Using agent-based modelling and simulation to model performance measurement in healthcare

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I dedicate this thesis to my mother and the memory of my father

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ABSTRACT

One of the priority areas of the UK healthcare system is urgent and emergency care, especially accident and emergency departments (A&E departments). Currently, there is much interest in studying the unintended consequences of the current UK healthcare performance system. Simulation modelling has been proved to be a useful tool for modelling different aspects of the healthcare systems, particularly those related to the performance of A&E departments. Most of the available literature on modelling A&E departments focus on supporting operational decision-making and planning in specific healthcare units to study particular problems such as staff scheduling, resource utilisation, and waiting time issues. That is, most simulation studies focus on analysing how different configurations of healthcare systems affect their performance.

However, to our knowledge, few simulation studies focus on explaining how human behaviour affects the performance of the system, and very few have studied how, in turn, performance targets set for A&E departments affect human behaviour in healthcare systems.

Some aspects of human behaviour have been incorporated within existing simulation models, though with limitations. In fact, most studies have aimed to study patients' behaviour, and few have included some aspects of the behaviour of clinical staff. Here we consider how to model clinician behaviour in relation to the performance of A&E departments.

This thesis presents an exploratory study of the use of agent-based modelling and simulation (ABMS) and discrete event simulation (DES) to demonstrate how to model clinician behaviour within an A&E department and how that behaviour is related to waiting time performance. Clinical behaviour, incorporated in the simulation models developed here, employs a framework called PECS that assumes that behaviour is influenced by Physical (P), Emotional (E), Cognitive (C) and Social (S) factors. A discussion of the advantages and limitations of the use of ABMS and DES to model such behaviour is included.

The findings of this research demonstrate that ABMS is well suited to simulate human behaviour in an A&E department. However, it is not explicitly designed to model processes of complex operational and queue-based systems such as accident and emergency departments. In addition, this research work also demonstrates that DES is an adequate tool for modelling A&E's processes and patient flows, that can, in fact, incorporate different aspects of human behaviour. Furthermore, the process of modelling human behaviour in DES is complex because, though most

DES software allows the representation of reactive behaviour, they make it difficult to model other types of human behaviour

The main contributions of this thesis are: 1) a comparison and evaluation of how suitable ABMS and DES are for modelling clinical behaviour, 2) an approach to model the relationship between human behaviour and waiting time performance, considering four aspects of human behaviour (physical, emotional, cognitive and social).

CHAPTER 1: INTRODUCTION

1.1 Problem definition

Waiting for health provision is a common situation in any healthcare system. Particularly within the NHS, in the absence of a price device to access hospital services, limited resources are rationed by waiting times. Yet long waiting times are never desired and, therefore, governments have been continuously endeavouring to improve the delivery of services and have created mechanisms based on performance measurements that have developed gradually since the creation of the NHS in 1948.

However, one of the most significant current discussions in regimes based on performance measurements concerns the unintended consequences that those mechanisms may have (Pidd, 2005; Smith, 1995, 2005; Mannion & Braithwaite, 2012; Mannion, Goddard, & Smith, 2019). For many years, there has been an increasing interest in analysing the effects of the performance framework implemented in hospitals on different parts of the system and on people's behaviour (Appleby, 2019; Nuti et al., 2018; Audit Commission, 2003; Bevan, 2009; Department of Health, 2009; Dimakou, Parkin, Devlin, & Appleby, 2009; Günal, 2008; Günal & Pidd, 2006; Mannion & Braithwaite, 2012; Robinson, 2007; Santry, 2008; Silvester, Lendon, Bevan, Steyn, & Walley, 2004; Triggle, 2005, NHS, 2017).

In particular, one of the priority areas of the healthcare system is urgent and emergency care, especially accident and emergency departments. Emergency departments provide emergency care 24/7, principally for patients that are severely injured or seriously ill. Because of the complexity that characterises accident and emergency departments, together with other elements of healthcare systems such as planned hospital care and other community healthcare services, simulation modelling methodologies such as discrete event simulation (DES) and system dynamics (SD) have been some of the most widely used tools to address these problems (Brailsford, 2007; Günal & Pidd, 2010; Koelling & Schwandt, 2005, Gul & Guneri, 2015; Salleh et al., 2017). They allow modelling diverse aspects of healthcare provision and have been extensively used for decades to model patient flows, eliminate bottlenecks, and to understand how different parts of the hospital operate together (Bayer, Köberle-Gaiser, & Barlow, 2007; Bowers, 2009; Brailsford, Lattimer, Tarnaras, & Turnbull, 2004; Fone et al., 2003; Günal, 2008; Jun, Jacobson, & Swisher, 1999; Rohleder, Bishcak, & Leland, 2007; Royston, Dost, Townshend, & Turner, 1999; Van Ackere & Smith, 1999; Worthington 1991)

DES has probably been the most preferred tool to analyse operational hospital issues since it allows representation of patient characteristics and their flows through the system (Günal, 2008; Gul & Guneri, 2015). On the other hand, SD has also been recognised as a suitable tool to deal with the complexity inherent in such social systems, since it allows modelling of the interaction among different parts of the system and provides a global picture of its structure (Sterman, 2000, Gul & Guneri, 2015).

Agent-based modelling and simulation (ABMS) is also a well-recognized methodology to study complex systems (North & Macal, 2007) and has also been used in several applications in healthcare but it is not as popular as DES and SD for modelling the performance of emergency departments (Gul & Guneri, 2015; Salleh et al., 2017).

In order to assess the effect of any performance measurement mechanism on an accident and emergency department's performance, it might be necessary to consider factors such as people's perceptions and interactions and communication between the different actors that make decisions within the department. Therefore, assessing performance through changes in capacity or improvements on the pathway might not be enough. It may be necessary to model human decision-making processes present in the system.

Although decision-making processes have been usually modelled with either DES or SD, SD does not allow the inclusion of an individual's behaviour in the model. Therefore, it might not be possible to develop an SD model of an emergency department with the appropriate level of detail required. On the other hand, although DES allows individual representation, in many cases, individuals are modelled as passive entities that do not react easily to changes in the environment.

DES allows the inclusion of diverse types of human behaviour within the model. Depending on the level of detail, an entity in a DES model could act as an agent, which follows diverse sets of rules and modifies its behaviour based on the information available on the environment. An example of that can be seen in the research conducted by Günal and Pidd (2006), where doctors respond to long waiting times through task switching, modelled through "mini-doctors" that represent multiple simultaneous tasks. That is, each doctor is represented by several fractional doctors so that one doctor could see several patients at the same time.

However, doctors may also need to make different decisions that can affect not only accident and emergency department performance but may also affect other hospital units' performance. For example, during slack periods, doctors may have more time to perform extra tests on patients, so they can investigate in more detail every patient's condition and give more accurate diagnoses. On the other hand, during busy periods, doctors may order only the necessary tests and yet may have to wait longer for the results of investigations. That may mean that they do not order extra tests and, as a result, may have to admit patients with less critical conditions into the hospital.

The ability to represent individual behaviour is key a feature of ABMS, which allows the modelling heterogeneous entities that can learn and modify their behaviours so that their interactions create the overall system behaviour (Bonabeau, 2002; C. Macal & North, 2010; North & Macal, 2007).

1.2 Research objectives and contribution

This research aims to gain insight into the overall value of including human behaviour in an A&E simulation and to contrast how it can be done using Discrete Event Simulation (DES) and by Agent-Based Simulation (ABMS). The appropriate level of detail to include in the models is an important issue to consider in this thesis. I do not develop a fully realistic and detailed model since the aim is to gain some insight into the overall value of modelling human behaviour using DES and ABMS. That may warrant further research if my work shows the value of modelling human behaviour.

Although *waiting times performance modelling* has been widely studied using simulation methodologies in many application areas, the literature reports few studies on the use of DES for modelling the effects of waiting time targets on the performance of A&E departments (Günal, 2008; Eatock, 2011). For example, Günal (2008) developed an interconnected DES model of Emergency, Outpatient and Inpatient Departments of a hospital with the purpose of understanding the effects of waiting time targets on hospital performance. The Emergency component of the model can be used to simulate the performance of a department.

Günal and Pidd (2009) show that the model was effective in assessing the actual performance of the department, though it failed to capture some effects that might be caused by interventions as a patient's waiting time approaches 4 hours. Though close, the differences between the actual and simulated waiting times might be due to different reasons. One possible reason is that the *level of detail* included in the model was not sufficient to represent the components that affect the performance of the accident and emergency departments under performance measurement schemes that require meeting specific targets. Another reason might be that the way that *humans are represented* in the model ignores some of the critical factors of the staff's and patient's behaviour that have an important effect on the accident and emergency department's performance.

The Existing body of literature show that ABMS has gained popularity in healthcare applications (Cabrera, Luque, Taboada, Epelde, & Iglesias, 2012a; Kanagarajah, Lindsay, Miller, & Parker, 2006; Laskowski et al., 2011; Nealon & Moreno, 2003; Sibbel & Urban, 2001; Stainsby, Taboada, & Luque, 2009; M. Taboada, Cabrera, Epelde, Iglesias, & Luque, 2012; M Taboada, Cabrera, Epelde, Iglesias, & Luque, 2013; M. Taboada, Cabrera, & Luque, 2011, Pförringer 2018, Gul & Guneri, 2015; Salleh et al., 2017). However, there are few studies of ABMS for modelling human behaviour in A&E departments (Yousefi et al., 2018; Kanagarajah et al., 2006; Taboada, Cabrera, & Luque, 2011; Stainsby et al.,2010, Cabrera et al., 2012a; Al-Refaie, Fouad, Li, & Shurrab, 2014; Rahmat et al., 2013, Laskowski, et al., 2009; Lim et al., 2013, Liu et al., 2017).

This research began with an investigation of how useful ABMS can be in the healthcare area, which led me to consider two main questions in this research:

1: How well suited is ABMS to modelling human behaviour in an accident and emergency department?

2: What benefit does ABMS bring to the study of waiting time performance in an accident and emergency department over DES?

This thesis presents an exploratory study of the use of agent-based modelling and simulation (ABMS) and discrete event simulation (DES) to demonstrate how to model clinician behaviour within an A&E department and to understand how that behaviour is related to waiting time performance. In particular, it shows how the relationship between system performance and clinician behaviour can be modelled in a dynamic simulation of the activity in an A&E department.

Therefore, the contribution of this thesis can be seen in three main aspects. Firstly, I will compare and evaluate how suitable ABMS and DES are for modelling clinical behaviour, second, it offers an approach to model the relationship between human behaviour and waiting time performance, considering four aspects of human behaviour (physical, emotional, cognitive and social), and third, it proposes a different representation of the service times using random variables with distribution parameters that are dynamic and stochastic.

1.3 Document overview

The overall structure of this document takes the form of nine chapters, including this introduction. Chapter two describes performance measurements in healthcare systems. It begins by pointing out some questions that need to be addressed when planning and implementing performance measurement systems: why to measure performance, how to measure it, what the perverse effects of performance measurement are and how side effects can be avoided. It then describes the evolution of the NHS performance framework since its creation to date and discusses some views provided in the literature about the effects of the NHS performance measurement framework in the UK.

Chapter three reviews how modelling and simulation has been used in healthcare to understand the unintended consequences of the NHS performance framework and to support control in healthcare systems. First, it summarizes the main uses of simulation models, and then it reviews the use of the three main simulation methodologies in healthcare: system dynamics (SD), discrete event simulation (DES) and Agent-Based Modelling Simulation (ABMS). Finally, it reviews the use of simulation for modelling accident and emergency departments. The chapter concludes that most of the simulations on healthcare, specifically of accident and emergency departments, have ignored relevant aspects of human behaviour that may affect the performance of healthcare systems.

