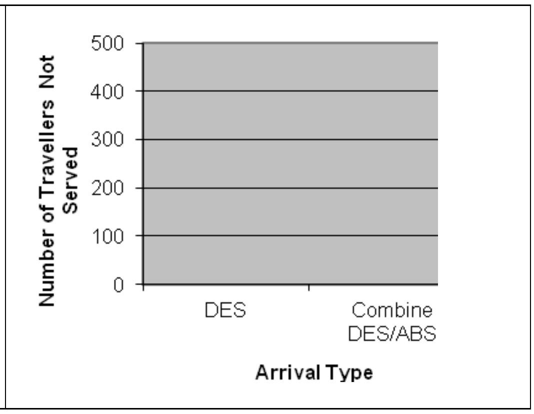
(a) Travellers waiting times



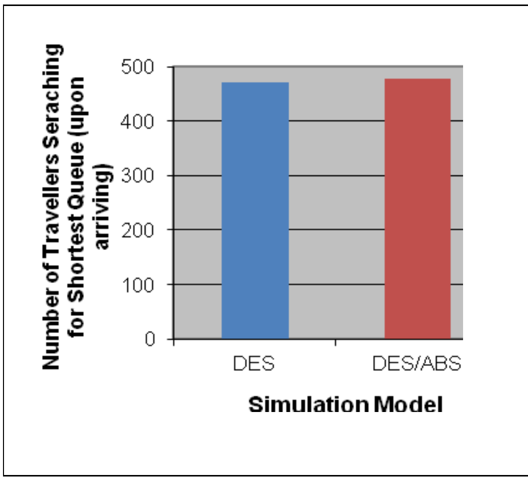
(b) Counter staff utilisation



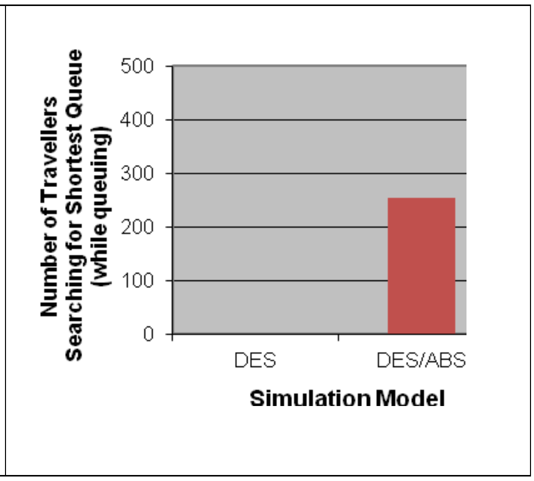
(c) Number of travellers served



(d) Number of travellers not served



(e) Number of travellers searching for shortest queue (upon arrival)



(f) Number of travellers searching for shortest queue (while queuing)

Figure 6.7 : Bar charts of the results in Experiment A2-2

Table 6.10 : Results of T-test in Experiment A2-2

Performance Measures	DES vs. Combined DES/ABS	
	P-value	**Result**
Travellers waiting times	P = 0.000	Reject
Counter staff utilisation	P = 0.673	Fail to reject
Number of travellers served	P = 0.480	Fail to reject
Number of travellers not served	P = 0.512	Fail to reject
Number of travellers searching for shortest queue (upon arrival)	P = 0.837	Fail to reject
Number of travellers searching for shortest queue (while queuing)	Statistical test is not available	

Table 6.9 and Figure 6.7 (a-f) show similarities in the patterns of results in staff utilisation, the number of travellers served, number of travellers not served and number of travellers searching for shortest queue (upon arrival). The most significant differences in results are found in travellers waiting time and the number of travellers searching for the shortest queue (while queuing).

The T-test results illustrated in Table 6.10 confirms that the travellers waiting time and the number of travellers searching for shortest queue (while queuing) for both simulations are statistically different: the test produced p-values that are lower than the level of significant value. Thus, $Ho_{A2\text{-}2\_1}$ and $Ho_{A2\text{-}2\_6}$ hypotheses are rejected. Furthermore, the $Ho_{A2\text{-}2\_2}$, $Ho_{A2\text{-}2\_3}$, $Ho_{A2\text{-}2\_4}$ and $Ho_{A2\text{-}2\_5}$ hypotheses for the counter staff utilisation, the number of travellers served , the number of travellers not served and number of travellers searching for shortest queue (upon arrival) respectively, are failed to be rejected as their p-values are higher than the level of significant.

The analysis discovered that the proactive behaviour has affected both the performance measures of the DES model and those of the DES/ABS model. Eventhough, the combined DES/ABS model is modelled more realistic in term of travellers' behaviours, but the impact only shown in waiting time and number of travellers searching for shortest queue (while queuing).

The counter staff utilisation, number of travellers served and not served does not show any differences between the two simulation models, probably because the number of counters staff are not the bottleneck in this case study. However, the study found that the impact on the DES/ABS model is much more noticeable as it is capable of modelling the more realistic human behaviours, thus influencing the simulation results.

Experiment A2-3: Mixed Reactive and Sub-3 Proactive Behaviours

The third proactive behaviour that has investigated in this case study is the behaviour under Type 3 (Chapter 3: Section 3.2). This proactive behaviour is initiated by the supervisor and is related with the removal of suspicious travellers while they are queuing to get served. The proactive behaviour of a supervisor is modelled using a slightly different solution in both simulation models. Appendix C.5 (a-b) and Appendix C.6 (a-b) show the decisions flow and pseudo codes for modelling proactive behaviour in the DES and combined DES/ABS models.

In Experiment A2-3, five performance measures are used, including four from Experiment A1 plus the number of travellers moved to the office (the investigated proactive behaviour). The hypotheses for T-test in Experiment A2-3 use the same four performance measures as in Experiment A1 but these performance measures are tested with a name link to Experiment A2-3 as follows: $Ho_{A2\text{-}3\_1}$, $Ho_{A2\text{-}3\_2}$, $Ho_{A2\text{-}3\_3}$, and $Ho_{A2\text{-}3\_4}$, for (in the same order) the travellers waiting time, the counter staff utilisation, the number of travellers not served and the number of travellers served, respectively. In addition, the hypothesis for the investigated proactive behaviour in Experiment A2-3 is:

$Ho_{A2\text{-}3\_5}$: The number of travellers moved to the office resulting from the mixed reactive and proactive DES model is not significantly different from the mixed reactive and proactive combined DES/ABS model.

Results for Experiment A2-3 are shown in Table 6.11 and Figure 6.8(a-e), and the results of the T-test are shown in Table 6.12 below:

Table 6.11 : Results in Experiment A2-3

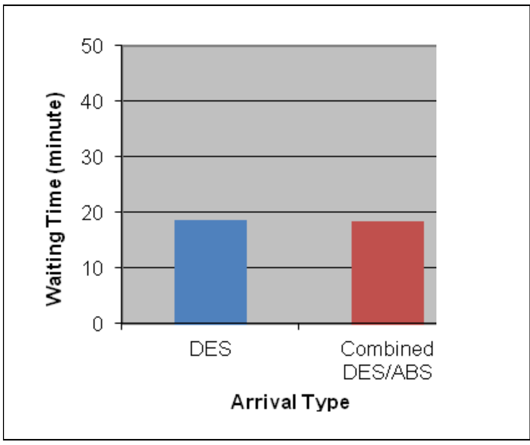
Performance measures		**DES**	**Combined DES/ABS**
Travellers waiting times (minute)	Mean	18.23	17.95
	SD	22.78	24.55
Counter staff utilisation (%)	Mean	65	65
	SD	17.55	18.97
Number of travellers served (people)	Mean	476	477
	SD	21.38	25.8
Number of travellers not served (people)	Mean	1	0
	SD	0	0
Number of travellers moved to the office (people)	Mean	20	22
	SD	15.22	16.44

Unexpectedly, as illustrated in Table 6.11 and Figure 6.8 (a-e), the Experiment A2-3 shows a similar pattern of simulation results between the DES and combined DES/ABS models. The similarities in pattern of the histograms in both simulation models are probably due to the same decisions logic in executing the investigated proactive behaviour.

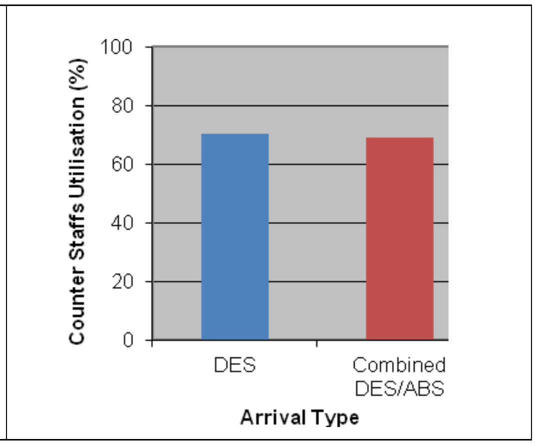
To confirm the results found in Experiment A2-3, a statistical test is conducted. The T- test results in Table 6.12 reveal similarities, where the p-values from all performance measures are higher than the chosen level of significant value (0.05). Therefore the $Ho_{A2\text{-}3\_1}$, $Ho_{A2\text{-}3\_2}$, $Ho_{A2\text{-}3\_3}$, $Ho_{A2\text{-}3\_4}$, and $Ho_{A2\text{-}2\_\_5}$, hypotheses are failed to be rejected. The simulation results in the mixed reactive and proactive DES and combined DES/ABS models are not statistically different.

The statistical test has confirmed that the impact of the supervisor's proactive behaviour in identifying the suspicious travellers shows no significant difference in both simulation models, which has then produced a similar impact for other performance measures. Although slightly different modelling solutions are implemented to mimic the proactive behaviour, the solution has not affected the overall results of both simulation models if the proactive behaviour has been executed using similar decisions logic. Overall, DES is capable of modelling realistic human behaviour similar to the one that has been modelled in combined DES/ABS.

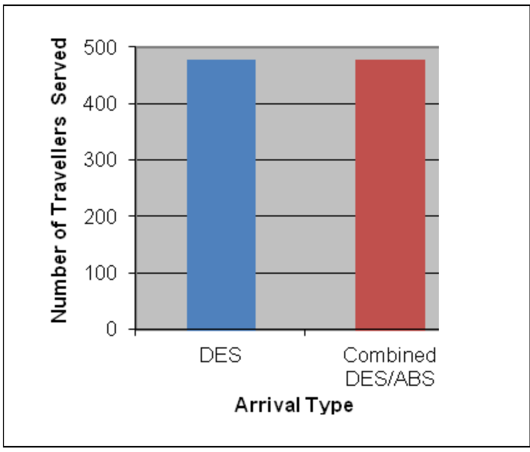
Next, the proactive behaviours in Experiment A2-1, A2-2 and A2-3 is combined in Experiment A2-4 to examine the performance of DES and combined DES/ABS models when modelling various proactive behaviours at the same time.



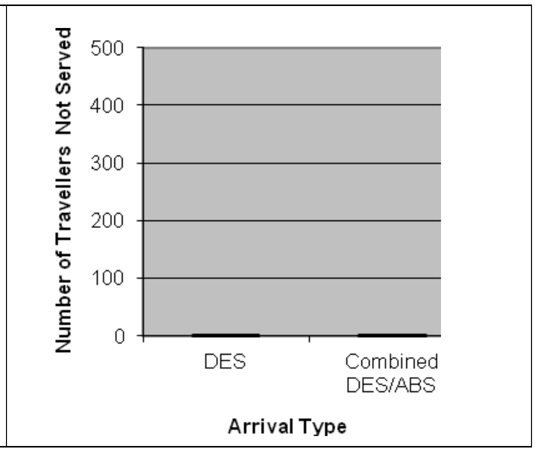
(a) Travellers waiting times



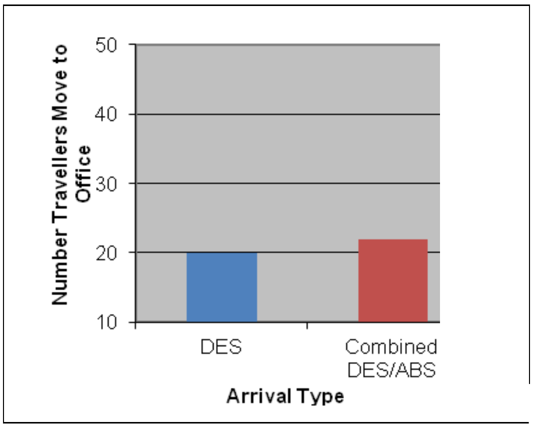
(b) Counter staff utilisation



(c) Number of travellers served



(d) Number of travellers not served



(e) Number of travellers moved to the office

Figure 6.8 : Bar charts for results in Experiment A2-3

Table 6.12 : Results of T-test in Experiment A2-3

Performance Measures	DES vs. Combined DES/ABS	
	P-value	Result
Travellers waiting times	P = 0.624	Fail to reject
Counter staff utilisation	P = 0.480	Fail to reject
Number of travellers served	P = 0.471	Fail to reject
Number of travellers not served	P = 0.512	Fail to reject
Number of travellers moved to the office	P = 0.871	Fail to reject

Experiment A2-4: Mixed Reactive and Sub- Proactive 4 Behaviours

Experiment A2-4 has investigated the modelling of the mixed reactive and combination of Type 1, Type 2 and Type 3 proactive behaviours that are modelled earlier in this case study (Experiment A2-1, A2-2 and A2-3). The purpose of such combination is to examine the impact of the simulation results on both simulation models when modelling various human behaviours in one model. In addition, the experiment sought to find out what could be learnt from the simulation results when modelling complex proactive behaviours for the realistic representation of the real–life system.

To execute the proactive behaviours, the same solutions (proactive decision-making and pseudo codes) as in Experiment A2-1(sub-1 proactive), Experiment A2-2 (sub-2 proactive) and Experiment A2-2 (sub-3 proactive) are used for the current experiment.

Seven performance measures are used, including four from Experiment A1 and an additional four from the investigated proactive behaviours (number of requests to work faster, number of travellers searching for shortest queue (upon arriving), number of travellers searching for shortest queue (while queuing) and number of travellers moved to the office.

The hypotheses for T-test in Experiment A2-4 are the same with the four performance measures in Experiment A1 but these performance measures are tested with a name link to Experiment A2-4 as follows: $Ho_{A2\text{-}4\_1}$, $Ho_{A2\text{-}4\_2}$, $Ho_{A2\text{-}4\_3}$, and $Ho_{A2\text{-}4\_4}$, for the travellers waiting time, the counter staff utilisation, the number of travellers not served and the number of travellers served, respectively. In addition, the hypotheses for the investigated proactive behaviours in Experiment A2-4 are:

$Ho_{A2\text{-}4\_5}$: The number of requests to work faster resulting from the mixed reactive and proactive DES model is not significantly different from the mixed reactive and proactive combined DES/ABS model.

$Ho_{A2\text{-}4\_6}$: The number of travellers searching for the shortest queue (upon arrival) resulting from the mixed reactive and proactive DES model is not significantly different from the mixed reactive and proactive combined DES/ABS model.