Chapter four begins by reviewing how human behaviour has commonly been modelled in the three main simulation techniques. It then explores some theories of human behaviour, such as rational behaviour, intuitive behaviour and the role of emotions, intuition and bounded rationality on human behaviour. Next it presents an introduction to Agent-based modelling and simulation and its potential for modelling human behaviour. Finally, the chapter gives an overview of two popular agent frameworks that have been used to model human behaviour: BDI (Belief-Desire-Intention) and PECS (Physics, Emotion, Cognition, Social status) frameworks.

Chapter five describes the ABMS Model design and development process. It starts by providing an overall description of the situation to be modelled, the identification of processes and entities that will be considered in the model and the environment where entities will be interacting. Then, it develops a conceptual model that includes the definition of the agents and their behaviour, the interactions between the agents and between the agents and the environment and also the data requirement. Finally, it shows the implementation of the PECS framework for modelling doctors' behaviour on the ABMS model is described.

Chapter six presents the ABMS model implementation process and simulation results. First, it shows the implementation process of the ABMS model in Repast Simphony Java. After that, it describes the model inputs and the methods implemented for each type of agent. Following that, the DES model developed by Günal (2008) was used as the start point to implement the ABMS model of an A&E department using the same data, and process flow described in Günal's model.

The ABMS model, named here as ABMS_A&E, uses the same data and most of the information used in Günal's model. The validation processes focus on comparing the ABMS model against the DES model rather than comparing the ABMS model against the real world. Experimentation involves implementing PECS in the ABMS model; therefore, some rules were defined for the doctors in the model to evaluate the impact of the four-hour standard on a doctor's behaviour and the performance of the whole accident and emergency department.

Chapter seven presents the development of a DES model of an accident and emergency department that includes the modelling of human behaviour with the same PECS framework used in the ABMS model presented in chapters five and six. The DES model named here as DES_A&E was developed in SIMUL8® and demonstrates that though it does model the effect of waiting time performance on human behaviour, doing so requires considerable ingenuity.

Chapter eight discusses the findings of this research and concludes it by considering the research questions stated in this chapter. The chapter starts discussing why simulation is an important tool to model accident and emergency departments. Then it compares how human behaviour can be modelled in DES and ABMS and examines how accident and emergency departments can be modelled with both approaches. Then it discusses the strengths and limitations of the use of DES and ABMS for modelling healthcare systems. Finally, it presents the findings, contributions and limitations of this research, and proposes some ideas for potential further research.

CHAPTER 2: PERFORMANCE MEASUREMENT IN HEALTHCARE SYSTEMS

2.1 Introduction

Waiting for healthcare is a common situation in all healthcare systems. Within the NHS, the absence of a price mechanism to access hospital services means, in effect, that limited resources are rationed by waiting times. That is, instead of paying money, people pay by the time they spend waiting for care, particularly for elective care. However, for most people, long waiting times are undesirable even though they have been a feature of the NHS since its creation in 1948.

Over the intervening years, successive governments have sought improvements in the delivery of services and, to support this, have established mechanisms based on performance measurement. These have included performance management frameworks that have passed through different iterations over the years. Such performance management has aimed to encourage healthcare providers to organise themselves so that waiting times are reduced and kept low. That has been attempted through incentive systems such as star ratings, and by setting targets and standards.

It is, however, well-known that performance measurement in public services usually has at least some unintended consequences, and several authors discuss these and suggest how some of the worst side effects can be avoided (Pidd, 2005; Smith, 1995, 2005). Recently, there has been an increasing interest in analysing the behavioural consequences of the NHS performance framework implemented in hospitals. One major topic to be considered later in this thesis is how modelling and simulation can be used to assess the behavioural consequences of the waiting times' standards indicators (previously called targets) in healthcare systems.

This chapter aims to describe the practice of performance measurement in healthcare and to provide a general description of the changes in the NHS performance framework over the years, particularly concerning the actions taken by the government, and some of its effects on the health system. This chapter also shows how the NHS has incorporated policies that aim to empower patients to have better control over their health and to enable clinicians to make decisions about the patients, focusing on the health outcomes and quality of care. That implies a belief that human behaviour plays an essential role in NHS performance since it depends not only on logistic and administrative processes but also on clinical judgment and patients' choices. This chapter forms the foundation for the research design of this thesis since the NHS framework provides guidelines and policies on which the A&E simulation models of this research will be based.

2.2 Performance measurement in healthcare

For the healthcare sector, as for any other public sector, information is important not only for providers but also for those who use their services. On the one hand, providers are continually looking for mechanisms to improve their services; on the other hand, users are always looking for efficient and effective services. Therefore, the collection and the use of healthcare system performance data are crucial for improvements in the delivery of any public service (Pidd, 2005, 2012; Smith, 1995, 2005; Pross et al., 2017).

However, some issues need to be addressed when planning and using performance measurement (Boland & Fowler, 2000; Miller, 2005; Pidd, 2005, 2012; Smith, 1995). Important questions are (Pidd, 2005, 2012; Smith, 1995):

1: *Why measure performance*?
2: *How can it be measured?*
3: *What are the perverse effects of performance measurement?*
4: *How can side effects be avoided?*
5: When is it necessary to measure performance?
6: Who are the customers and users of the services to be measured?
7: How should the information obtained from measuring performance be used?

Here the focus will be on the first four questions.

2.2.1 Why measure performance?

In order to address the first question, Why *measure performance*, Pidd (2012) summarises and consolidates within six categories the views of Behn (2003) Poister (2003) and Bird et al. (2005), regarding the reasons for measuring performance:

1: *Planning and improvement*: to see what works, why it works or does not work, and how to improve performance.
2: *Monitoring and control*: to monitor performance and direct managers and subordinates towards desired performance.

3: *Evaluation and comparison*: to identify high performance and understand what it entails, and to evaluate performance in terms of inputs, outcomes and desired performance.
4: *Accountability*: To support public accountability, to promote quality services, and to inform current performance.
5: *Financial budgeting and planning*: to support resource allocation and strategic planning.
6: *Individual performance management*: to celebrate success and therefore encourage people involved in the process of achieving high performance.

Section 2.3 will describe how performance measurement has been done in the NHS and the purpose of the plans designed for the different stages of the evolution of the performance measurement framework within the NHS.

2.2.2 How to measure performance

To address the second question of *how to measure performance*, Neely et al. (2003) classify the approaches to measuring performance in three generations of measurement. The first generation is the most common measurement framework used to date. That is based on balanced measurement systems such as the balanced scorecard developed by Kaplan and Norton (1996), the perform prism developed by Neely et al. (2002) and Skandia's Navigator, developed by Edvinsson and Malone (1997).

The second generation considers mapping the flows and transformations and includes strategy maps (Kaplan & Norton, 2001), which are an extension of balanced scorecards, success and risk maps (Neely et al., 2002), and the IC-Navigator model (Roos & Dragonetti, 1997).

The third generation proposes linking financial to non-financial dimensions of performance systems. The challenge of this generation, according to Neely (2003 p. 132) "is to maintain the usefulness of the second generation approaches in addressing the key business areas but to do so in a way which extends the measurement to flows of cash".

Some of the performance framework used in the NHS is based on the balanced scorecard approach, in which performance information and incentives are used to achieve desired objectives (Smith, 2005). Pross et al. (2017) investigate how hospital performance has been measured, reported and rewarded in different countries and summarise the NHS approach to evaluate hospital performance, which includes clinical audit and registries, indicators, data hospital trust and physician levels and national patient experiences survey reports. It seems that for the UK healthcare system, the performance framework works mainly as a mechanism of management and control. Smith (2002) defines performance management in the NHS as a "set of managerial instruments designed to secure optimal performance of the health care system over time, in line with policy objectives". Similarly, Pidd (2005) suggests that management for control includes a feedback control process in which the gap between performance targets and performance outcomes leads to the application of corrective actions that help to reduce that gap.

The control feedback process is discussed by Pidd (2012 p. 83), who suggests a simple input:output transformation notion to represent a common view of process management (Figure 2-1).

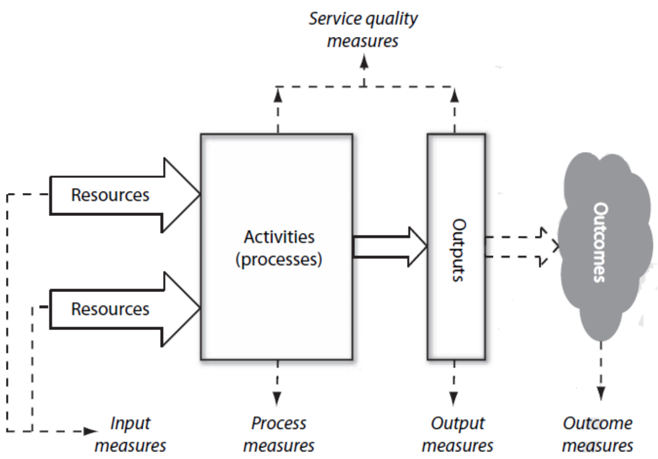


Figure 2-1. Input:output transformation theory (Pidd, 2012: Figure 1.2, p.16)

This input:output transformation theory applied in public services (Pidd, 2012) states that:

- Input (resources) may include people's time and money
- Activities are the means to achieve the transformation process. The transformation process then includes those activities that need to be done to meet the objectives of the organisation.
- Products that are outputs (tangible products) and outcomes (value-added).

2.2.3 What are the effects of performance measurement systems?

The third question examines *what the effects of performance measurement systems* are. Smith (1995) identifies eight unintended consequences of performance measurement in the public sector:

1. *Tunnel vision*: emphasis on what can be quantified, ignoring other un-quantified aspects of performance.

2. *Sub-Optimization*: emphasis on own, local objectives, ignoring the objectives of the whole system.
3. *Myopia*: emphasis on short time objectives, ignoring long term outcomes.
4. *Measure fixation*: emphasis on performance indicators, ignoring underlying objectives.
5. *Misrepresentation:* publishing false “good looking” reports distorting real performance.
6. *Misinterpretation*: misunderstanding of the performance data.
7. *Gaming*: under-achieving performance to avoid higher targets in future.
8. *Ossification*: lack of innovation when the performance measurement system loses its purposes.

Similarly, De Bruijn (2002) discusses not only the ‘perverse’ effects but also the positive effects of performance measurement in the public sector. Some perverse effects coincide with the ones identified by Smith (1995) and are (De Bruijn, 2002, p.581): “performance measurement prompts game playing”, “performance measurement adds to internal bureaucracy”, “performance measurement blocks innovation”, “performance measurement blocks ambitions”, “performance measurement affects professionalism,” “performance measurement kills system responsibility”, and “performance measurement punishes good performance”. In contrast, possible positive effects include (De Bruijn, 2002, p.580): “performance measurement brings transparency”, “performance measurement is an incentive for output” and “performance measurement is an elegant way of shaping accountability”.

Literature has emerged, offering diverse points of view about the effects of the NHS performance measurement framework in the UK. On the one hand, it has been argued that performance measurement has been beneficial for the NHS. For instance, Triggle (2005) reports that targets that focus on outcome may be beneficial, especially when they require the use of knowledge and the skill of clinicians. Additionally, Lewis and Appleby (2006) suggest that well-conceptualised targets seem to be effective in reducing waiting times. Similarly, Bevan (2009) believes that the introduction of targets in England has led to sustained improvements in performance and real improvements in care.

On the other hand, it has also been argued that targets have distorted the quality of care and clinical priorities in healthcare service delivery. The following examples of some perverse consequences of performance measurement in the NHS identified in the literature, serve to illustrate the categories mentioned above of Smith’s unintended consequences (1995).

Some good examples of tunnel vision within the NHS can be found in the works of Kelman and Friedman (2009 p. 923), Bowers (2009), Triggle (2005) and Jones and Schimanski (2010). Kelman and Friedman, for example, suggest that reductions in waiting times in an accident and emergency department may be obtained at the expense of service care quality. Similarly, Bowers believes that avoiding waits may lead to clinical distortion. Triggle reports that patients may not always be treated based on clinical needs as a consequence of the pressure that the targets have over the hospital staff. Jones and Schimanski discuss whether mortality rates may be related to emergency admissions.

Bevan (2009) and Kelman and Friedman (2009 p. 923) provide examples of the *Sub-Optimization* consequences of performance measurement in the NHS. Bevan suggests that the targets may affect the local leadership in hospitals units since the central NHS controls them and that their design has focused on specific problems rather than on the whole system. Kelman and Friedman suggest that Emergency waiting time targets may sometimes be met by redirecting resources from other areas. Additionally, Bevan (2009) also provides a good example of *myopia,* suggesting that patient care could be neglected because of the focus on waiting time targets.

Günal and Pidd (2009), Mason et al. (2012), Kelman and Friedman (2009) and Bowers (2009) discuss some unintended consequences of performance measurement in the NHS that can be grouped in the *Measure fixation* category. Günal and Pidd argue that waiting time targets may have ignored possible interactions with other performance indicators and other targets. In the same way, talking about emergency departments, Mason et al. (2012) argue that some Emergency departments perform to achieve targets and may ignore improvement in overall care. Kelman and Friedman identify some examples in this category; they say that focusing on reducing waiting times for patients may lead to reducing quality of care, or that improvement in accident and emergency departments waiting times may lead to reductions in performance in other parts of the system. In turn, Bowers also suggests that the nature of waiting time distribution may be affected by the waiting time target.

The suggestion of Mason et al. (2012) that hospitals may alter their discharge times to appear to meet the targets is an example of *misrepresentation*. An example of *Gaming* may be the observed increase in in-patient admissions of emergency patients reaching the 4-hour threshold (Bowers, 2009; Kelman & Friedman, 2009).

2.2.4 What can be done to avoid the perverse effects of performance measurement for public services?

The fourth and final question opens the debate about *what can be done to avoid the perverse effects of performance measurement for public services*. Pidd (2005) argues that those effects occur not only because of malpractice but can also appear even when people make their best effort to achieve the desired performance. Moreover, Pidd (2012 p.26) proposes that successful performance measurement may be based on three criteria. The first is “that the measurement needs to be done properly or not at all”. The second is “that performance measurement is not a new fad that will pass away in time, especially if ignored”. The third is “that performance measurement in public services is usually multidimensional, which can make it difficult to do properly”.

In summary, when planning and using performance, it is important consider different aspects such as why and how to measure performance, what the perverse effects of performance measurement are, and how they can be avoided. The next section will look at how and why performance measurement in the UK is used.

2.3 The NHS performance framework: Evolution

The NHS is funded by national taxation and provides, free of charge, most healthcare services in the UK through primary, secondary and tertiary care services. The NHS was created in 1948 under three core principles (NHS, 2009):

1: that it meets the needs of everyone;
2: that it be free at the point of delivery;
3: that it be based on clinical need, not ability to pay.

In this period, the NHS was divided into primary, secondary and tertiary care. Primary care acted as a front door to the health system since it is the first point of contact for most of the patients. Services in this sector are delivered by GPs, dentists, opticians, and pharmacists, among others. Secondary care, also called acute care, is either elective, for those patients whose specialist medical care can be planned, or emergency (unplanned) care, for those patients who need immediate attention. Tertiary care provides support for the elderly and those with long-term conditions; also, tertiary care services may support people after discharge from the hospital.

Despite many attempts to provide efficient services, waits have been part of the NHS since its establishment (Department of Health, 2009). As mentioned earlier, since there is no price mechanism, waiting for service appears as a rationing device, creating a buffer that enables demand and supply to operate in some equilibrium. However, long waits have been a matter of dissatisfaction for many years (Gubb, 2009; Triggle, 2005), and it was not unusual for patients to wait two years for elective orthopaedic surgery in the late 20th Century. Therefore, in order to improve the delivery of the service, waiting lists and waiting times have been the main focus of attempted performance improvement. The reduction in waiting lists and waiting times was a major purpose of the Labour government's election manifesto in 1997 and, after the election, the government introduced policies aimed at their reduction.

Performance measurement in the NHS developed through seven stages:

1: the creation of the NHS in 1948,
2: the establishment of performance indicators in 1983,
3: the creation of a "quasi" market in 1991,
4: the introduction of the performance framework with specific targets in 1997
5: the beginning of planning for NHS reforms in 2000
6: the presentation of the Outcomes Framework in 2010
7: the implementation of the reforms in 2013

2.3.1 The creation of the NHS in 1948

The first period started in 1948 when the NHS was established. Appleby and Thorlby (2008) discuss the history of waiting lists alongside the history of the NHS and report that in 1948, waiting lists totalled over 476,000 patients, and this figure increased to 504,000 patients by 1951. That worsening situation was attributed to a limited investment in facilities such as the number of beds. Total waiting lists started to drop after 1951, though the waiting lists for some particular conditions increased despite investments in bed capacity in 1952. In the following year, the number of beds and treated patients increased, but waiting lists also increased. Some thought that the solution was increasing the efficiency in bed usage (reducing the idle time of beds), and this appeared to be an effective tactic for some time. However, the improvement could not be sustained in subsequent years.

During this first stage of the early NHS, the focus was on reducing waiting lists rather than on waiting times, though data on inpatient waiting times was published during the 1950s. The first attempt to consider the waiting times as a source of information was during the fifties when the first set of data regarding waiting times was published for Inpatients. Forty years later, information was published about Outpatient waiting times (Appleby & Thorlby, 2008).

2.3.2 The establishment of performance indicators in 1983

In 1983, the government defined and published performance indicators to *inform* local managers about the efficiency of all hospitals to assist them in improving performance. The indicators were initially focused on financial information at the national, regional and district level, and were modified later to include several process indicators such as length of stay and waiting times in hospitals (Smith, 2005).

2.3.3 The creation of a "quasi" market in 1991

The previous stages outlined above focused on monitoring performance, which resulted in the definition of some actions for improvement in cases of undesired performance (Smith, 2005). In this stage of development, the system of performance indicators continued, although they were given a shallow profile by the national ministry and local health authorities (Smith, 2005). Instead, a pseudo *competition* between NHS providers was introduced in 1991 by the "NHS internal market". The aim was to increase service efficiency (West, 1998). By, 1995, the providers were asked to adhere to their budgets and to work to meet patients' expectations of waiting times specified in the NHS's Patient's Charter (Smith, 2005).

2.3.4 The introduction of specific targets in 1997

1997 saw the introduction of the 'new NHS' looking to improve performance across the NHS and to *tackle the inequitable variations (mainly related to quality, safety, equity, outcomes, money and services)* (NHS Executive, 1998). The purpose was to introduce a plan focused on the needs of patients, based on partnership and driven by performance (NHS Executive, 1998).

In 1997, the performance assessment framework included 60 indicators which sought improvements in six areas (NHS Executive, 1998):

1: *Health Improvement*: involving the overall population´s health, considering social and environmental factors and individual behaviour as well as care provided by the NHS and other agencies.

2: *Fair Access*: this was aimed at equitable provision of services concerning geographical, socio-economic, demographic needs, among others.

3: *Effective delivery of appropriate healthcare*: that is, services which are clinically effective, appropriate to need, timely, in line with agreed standards, provided according to best practice service organisation, and delivered by appropriately trained and educated staff.

4: *Efficiency*: that is, the provision of services at a lower cost per unit of care/outcome, higher productivity of the capital estate and improved labour productivity.

5: *Improved Patient/carer experience*: which includes patient perceptions such as the responsiveness of care providers to individual needs and preferences, the skill, care and continuity of service provision, patient involvement, right information and choice, waiting times and accessibility, the physical environment and the organisation and courtesy of administrative arrangements.

6: *Improved Health outcomes of the NHS*: success in using its resources to reduce levels of risk factors, reduce levels of disease, impairment and complications of treatment, improve quality of life for patients and carers, and reduce premature deaths.

2.3.5 The beginning of the planning of the NHS reforms

In 2000, based on the knowledge obtained from the application of the specific targets introduced in 1997, the government updated the NHS performance framework by focussing on maximum waiting times rather than on the size of the waiting list and by introducing other clinical targets (Appleby & Thorlby, 2008). The same year, the government began a journey towards the reform of the NHS by producing *The NHS plan: a plan for investment- a plan for reform* (Department of Health, 2000). The plan aimed to redesign the health service around the needs of the patients. It established a set of ten core principles that are the basis of the NHS transformation (Department of Health, 2000, pp. 3):

1: the NHS will provide a universal service for all based on clinical need, not on the ability to pay,

2: the NHS will provide a comprehensive range of services,

3: the NHS will shape its services around the needs and preferences of individual patients, their families and their careers,

4: the NHS will respond to the different needs of different populations,

5: the NHS will work continuously to improve quality services and to minimise errors,

6: the NHS will support and value its staff, *7: public funds for healthcare will be devoted solely to NHS patients,*

8: the NHS will work together with others to ensure a seamless service for patients,

9: the NHS will help keep people healthy and work to reduce health inequalities,

10: the NHS will respect the confidentiality of individual patients and provide open access to information about services, treatment and performance.

Later, from 2004 to 2008, the Government took a more holistic view, aiming to tackle waits along a patient's care pathway. The previous target regime was strengthened, and there was a particular focus on two targets. The first was what became known as the RTT (Referral to Treatment) target, which specified that patients must wait no more than 18 weeks from the date of a GP referral to their admission as inpatients or the commencement of proper outpatient care. That requires hospitals to organise themselves so that patients were given early specialist appointments and that, if inpatient admission were needed, this would occur no later than 18 weeks after GP referral.

The second target that generated much public interest was the requirements that treatment within an accident and emergency department be completed within 4 hours of a patient's arrival at accident and emergency department *(Department of Health, 2007)*. The original notion was that NHS Trusts would be penalised if any patients spent longer than 4 hours in accident and emergency department. However, this was quickly relaxed to 98% when it was pointed out to policymakers that incidents such as serious road traffic accidents made this impossible. Most NHS Trusts were achieving this 98% standard of performance by the end of 2008 – though some authors (Bevan & Hood, 2006) questioned whether gaming might have been employed to achieve this. Later this target was relaxed to 95% in stage 5 (2010/2011), and this continued in the 2012/2013 operating framework (Department of Health, 2011a, 2011b).

In 2009, the Government presented the plan of *High-Quality Care for All,* which highlights patient experience as an essential factor of high-quality care. The plan proposed that additional capacity and reform instruments were to be used to provide higher quality care for patients and value for money for the taxpayer (Department of Health, 2008). The NHS continued with the same priorities established initially, working on reductions in waiting times, continuing to prevent illness and maintaining financial stability as minimum standards rather than targets to hospitals. The implementation of the plan of *High-Quality care for all* assumes quality in three areas: safety, effectiveness and patient experience (Department of Health, 2008). That is intended to cover four aspects:

1: Helping people to stay healthy; which requires more effective cooperation between the NHS and its national and local partners in health promotion.
2: Empowering patients; giving them more rights and control over their own health and personal care.
3: Providing the most effective treatment to patients through improvements in access to treatments as well as improvements in diagnosis to allow earlier disease detection.
4: Keeping patients as safe as possible; offering clean environments and reducing avoidable harm.

2.3.6 Presentation of the Outcomes Framework

In July 2010, the new Conservative-Liberal Democrat Coalition Government published the white paper: *Equity and Excellence*: *claiming to liberate the NHS* (Department of Health, 2010a) It proposed two main changes for the future of the NHS: moving away from centrally driven process targets that interfere with patient care and focusing on clinical outcomes for people. The white paper included plans for putting patients and the public at the heart of the NHS, improving healthcare outcomes and empowering clinicians to make decisions about the patients.