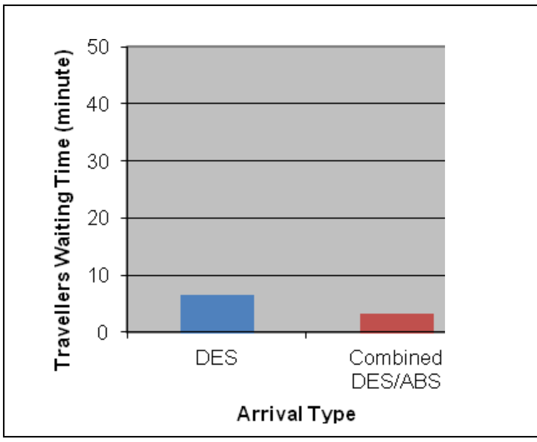
$Ho_{A2\text{-}4\_7}$ The number of travellers searching for the shortest queue (while queuing) resulting from the mixed reactive and proactive DES model is not significantly different from the mixed reactive and proactive combined DES/ABS model.

$Ho_{A2\text{-}4\_8}$: The number of travellers moved to the office resulting from the mixed reactive and proactive DES model is not significantly different from the mixed reactive and proactive combined DES/ABS model.

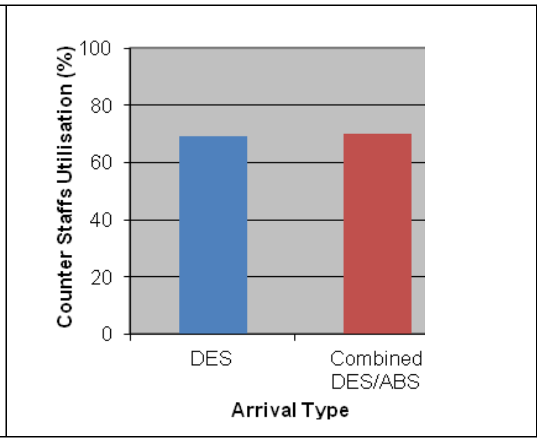
Results for Experiment A2-4 are shown in Table 6.13 and Figure 6.9(a-h), and the results of the T-test are shown in Table 6.14:

Table 6.13 : Results of Experiment A2-4

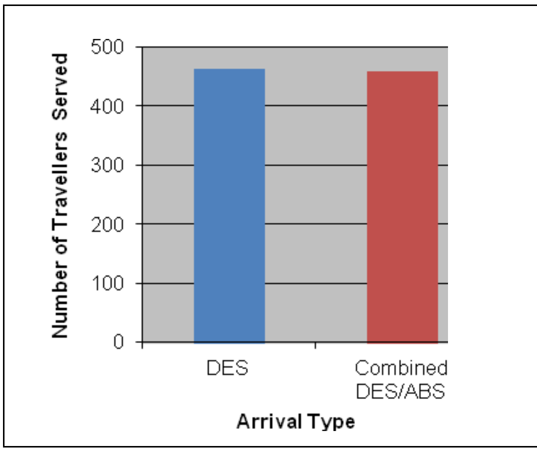
Performance measures		DES	Combined DES/ABS
Travellers waiting times (minute)	Mean	6.44	3.12
	SD	10.18	8.17
Counter staff utilisation (%)	Mean	69	70
	SD	18.21	18.7
Number of travellers served (people)	Mean	462	459
	SD	24.19	25.1
Number of travellers not served (people)	Mean	0	0
	SD	0	0
Number of requests to work faster	Mean	1	0
	SD	1.25	0.19
Number of travellers searching for the shortest queue (upon arriving) (people)	Mean	477	478
	SD	25.18	50.89
Number of travellers searching for the shortest queue (while queuing) (people)	Mean	n/a	223
	SD	n/a	42.18
Number of travellers moved to the office (people)	Mean	15	17
	SD	10.15	11.83



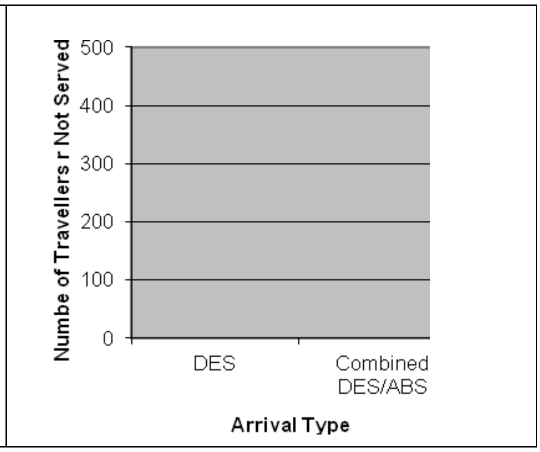
(a) Travellers waiting times



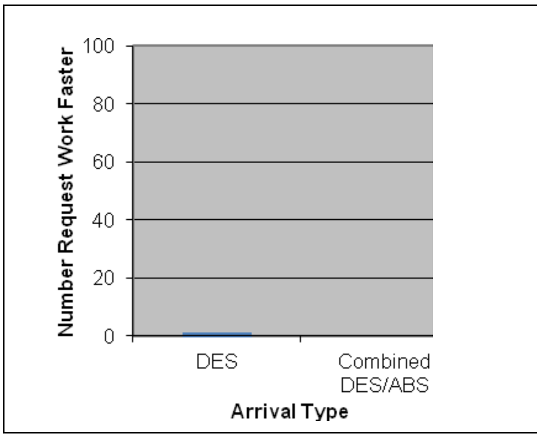
(b) Counter staff utilisation



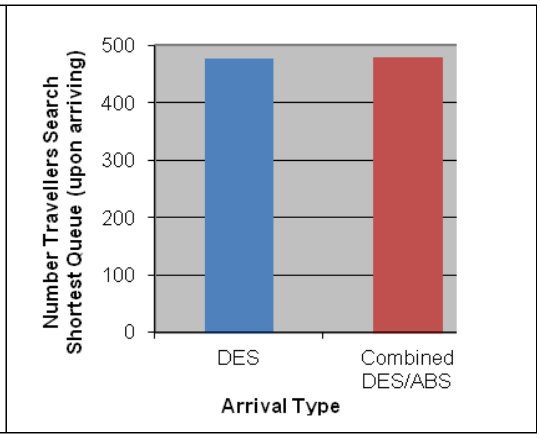
(c) Number of travellers served



(d) Number of travellers not served

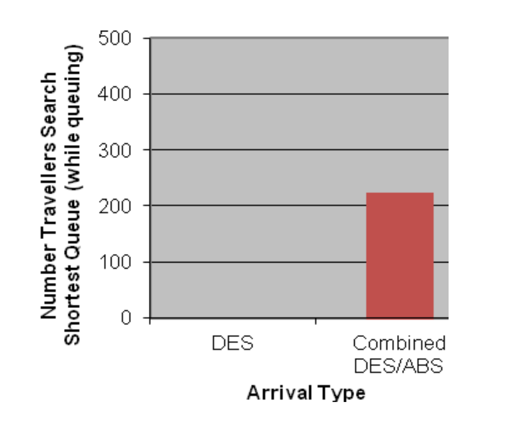


(e) Number of requests to work faster

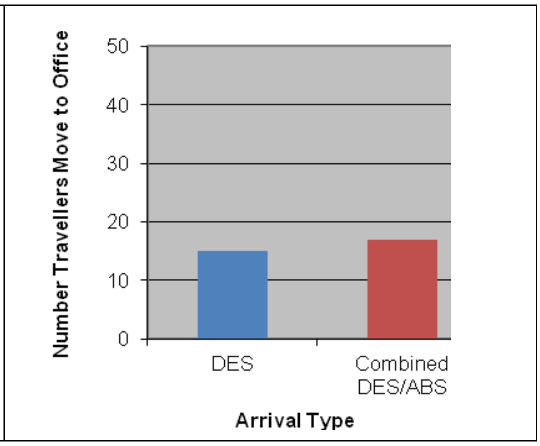


(f) Number of travellers searching for shortest queue (upon arrival)

Figure 6.9: Bar charts for results in Experiment A2-4



(g) Number of travellers searching for shortest queue (while queuing)



(h) Number of travellers moved to the office

Table 6.14 : Results of T-test in Experiment A2-4

Performance Measures	DES vs. Combined DES/ABS	
	P-value	Result
Travellers waiting times	P = 0.000	Reject
Counter staff utilisation	P = 0.486	Fail to reject
Number of travellers served	P = 0.612	Fail to reject
Number of travellers not served	P = 0.218	Fail to reject
Number of requests to work faster	P = 0.000	Reject
Number of travellers searching for shortest queue (upon arriving)	P = 0.766	Fail to reject
Number of travellers searching for shortest queue (while queuing)	Statistical test is not available	
Number of travellers moved to the office	P = 0.572	Fail to reject

Similarities and dissimilarities of results between DES and combined DES/ABS are found in this combined-proactive experiment, as shown in Table 6.13

and Figure 6.9 (a-h). Significantly, the combined DES/ABS model has produced a shorter waiting time, a lower number of requests to work faster and a higher number of travellers searching for the shortest queue while queuing compared to the DES model. This impact is significant, probably due to the extra individual behaviour that is modelled in the combined DES/ABS model. Such behaviour (travellers searching for shortest queue while queuing) is frequent in the system under study and has affected the travellers' wish to be served more quickly; therefore no queue is longer than another. The statistical test has confirmed, these three performance measures (Figure 6.15 - a, e and g) have shown lower p-values than the chosen level of significant value (0.05). Therefore, the $Ho_{A2\text{-}4\_1}$, $Ho_{A2\text{-}4\_5}$ and $Ho_{A2\text{-}4\_7}$ hypotheses are rejected.

In addition, the statistical test has confirmed that there are no significant differences in both simulation models' results between counter staff utilisation, number of travellers served, number of travellers not served, number of travellers searching for shortest queue upon arrival and number of travellers moved to the office, as their p-values are higher than the level of significant value. The $Ho_{A2\text{-}4\_2}$, $Ho_{A2\text{-}4\_3}$, $Ho_{A2\text{-}4\_4}$, $Ho_{A2\text{-}4\_6}$ and $Ho_{A2\text{-}4\_8}$ hypotheses are therefore failed to be rejected. As an overall result, modelling combined-proactive behaviours for both DES and combined DES/ABS models is statistically different in their simulation results performance.

Modelling various proactive behaviours in the airport check-in services has proved that the behaviour of travellers who always seek faster service is the main reason that has influenced the performance of both simulation models. However, this is more noticeable in combined DES/ABS as modelling travellers' behaviours is more realistic than in the DES model. The performance of the combined DES/ABS model in modelling realistic human behaviours has a significant impact on the simulation study.

Conclusions on Experiment A1 and Experiment A2

Experiment A1 has revealed similarities in results between the DES and combined DES/ABS models, so the main hypothesis Ho_1 for this experiment is failed to be rejected. In contrast, both similarities and dissimilarities of statistical results are found in Experiment A2: In Experiments A2-1, A2-2 and A2-4 the simulation results between both models are statistically different while in Experiment A2-3 the results are the same. As a result, the main hypothesis Ho_2 for Experiment A2 is rejected, as three results of experiments (Experiments A2-1, A2-2 and A2-4) have been rejected and only one (Experiment A2-3) has accepted.

The model result investigation has proved that DES is capable of producing similar results to those of combined DES/ABS when modelling the reactive human behaviour, but that further complex proactive modelling with different decision logic also has produced different results. This study seeks to answer the research questions 1 and 2 (Chapter 1) while establishing the best choice of simulation model for the current case study problem or for a similar service-oriented problem. It therefore next examines the performance of both simulation models (DES and combined DES/ABS) in terms of model difficulty.

6.5.3 Set B : Model Difficulty Investigation

Experiment B1: Reactive Human Behaviour

The model difficulty investigation in Set B begins with Experiment B1: Reactive Human Behaviour, which has investigated the difficulty of Experiment A1 (Section 6.5.1 above) concerning modelling reactive behaviour using DES and combined DES/ABS approaches. The objective and conduct of this investigation has been explained in Chapter 3 (Section 3.5.3).

Experiments B1 have used the results of comparing the measures of model difficulty (model building time, model execution time and model LOC) from the modeller's view point or so called second result (refer Chapter 4:Section 4.5.3). Thus, the main hypothesis to test in this Experiment B1 is Ho_3 as stated in Chapter 3 (Section 3.5.1).

All results of model difficulty (model building time, model execution time and model LOC) are converted into the standard scale of model difficulty using Equation 3.1 as discussed in Chapter 3 (Section 3.5.3). For example, the model building time is 25 hours and 55 hours in the DES and combined DES/ABS models respectively. With reference to the Equation 3.1 (Chapter 3: Section 3.5.3), the result of model difficulty i.e. DES model building time (25 hours) is divided by the result of maximum model difficulty, i.e. combined DES/ABS model building time (55 hours). The deviation result of 25 / 55 is then multiplied with the total number of scales of model difficulty (10) (Chapter 3: Section 3.5.3). From the calculation to convert into the standard scale of model difficulty, scale 5 is obtained for the DES model.

Next, the same process of calculation is carried out for the combined DES/ABB model and a scale of 10 is calculated. Table 6.15 presents the results for measures of model of difficulty from Experiment B1. RV (Result Value) represents the results of measures of difficulty from Experiment A1, while DV (Difficulty Value) represents the RV results that are converted into the scale of difficulty.

Table 6.15 : Results from modeller's modelling experience for model difficulty measures in Experiment B1

Performance Measures	DES		Combined DES/ABS	
	RV	DV	RV	DV
Model Building Time	25 hours	5	55 hours	10
Model Execution Time	7.5 seconds	4	19.1 seconds	10
Model LOC	3402 lines	9	4012 lines	10

Similar in case study 1 (Chapter 4: Section 4.5.3) and case study 2 (Chapter 5: Section 5.5.3), the quantitative approach is used to compare the results of model difficulty between DES and combined DES/ABS in Table 6.15. The histograms in Figure 6.10 are compared between the results of model difficulty of DES and combined DES/ABS while qualitative approach is used to answer the hypothesis (Ho_5) in Experiment B1. A qualitative approach, as described in Chapter 3: Section 3.5.3, is chosen because the results for all data of model difficulty measures contains insufficient data samples to execute the statistical test.

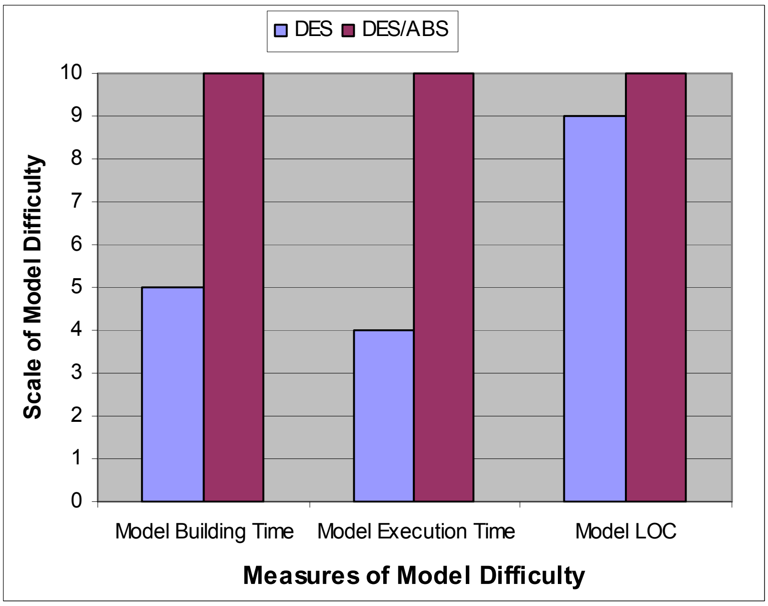


Figure 6.10: Bar charts of the first result of model difficulty measures (modellers' experience) in Experiment B1.