The first plan, the idea *of "Putting patients and the public at heart? of the NHS"* is that the patients can have more choice and control. They are involved in the decision-making choices about their care and treatment helped by easy access to the information, data and support they need. The improvement of information access can encourage providers to improve the healthcare provision since the patients can choose the best providers by comparing information from different providers about safety (e.g. avoidable deaths), effectiveness (e.g. emergency readmission rates) and patient experience (e.g. average and maximum waiting times).

The second plan, the aim of "*improving healthcare outcomes"* is that the service focuses on the outcomes and quality of care rather than on the process targets. The clinically justifiable targets continued or were adjusted, but the ones that had no clinical relevance were abolished.

In 2010 the Department of Health introduced the *NHS Outcomes Framework (Department of Health, 2010b),* which has been updated yearly (Department of Health, 2012, 2013b, 2014). The *NHS Outcomes framework* replaced the previous performance framework. That new framework contains 68 indicators for measuring performance in the health and care system. Those indicators are grouped into five domains divided in three main areas: *the effectiveness of the treatment and* *care, the safety of the treatment* and *care provided to patients and the broader experience patients have of the treatment and care they receive*.

- *The effectiveness of the treatment and care provided to patients contains:*

  Domain 1: *Preventing people from dying prematurely*

  Domain 2: *Enhancing the quality of life for people with long-term conditions*

  Domain 3: *Helping people to recover from episodes of ill health or following injury*

- *The safety of the treatment and care provided to patients contains:*

  Domain 4: *Ensuring that people have a positive experience of care, and*

- *The broader experience patients have of the treatment and care they receive contains:*

  Domain 5: *Treating and caring for people in a safe environment and protecting them from avoidable harm*

The third plan, "*empowering clinicians",* claimed to liberate professionals and providers from government control to make decisions about the patients focussing on the quality of the care and to provide their services according to the needs and choices of patients.

2.3.7 The implementation of the 2012 reforms

The Health and Social Care Act 2012 introduced changes in the NHS structure, accountabilities, funding arrangements and working relationships (Department of Health, 2013a).

From 1 April 2013, those changes became operational with a new healthcare system (Department of Health, 2013a). The structure of the new NHS is composed of clinical commissioning groups (CCGs) that replace the Primary care trusts existing in the old NHS structure and include doctors, nurses and other professionals. Health and Wellbeing Boards which work in partnership with local organisations to improve health and wellbeing and respond to patient's needs; Healthwatch, which is an organization, that provides a voice for patients and local communities.

The Health and Social Care Act 2012 also placed clinicians at the centre of healthcare commissioning, gave providers freedom to innovate and to deliver quality services, enabled patients to select services that best meet their needs and integrated health and social care with the Department of Health and social care (Nichols, 2018; Department of Health & Social Care, 2012).

2.3.8 The publication of the five-year forward view in 2014

The NHS published in 2014 the five-year forward view that discusses the possibilities to make changes in the NHS on aspects such as health, healthcare service provision and the management of their funding (NHS, 2014). The five-year forward view presents some options to create the integration of community health services, hospital specialists, physical and mental health care and health and social care and alternatives to improve different areas, such as prevention, empowering patients and engaging communities (NHS, 2014).

First, *prevention* covers five aspects. The first aspect is *incentivising and supporting healthier behaviour*, particularly with actions on obesity, smoking, alcohol and other major health risks. The second relates to *local democratic leadership on public health*, which means that local governments and elected mayors have statutory responsibility for improving the health of the people and will be able to promote local democratic decisions on public health. The third is *targeted prevention,* where proactive primary care plays an important role by using systematic evidence-based intervention strategies and stablishing preventive services. The fourth refers to *NHS support to help people get and stay in employment,* which aims to provide targeted health support to help employees improving their wellbeing and preserving their livelihoods. The fifth is *workplace health* by developing and supporting ideas for improving health in the workplace.

The second aspect mentioned above, *empowering patients*, means that the NHS will work on improving healthcare provision by bettering the information available to people and the access to it, supporting people to gain better control of their own health and increasing the direct control patients have over the care they are receiving by allowing them to choose where and how they receive care.

The third aspect *involves communities* to participate directly in decisions about the future of health and health care services. The NHS will work to support caregivers, encourage the community to participate in volunteering and strengthen the partnership with charities, volunteers and local communities.

2.3.9 The NHS Long Term Plan 2019

On January of 2019, the NHS published the NHS Long Term Plan 2019 that established a direction for the future of the health service and set out priorities for healthcare and NHS funding management based on with the experience of patients, staff and national experts aiming to improve care for patients over the next ten years (NHS, 2019a). The plan seeks to build an NHS suitable for the future by *allowing everyone to have the best start in life, helping communities live well, helping people age well* (NHS, 2019c). The NHS Long Term Plan includes different measures, explained in six chapters (NHS, 2019a).

First, the plan indicates that patients will have the right to access to digital primary care. It means that that patients will have more options to choose and timely access to the care they need and the NHS will relieve pressure on Primary Medical and Community services as well as on A&Es.

Second, the plan draws up new actions to improve the NHS contribution to prevention and health inequalities. Prevention relates to incentivising and supporting healthier behaviour, for example, by improving programs to reduce smoking, obesity, and respiratory illness related to air pollution and alcohol-related A&E admissions. Reducing inequalities aims to avoid patients' inequalities related to their health and their needs and the provision of health care.

Third, the Plan delineates priorities for care quality and outcomes improvement for the next decade. The plan states that the quality of care and the outcomes for patients are now better measured than the past decade. Although there has been improvement in different areas such as childbirth, cancer survival, deaths from cardiovascular disease, among others, the NHS considers that things can be done better. That is in part because there is a difference in service quality within the NHS, also because there are some needs that are still unmet and require attention, such as mental health services for young people.

Fourth, the plan establishes that the NHS will work to help staff get the support they need. The NHS will take actions to ensure that there are enough people with right experience and skills, so there is enough staff to provide timely and effective care to patients; ensure that employees have rewarding jobs and are working in a right work environment and; improve and support good leadership that is compassionate and diverse at all levels.

Fifth, The NHS establishes a plan to upgrade technology and to provide digital attention across the NHS. For instance, patients will have a better management of their conditions by digital accessing the NHS services and clinicians will access patients' information with digital tools and will be able to use decision support systems and artificial intelligence in their practice.

Sixth, the plan sets out how the NHS funding settlement will be used to maximum effect. It means that *"the NHS will return to financial balance; the NHS will achieve cash-releasing productivity growth of at least 1.1% a year, with all savings reinvested in frontline care; the NHS will reduce the growth in demand for care through better integration and prevention; the NHS will reduce variation* *across the health system, improving providers' financial and operational performance; the NHS will make better use of capital investment and its existing assets to drive transformation"* (NHS, 2019a, pp.100)

After the NHS long term plan was launched, the NHS National Medical Director was asked to clinically review the targets related to the provision of care in the *"Interim Report from the NHS National Medical Director"* (NHS National Medical Director, 2019). The purpose was to update and supplement the old targets with new ones that are aligned with the NHS Long Term-Plan looking to improve clinical quality outcomes, short waits to a wide range of services, track patients experience in A&E and elective care, help hospitals to modernise their care, among others.

The NHS medical director said that *"we began by reviewing what is already known about how current targets operate and influence behaviour. This was then mapped against the NHS Long Term Plan to examine how performance measures can help transform the health service and deliver better care and treatment."* (NHS National Medical Director, 2019, p.p. 7). The interim report proposes standards for the most significant areas of health care, including mental health, cancer, urgent and emergency care and elective care.

In particular, concerning the urgent and emergency care, the report shows that there are several issues about the current four-hour standard for A&E's because it focusses only in one aspect of the urgent and emergency care system. The report describes five issues related to the four-hour standard (NHS National Medical Director, 2019, p.p. 23):

- *the standard does not measure total waiting times*
- *the standard does not differentiate between severity of condition*
- *the current standard measures a single point in often very complex patient pathways*
- ***there is strong evidence that hospital processes, rather than clinical judgement, are resulting in admissions or discharge in the immediate period before a patient breaches the standard***
- *the standard is actually not well understood by the public*

The report proposed several standards to help measure what is most important clinically and to patients based on the mentioned issues. For example, they introduced standards to measure time to assessment, so that patients can be seen quicker than they currently are, and patients with more severe conditions can start treatment sooner. Another example is the measure of the mean waiting time for all patients rather than total waiting times, which helps to reduce the risk of patients' harm because of long waits.

2.4 Conclusion of the chapter

This chapter presented a brief review of the evolution of the NHS performance measurement. Given all that has been mentioned in this chapter, it is evident the NHS has made considerable efforts to improve performance in hospitals including investments in improving capacity, the introduction of indicators and standards and promoting high-level quality services. However, as in any other public system based on performance measurement, some perverse consequences have been presented.

This chapter is particularly useful in this research for understanding how human behaviour is becoming an essential aspect of the NHS performances system: now clinician and patients are empowered, and their decisions now have more impact than before. Although the NHS has been making substantial investments to provide quality services, human decision making has also become an essential factor for improving performance. Therefore, human behaviour is considered in this research as a critical factor to understand how waiting time targets effects A&E performance.

Since this research set out to gain insight into the overall value of including human behaviour in an A&E simulation and to contrast how it can be done by Discrete Event Simulation (DES) and by Agent-Based Modelling and Simulation (ABMS), this chapter supports the research design of this project since it allows to identify elements that were considered in the choice of the simulation tools used in thesis and therefore in the conceptual modelling process carried out. The elements considered are related to operational processes, such as patient flows, workforce scheduling, and waiting times as well as some aspects of human behaviour such as doctors' decision-making processes. Literature review will show that DES has been widely used in healthcare to represent operational processes and some aspects of human behaviour and will discuss the suitability of ABMS for modelling human behaviour.

The next chapter will discuss the role of modelling and simulation for understanding performance measurement in healthcare.

CHAPTER 3: MODELLING AND SIMULATION IN HEALTHCARE

3.1 Introduction

Chapter 2 discussed several themes that underpin the need for the research described in this thesis. It briefly described the development of the NHS performance framework and argued that performance measurement can be carried out in different ways, for different purposes and may have different consequences from those originally intended, as discussed by academics and also by the media.

In order to help gain understanding about the unintended consequences of the NHS performance framework and to support control of healthcare systems, modelling and simulation methodologies have been commonly used. This chapter introduces the role of different modelling and simulation methods for studying different aspects of healthcare systems. It discusses the use of modelling and simulation in healthcare, particularly for modelling A&E departments.

3.2 The use of simulation in healthcare

Simulation methods have long been used to model elements of healthcare systems with a view to understanding and improvement. It has been suggested that healthcare simulation applications can be classified into those concerned with the strategy and policy level, the tactical and operational level, and with disease prevention and epidemiology (Brailsford, 2007; Koelling & Schwandt, 2005). Here the emphasis is on the first two levels.

Becker et al. (2005) argue that there are two intended uses of simulation models; *descriptive* models that are used for description, explanation and prediction; and *normative* models that are used for decision support purposes. However, this binary view seems too restrictive. Discussing OR/MS modelling in general, Pidd (2009) suggests four modes of model use: 1: d*ecision automation, 2: routine decision support, 3: system investigation and 4: improvement* and *providing insights for debate*. Heath et al. (2009), focusing on agent-based simulation, suggest three different archetypal approaches to simulation modelling, based on the modeller's level of understanding of the system to be simulated. As shown in Figure 3-1, Heath et al. argue that, when the level of understanding is high, a simulation can be used as a *predictor*; that is, as a machine that produces precise predictions about the system's behaviour under defined conditions. When the level of understanding is low, Heath et al. suggest the use of a simulation model as a *generator* to support the generation of hypotheses and theories about system behaviour, but not in a precise manner. When the level of understanding is neither high nor low, Heath et al. suggest that a simulation model be used as a *mediator*, which provides insight into the behaviour of the system without offering a complete representation of that behaviour. Clearly, these are three archetypal positions, and many models will display characteristics that make them a mixture of predictor and mediator, or mediator and generator. Heath et al. ’s three categories (2009) tally, more or less, with the last three of the four types suggested by Pidd.