Figure 6.10 shows dissimilarity in the results for scale of difficulty between the same model difficulty measures of DES and combined DES/ABS models. In this case study has appeared that the model building and execution time in the DES model has produced a lower scale of difficulty: scale 5 and scale 4 compared to scale 10 for both measures in the combined DES/ABS model. In contrast, only a small difference is found in model LOC for DES (scale 9) and combined DES/ABS models (scale 10). The scale of difficulty shows that a higher value represents a greater degree of difficulty in one simulation model.

Thus, in term of level of difficulty in modelling reactive behaviour, the DES model is 50% faster in model building time, 60% faster in model execution time and 10% more of LOC than the combined DES/ABS model. This graphical comparison suggests that the DES approach provides a better performance in the level of simulation modelling difficulty than the combined DES/ABS when modelling human reactive behaviour for this case study.

The model difficulty performance of DES in modelling reactive behaviour for case study 3 is found similar with the result gained in case study 1 (Chapter 4: Section 4.5.3) and case study 2 (Chapter 5: Section 5.5.3). Thus, to answer the Ho_3 hypothesis in Experiment B1 of case study 2, the result of Ho_3 hypothesis in Case study 1 (Chapter 4 : Section 4.5.3) which is based on statistical test is referred. According to the result of Ho_3 hypothesis from case study 1, the hypothesis Ho_3 in case study 3 is understandable failed to be rejected.

The result of Ho_3 hypothesis in this case study has confirmed that simulation difficulty for reactive DES and combined DES/ABS models are statistically not the same. The similar understanding of DES and combined DES/ABS performance in this model difficulty experiment can be practised for modelling a complex queuing system in any other similar service-oriented problems.

Experiment B2: Mixed Reactive and Proactive Behaviours

Experiment B2 has investigated the difficulty of Experiment A2 (Section 6.5.2 above) in modelling mixed reactive and proactive behaviour using DES and combined DES/ABS approaches. The objective and conduct of this investigation has been explained in Chapter 3 (Section 3.5.3). As in Experiment B1, model building (in hours), model execution time (in seconds) and model LOC (in lines) are the measures of model difficulty for the current experiment.

As discussed in case studies 1 and 2, results for the measures of model difficulty are gained from the modelling work in Experiment A2 (A2-1, A2-2, A2-3 and A2-4). In order to avoid further confusion, the model difficulty' results in Experiment A2-1, A2-2, A2-3 and A2-4 is placed in Experiment B2-1, B2-2, B2-3 and B3-4 respectively. The Ho_4 hypothesis as stated in Chapter 3 (Section 3.5.1) is tested in this Experiment B2.

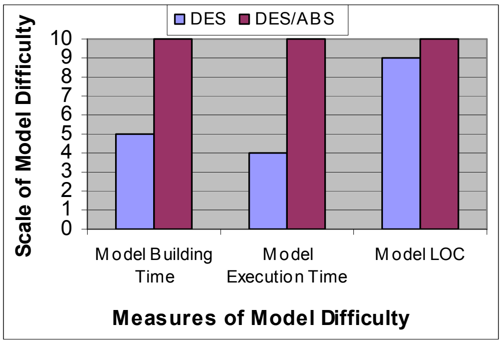
All results of measures of difficulty for DES and combined DES/ABS models are converted to the scale of difficulty using Equation 1 in Chapter 3 (Section 3.5.3). The same procedure to convert the model difficulty's results as in Experiment B1 above is conducted in Experiment B2. Table 6.16 and Figure 6.11 summarise the results of comparing measures of model difficulty for both DES and combined DES/ABS models.

As shown in Table 6.16 and Figure 6.11 (a-d), dissimilarities in results are found in the scale of difficulty for the four sub-experiments between the measures of difficulty in DES and combined DES/ABS models. Results of model difficulty in both Table 6.16 and Figure 6.11(a-d) show that the DES model is on average 50 % faster in model building time, 60% faster in model execution time and 10% smaller in model LOC than the combined DES/ASB model for all experiments within Experiment B2. The results of Experiment B2 have demonstrated that the greatest impact of DES model difficulty performance is seen in model building time and model execution time.

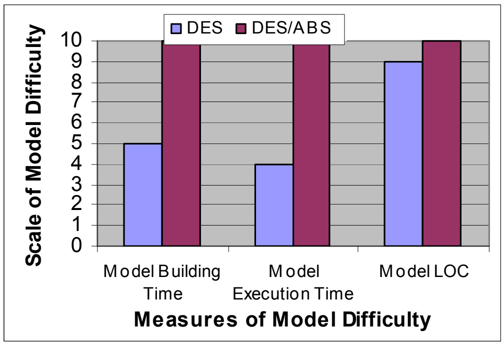
Table 6.16 : Results from modeller's experience for model difficulty in Experiment B2

Measures of Model Difficulty	**DES**							
	Exp B2-1		**Exp B2-2**		**Exp B2-3**		**Exp B2-4**	
	RV	**DV**	**RV**	**DV**	**RV**	**DV**	**RV**	**DV**
Model Building Time	30 hours	5	36 hours	5	36 hours	5	42 hours	4
Model Execution Time	8.3 seconds	4	9.4 seconds	4	8.9 seconds	4	10.5 seconds	4
Model LOC	3916 lines	9	4015 lines	9	3896 lines	9	4814 lines	10
Measures of Model Difficulty	**Combined DES/ABS**							
	Exp B2-1		**Exp B2-2**		**Exp B2-3**		**Exp B2-4**	
	RV	**DV**	**RV**	**DV**	**RV**	**DV**	**RV**	**DV**
Model Building Time	60 hours	10	72 hours	10	67 hours	10	115 hours	10
Model Execution Time	20.2 seconds	10	22.8 seconds	10	21.8 seconds	10	23.5 seconds	10
Model LOC	4274 lines	10	4400 lines	10	4312 lines	10	4902 lines	10

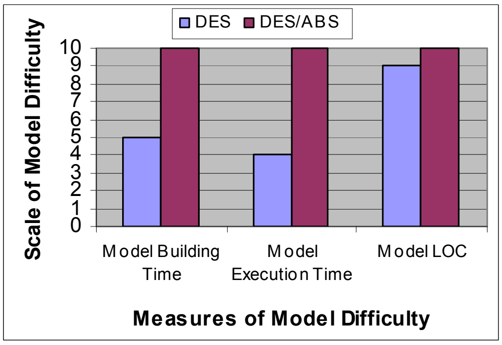
To summarise, with regards to model difficulty, the DES model has achieved a better performance in model difficulty investigation when modelling human mixed reactive and proactive behaviour for the investigated service-oriented system, compared to the combined DES/ABS model. The results of model difficulty are the same as those found in case studies 1 and 2. The results of model difficulty in case study 1 is referred as they have been statistically analysed using the statistical test. By referring to the results of Ho_4 hypothesis in case study 1(Section: 4.5.2), therefore, the Ho_4 hypothesis in case study 3 is rejected. The result of Ho_4 hypothesis has confirmed that the simulation difficulties for mixed reactive and proactive DES and combined DES/ABS models are statistically not the same.



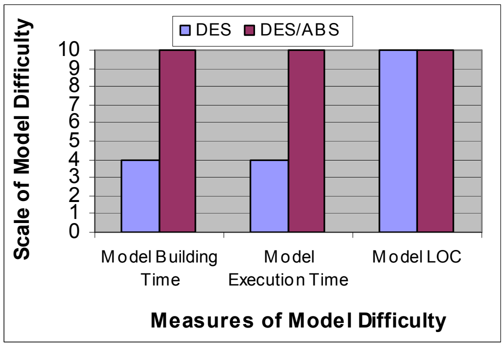
(a) Results of Experiment B2-1



(b) Results of Experiment B2-2



(c) Results of Experiment B2-3



(d) Results of Experiment B2-4

Figure 6.11 : Bar charts of the first result of model difficulty measures (modeller's experience) in Experiment B2

Conclusions on Experiment B1 and Experiment B2

It can be concluded that the DES model is found to be less difficult for modelling the same reactive and mixed reactive/proactive behaviour problems compared to the combined DES/ABS model, in relation to model building time, execution time and LOC. Overall, it can be suggested that the DES model has produced a better modelling difficulty performance when modelling human behaviour in this case study and in any other similar service-oriented system compared to combined DES/ABS model.

6.5.4 Comparisons of Results

This section discusses the correlation between the simulation approaches in the sets of experiments (A1 vs. A2 and B1 vs. B2) presented in Section 6.5.2 and 6.5.3 above. Refer Chapter 3 (Section 3.5.4) for further understanding about this section. Simulation results performance when modelling reactive and mixed reactive and proactive behaviours are investigated in Experiments A1 and A2, and the results are compared. In order to see the impact on one simulation model when modelling reactive behaviour compared with mixed reactive and proactive behaviours, the T- test is performed according to the Ho_5 as stated in Chapter 3 (Section 3.5.4).

Experiment A1 is chosen as the reference point to be compared with the sub-experiments in Experiment A2 (Experiments A2-1, A2-2, A2-3 and A2-4). Two identical performance measures are used in this comparison – travellers waiting time and number of travellers not served. The first hypothesis to test is as follow:

Ho_{A3_1} : The travellers waiting time resulting from the DES model is not significantly different in Experiments A1 and A2-1.

Next, similar to the Chapter 4 (Section 4.5.4) the travellers waiting time resulting from the DES model in Experiment A1 is compared with Experiment A2-2, A2-3 and A2-4 using the following hypotheses: Ho_{A3_2}, Ho_{A3_3} and Ho_{A3_4} (in the same order). Same with combined DES/ABS model, the result from Experiment A1 is also compared with Experiment A2-1, A2-2, A2-3 and A2-4 with the following hypotheses: Ho_{A3_5}, Ho_{A3_6}, Ho_{A3_7} and Ho_{A3_8} (in the same order).

To compare the number of travellers not served in the four experiments of DES and combined DES/ABS, the following hypotheses are tested: Ho_{A3_9}, Ho_{A3_10}, Ho_{A3_11} and Ho_{A3_12} for DES - Experiment A1 vs. Experiment A2-1, A2-2, A2-3 A2-4, A2-5 and Ho_{A3_13}, Ho_{A3_14}, Ho_{A3_15} and Ho_{A3_16} for combined DES/ABS - Experiment A1 vs. Experiment A2-1, A2-2 and A2-3.

To test the sub-hypotheses, a test similar to that in the Experiment section 6.5 above – the T-test - is conducted and the significant level used is 0.05. Table 6.17 shows the results of p-values from the T-test comparing Experiment A1 with A2-1, A2-2, A2-3 and A2-4.

Table 6.17 shows the simulation results of two performance measures from each experiment in Experiment A1 and A2 (Section 6.5.2 above) while Table 6.18 shows the p-values results from the T- test.

Table 6.17 : The data of the chosen performance measures for the correlation comparisons

Experiment	DES		Combined DES/ABS	
	Travellers Waiting Time	Number of travellers not served	Travellers Waiting Time	Number of travellers not served
A1	7.86	8	6.78	7
A2-1	6.42	0	6.18	0
A2-2	5.79	0	3.88	2
A2-3	7.45	7	7.11	7
A2-4	4.77	0	2.45	0

Table 6.18: Results of T-test comparing Experiment A1 with Experiment A2-1, A2-2, A2-3 and A2-4.

Experiments	**Performance measures**	**DES**	**DES/ABS**
		P-Value	**P-Value**
A1 vs. A2-1	Travellers waiting time	0.000	0.000
	Number of travellers not served	0.000	0.000
A1 vs. A2-2	Travellers waiting time	0.000	0.000
	Number of travellers not served	0.000	0.000
A1 vs. A2-3	Travellers waiting time	0.031	0.064
	Number of travellers not served	0.067	0.042
A1 vs. A2-4	Travellers waiting time	0.000	0.000
	Number of travellers not served	0.000	0.000

Table 6.18 illustrates that all p-values for travellers waiting time and number of travellers not served in both DES and combined DES/ABS models for Experiment A1 compared with Experiments A2-1, A2-2 and A2-4 are lower than the chosen significance level (0.05). Thus, all the related hypotheses of Experiment A1 against Experiments A2-1, A2-2 and A2-4 above are rejected.

In contrast, Experiment A1 compared with Experiment A2-3 has showed the p-values to be higher than the level of significance for both performance measures (travellers waiting time and number of travellers not served) in both simulation models (DES and combined DES/ABS). Thus, all related hypotheses with Experiment A1 against Experiment A2-3 above are failed to be rejected.

Overall, the hypothesis Ho_5 is rejected due to dissimilarities in results found when similarities are rejected by three of the experiments (Experiments A2-1, A2-2 and A2-4) and accepted by only one (Experiment A2-3).

The comparison of results between Experiment A1 and A2 indicates that modelling mixed reactive and proactive behaviours have a great impact on the performance of travellers waiting times and number of travellers not served for both DES and combined DES/ABS models in this case study. The greater impact of proactive implementation seen in both simulation models is due to the faster service given to travellers and to the fact that more travellers have managed to obtain service within the operation time.

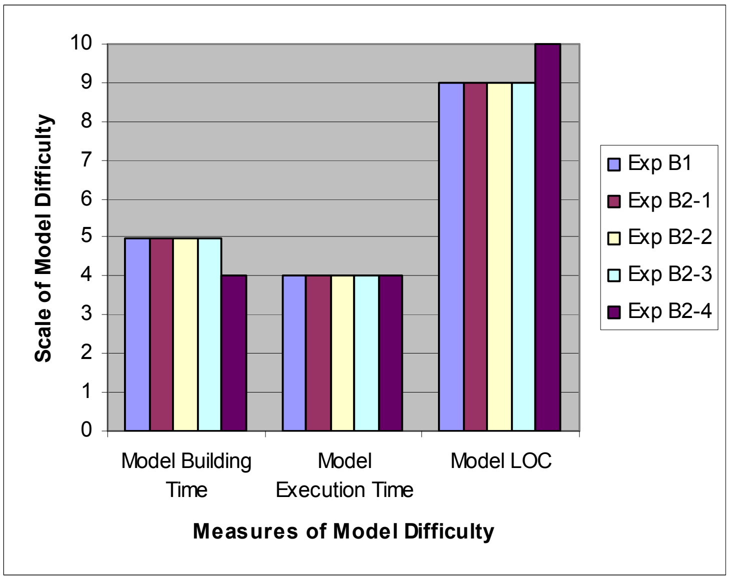
On the other hand, the small size of proactive behaviour demonstrated in Experiment A2-3, has not greatly influence the overall system performance in DES and combined DES/ABS models, explaining why the travellers waiting time and number of travellers not served are not reduced when compared the reactive behaviour against mixed reactive and proactive behaviours.

So far the comparison between results in the experiments (Experiment A1 against Experiment A2) has proved that it is worth modelling proactive behaviour in this case study from the perspective of simulation results and the impact of modelling proactive behaviours is greatly found in DES/ABS model than DES model. The issue of modelling proactive behaviours is next investigated in Experiments B1 and B2 in terms of the model difficulty.