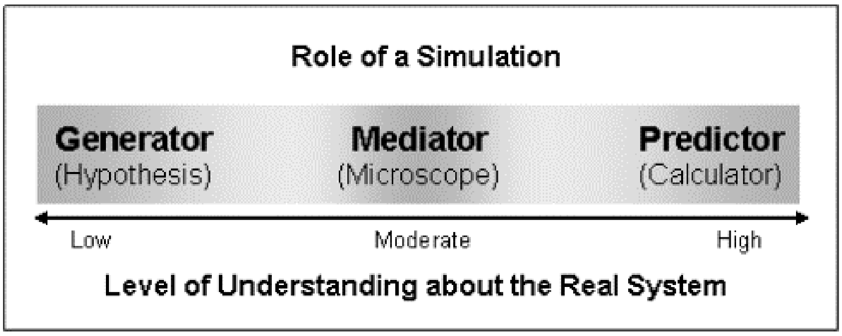


Figure 3-1. Roles of simulation models (from Heath et al., 2009)

The most common simulation methodologies used in healthcare are discrete event simulation (DES), system dynamics (SD) and agent-based modelling and simulation (ABMS). DES has usually been preferred when analysing hospital operational issues since it allows the representation of an individual patient’s characteristics and their flows through the system (Brailsford, 2007; Brailsford & Harper, 2008; Günal & Pidd, 2006). SD is also regarded as a suitable tool to deal with the complexity inherent in such social systems and has been used in defining generic structures and identifying general behavioural insights (Sterman, 2000; Wolstenholme, 2003). Agent-Based Simulation (ABS) on the other hand, has not enjoyed the same popularity as DES and SD in healthcare system studies. However, ABS has been used to study other classes of complex systems, in which people and their social interactions are modelled (Macal & North, 2008).

The remaining part of this chapter will discuss the use of DES and SD in the healthcare area, reviewing the use of each simulation method for modelling hospital performance and especially for modelling Emergency Departments.

3.3 The use of system dynamics in healthcare systems

Even though System Dynamics for healthcare systems modelling is not as common as other OR methodologies such as discrete event simulation (Brailsford & Harper, 2008), there is a considerable amount of literature in this area. This section summarises some reviews of the literature on general aspects of SD healthcare modelling and specifically for hospital performance modelling.

Whether it is appropriate to use SD in healthcare systems modelling depends on the intended purpose of the model (Pidd, 2002). For instance, there are some situations with defined objectives in focused problems with easily quantifiable components (Royston et al., 1999), for which SD might be used as a tool to evaluate different policies seeking improvements (Dangerfield, 1999). Additionally, there are wider and more complex systems with higher levels of uncertainty, in which SD may be useful as a tool to structure an issue and to obtain better understanding of it (Dangerfield, 1999; Royston et al., 1999).

SD modelling can be broadly divided into qualitative and quantitative streams. Qualitative SD models are useful as a preliminary step before developing fully quantified models (Sterman, 1992) or might be an end in themselves, offering a form of problem structuring. Wholly qualitative modelling, based on influence diagrams, appeared in the 1980s (Wolstenholme, 2004; Wolstenholme, Monk, McKelvie, & Smith, 2004; Wolstenholme, Monk, Smith & McKelvie, 2004) and is still in use. Dangerfield (1999) and Wolstenholme (2003) suggest that SD at the qualitative level is useful to support debate and communication as well as being a tool to structure problems due to the use of influence diagrams to expose system structures (Koelling & Schwandt, 2005) which generate system behaviour. Qualitative SD is also useful because it can embody generic structures that describe common patterns of behaviour (Wolstenholme, 2003, 2004). These generic structures (system archetypes) were defined initially by Senge (1990) and have been applied in different areas of healthcare (Wolstenholme, 1993; 1999b, 2004).

However, fully quantified models of SD are often needed to extend the value of the modelling process and to test the dynamic hypothesis formulated from the qualitative analysis. Fully developed quantitative SD models have been used in different areas of healthcare such as capacity planning (Lane, Monefeldt, & Rosenhead, 2000), waiting list management (Van Ackere & Smith, 1999) and disease control and management (Brailsford et al., 2004). Since the purpose of this work is understanding hospital performance, the next section will focus on how hospital performance has been modelled in system dynamics.

The first serious discussion and analysis of the literature of SD in healthcare emerged during the late 1990s with Dangerfield (1999) and Royston et al. (1999). Although these are excellent surveys of the literature, they cover only some of the investigations conducted by that time. In addition, since powerful SD software was only emerging at that time, the difficulties faced by users of earlier software may have influenced the orientation and level of modelling. Dangerfield (1999) classifies the literature around whether the reports addressed qualitative or quantitative modelling and provides an evaluation of excellent examples of applications of these two perspectives in different applications. That review argues that quantitative modelling is appropriate in epidemiology and disease modelling and discusses three studies conducted between 1984 and 1994 (Wolstenholme, 1993; Coyle, 1984; Van Ackere and Smith, 1997, with a detailed treatment of one fully developed example: AIDS transmission.

Qualitative modelling is discussed by Dangerfield as a tool for structuring problems and as a vehicle for debate, using three examples. In the first example, Wolstenholme (1993) examines the consequences of government policies on the community and healthcare sectors. The second example includes the work of Coyle (1984), which discusses the management of a hospital for short term psychiatric patients. That shows how improvements in system performance, such as waiting times and the relation between hospital capacity and duration of treatment are related to changes in the admission policies of a hospital. The final example is the management of waiting lists for elective patients by Van Ackere and Smith (1997).

Each of the three cases analysed by Dangerfield (1999) considers the impact of different policies on waiting lists. Dangerfield found that Wolstenholme argues that increasing waiting lists were the result of the implementation of government policy on isolated parts of an interconnected system. Coyle investigated the waiting lists for a specific patient group and showed that a waiting list could be affected by different admission policies and treatment durations. Van Ackere and Smith's application suggests that temporary injections of resources as a result of long waiting list tend to attract more patients which in turn increases the waiting lists.

The second review considered here is Royston et al. (1999), which summarises the work done by operational research analysts in the Department of Health in England. The angle from which the literature was reviewed does not differ too much from that of Dangerfield (1999). For instance, as in Dangerfield's review, the examples include problems related to diseases as well as more complex and organisational problems within healthcare. However, Royston et al., unlike Dangerfield, analyse the applications of SD in HC according to whether the modelling is solution-oriented or learning-oriented. That distinction seems to be driven by the complexity of the system. For relatively simple and focused systems, which may be comparable to engineering or production processes, Royston et al. (1999) suggest that SD can be used to find solutions, sometimes optimal, to practical problems. For example, such solution-oriented modelling could be used for particular acute or chronic disease such as screening for cervical cancer and Chlamydia. On the other hand, for systems that have a higher level of complexity, SD is best used as a tool to support learning.

Both reviews, Dangerfield (1999) and Royston (1999), agree with Vennix (1999) that the more complex the problem is, the more group - based modelling is appropriate; a view also espoused in Wolstenholme (1999a). Dangerfield regards these more complex problems as suited to a qualitative approach, though Royston et al. do not ignore the power of quantitative analysis for those highly complex problems as a step which involves stakeholder participation on the way to more quantitative approaches. Other discussions of quantitative versus qualitative modelling can be found in Lane (1994), Coyle(2000), Wolstenholme (2004) and Brailsford (2008).

Other surveys such as that conducted by Koelling and Schwandt (2005) and Milstein and Homer (2005) stress the importance of qualitative modelling to expose the structure of the system as well as quantitative modelling to extend the value of the modelling process. However, their surveys do not show whether the applications were qualitative or quantitative.

Koelling and Schwandt provide an overview of 220 SD healthcare applications between 1965 and 2004 using the System Dynamics Society (SDS) bibliography. That classifies applications into six main areas, as shown table in Table 3-1, showing that SD use has more often been at a strategic or policy level rather than for individual or population health. Its other primary use seems to have been for focused studies at a tactical level.

Table 3-1. The Koelling and Schwandt (2005) classification

	Area		**Number of papers**
1	Health systems strategy & policy	National & international	33
2		Regional & metropolitan	47
3		Single organisation or facility	43
4	Tactically focused delivery		32
5	Disease prevention		5
6	Epidemiology		60

Koelling and Schwandt complement the argument in Dangerfield (1999) that system dynamics can be used as a tool for persuasion at the national or regional level in situations characterised by lack of understanding, or as a tool for evaluation of tactical studies to provide a scenario in which tactical decisions can be better evaluated.

Milstein and Homer (2005) analyse SD use in Public Health, examining 21 applications between 1974 and 2006 and classifying them into six groups: healthcare reform, HMO planning, patient flows, performance assessment, public health emergencies and public health planning. By contrast with Koelling and Schwandt (2005), this review reports the majority of applications as being focused on individual and population health rather than managerial and planning issues.

Brailsford (2007) is a more general review of simulation approaches in healthcare, including both DES and SD. Similarly, to Dangerfield (1999), Royston et al. (1999) and Koelling and Schwandt (2005), the taxonomy proposed by Brailsford considers modelling at three levels: the strategic, the tactical and the human body levels. Brailsford points out that SD has been most commonly used at the strategic and policy level, whereas Discrete-Event simulation has been more often used to analyse situations at the tactical level, such as bottlenecks.

Other surveys include the work of Katsaliaki & Mustafee (2011) and Mustafee, Katsaliaki, & Taylor (2010). Katsaliaki & Mustafee (2011) surveyed the application of simulation in healthcare. They selected 139 papers from 1997 to 2007 and found that 17 of those papers used system dynamics as the simulation method and grouped them into four categories (see Figure 3-2):

- Public health policy evaluation and economic models: Includes models for harm reduction policies, treating strategies, long-term health impact, disease population dynamics, reconfiguration of health services and health insurance strategies.
- Modelling healthcare systems and infrastructure disruption: includes models for unscheduled care, A&E demand pattern, resource deployment, parallel hospital processes, health infrastructure disruptions and disasters.
- Training tool: health policymakers–understanding the dynamics of diseases, students' experimentation with pharmacological systems.
- Review

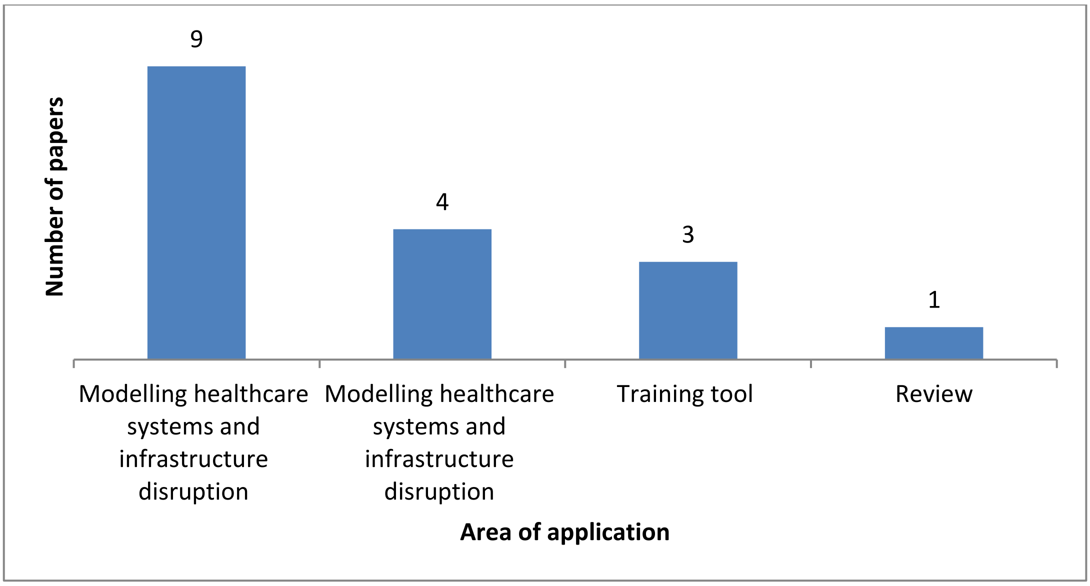


Figure 3-2. Areas of application of SD in healthcare (from Katsaliaki & Mustafee, 2011)

A More recent survey is the review of Kunc et al. (2018). They found that System Dynamics has been used in healthcare in different areas. First, there is a group of papers that focus on healthcare as a complex system modelling aspects of workforce management in healthcare. Second, some papers explore the relation between System Dynamics and other OR approaches. Third, papers that focus on methodological issues of System Dynamics in healthcare. Fourth, some work is related to supporting health emergency and healthcare improvement programmes, also there is work related to the role of SD as a dynamic and behavioural theory of strategy. Finally, some papers explore the use of SD to support policymaking in healthcare, mainly because of its ability to represent populations, chronic disease progression, epidemics, service treatments, patient pathways and workforce.

3.3.1 SD for modelling Emergency Departments

In 1995, the OR Group of the UK Department of Health (Royston et al., 1999) began to use system dynamics to understand and improve the performance of Emergency Departments. The initial aim was to expose the structure of the UK healthcare system by considering the interactions among its different parts. The idea was to help different stakeholders develop their understanding of system behaviour resulting from the system structures often found in healthcare. That work demonstrated meaningful relationships among different sectors of the healthcare system, such as the observation that longer waiting times in GP consultations tend to elevate the number of arrivals at accident and emergency departments. Another important finding of this model is that behaviour changes (e.g. willingness to admit patients?) have a more significant effect than changes in capacity.

Lane et al. (2000) describe the use of SD to understand the different factors contributing to the long delays for unplanned, urgent admission to acute hospitals in the UK and to explore the dynamics of the system of which the accident and emergency department is one element. The model considers interactions between the demand pattern, A&E department resource deployment, other hospital processes and bed capacity. The main finding is that although some delays in the patient's pathway are inevitable, a selected augmentation of A&E resources may lead to some reductions in those delays. Additionally, the study demonstrated that reductions in bed capacity have more impact on elective surgery cancellations than on waiting times for emergency admissions. Similarly, Brailsford et al. (2004) developed a system dynamics model of the health-care system of a city related to emergency care. The purpose of the model was to simulate patient flows and to identify bottlenecks.

Salmon et al. (2018) analysed the literature of simulation modelling applied to emergency departments and found SD models that have been used to analyse some effects of external factors on waiting times within emergency departments. In general terms, simulation in healthcare has been widely used to study Emergency Departments processes and performance, resource and capacity issues, and workforce planning. They presented examples of the use of SD for modelling flows within emergency departments and with other hospital units.

In summary, most SD applications have investigated the relationships between healthcare demand, healthcare capacity and within-hospital delays; others have investigated the interactions between different units of a hospital and other sectors of the healthcare system. The SD models of emergency departments have mainly focused on understanding how the fundamental structure of the healthcare system affects the performance of emergency departments and to represent A&E patient flows. Besides, it was shown that some SD models of A&E departments have explored how not only changes in capacity affect performance but also how changes in people's behaviour also play an essential role in performance improvement. However, it is known that SD only allows for the modelling of human behaviour at an aggregated level, making it inappropriate for modelling heterogeneous populations at an individual level, which is a disadvantage for modelling human behaviour within A&E departments, since individual characteristics of clinicians and patients as well an individual interaction between them are relevant to represent most of the aspects related to A&E performance. Therefore, it is not surprising that there is no evidence in the literature of SD research that studies the relationship between individual behaviour and the performance of A&E departments.

The next section will analyse the use of discrete event simulation in healthcare, particularly for modelling emergency departments.

3.4 The use of DES in healthcare systems

A considerable amount of literature has been published on Discrete-Event simulations in healthcare systems. Several systematic reviews of the use healthcare simulation include Fone (2003), Jun et al. (1999), Günal and Pidd (2010), Brailsford et al. (2009) and Mielczarek (2016). The literature review of Günal and Pidd (2010) reports that most of the research carried out in healthcare systems using DES is done to support operational decision-making and planning in specific healthcare units to study particular problems such as staff scheduling, resource utilisation and waiting time issues. They also found that most of the reported simulations focus on specific facilities and seem not to be reused. Similarly, Brailsford et al. (2009) report that most of the papers reported in the literature show that simulation is mainly used for planning or system resource utilisation, whereas human behaviour and segmentation are rare areas of application of simulation models. Mielczarek (2016) reports that DES is frequently used to support decision-making in healthcare systems operation, usually applied to single units or mutually related clinics to tackle issues related to staff scheduling, resource allocation and planning.

Brailsford (2007) discusses some of the challenges to be faced by those attempting using simulation in healthcare and proposed a taxonomy for simulation modelling in healthcare that includes three primary levels of applications:

- Level 1 includes models of the human body (also known as well disease models), where the main purpose is to model the physiological, biological and clinical processes of individuals.
- Level 2 refers to operational and tactical models. In this level, the main purpose is to model the flow of patients around clinics, wards or hospital departments and is commonly used for capacity planning, resource allocation and process redesign.
- Level 3 represents the strategic models. In this level, the majority of the models deal with the study of long-term system behaviour rather than modelling individual behaviour.

According to Brailsford (2007), DES is more commonly used in levels 1 and 2 for disease models and operational and tactical models, whereas SD is commonly used in level 3.

The next section will discuss the use of DES in levels 1 and 2, particularly for modelling Emergency Departments.

3.4.1 DES for modelling Emergency Departments

Existing literature on healthcare simulation reveals that one of the most popular areas for DES in healthcare systems is A&E departments (Günal and Pidd, 2010; Gul and Guneri, 2015; Mielczarek, 2016; Mohiuddin et al., 2017; Salmon et al., 2018), which are the central area of interest of the research discussed in this thesis. The popularity of A&E departments for DES may be because an A&E department is a relatively self-contained system that allows relatively easy observation of its processes (Günal & Pidd, 2006) and because DES allows the representation of patient characteristics and their flows through the system (Günal, 2008). Numerous studies have attempted to use DES in A&E departments to improve performance; study patient flows, bed occupancy and length of stay; and for scheduling and capacity planning (Günal, 2008; Jun et al., 1999).

Up until now, several studies have surveyed the existing literature on the use of DES for modelling A&E Departments. For example, Gil and Gulneri (2015) reviewed existing literature simulation modelling applied to emergency departments facing typical and disaster situations. They reviewed approximately 106 papers and found that DES is the most popular methodology for modelling Emergency Departments. They identified that around 62% of the papers used only DES as the principal methodology, 33% used DES and other OR methodologies, 3% used only ABMS and the remaining 2% used ABMS with other methodologies.

They argue that the popularity of DES is due to its flexible methodology, which allows the modelling of stochastic, complex and non-linear systems. That approach also allows the modeller to include individual patients' characteristics and represent process-oriented systems using visual representation of patient flows. Similarly, they found that ABMS also offers similar opportunities for modelling Emergency Departments, but they believe that the strength of DES is the modelling of process-oriented systems, while the strength of ABMS the modelling of interacting decision-making behaviours. Although their review did not focus on modelling human behaviour, they suggest that multi-method modelling, for instance, DES and ABMS, could be valuable to represent human behaviour in ED simulations.

Similarly, Salmon et al. (2018) conducted a structured literature review of simulation modelling applied in Emergency Departments, focusing on simulations that actually represent the emergency department's problems and that can support decision making. They found that most of the simulations of emergency departments are focused on processes and performance, resource and capacity issues, and workforce planning, whereas medical decision making and individual patient behaviour, are uncommon. Salmon et al. also reported that the majority of Emergency Departments studies used DES as the primary simulation methodology, particularly to study operational issues. On the other hand, ABMS has been gaining popularity to study such systems, frequently used to model patient behaviour. They did not find many studies that focus on clinicians' behaviour in emergency departments.

Although simulation methodologies have been commonly used to model performance in healthcare (Brailsford et al., 2009; Günal & Pidd, 2005), there is little published research on the use of DES for modelling the effect of the 4-hour waiting time target on the people's behaviour and performance of the A&E departments. For instance, Günal and Pidd (2009) developed an interconnected DES model (DGHPSim) of Emergency, Outpatient and Inpatient Departments of a hospital to understand the effects of waiting time targets on hospital performance. The A&E component of the DGHPSim model can be used to simulate the performance of an A&E department and allows comparison of actual and simulated performance in terms of patient waiting times. Günal and Pidd (2009) include performance graphs for two A&E departments, and in one of these, there are apparent differences between the actual and simulated waiting times as patients approach the 4-hour target. That, the authors say, is because the model was not designed to capture panic interventions that might occur as a patient's waiting time approaches four hours but shows what would happen if processes were allowed to proceed normally without such interventions. The differences between the actual and simulated waiting times might be due to different reasons. One possible reason is that the *level of detail* included in the model is not sufficient to represent the components that affect the performance of the Emergency Departments under performance measurement schemes that require meeting some specific targets. Another reason might be that the way that *humans are represented* in the model ignores some of the essential factors of the staff's and patient's behaviour that have an important effect on the Emergency Department's performance.

Eatock et al. (2011) also built a DES model that represents the actual A&E department's process to study strategies towards meeting the 4-hours target. Their focus was on patients' throughput issues, examining how changing patients' priorities when approaching 4-hour time affects the department's performance. Human behaviour in their model is included either as reactive behaviour or countable variables (or resources) that are seized and released at activities. For instance, patients are active entities whose behaviour includes joining a queue and engaging in an activity. A priority system defines Patients' behaviour in a queue, and priorities are updated every specific time to check whether a patient is close to approaching the 4-hour time, when this happens, their priority is increased, and they are redirected to another fast-track path.

On the other hand, it seems that staff are treated as resources that interact with patients in the activities and take breaks on their quiet periods; however, it seems that their decision making depends only on the simulation process (reactive behaviour that depends only on the sequence of scheduled events) rather than on their own needs. Although they found that their model represents sufficiently accurate the performance of the A&E department, they did not reproduce closely enough the number of patients breaching the target. They believe that the difference between observed and simulated behaviour may be due to some informal process they did not consider in their simulation model. They argue that the complexity of modelling A&E departments concerning strategies to prevent breaches of the four-hour target may be due to the difficulty of tracking patients approaching the four-hour target and the modelling of staff behaviour.

The literature on the use of DES for modelling Emergency Departments has demonstrated that one of the most significant challenges for simulation models is incorporating human behaviour. DES has widely used to represent operational issues and some human factors such as workload capacity, multi-tasking, workforce planning, patient flows and patients' priorities; however, there has been little discussion on the value of including human behaviour and its relation to the A&E 4-hour target. ABMS has been gaining popularity for modelling healthcare systems, and it has been mainly used to represent people's interactions in complex systems. The next section will describe the main areas of application of ABMS and discuss the use of ABMS in healthcare systems.

3.5 Agent-based modelling and simulation: terminology

Agent-based applications have roots in different disciplines and, were originally motivated by investigations of adaptation and emergence in biological systems (North & Macal, 2007). It is common then, to see the term "agent" used in different disciplines for different purposes (Gilbert & Terna, 2000) and it is possible to find agent-based applications in fields such as artificial intelligence, social science, complex science, economics. (Borshcev & Filippov, 2004).