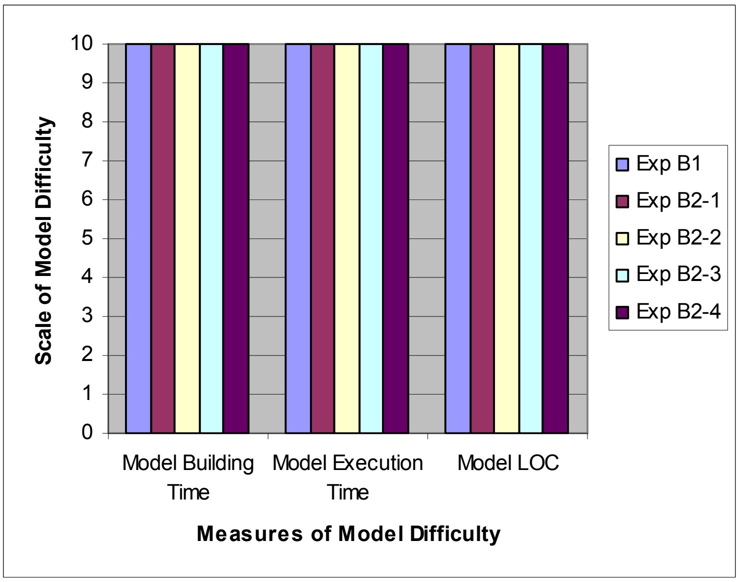
In Experiments B1 and B2 (Section 6.5.2 above), the DES model has showed an effective performance in modelling difficulty than the combined DES/ABS models. In order to see the relationship between Experiments B1 and B2 in one simulation model, the Ho_6 hypothesis as stated in Chapter 3 (Section 3.5.4) is tested.

The results of model difficulty measures from the modeller's experience between reactive against mixed reactive and proactive behaviours are illustrated using the graphical approach. The graphical comparison is chosen as the available data of modeller's experience is not enough to perform the non-parametric test (i.e. T- test).

For current correlation investigation, Experiment B1 is chosen as the reference point. Each of the sub-experiments (Experiments B2-1, B2-2, B2-3 and B2-4) in Experiment B2 is compared with Experiment B1. Figure 6.12 (a) illustrates the results of the comparison of Experiment B1 with B2 (B2-1, B2-2, B2-2 and B2-4) for the DES and while Figure 6.12 (b) for combined DES/ABS models.



(a) Model difficulty results in DES model for Experiment B1 and B2



(b) Model difficulty results in combined DES/ABS model for Experiment B1 and B2

Figure 6.12 : Histograms for Model Difficulty in Experiment B1 and B2

The model difficulty results as shown in Figure 6.18 (a-b) above have indicated similar patterns between reactive and mixed reactive and proactive behaviours for DES – Figure 6.18 (a) and combined DES/ABS models – Figure 6.18 (b). The model difficulty results in case study 3 have shown similar model difficulty results to those in case study 1 (Chapter 4: Section 4.5.4) and case study 2 (Chapter 5: Section 5.5.4).

As in case study 1, the comparison results of model difficulty between Experiment B1 against B2 (B2-1, B2-2, B2-3, B2-4) are statistically compared using a standard paramedic test (T- test); these results are therefore adopted in the current investigation in order to answer the Ho_6 hypothesis. Due to the similarity of results found through a visual inspection of case study 1 (Chapter 4: Section 4.5.3) and case study 3, Ho_6 hypothesis in case study 3 is rejected.

The result of investigating the Ho_6 hypothesis has confirmed that the simulation difficulty for reactive behaviour compared with mixed reactive and proactive behaviour for both DES and combined DES/ABS models is statistically not the same. Overall, DES model has produced a better performance in model difficulty investigation when modelling human reactive and proactive behaviours.

Conclusions of comparison results

The investigation of simulation results and difficulty comparing reactive against mixed reactive and proactive behaviours helps to explain the performance of the simulation models (DES and combined DES/ABS) when modelling human behaviours in case study 3. From the perspective of simulation results correlation, modelling mixed reactive and proactive behaviours in case study 3 has shown a bigger impact rather than modelling only reactive behaviour in combined DES/ABS and DES approaches.

On the other hand, a similar pattern of results in model difficulty scale is found in DES and combined DES/ABS when comparing both the reactive and mixed reactive and proactive behaviours of the simulation models. However, the DES model has demonstrated more efficient performance in modelling difficulty than combined DES/ABS, especially in model building time and execution time.

6.6 Conclusions

Based on the investigation in the experiments section above, both DES and combined DES/ABS models have been found to produce similar simulation results in modelling the same decision logic of reactive behaviours (simple behaviours), with less modelling difficulty compared to combined DES/ABS model.

Modelling mixed reactive and proactive behaviours, on the other hand, has been found to produce a dissimilarity of simulation results between the DES and combined DES/ABS models, with less modelling difficulty in DES model. Such investigation shows that modelling complex human behaviours using different decisions logic in the DES and combined DES/ABS models produces different results. In addition, modelling mixed reactive and proactive behaviours using DES and combined DES/ABS approaches has produced a greater impact on performance of simulation results than modelling reactive behaviour for case study 3.

As a conclusion, either DES or combined DES/ABS is found to be suitable for modelling the human behaviour problem, using different decisions logic for understanding different simulations with varying levels of modelling difficulty.

Overall, the investigation of model result and model difficulty when modelling reactive and mixed reactive and proactive behaviour have revealed a major difference in the performance of the system in this case study: the combined DES/ABS model has produced a big impact in model results investigation when modelling mixed reactive and proactive behaviours, while the DES model is observed to be effective in the model difficulty investigation for both human reactive and proactive modelling.

In order to understand the relationship of the conclusions that have been drawn in each case study (case study 1: Chapter 4, case study 2: Chapter 5 and case study 3: Chapter 6), a detail summary is presented in Chapter 7.

CHAPTER 7

CONCLUSIONS

7.1 Conclusions

An investigation of human behaviour modelling using DES and combined DES/ABS is presented in this thesis as a comparison novel for modelling reactive and different level of detail of proactive behaviour in the service-oriented systems. Knowledge to produce the human behaviour modelling comparison is obtained from the evidences of simulation results and difficulty performances of DES and combined DES/ABS. Both simulation models are investigated in modelling human behaviour (reactive and proactive) for different types of service-oriented systems.

DES and combined DES/ABS models are chosen as the two methods due to their suitability in modelling human behaviour at the individual abstraction level. Three case studies from a service-oriented system based on a queuing environment - a department store, a university and an airport - are selected for the investigation into the suitability of both simulation methods in modelling the investigated human behaviour (reactive and proactive).

For all three case studies, two sets of experiments, Set A (model result investigation) and Set B (model difficulty investigation) are conducted in order to achieve the study objectives 1 and 2 respectively (Chapter 1). Both experiments are concerned with comparing the performance of simulation results and difficulties (i.e. model building time, model execution time and model LOC) when modelling reactive and mixed reactive and proactive behaviour in the DES and combined DES/ABS models.

A statistical test (the T- test) is selected as the method to compare the results from both sets of experiments (Set A and Set B), by testing a number of hypotheses. The results from the model result and model difficulty investigations of the three case studies are correlated in order to understand the comparison of DES and combined DES/ABS in modelling human behaviour focus on modelling the different level of detail for proactive behaviour.

DES is identified as the best simulation method to model reactive human behaviour in services by presenting the similar simulation results as combined DES/ABS and less modelling difficulty. In addition, DES is also found suitable for modelling mixed reactive and the less complex aspects of realistic proactive human behaviour, as DES contains dependent entities. Additional complex and realistic proactive behaviours could only be modelled in combined DES/ABS due to the use of independent agents.

Modelling the service-oriented system as realistically (proactive behaviour) as possible is found important because modelling such detail has a significant impact on the overall system performance. Overall, DES and combined DES/ABS are found suitable for modelling most of levels of proactive behaviour. In addition, combined DES/ABS is found more suitable for modelling higher levels of proactive behaviour (complex behaviour). Another finding from the experiments is that it is only worth representing complex proactive behaviour if it occurs frequently in the real system (considering the relation between modelling effort and impact).

7.2 Achievement of Aim and Objectives

The aim of this thesis is to establish a comparison in modelling human reactive and different level of detail of proactive behaviours in the service sector using DES and combined DES/ABS techniques. To achieve this aim, two research objectives as identified in Chapter 1 Section 1.3 are re-evaluated according to the evidence found in case studies 1, 2 and 3 (Chapter 4, 5 and 6), as follows:

Objective 1: To investigate the similarities and differences in the model results performance for DES and combined DES/ABS.

In case studies 1, 2 and 3 similarities are found between the simulation results in the model result investigation of both DES and combined DES/ABS models when using similar logic decision for executing the human behaviours in Experiments A1 and A2.

Case study 2 (Chapter 5: Section 5.5.1) provides a new insight in that modelling those complex proactive behaviours which could only be modelled in combined DES/ABS (e.g. customers skip from queue while queuing) and which occur less frequent does not have a big impact on the overall system performance in the combined DES/ABS model. This explains the similarity between the simulation results for both simulation models in case study 2. Modelling a system as realistically as possible is found to be insignificant in solving a problem similar to that presented in case study 2.

In contrast to case study 2, different results are found when modelling the proactive behaviours using the different decision logic in case study 3 (Chapter 6: Section 6.5.1-Experiment A2-1, A2-2 and A2-4). More realistic human proactive behaviour is modelled in the combined DES/ABS model, so a different concept of complex decision logic is applied. As discussed in Chapter 6, some proactive behaviour is difficult to model in DES and for that reason such behaviour is excluded from modelling.

Regarding the simulation results, the complex and realistic proactive behaviours that habitually occur in the real system are worth modelling in a case study 3 situation as it has demonstrated a big impact to the overall system performance in combined DES/ABS model.

From the evidence presented in case studies 1, 2 and 3, modelling reactive versus mixed reactive and proactive behaviours does emphasise the value of implementing the proactive behaviours, as the overall performance measures have an impact on both DES and combined DES/ABS models. The greatest impact on the performance measures when modelling proactive behaviours in the three case studies is the reduction in customer waiting time and in the number of customers not served.

To conclude from the perspective of the model results investigation, DES is a suitable simulation approach for modelling simple proactive behaviour problems as in case studies 1 and 2, while combined DES/ABS should be the preferred choice when the need arises to model complex and frequently occurring proactive behaviour. This result is supported by the evidence offered by the survey from the viewpoint of the simulation expert (refer Chapter 3: Section 3.5.5).

Complex and infrequent occurring proactive behaviour does not seem have a big impact on results and therefore it is recommended to use DES in these cases and ignore modelling the complex proactive behaviour as the cost/benefit ratio for modelling it would be quite low.

Objective 2: To investigate the similarities and differences in the model difficulty performance for DES and combined DES/ABS.

The investigation into model difficulty in the three case studies reveals that the DES models are less difficult to build and run quicker, compared to the combined DES/ABS models. However, the model LOC investigation shows the same scale of difficulty in both models.

The results on building time are supported by the evidence from the survey results given by the simulation expert in Chapter 3: Section 3.5.5. However, the findings from the survey on model LOC do not match the result from the model difficulty investigation of this study. As the result from the survey is from the opinion of the simulation expert, it is difficult to judge whether this is completely accurate. But when reference is made to the empirical study conducted among the simulation beginners in case study 1 (Chapter 4: Section 4.5.3), the model LOC is found to be similar in both DES and combined DES/ABS models. The result of model LOC from the empirical study is therefore more reliable for this case.

Drawing from the conclusions of the investigations into model result and model difficulty, presented in case studies 1, 2 and 3, modelling reactive behaviour is deemed suitable for modelling in DES as it has less modelling difficulty (i.e. model building and execution time). The empirical evidence of the three case studies demonstrates that DES is suitable for modelling reactive behaviour since it offers straightforward process-oriented modelling. In addition, the existing enterprise library object in the Anylogic software used in this study has contributed to faster DES model development.

Modelling mixed reactive and simple proactive behaviours is considered suitable for modelling in DES since it has less modelling difficulty, but only for case studies 1 and 2. On the other hand, combined DES/ABS approach is deemed suitable for modelling the mixed reactive and complex proactive behaviours in case study 3, although there is a high level of model difficulty.

The new knowledge that has been gained from the investigations into model result and model difficulty has produced a summary of comparison results in modelling human behaviour using DES and combined DES/ABS which is presented in the next section.

7.3 Contribution to knowledge

The comparison of human behaviour modelling especially in modelling the different level of detail of proactive behaviour in DES and combined DES/ABS is a key contribution to simulation and operational research. Knowledge of this comparison is valuable for the simulation users as it is very important they have some understanding of the capability of DES and combined DES/ABS in modelling different level of detail of human behaviour. With the intention of human behaviour modelling comparison, a careful choice of simulation model can be made for solving the problem they have identified.

The exploration carried out in the present study reveals that overall it is worth modelling proactive behaviour as it provides a big impact to the simulation results to be drawn from the investigated problem. In addition, the empirical study presented here, also reveals the similarities and dissimilarities between DES and combined DES/ABS when investigating a similar problem domain using similar and different modelling solutions from the perspective of model result and model difficulty. This insight is essential as it then reveals the benefits and the weaknesses of both simulation models relating to the problem under investigation.

The new knowledge that has been gathered is valuable not only to the user of simulation and OR study but also in contributing to the literature in comparing DES and combined DES/ABS models for human behaviour modelling.

7.4 Limitation of Comparison Study

The scope of the comparison is limited to research study in modelling human reactive and proactive behaviours for DES and combined DES/ABS models. Only three types of proactive behaviours have been investigated (see Chapter 3.2). In addition, this comparison is only suited to understand those problems of a service-oriented system that are based on processes and queues. Due to the limitation of the time frame of the present research, only three case studies are used to develop this practice.

Other than the limitation of scope and time, the simulation software used in this study also consist of some modelling limitation. A combined DES/ABS approach could be impressive in modelling human behaviour for service-oriented systems, but its development and execution times are far longer than in the DES approach.

The main reason for the longer development time is due to modelling a service-oriented system based on a queuing environment is not straightforward in the combined DES/ABS model due to the fact that there is no easy plug and play library in Anylogic ™ (XJTechnologies 2010). The queuing algorithm has to be first developed to allow the first in first out queuing policy. In contrast, the queuing process is easily modelled using the DES approach as there is an existing library for queues, included together with a queuing policy in the DES simulation software.

7.5 Future Work

This final section presents recommendations for future work to address the limitation of this study, as presented in Section 7.4 above. This includes ideas for improving the validity of the comparison results from the model result and model difficulty investigations.

Potential Validity Improvement of the Results from Model Result and Model Difficulty Investigation of the Current Study

- Investigate the performance of DES and combined DES/ABS in further real life case studies of a service-oriented system.
- Investigate the performance of DES and combined DES/ABS in a large sample with more complex proactive behaviours.
- Conduct a laboratory survey on simulation expertise for improving the validity of results in model difficulty investigations.

Potential Investigation for Improving the HBMP

- Add more comparison measures i.e. model architecture or model use.
- Add Agent Based Simulation (ABS) as the third simulation approach in investigating a non-queue environment in the service-oriented system - to provide a clear distinction between DES, combined DES/ABS and ABS in modelling human behaviours.

BIBLIOGRAPHY

A.Tako, A. and S. Robinson (2006). Towards An Empirical Comparison of Discrete-Event Simulation and System Dynamics in the Supply Chain Context S. R. In the Proceedings of the 2006 OR Society Simulation Workshop, S. Taylor, S. Brailsford and J.Garnett, eds.

A.Tako, A. and S. Robinson (2008). Comparison of Model Building in Discrete-Event Simulation and System Dynamics. Operational Research Society 4th Simulation Workshop (SW08).

A.Tako, A. and S. Robinson (2009). "Comparing discrete-event simulation and system dynamics: Users' perceptions." Journal of the Operational Research Society **60**: 296-312.