Although there is no complete general agreement on what an "agent" is, there are some common characteristics in its definition. For instance, in the Multi-Agent Systems area of study, Ferber (1999, p.9) defines an agent as: "a physical or virtual entity that can act, perceive its environment (in a partial way) and communicate with others, is autonomous and has skills to achieve its goals and tendencies". By physical entities, Ferber refers to entities that exist in the real world, and by virtual entities to entities that do not exist in the real world but act in a virtual environment.

Taking a different tack, Jennings and Wooldridge (1998, p.8) define an agent within the software engineering area as "a computer system, situated in some environment, that is capable of flexible, autonomous action in order to meet its design objectives." Bonabeau (2002), considering simulation modelling, provides a more general description of an agent considering an agent as an autonomous decision-making entity which makes decisions based on a set of rules. Similarly, North and Macal (2007) consider an agent as anything that makes choices in a system.

There are different terms used to describe agent-based methods in simulation, including Agent-Based modelling (ABM), Agent-Based simulation (ABS), Agent-Based modelling and simulation (ABMS) and Individual-Based modelling (IBM). Despite this, writers agree that a model consists of a set of agents that follow a group of rules that represent individuals' behaviour in the system. The simulation emulates those types of behaviours through model execution (Borshcev & Filippov, 2004; Van Dyke Parunak, Savit, & Riolo, 1998). Here, the term agent-based modelling and simulation (ABMS) is used for such applications.

3.6 The use of ABMS in OR/MS

In the OR/MS area, AMBS is not as popular for healthcare modelling as DES or SD. Moreover, literature shows that agent-based methodologies are not as popular in OR/MS as in other fields such as Computer Science. Browsing the string '((agent*) AND (model* or simulation))' in the topic search of the Web of Science (WoS) produced 228,787 hits from 2000 to 2019 when executed in July 2019. Using WoS analysis tools allows the identification of the main subject areas of application of agent-based methodologies. Figure 3-3 shows that the main subject area is Computer Science, with 17.95% of the total papers. OR/MS enjoys much less popularity, with only 1.91% of the total records.

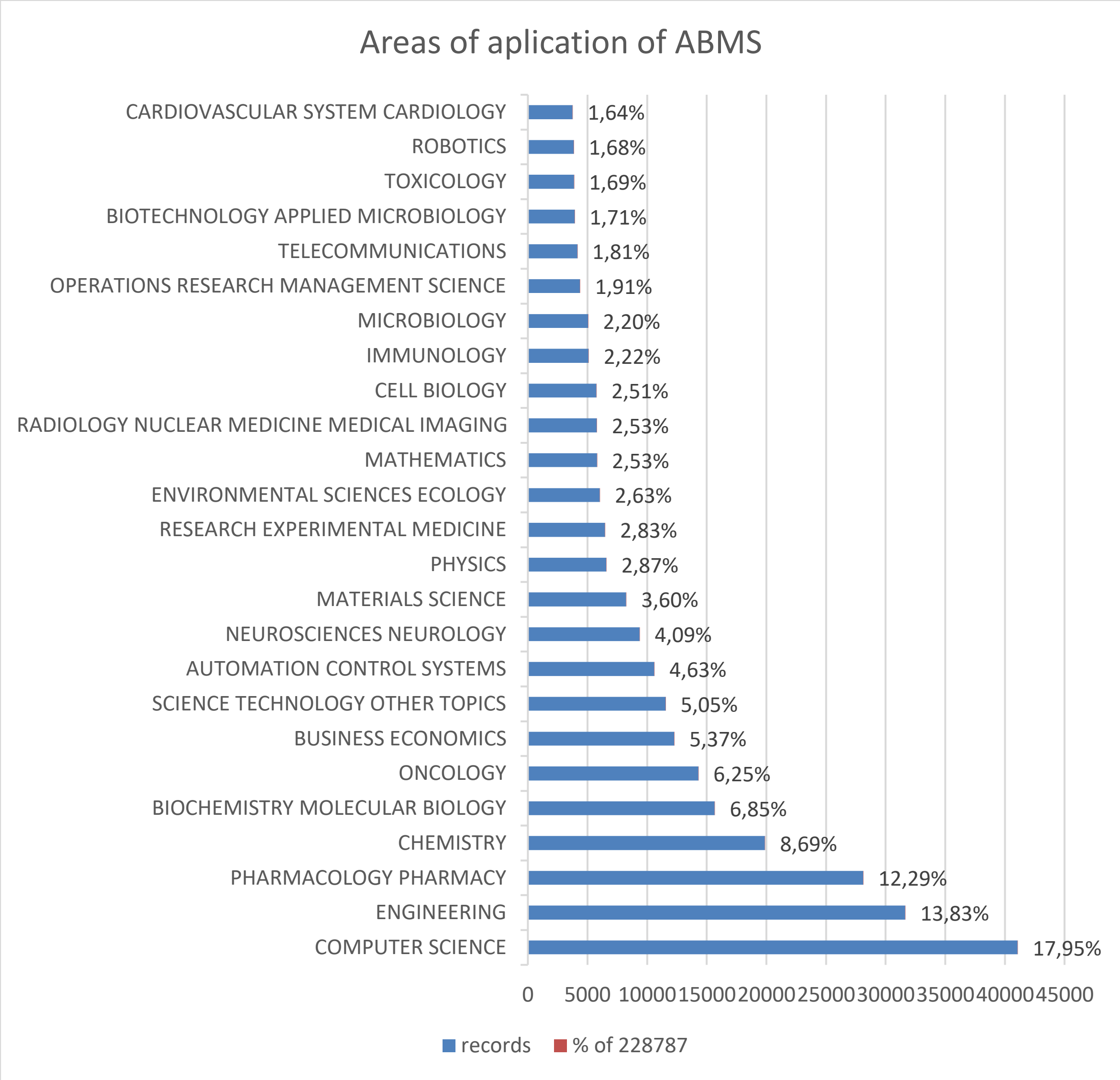


Figure 3-3. Agent-based modelling by subject area.

It is not surprising that the majority of the studies of ABMS have been carried out in the Computer Science field since the roots of ABMS are in the concepts of cellular automata and artificial intelligence (Brailsford, 2014; North & Macal, 2007) which are areas commonly studied in Computer Science. Moreover, there are some other concepts in computer science related to agent-based modelling and simulation. North, M & Macal, C (2007 p. 46) list “individual-based/ actor-based/ particle simulation, autonomous agents, and multi-agent systems (MAS), swarm intelligence, artificial life and artificial societies, self-organisation, evolutionary programming” among others.

Usually, the area of Computer Science includes research about the development of software, where the agents commonly represent and act on behalf of the users and as the users; they also behave according to their different goals and motivations (Wooldridge, 2002). However, agent methodologies have been applied not only in Computing Science fields but also have been commonly developed and used in Economy, Biology and Social Science fields (Heath et al., 2009).

The following sections will analyse the uses of ABMS in healthcare and particularly for modelling Emergency Departments.

3.7 The use of ABMS in healthcare systems

As discussed previously, a considerable amount of literature has been published on simulation in healthcare (Brailsford & Harper, 2008; Brailsford et al., 2009; Dangerfield, 1999; Eldabi & Young, 2007; Gill & Paranjape, 2009; Günal & Pidd, 2010; Homer & Hirsch, 2006; Katsaliaki & Mustafee, 2011; Leischow & Milstein, 2006; Mustafee et al., 2010; Royston et al., 1999). However, it seems that ABMS applications mainly appear in non-healthcare domains (Shi, 2008) and that few have been carried out in healthcare (Kanagarajah et al., 2006; Moreno, 2003; Sibbel & Urban, 2001; Stainsby, Taboada, Luque, 2009; Taboada et al., 2013). To illustrate this, a more detailed search of Web Science was conducted in July 2019.

Browsing for papers from 2000 to 2019 that contains the string *'((("Agent-based") AND (model* OR simulation)) AND (health* OR hospital))'* in the topic, produced 997 records. The results of this query allow the main subject areas of application of ABMS in healthcare to be identified Figure 3-4 shows that the most popular subject area of ABMS literature in healthcare remains *Computer Science* with 36.47% of the records, followed by *Engineering* with 19.22%, *Public Environmental Occupational Health* with 10.98% and *OR/MS* with 7.65% of the records. Areas such as *Mathematics, Mathematical Computational Biology and Health Care Sciences Services* appear with less than 5% of the total records.

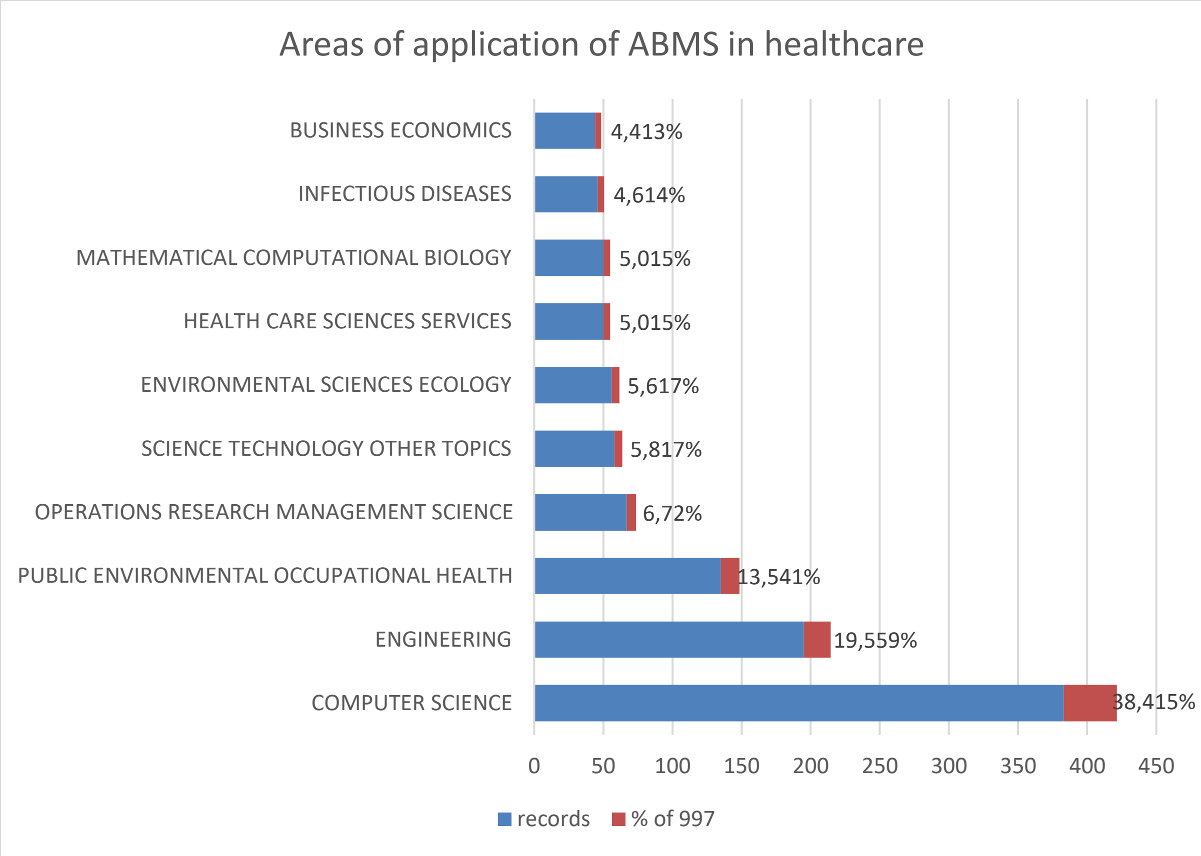


Figure 3-4. ABMS in healthcare by subject areas.

As expected, most of the papers located by the WoS search discuss mobile agents or software agents and use different techniques of Computer Science such as Artificial Intelligence, Multi-Agent Systems, Agent Software and other software approaches. Typical applications of this field focus on software development, using artificial intelligence methodologies to learn and automate some specific procedures and processes and to support real-time decision making.