Bakken, D. G. (2006). Agent-Based Simulation for Improved Decision-Making. Proceedings of the Sawtooth Software Conference Florida.

Banks, J. (1998). Handbook of Simulation: Principles, Methodology, Advances, Applications and Practice. United States of America, John Wiley & Sons,Inc.

Banks, J. (2000). Introduction to Simulation. Proceedings of the 2000 Winter Simulation Conference.

Banks, J., et al. (2005). Discrete-Event System Simulation United States of America Prentice Hall.

Barton, P., et al. (2004). "Modelling in the economic evaluation of health care: selecting the appropriate approach." Journal of Health Services Research & Policy **9**(2): 110-118.

Baysan, S., et al. (2009). Modeling People Flow:A Real Life Case Study in ITU Science Center.

Bazzan, A. L. C., et al. (1999). Agents in Traffic Modelling: From Reactive to Social Behaviour, Springer Berlin / Heidelberg.

Beasley, J. E. (2010) "Lectures Notes : OR Notes."

Becker, M., et al. (2006). Agent-based and Discrete Event Simulation of Autonomous Logistic Processes,. Proceedings of the 20th European Conference on Modelling and Simulation. W. O. Borutzky, A. Zobel, R., eds.,**:** 566-571.

Bonabeau, E. (2001). "Agent-based modeling: methods and techniques for simulating human systems." In Procceding of National Academy of Sciences **99**(3): 7280-7287.

Borshchev, A. and A. Filippov (2004). From System Dynamics and Discrete Event to Practical Agent Based Modeling: Reasons,Techniques,Tools. Proceedings of the 22nd International Conference of the System Dynamics Society. Oxford, England.

Brailsford, S. and K. Katsaliaki (2007). "Using simulation to improve the blood supply chain." Journal of the Operational Research Society **58**: 219-227.

Brailsford, S. and D. Stubbins (2006). Using Discrete-Event Simulation to MOdel Emergency Evacuation of a Public Building. Proceedings of the 2006 OR Society Simulation Workshop S. Robinson, S. Taylor, S. Brailsford and J.Garnett, eds.

Brailsford, S. C. and N. Hilton (2000). A Comparison of Discrete Event Simulation and Ssystem Dynamics for Modelling Healthcare Systems. In: Riley J (ed) Proceedings from ORAHS 2000. Glasgow, Scotland**:** 18-39.

Brailsford, S. C., et al. (2006). Incorporating Human Behaviour in Healthcare Simulation Models. In Proceeding of the 38th Winter simulation Conference, Monterey, California.

Brooks, R. J. (1996). A framework for choosing the best model in mathematical modelling and simulation. Faculty of Engineering, University of Birmingham. **PhD**.

Buxton, D., et al. (2006). The Aero-Engine Value Chain Under Future Business Environments: Using Agent-Based Simulation To Understand Dynamic Behaviour. MITIP2006. Budapest

Carson, J. S. (2003). Introduction to Modeling and Simulation. Proceedings of the 2003 Winter Simulation Conference S. Chick, P. J. Sánchez, D. Ferrin, and D. J. Morrice, eds.

Chahal, K. and T. Eldabi (2008). System Dynamics and Discrete Event Simulation : A Metacomparison. In the proccedings of UK Operational Reserach Society Simulation Workshop 2008 (SW08). England,UK.

Checkland, P. (1981). System Thinking, Systems Practice. UK, John Wiley and Sons.

Cheng, L. and M. A. Duran (2004). "Logistics for world-wide crude oil transportation using discrete event simulation and optimal control " Computers & Chemical Engineering **28**(6-7): 897-911.

Crant, J. M. (2000). "Proactive Behaviour in Organizations, In Proceedings of Journal of Management." **26**(3): 435-462.

Darley, V., et al. (2004). An agent-based model of a corrugated-box factory: The trade-off between finished goods stock and on-time-in-full delivery. Proceedings of the 5th Workshop on Agent-Based Simulation. Lisbon, Portugal.

Davidsson, P. (2001). Multi Agent Based Simulation:Beyond Social Simulation, Spinger Berlin.

Dubiel, B. and O. Tsimhoni (2005). Integrating Agent Based Modelling Into Discrete Event Simulation Proceedings of the 2005 Winter Simulation Conference.

Eldabi, T., et al. (2007). "Simulation modelling in healthcare: reviewing legacies and investigating futures." Journal of the Operational Research Society **58**: 262-270.

Emrich, Š., et al. (2007). Fully agent based modellings of epidemic spread using AnyLogic. Proceedings of the European Simulation (EUROSIM) 2007. Ljubljana, Slovenia.

Ferber, J. and A. Drogoul (1991). Using Reactive Multi-Agents Systems in Simulation and Problem Solving. Distributed Artificail Intelligence : Theory and Praxis. Netherlands, Kluwer Academic Publishers.

Fishman, G. S. (1973). Concepts and Methods in Discrete Event Digital Simulation. New York, John Wiley & Sons.

Forrester, J. W. (1958). "Industrial Dynamics: A Major Breakthrough for Decision Makers." Harvard Business Review **36**(4): 37-66.

Grant, A. M. and S. J. Ashford (2007). "The Dynamic of Proactivity at Work." Research in Organizational Behavior.

Halpin, T. and G. Wagner (2003). Modeling Reactive Behavior in ORM Conceptual Modeling - ER 2003 Springer Berlin / Heidelberg.

Hlupic, V. and G.-J. D. Vreede (2005). "Business process modelling using discrete-event simulation: current opportunities and future challenges." International Journal of Simulation and Process Modelling.

Hollocks, B. W. (2004). Still Simulating After All These Years - Reflections on 40 Years in Simulation. Proceedings of the 2004 Operational Research Society Simulation Workshop (SW04).

Jan, T. S. and J. H. Chen (2005). "A system dynamics model of the semiconductor industry development in Taiwan." Journal of the Operational Research Society **56**: 1141-1150.

Jennings, N. R., et al. (1998). "A Roadmap of Agent Research and Development. ." International Journal of Autonomous Agents and Multi-Agent Systems **1**(1): 7-38.

Kadar, B., et al. (2005). Building Agent-Based Systems in a Discrete-Event Simulation Environment. Multi-Agent Systems and Applications IV, Springer Berlin / Heidelberg.

Kalpakjian, S. and S. R. Schmid (2001). Manufacturing Engineering and Technology. New Jersey, Prectice-Hall.

Kelton, W. D., et al. (2007). Simulation with ARENA. New York, USA., McGraw-Hill.

Kendall, E. A., et al. (1998). Patterns of Intelligent and Mobile Agents. In the Procedings of International Conference on Autonomous Agents 92-99.

Komashie, A. and A. Mousavi (2005). Modeling emergency departments using discrete event simulation techniques. Proceedings of the 37th conference on Winter simulation

Korhonen, T., et al. (2008). FDS+Evac: An Agent Based Fire Evacuation Model Pedestrian and Evacuation Dynamics 2008 Springer Berlin Heidelberg.

Korhonen, T., et al. (2008). FDS+Evac: Modelling Social Interactions in Fire Evacuation. 7th Intl. Conf. on Performance-Based Codes and Fire Safety Design Methods.

Law, A. M. and W. D. Kelton (2000). Simulation Modeling and Analysis: Fourth Edition. . New York McGraw-Hill.

Law, A. M. and M. G. McComas (1997). Simulation of Manufacturing Systems. Proceedings of the 1997 Winter Simulation Conference**:** 49-52.

Lorenz, T. and A. Jost (2006). Towards an orientation framework in multi-paradigm modeling. Proceedings of the System Dynamics Society Conference. Nijmegen, The Netherlands.

Macal, C. M. and M. J. North (2005). Tutorial on Agent-Based Modelling and Simulation. In the Proceedings of the 2005 Winter Simulation Conference. N. M. S. M. E. Kuhl, F. B. Armstrong, and J. A. Joines**:** 2-15.

Macy, M. W. and R. Willer (2002). "From Factors to Actors :Computational Sociology and Agent-Based Modeling." Annual Review Sociol **28**: 143-66.

Mahoney, E. J., et al. (2005). "Lessons Learned from a Nightclub Fire: Institutional Disaster Preparedness." Journal of Trauma-Injury Infection & Critical Care **58**(3): 487-491.

Majid, M. A., et al. (2010). Modelling Reactive and Proactive Behaviour in Simulation Operational Research Society 5th Simulation Workshop (SW10). Worcestershire, England.

Maria, A. (1997). Introduction to Modeling and Simulation. Proceedings of the 1997 Winter Simulation Conference ed.S.Andradottir, K.J.Healy, D.H.Withers, and B.L.Nelson.

Marin, M., et al. (2006). System Dynamics and Agent-Based Simulations for Workforce Climate, In the Proceedings of the 2006 Winter Simulation Conference**:** 667-671.

McHaney, R. (1991). Computer Simulation: A Practical Perspective. London, Academic Press, Inc.

Minitab (2000). Minitab Inc.

Morecroft, J. and S. Robinson (2006). Comparing Discrete Event Simulation and System Dynamics: Modelling Fishery. The OR Society Worksop Proceedings**:** 137-148.

Nehme, C., et al. (2008). Using Discrete-Event Simulation to Model Situational Awareness of Unmanned-Vehicle Operators. Virginia Modeling, Analysis and Simulation Center Capstone Conference. Norfolk, VA.

Owen, C., et al. (2008). Selection of Simulation Tools for Improving Supply Chain Performance. Proceedings of the 2008 OR Society Simulation Workshop 199-207.

Page, B., et al. (1999). A Discrete Event Simulation Framework for Agent-Based Modelling of Logistic Systems. Proceedings of 11th European Simulation Symposium and Exhibition.

Parker, S. K., et al. (2006). "Modeling the Antecedents of Proactive Behavior at Work." Journal of Applied Psychology **91**(3): 636-652.

Parunak, H. V. D., et al. (1998). Agent-Based Modeling vs. Equation-Based Modeling: A Case Study and Users' Guide Multi-Agent Systems and Agent-Based Simulation

Pew, R. W. and A. S. Mavor (1998). Modeling Human and Organizational Behavior: Application to Military Simulations. National Academy Press. A. S. (Eds.). Washington DC, National Research Council.

Pidd, M. (1984). Computer Simulation in Management Science. West Sussex, England, John Wiley & Sons,Inc.

Pidd, M. (1998). Computer Simulation in Management Science, Wiley.

PractilineSoftware. (2009). from http://sourcecount.com/support.htm.

ProModel (2010). "Justifiying Simulation."

Pugh, G. A. (2006). Agent-Based Simulation of Discrete-Event Systems , In Proceedings of the 2006 Illinois-Indiana and North Central Joint Section Conferences.

Raczynski, S. (2006). Modelling and Simulation. England, John Wiley & Sons,Ltd.

Rank, J., et al. (2007). "Proactive Customer Service Performance: Relationships with Individual, Task and Leadership Variable. In Proceedings of Journal of Human Performance." 20 **4**: 363-390.

Richardson, G. P. and A. L. Pugh (1981). Introduction of System Dynamics Modeling with DYNAMO. Cambridge, MA,USA, MIT Press.

Robinson, S. (1994). Successful Simulation : A Practical Approach to Simulation Projects. Berkshire,England, McGraw-Hill.

Robinson, S. (2004). "Discrete-event simulation: from the pioneers to the present, what next? ." Journal of the Operational Research Society **56**(no.6): 619–629.

Robinson, S. (2004). Simulation: The Practice of Model Development and Use West Sussex, England, John Wiley & Sons, Ltd.

Robinson, S. (2010). Modelling Service Operations : A mixed Discrete-Event and Agent Based Simulation Approach. Proceedings of the Operational Research Society Simulation Workshop 2010 (SW10).

Salt, J. D. (1993). "Keynote address- Simulation Should be Easy and Fun!" Proceedings of the 1993 Winter Simulation Conference 1-5.

Samek, M. (2009). Practical UML statecharts in C/C++ : event-driven programming for embedded systems, Newnes.

Scerri, D., et al. (2010). An Architecture for Modular Distributed Simulation with Agent-Based Models. The 9th International Conference on Autonomous Agents and Multiagents Ssystems. Toronto,Canada.

Schenk, T. A., et al. (2007). "Agent-based simulation of consumer behavior in grocery shopping on a regional level " Journal of Business Research **60**(8): 894-903

Semini, M., et al. (2006). Applications of discrete-event simulation to support manufacturing logistics decision-making: a survey. Proceedings of the 38th conference on Winter simulation

Shah, A. P., et al. (2005). Analyzing Air Traffic Management Systems Using Agent-Based Modeling and Simulation. 6th USA/Europe Air Traffic Management Research and Development (ATM R&D) Seminar Baltimore, Maryland.

Shannon, R. E. (1975). Systems Simulation – The Art and Science, Prentice-Hall.

Shendarkar, A., et al. (2006). Crowd Simulation for Emergency Response Using BDI Agent Based on Virtual Reality. Proceedings of the 2006 Winter Simulation Conference

Siebers, P.-O. (2004). The Impact of Human Performance Variation on the Accuracy of Manufacturing System Simulation Models. School of Industrial and Manufacturing Science, University of Cranfield, UK. **PhD**.

Siebers, P.-O., et al. (2007). Using Intelligent Agents to Understand Management Practices and Retail Productivity. Proceedings of the 2007 Winter Simulation Conference

Siebers, P.-O., et al. (2008). An Agent-Based Simulation of In-Store Customer Experiences. In Proceedings of the 2008 Operational Research Society Simulation Workshop, Worcestershire, UK.

Siebers, P.-O., et al. (2010). "Towards The Development of a Simulator for Investigating the Impact of People Menagement Practices on Retail Performance." Proceedings of Journal of Simulation

Siebers, P.-O., et al. (2010). "Discrete-event simulation is dead, long-live agent -based simulation!" Journal of Simulation **4**(3): 204-210.

Sterman, J. D. (2000). Business Dynamics:System Thinking and Modeling for a Complex World, Mc GrawHill.

Sweetser, A. (1999). A Comparison of System Dynamics and Discrete Event Simulation. Proceedings of 17th International Conference of the System Dynamics Society and 5th Australian & New Zealand Systems Conference. Wellington, New Zealand.

Tilanus, C. B. (1985). "Failures and successes of quantitative methods in management." Journal of Operational Research Society(19): 170-175.

Tumay, K. (1996). Business Process Simulation. . Proceedings of the 1996 Winter Simulation Conference

Twomey, P. and R. Cadman (2002). "Agent-based modelling of customer behaviour in the telecoms and media markets."

Vlachos, D., et al. (2007). "A system dynamics model for dynamic capacity planning of remanufacturing in closed-loop supply chains." Computers & Operations Research **34**(2): 367-394.

Wakeland, W., et al. (2004). Comparison of System Dynamic and Agent-Based Simulation Applied to the Study of Cellular Receptor Dynamics. In Proceedings of the 37th Hawaii International Conference on System Sciences.

Wakeland, W., et al. (2005). A Tale of Two Methods- Agent-based Simulation and System Dynamics- Applied in a Biomedical Context: Acute Inflammatory Response. 6th European Congress of System Science.

Wang, W. and R. J.Brooks (2007). Empirical investigations of conceptual modeling and the modeling process. Proceedings of the 2007 Winter Simulation Conference.

Ward, S. (2010) "8 Rules For Good Customer Service." Good Customer Service Made Simple.

Ward, S. C. (1989). "Arguments for constructively simple models." Journal of Operational Research Society **40**(2): 141-153.

Werker, G. and A. S. S. Shechter (2009). "The use of discrete-event simulation modelling to improve radiation therapy planning processes " Radiotherapy and Oncology **92**(1): 76-82.

Wray, R. E. and J. E. Laird (2003). Varibility in Human Behaviour Modeling for Military Simulations. In Proceeding of the Behaviour Representation in Modeling & Simulation Conference (BRIMS).

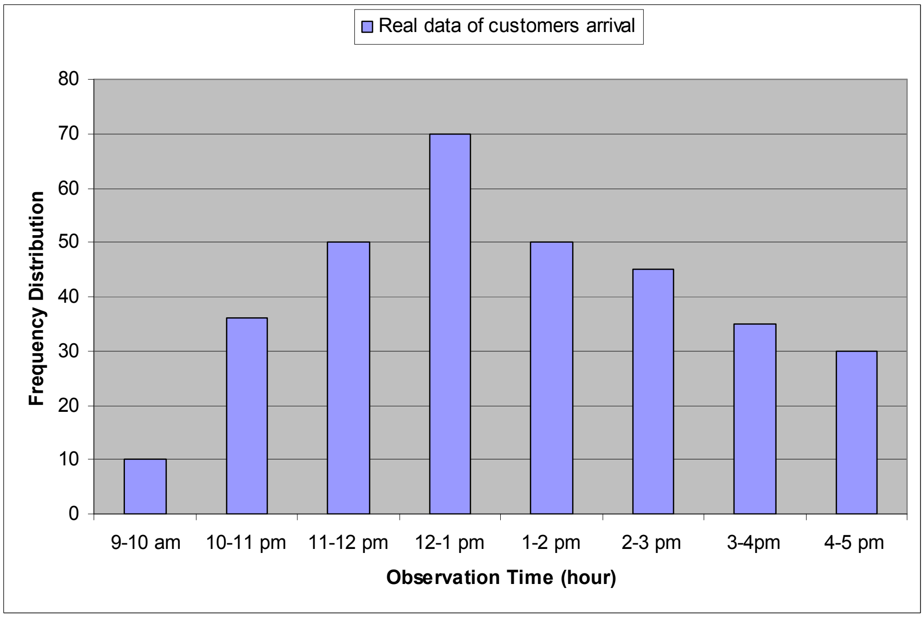
Wooldridge, M. (2002). An Introduction to Multiagent Systems. England, John Wiley & Sons Inc.

XJTechnologies. (2010). from http://www.xjtek.com/support/documentation/.

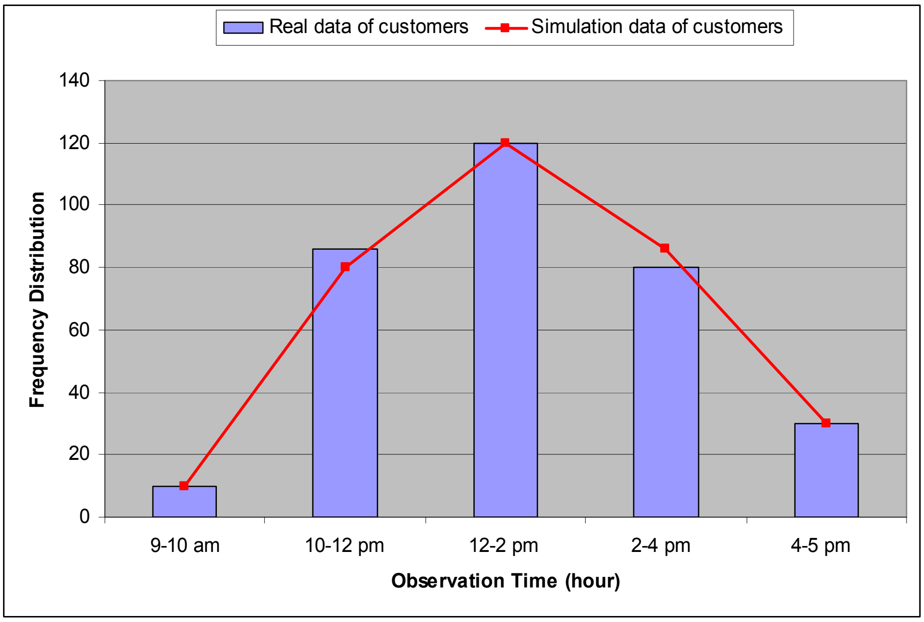
Yu, T.-T., et al. (2007). Agent-Based and Discrete-Event Modelling: A quantitative approach,. Proceedings of the 7th AIAA Aviation Technology, Integration and Operation Conference, ATIO. Belfast, Northern Ireland.

Zaigler, B. P., et al. (2000). Theory of Modelling and Simulation. United States of America, Academic Press.

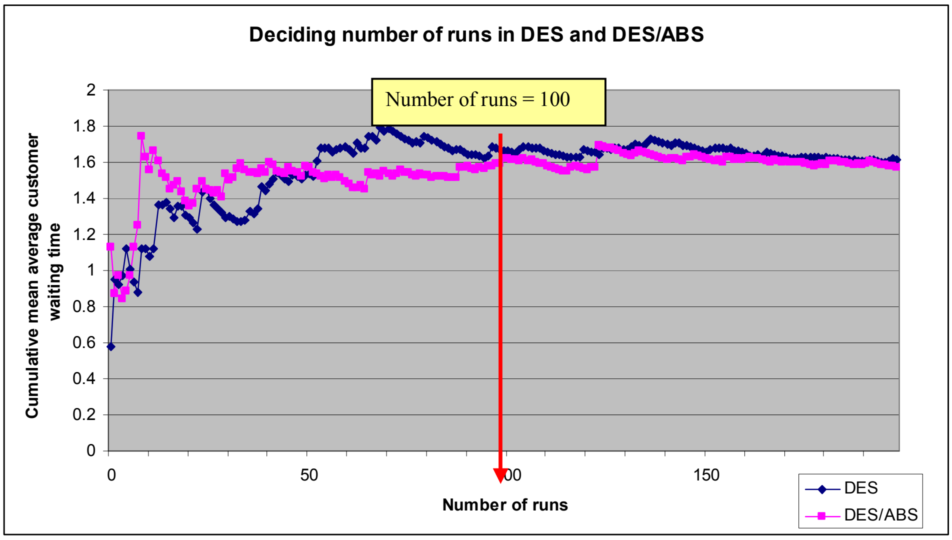
Appendix A



Appendix A.1: Distribution of customers arrival in the real system on a typical day



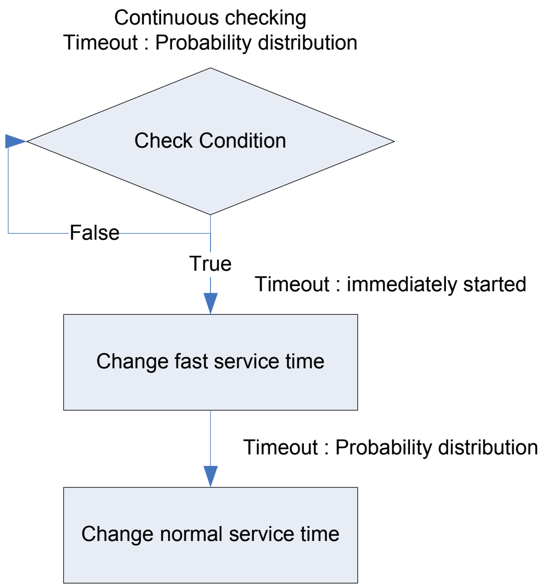
Appendix A.2: Data of real system compared with data of the simulation model input



Appendix A.3: Deciding number of runs by plotting the cumulative mean average of customers waiting time from DES and DES/ABS models.

Customers arrival			
Arrival Time	**Arrival Pattern 1 (people per hour)**	**Arrival Pattern 2 (people per hour)**	**Arrival Pattern 3 (people per hour)**
9.00 – 10.00 am	10	13	22
10.00 – 12.00pm	40	46	78
12.00 – 2.00 pm	60	78	131
2.00 – 4.00 pm	43	56	95
4.00 – 5.00 pm	30	39	66

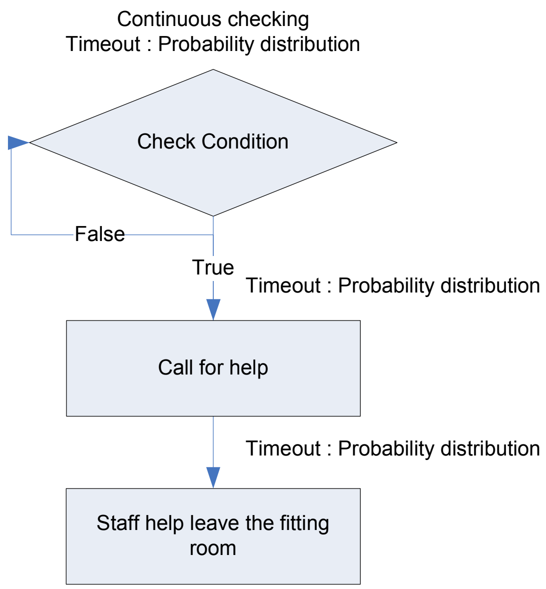
Appendix A.4: The three arrival patterns for the customers arrival in the fitting room operation



Appendix A.5 : Flow chart illustrating human proactive behaviour decision-making flow chart for DES and combined DES/ABS in Experiment A2_1

```
Event Check Condition

for ( all fitting room cubicles )
  if ( fitting room cubicles is busy = false && customer
       waiting in entry queue >= number waiting )
       start event change service time without delay;

  else if ( customer waiting in return queue >= number waiting )
        start event change service time  without delay;

  else if ( customer waiting in help queue >=  number waiting )
        start event change service time without delay;

Event Change Service Time

for (staff )
     existing service time = new service time;
     count the service time changes;
     start event change to existing  service time by delay  (probability
     distribution);

Event Change To Existing Service Time
for (staff )
     existing service time =  existing  service time;
```

Appendix A.6: Human proactive behaviour decision-making pseudo codes for DES and combined DES/ABS in Experiment A2-1.



Appendix A.7 : Human proactive behaviour decision-making flow chart in Experiment A2-2

Event Check Condition

```
for (all fitting room cubicles )
 if ( fitting room cubicles is busy =  false && customer waiting in
      entry queue >= number waiting )
     start event call for help without delay;

 else if (customer waiting in return queue >= number waiting )
     start event  call for help without delay;

 else if ( customer waiting in help queue >= number waiting )
     start event  call for help without delay;
```

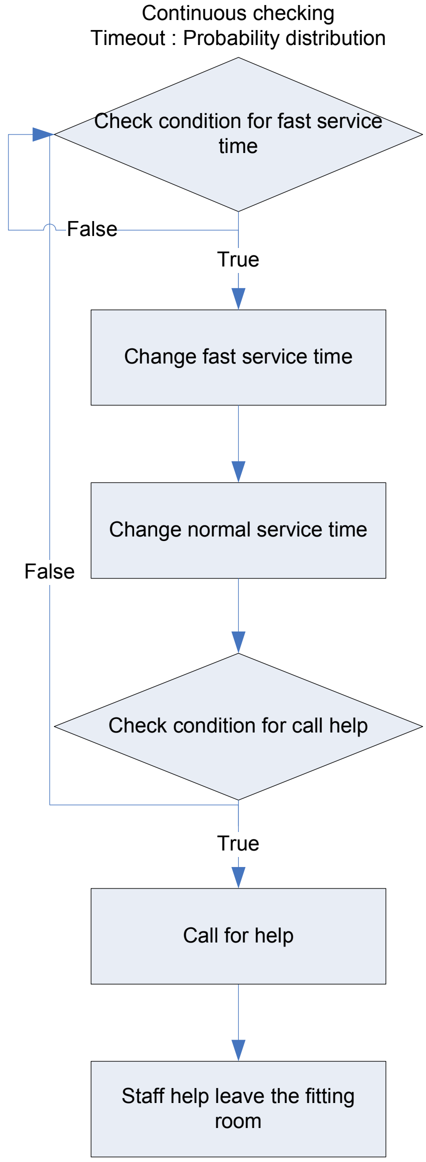
Event Call for help

```
for ( all staff )
    add one staff;
    count the number of call for help;
    start event staff help leave  (probability distribution);
```

Event Staff help leave

```
for (staff )
    remove one staff;
```

Appendix A.8 : Human proactive behaviour decision making pseudo code in Experiment A2-2



Appendix A.9 : Human proactive behaviour decision-making flow chart in Experiment A2-3

Event Check Condition

```
For < all fitting room cubicles >
  If < fitting room cubicles is busy =
      false && customer waiting in entry
      queue >= number waiting >
      start event change service time
      without delay;
  else
  If < customer waiting in return queue
      >= number waiting >
      start event change service time
      without delay;
  else
  If < customer waiting in help queue >=
      number waiting >
      start event change service time
      without delay;
```

Event Change Service Time

```
For < staff >
     existing service time = new service
     time;
     count the service time changes;
     start event change to existing
     service time by delay
     (probability distribution);
```

Event Change To Existing Service Time

```
For < staff >
     existing service time =  existing
     service time;
```

Event Check Condition

```
For < all fitting room cubicles >
  If < fitting room cubicles is busy =
      false && customer waiting in entry
      queue >= number waiting >
      start event call for help
      without delay;
  else
  If < customer waiting in return queue
      >= number waiting >
      start event  call for help
      without delay;
  else
  If < customer waiting in help queue >=
      number waiting >
      start event  call for help
      without delay;
```

Event Call for help

```
For < staff >
     add one staff;
     count the number of call for help;
     start event staff help leave
     (probability distribution);
```

Event Staff help leave

```
For < staff >
     remove one staff;
```

Appendix A.10 : Human proactive behaviour decision making pseudo code in Experiment A2-3

Hardware	**Specification**
Operating system	Microsoft Windows XP Professional 20002
Processor	1.86GHz Intel (R) Core (TM) 2 CPU
Memory of Ram	2.5GB
Capacity of Hardisk	75GB

Appendix A.11 : Specification of the computer hardware

APPENDIX A:12

MODEL DIFFICULTY INVESTIGATION

Instructions

First : You need to develop a conceptual model e.g. using a flow chart to describe the given problem. Please stop designing the model after 15minutes.

Second : You need to develop 3 simulation models either using Discrete Event Simulation (Model A, B, C) or combined Discrete Event and Agent Based Simulation (Model D, E, F). Please refer to the provided user manual for this purpose. Please ask if you have problems to understand the user manual.

Third : While developing the simulation model, please answer the provided questionnaires which is based on the simulation model performance.

Case Study Scenario

The case study is about the fitting room operation in one department store. When the customer arrived at the fitting room, the staff member reacts to the customer by counting their clothes and will give a card to them which contains the number of clothes. After trying their clothes, the customer will return the card to the sales staff together with their unwanted clothes. The sale staff will react to the customer by receiving the card and the clothes. The customer can request help from the sales staff while in the fitting room's cubicle and the staff will react to the customer by providing help.

The scenario describes above is about the reactive behaviour of a sale staff towards the customers which modelled in Model A (DES) or Model D (DES/ABS). Then we extended the scenario by adding one proactive behaviour in Model B (DES) or Model E (DES/ABS) and another one proactive behaviour in Model C (DES) or Model F (DES/ABS).

Background Questions

1	Which simulation model you used before?	☐ **Discrete Event Model** ☐ **Agent Based Model**
2	How long is your experience in simulation?	☐ **< 1 year** ☐ **1 - 2 years** ☐ **> 2 years**

Model Performance Questions

1 Which model you will be developed in this survey?	☐ **Discrete Event Model** ☐ **Agent Based Model**
	☐ **Model A** ☐ **Model B** ☐ **Model C** ☐ **Model D** ☐ **Model E** ☐ **Model F**
2 Model Development Questions	
a. Draw a flow chart based on the case study scenarios in the provided sheet. *(only for Model A and Model D)*	**Start time :_______ End time : _______**
b. Model development time	**Start time : _______ End time :________**
c. Performance measures results	
i. Customer waiting time	**_________minutes**
ii. Staff utilisation 1	**__________%**
iii. Staff utilisation 2	**__________%**
iv. ServiceTimeChange	__________
v. CallHelp	__________
vi. Memory used	__________
vii. Speed of model	__________

3. What are the major impacts or differences when modelled reactive compared to reactive and proactive behaviour in your simulation models?
(eg: reducing customer waiting time, difficulty to develop the model, time consuming etc)

Flow Chart Diagram

Model Performance Questions

1 Which model you will be developed in this survey?	☐ **Discrete Event Model** ☐ **Agent Based Model**
	☐ **Model A** ☐ **Model B** ☐ **Model C** ☐ **Model D** ☐ **Model E** ☐ **Model F**
2 Model Development Questions	
a. Draw a flow chart based on the case study scenarios in the provided sheet. *(only for Model A and Model D)*	**Start time :_______ End time : _______**
b. Model development time	**Start time : _______ End time :________**
c. Performance measures results	
i. Customer waiting time	**_________minutes**
ii. Staff utilisation 1	**__________%**
iii. Staff utilisation 2	**__________%**
iv. ServiceTimeChange	__________
v. CallHelp	__________
vii.Memory used	__________
viii. Speed of model	__________
3. What are the major impacts or differences when modelled reactive compared to reactive and proactive behaviour in your simulation models? *(eg: reducing customer waiting time, difficulty to develop the model, time consuming etc)*	

Model Performance Questions

1 Which model you will be developed in this survey?	☐ **Discrete Event Model** ☐ **Agent Based Model**
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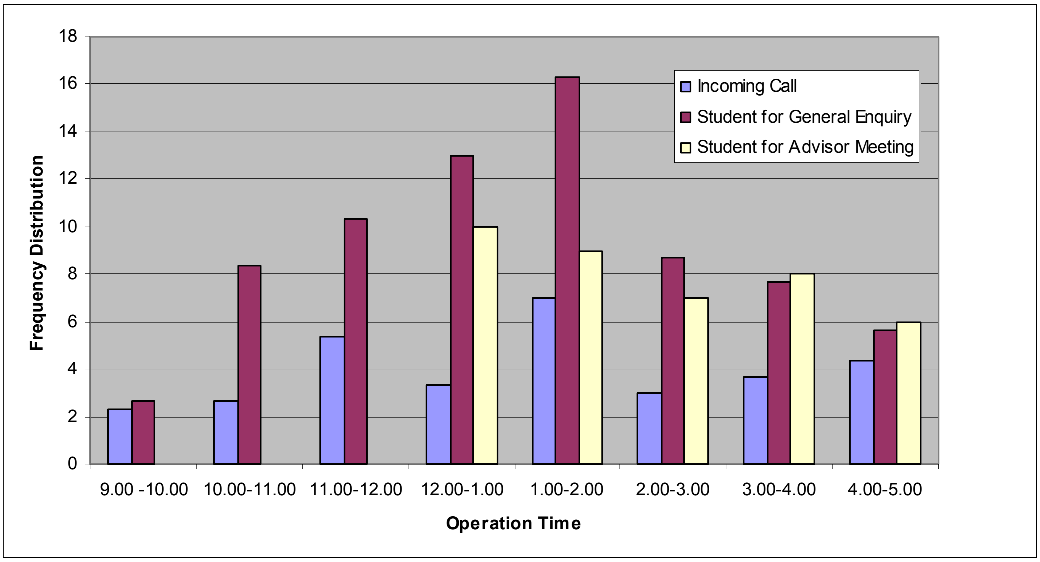
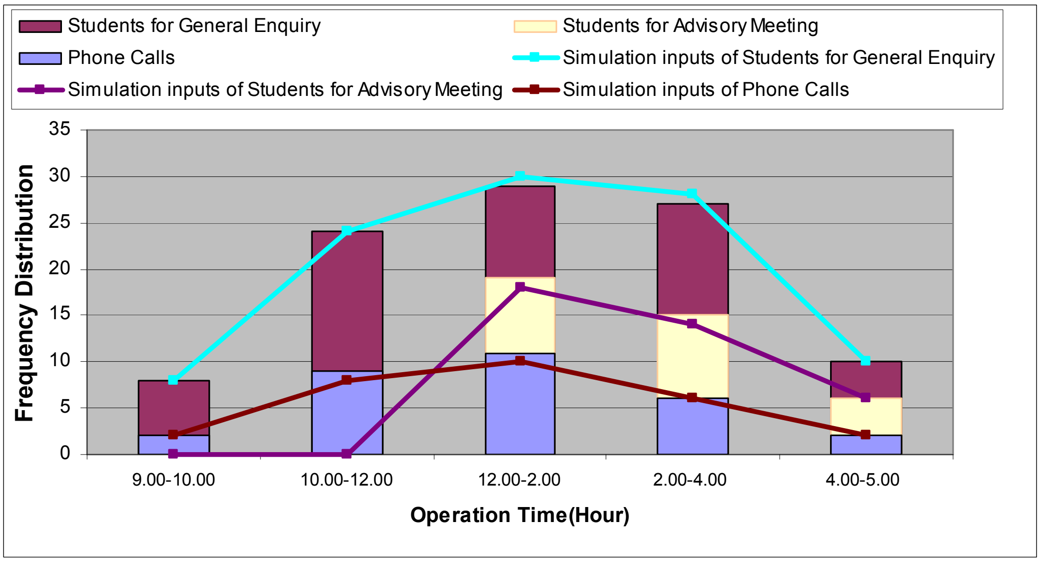
3. What are the major impacts or differences when modelled reactive compared to reactive and proactive behaviour in your simulation models? *(eg: reducing customer waiting time, difficulty to develop the model, time consuming etc)*

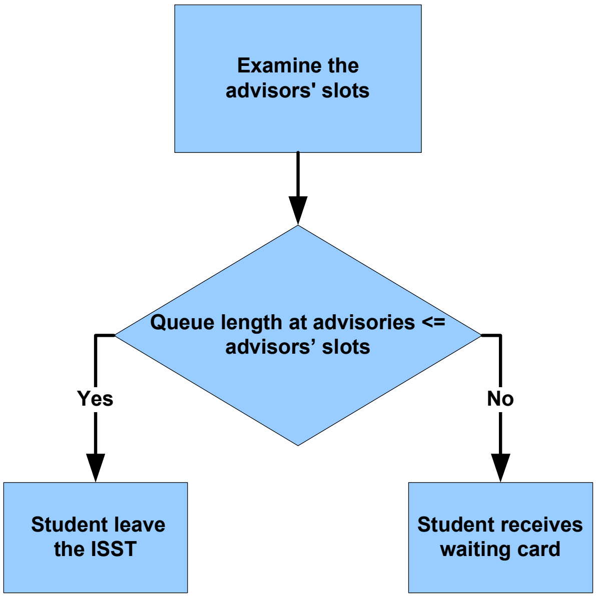
Appendix B



Appendix B.1 : Distribution of students' arrival and incoming calls in the real system on a typical day



Appendix B.2 : Data of real system compared with data of the simulation model input



Appendix B.3 : Decision-making flow chart of human proactive behaviour in Experiment A2-1

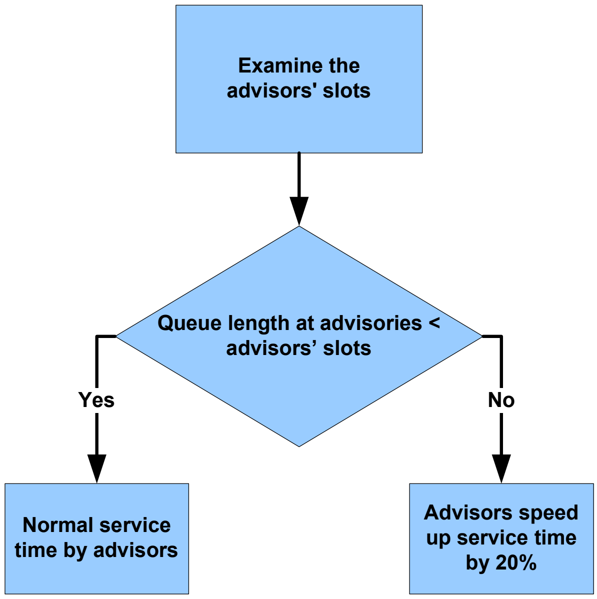
```
Function Check Available Slot

simulation time remaining;

available slots = simulation time
remaining / advisors student service
time;

Select output block

advisors queue length <= function
check available slot

if true, proceed to next process;

if false, remove the students out
from ISST;
```

(a) Proactive decisions pseudo codes in DES model

```
Function Check Available Slot

simulation time remaining;

available slots = simulation time
remaining / advisors student
service time;

Receptionist Agent

advisors queue length <= function
check available slot

if true, no message trigger;

if false, send message (TooBusy) to
student agent

Student Agent

if receive message (TooBusy),
remove the students out from ISST.
```

(b) Proactive decisions pseudo codes in DES/ABS model

Appendix B.4 : Human proactive behaviour decision-making pseudo codes for DES and combined DES/ABS in Experiment A2-1



Appendix B.5 : Human proactive behaviour decision-making flow chart in Experiment A2-2

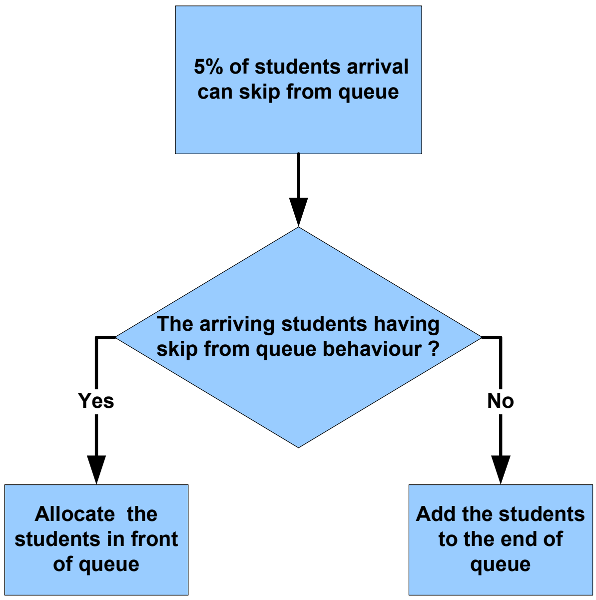
```
Function Check Available Slot ()

simulation time remaining;

available slots = simulation time
remaining / advisory student service
time;

Function Change Service Time ()

advisors queue length < function
check available slot

if true, no service time changes

if false, advisors speed up service
time by 20%

Advisors Service Block

call Function Change Service Time ()
```

(a) Proactive decisions pseudo codes in DES model

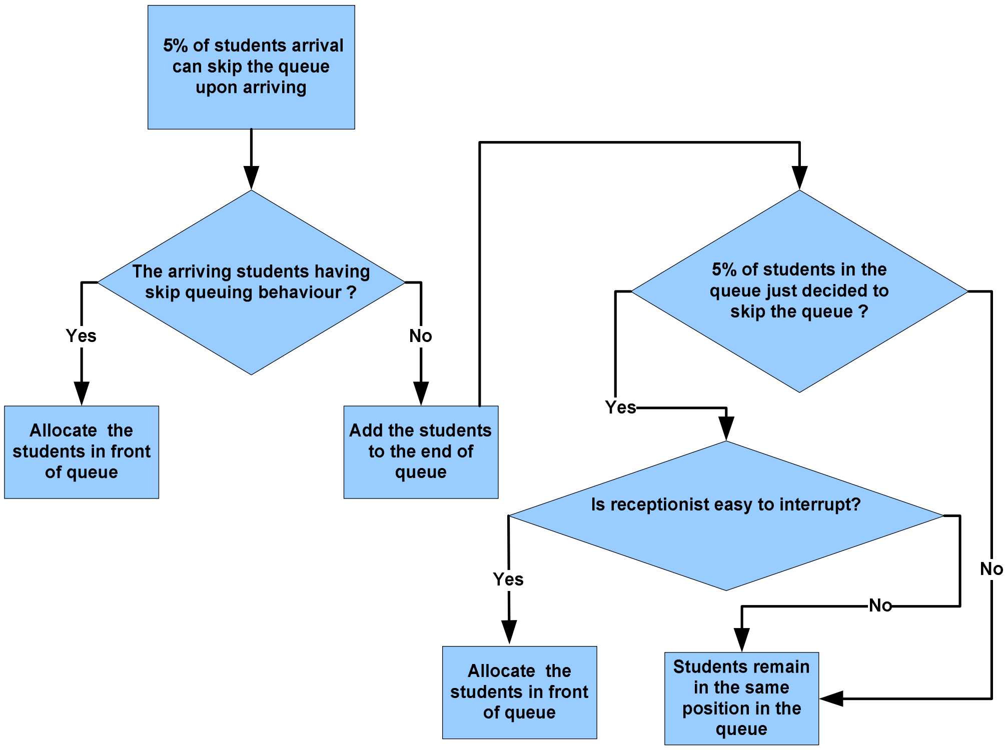
```
Function Check Available Slot ()

simulation time remaining;

available slots = simulation time
remaining / advisory student service
time;

Function Change Service Time ()

advisors queue length <  function
check available slotif true, no
service time changes

if false, advisors speed up service
time by 20%

Advisors Agent

call Function Change Service Time ()
```

(b) Proactive decisions pseudo codes in combined DES/ABS model

Appendix B.6 : Human proactive behaviour decision-making pseudo codes in Experiment A2



(a) Proactive decision-making flow chart in DES model



(b) Proactive decision-making flow chart in combined DES/ABS model

Appendix B.7 : Human proactive behaviour decision-making flow chart in Experiment A2-3

Student Arrival Block

//Random 5% of students arriving having the highest queue priority
 	
if (randomTrue = 0.05)
 	
student skip from queuing priority = 10;

Select Output Block
if the student arriving is having skip from queuing behaviour; if true, queuing at the receptionist block; //(block to serve skips from queuing students); if false, queuing at another receptionist block //(block for serving other students)

(a) Decision-making in DES model

Student Arriving State Chart

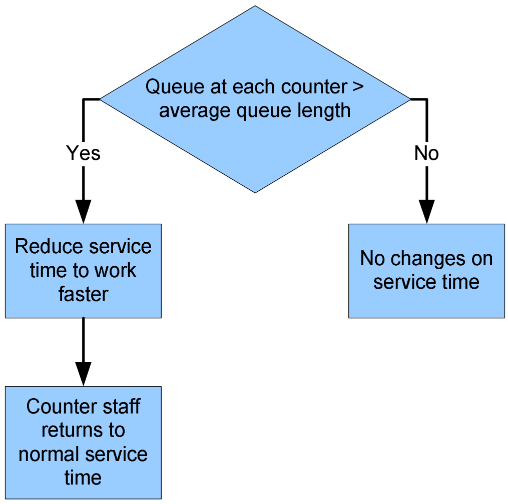
//Random 5% of students arriving is having skip queuing behaviour
 	
if (randomTrue = 0.05)
 	
student skip queuing priority = true;

Queuing State Chart
if the student arriving is having skip from queuing behaviour; if true, allocate the students in front of the queue; if false, allocate the students at the back of the queue;

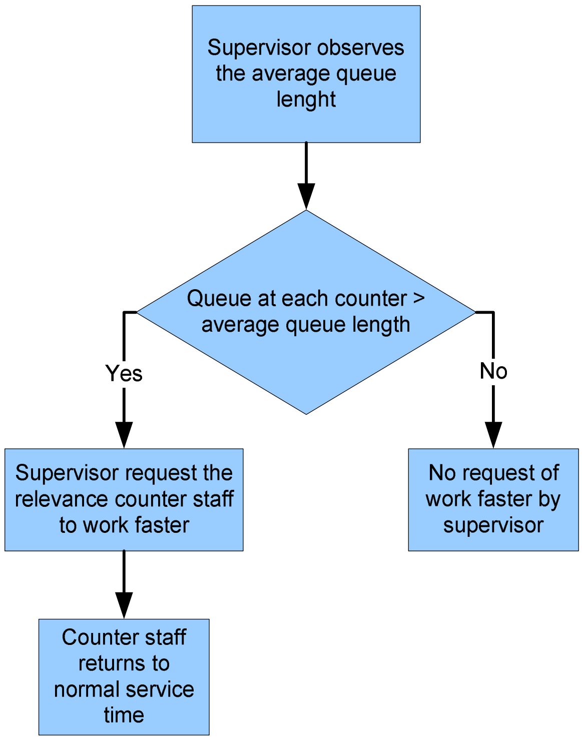
(b) Decision-making in DES/ABS model

Appendix B.8 : Human proactive behaviour decision-making pseudo code in Experiment A2-3

Appendix C



(a) Proactive decision-making in DES model



(b) Proactive decision-making in combined DES/ABS model

Appendix C.1 : Flow chart illustrating human proactive behaviour decision-making in Experiment A2-1

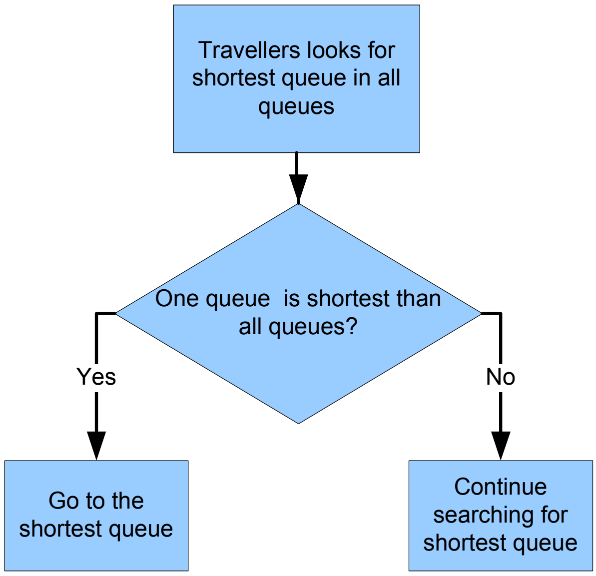
```
Function average queue length

Total travellers in queue/number of
counter

Function Calculate Service Speed

switch (CounterSource) {
case 1:
if
queue length at counter 1 > average
queue length;
reduce 10% of current service time;
after some delay by probability
distribution, return to normal
service time.

case 2:
if
queue length at counter 2 > average
queue length;
reduce 10% of current service time;
after some delay by probability
distribution, return to normal
service time.

case 3:
if
queue length at counter 3 > average
queue length;
reduce 10% of current service time;
after some delay by probability
distribution, return to normal
service time.

case 4:
if
queue length at counter 4 > average
queue length;
reduce 10% of current service time;
after some delay by probability
distribution, return to normal
service time.

case 5:
if
queue length at counter 5 > average
queue length;
reduce 10% of current service time;
after some delay by probability
distribution, return to normal
service time.

At each resource block

Call the calculate service speed
function;
```

(a) Proactive decisions pseudo codes in DES model

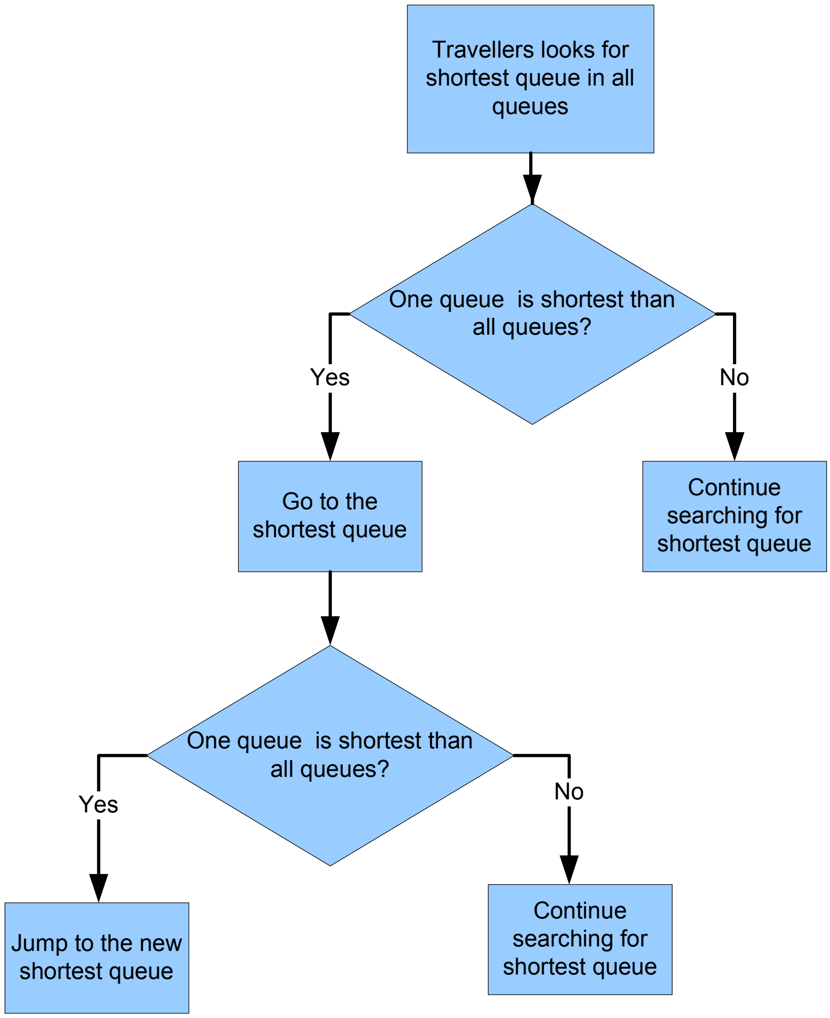
```
Function average queue length

Total travellers in queue/number of
counter

Supervisor Agent

Observes based on the probability
distribution;
if

queue at each counter > average
queue length;
send message to counter staff to
work faster;

Counter Staff Agent

receive message and work faster;
after some delay by probability
distribution, return to normal
service time;
```

(b) Proactive decisions pseudo codes in combined DES/ABS model

Appendix C.2 : Human proactive behaviour decision-making pseudo codes for DES and combined DES/ABS in Experiment A2-1



(a) Proactive decision- making in DES model



(b) Proactive decision-making in combined DES/ABS model

Appendix C.3 : Flow chart illustrating human proactive behaviour decision-making in Experiment A2-2

Function Calculate Shortest Queue

```
if queue1 <= queue2 &&
   queue1 <= queue3 &&
   queue1 <= queue4 &&
   queue1 <= queue5
   queue1 = shortest queue ;

else if
   queue2 <= queue1 &&
   queue2 <= queue3 &&
   queue2 <= queue4 &&
   queue2 <= queue5
   queue2 = shortest queue ;

else if
   queue3 <= queue1 &&
   queue3 <= queue2 &&
   queue3 <= queue4 &&
   queue3 <= queue5
   queue3 = shortest queue ;

else if
   queue4 <= queue1 &&
   queue4 <= queue2 &&
   queue4 <= queue3 &&
   queue4 <= queue5
   queue4 = shortest queue ;

else if
  queue5 = shortest queue ;
```

Select Output Block

```
//before entering counter queue

Call function calculate shortest
queue ();
```

(a) Proactive decision pseudo codes in DES model

Function Calculate Shortest Queue

```
if queue1 <= queue2 &&
   queue1 <= queue3 &&
   queue1 <= queue4 &&
   queue1 <= queue5
   queue1 = shortest queue ;

else if
   queue2 <= queue1 &&
   queue2 <= queue3 &&
   queue2 <= queue4 &&
   queue2 <= queue5
   queue2 = shortest queue ;

else if
   queue3 <= queue1 &&
   queue3 <= queue2 &&
   queue3 <= queue4 &&
   queue3 <= queue5
   queue3 = shortest queue ;

else if
   queue4 <= queue1 &&
   queue4 <= queue2 &&
   queue4 <= queue3 &&
   queue4 <= queue5
   queue4 = shortest queue ;

else if
   queue5 = shortest queue ;
```

Function Find Shortest Queue

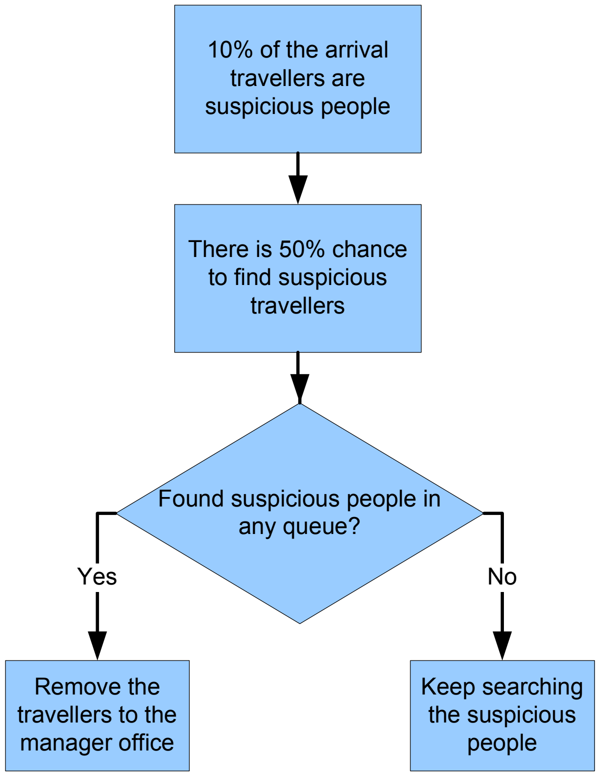
```
if others queues < current queue
   go to shortest queue
else if
   stay in current queue
```

Travellers Agent

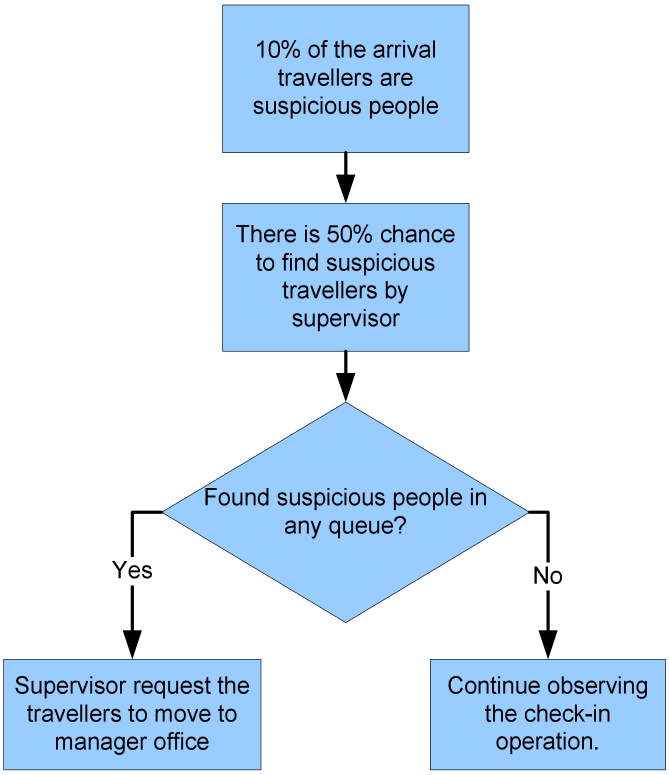
```
//before entering counter queue

Call function calculate shortest
queue()

Call function find shortest queue()
```

(b) Proactive decision pseudo codes in combined DES/ABS model

Appendix C.4: Human proactive behaviour decision-making pseudo codes in Experiment A2-2



(a) Proactive decision-making flow chart in DES model



(b) Proactive decision-making flow chart in combined DES/ABS model

Appendix C.5 : Flow chart illustrating human proactive behaviour decision-making in Experiment A2-3

```
Travellers Arrival Block

//random 10% of the arriving
travellers are suspicious travellers

Event Scan Suspicious Travellers

using probability distribution to
scan the suspicious travellers;

observation rate = 50%

for queue1,
 if there is chance to find
     suspicious travellers;
    if suspicious travellers exist;
      remove the travellers from the
      queue;
      take the suspicious travellers
      to the manager office.

for queue 2,
.
.
.
.
.
for queue 5,
```

(a) Proactive decisions pseudo codes in DES model

```
Travellers Agent

//random 10% of the arriving
travellers are suspicious travellers
(travellers type 2)

receive message from supervisor agent

Supervisor Agent

using probability distribution to
scan the suspicious travellers;

observation rate = 50%

for each queue,
 for all travellers in the queue,
   if there is chance to find
     suspicious travellers;
   if travellers are travellers type
     2;
      Send message to travellers
      agent to move to manager
      office;
```

(b) Proactive decisions pseudo codes in combined DES/ABS model

Appendix C.6 : Human proactive behaviour decision- making pseudo code in Experiment A2-3

APPENDIX D
SURVEY ON SIMULATION TECHNIQUES
Discrete Event Simulation vs. Agent Based Simulation

PhD Research Study

Intelligent Modelling and Analysis Research Group (IMA)
School of Computer Science
University of Nottingham, UK

Questions:

1. Which simulation technique do you use and how long is your experience with it? (You can tick more than one)

   ☐ **Discrete Event Simulation (DES)** ________ **year(s)**

   ☐ **Agent Based Simulation (ABS)** ________ **year(s)**

2. In your own experience and opinion, is there any difference between designing conceptual model for DES and ABS when modelling similar problem. Please justify your answer.

   ☐ **Yes** ☐ **No**

   Reason: ____

3. In your own experience and opinion, which level of proactive human behaviour can bemodelled easily in DES and ABS models? Please justify your answer. (You can tick more than one)

   DES:
   ☐ **Simple Proactive** ☐ **Medium Proactive** ☐ **Complex Proactive**

   ABS:
   ☐ **Simple Proactive** ☐ **Medium Proactive** ☐ **Complex Proactive**

   Reason: ____

4. In your own experience and opinion, which simulation technique takes longer simulation model building time, line of code, and speed when we modelled proactive human decision making with similar logic in DES model and ABS model? Please justify your answer.

   Model building time:
   ☐ **Discrete Event Simulation** ☐ **Agent Based Simulation**

   Model line of code:
   ☐ **Discrete Event Simulation** ☐ **Agent Based Simulation**

   Model speed:
   ☐ **Discrete Event Simulation** ☐ **Agent Based Simulation**

   Reason: ____