There are some reviews of the literature of applications of agent-software or mobile agents in healthcare. According to Isern et al. (2010), there are five main areas of application of Agent-Based *software* approaches in healthcare:

1: *Medical and data management systems*: to record and process medical data.
2: *Decision support systems:* to assist with different healthcare processes like treatment and diagnosis.
3: *Planning and resource allocation*: to coordinate and schedule different human and material resources.
4: *Remote care*: to remotely monitor the patient's status and, *composite systems*: which combine different aspects to provide complete and integrated solutions for healthcare management.

Other reviews (Moreno, 2003; Nealon, 2005; Nealon & Moreno, 2003) also consider studies in disease and epidemics areas. These studies often consider biological and medical knowledge of human behaviour in their models.

The initial query filtered by subject areas, considering only the records related to OR/MS applications, obtained a total of 45 items. These are classified into the three main groups of healthcare simulation applications in OR/MS discussed previously: the strategy and policy level, the tactical and operational level, and disease prevention and epidemiology. It can be seen from Table 3-2 that most of these applications are in the *disease prevention and epidemiology* area. Here, however, we focus on the first two groups.

At the strategy and policy level, it can be seen that most of the applications have focused on evaluating the effects and effectiveness of different strategies or policies on different areas of the healthcare system. At the tactical and operational level, the majority of the papers show the use of ABMS for supporting decision making within different areas of the healthcare system or within different healthcare units. However, most of the studies are limited to patients' behaviour and ignore relevant aspects of the behaviour of the healthcare providers that may also affect the performance of healthcare systems.

Table 3-2. Publications of ABMS in Healthcare by level of application

Level of application	Number of papers	Reference
Strategy and Policy	6	(Heffernan & McDonnell, 2007; Kanagarajah, Parker, & Xu, 2010; Kim & Yoon, 2014; Metcalf et al., 2013; Perez et al., 2005; Xu, Li, & Wu, 2008)
Tactical and operational	5	(Bhandari et al., 2011; Brailsford & Schmidt, 2003; Escudero-Marin & Pidd, 2011; Hagtvedt, Ferguson, Griffin, Jones, & Keskinocak, 2009; Knight, Williams, & Reynolds, 2012)
Disease prevention and epidemiology	11	(Aleman, Wibisono, & Schwartz, 2011; Barnes, Golden, & Wasil, 2010; Barnes, Golden, Wasil, Furuno, & Harris, 2011; Dougherty et al., 2012; Kelso & Milne, 2011; Liu & Hu, 2010; Lizon, Aleman, & Schwartz, 2010; Ma, Sartipi, & Ieee, 2014; Meng, Davies, Hardy, & Hawkey, 2010; Von Neubeck et al., 2013; F. Zhang, Li, & Xuan, 2009; J. Zhang et al., 2015)
Other	23	(Allen, 2011; Carneiro, et al., 2008; Cheon & Corbitt, 2009; Cole et al., 2008; Ferraz, Oliveira, Viera-Marques, & Cruz-Correia, 2010; Gibbons, 2007; C. Macal & North, 2011; Manley & Kim, 2012; Narzisi, Mincer, Smith, & Mishra, 2007; Natarajan, Ghosh, & Srinivasan, 2009; Pearce, Hosseini, Taaffe, Huynh, & Harris, 2010; Perez et al., 2009; Rahmandad & Sterman, 2008; Ramaekers, Bellemans, Janssens, & Wets, 2008; Roberts, 2011; Ryan & McAlpine, 2005; Sokolova & Fernandez-Caballero, 2009; Van Dam, Lukszo, & Srinivasan, 2009; Vermeulen et al., 2010; Walczak, 2009; H. Yang, Liu, Wu, & Li, 2009; X. Yang & Miao, 2011; W. Zhang, Li, Xiong, & Zhang, 2010)

In addition, this survey shows that several of the applications used ABMS together with other methodologies. One example is the research conducted by Dougherty et al. (2012). They modelled the U.S healthcare system by combining system dynamics, discrete event simulation and agent-based modelling and simulation. The purpose of the research was to develop a framework to support decision making at different levels and scales. In this study, SD was used to represent the structure of the healthcare system by representing its central relationships, DES was used to model queues and sequential processes, and ABMS was used to represent particular movement of patients.

Other papers showed the use of ABMS together with SD. For instance, Heffernan & McDonnell (2007) developed an SD model to analyse the interaction between the health and long-term care for elderly in Australia and extended the model using ABMS to represent geographical distribution of the agents that represent the demand and supply of the healthcare and long- term care for elderly. Similarly, Metcalf et al. (2013) focused on developing an SD model of the participation of adults in oral health promotion and implemented an agent-based approach to represent social interactions and geographic information systems.

Some other papers combine or complement DES with ABMS. Knight, Williams, & Reynolds (2012) used DES and ABMS to model the decisions of patients in choosing an appropriate hospital for their treatment. Hagtvedt et al. (2009) used different methodologies, including DES and ABMS, to evaluate some strategies for ambulance diversion from emergency departments to hospital wards. The DES model considered the patient flow in a hospital ward and the ABMS model included spatial patterns of different groups of patients. Although the work of Brailsford and Schmidt (2003) considered a DES model of patients' attendance for screening for diabetic retinopathy, it seems that the patient entities in their model play the role of simple agents. Each patient decides against attending the screening based on the values of internal variables that represent individual characteristics. Because of this, the work of Brailsford and Schmidt (2003) was included within the methodologies that use DES and ABMS together.

3.7.1 ABMS for modelling Emergency Departments

As mentioned before, ABMS has been gaining popularity to study Emergency Departments (Salmon et al., 2018; Gil and Gulneri, 2015). In order to limit the relevant literature within the scope of this research, which is Emergency Departments, the initial query was refined to those applications carried out within this subject. Therefore, considering the same time span, 2000 to 2019, and limiting the search for Emergency Departments applications, a new string was used in the <u>topic</u>: *'((((("Agent-based") AND (model* OR simulation)) AND (health* OR hospital)) AND ("A&E" OR" Emergency Department*" OR "ED")))'* obtaining 52 hits. The literature on simulation applied to

Emergency Departments has highlighted the benefit of using ABMS for modelling different aspects of human behaviour, such as clinicians and patients' interactions as well as their decision-making processes.

For instance, Yousefi et al. (2018) developed an ABMS model of patient's behaviour within an Emergency Department. The focus was on analysing interactions among patients and the effect of those interactions on patients' decision to leave the department before being attended. They used cellular automata techniques to define patients' decision-making processes based on their waiting time, overcrowding and neighbours' experience. Yousefi et al. proposed policies for improving performance that include increasing the number of triage nurses, fast-track treatment, increasing waiting room capacity, and reducing treatment time. Although their model provides a good representation of number of patients leaving unattended, this study focusses only on one specific aspect of patients' behaviour, which is related to their willing to stay up to the end of the attendance and ignores other factors of human behaviour such as clinicians' decision-making processes and their relation with the global performance of the department.

Similarly, Kanagarajah et al. (2006) reports a hypothetical ABMS of an Emergency Department with a focus on patients, mainly they assessed the effects of fluctuations in workload and economic forces on patient safety. The agents considered in the model were patients, doctors, nurses, technicians, treatment rooms and managers. All the agents were programmed to aim for minimising preventable adverse events while managing patient's outcomes. Patients were attended based on their condition. The time spent by medical staff with patients depends on demand pressures and patients' characteristics, and doctors may work faster or in busy periods to clear excessive queues. One important aspect of their model is that, as in this research, they also consider the 4-hour target as a trigger to modify the agent's behaviour. In their case, patients that stay more than 4 hours before being attended are considered as an adverse event, and their objective was to reduce these events by implementing different strategies like changing availability of resources and staff and reducing treatment time. However, the behaviour of the agents within the model is defined by elementary rules that only consider external factors rather than their internal state. For instance, doctors only reduce their consultation time based on queue size and ignore other aspects such as the pressure they feel to meet the targets or tiredness after working without breaks.

Taboada, Cabrera, & Luque (2011), Taboada et al. (2011), Stainsby et al. (2010), Cabrera et al. (2012a; 2012b; 2011), show examples of the use of ABMS as a decision support system for hospital emergency departments. For instance, Stainsby et al. (2009) described briefly the conceptual ABMS model of an Emergency Department model based on the interactions of the agents. The preliminary conceptual model considered five agent classes: patients; companions of patients; administrative staff; nurses and doctors. The rules of interactions depend on which agent initiates the interaction. The patient flows and interactions among agents in each process are captured in a conceptual model described in their paper. The purpose of their model was to help understand some important questions about people's behaviour in an emergency department. For instance, they claim that with the ABMS it will be possible to understand why some patients leave an emergency department while waiting for triage, or how the implementation of a fast track system affects the level of service as perceived by the patient. The general layout of the model shows at each stage the pathway of the interacting agents; however, it is not clear how these interactions occur. Additionally, the authors claim that the model will include aspects of human behaviour but fail to explain how this behaviour is represented in the model. However, there is no evidence that the model is being developed to help understand performance but rather to understand some specific behaviour of individuals within the system.

Another example of the use of ABMS as decision tool system is Taboada et al. (2011; 2012). They described an ABMS of an emergency department that includes two types of agents: active agents that represent people and other entities with proactive behaviour and passive agents that represent systems with reactive behaviour. The interactions between the agents were defined by state machines which define the different state variables of each agent. State variables are identifier, physiological variables such as age, medical history, origin, location within the emergency department, actions, physiological condition and symptoms, communication skills and level of experience. The behaviour of each agent can be defined externally by the use of probabilities and the actions triggered by the behaviour depend on the agent's characteristics and the agent's location. However, a limitation of their behavioural representation is that it may ignore other aspects of agents that may affect their behaviour, for example, psychological factors such as motivation may be related to the behaviour of the agents.

ABMS has also been used to study operational issues within Emergency Departments such as patient flows, resource allocation, and workforce scheduling and distribution. Examples of this include studying the effects of redistribution of nurses on the patients' waiting time (Al-Refaie, Fouad, Li, & Shurrab, 2014), representing patients with deteriorating conditions by representing re-triage structure inside the emergency department (Rahmat et al. 2013) and experimenting with emergency department policies for reallocating patients with noncomplex conditions (M Taboada et al., 2013).

Other examples of the use of ABMS at the operational level include Liu et al. (2017) who built an ABMS simulation of an Emergency Department aiming to develop a tool that helps understand complex behaviour, evaluate policy and improve efficiency of emergency departments. They modelled the behaviour of patients and staff using simple if/then rules that were mainly related to movement, engaging in activities, waits and staff scheduling. In addition, Laskowski, McLeod, Friesen, Podaima, & Alfa (2009) and Laskowski & Mukhi (2009) modelled an Emergency Department using ABMS, considering patient flows and access through the emergency department to assess healthcare policies and practise guidelines.

Similar work was performed by Lim et al. (2013) who developed a hybrid model of DES and ABMS, where DES is used to model patient flows and ABMS to represent physicians and their delegates and to evaluate the impact of their interactions on an Emergency Department. They argued that considering an agent-based approach in DES could be useful when the purpose of the model is to obtain optimal staff scheduling since the hybrid approach allows representing scheduled resource utilisation and patient throughput in a more accurate way.

Literature shows that ABMS models offer good opportunities to represent typical Emergency Department processes, but none of the lastly mentioned studies has explicitly defined human behaviour beyond what a DES model traditionally can do. Usual passive entities interact with each other in an observable process that involves arrivals, queues and activities, and there is no evidence of analysing the impact of human behaviour in emergency departments' performance. Moreover, ABMS in healthcare has been mainly used for studying disease prevention and epidemiology problems, and there are very few applications at the strategy and policy, and tactical and operational levels, especially for modelling emergency departments.

The reason why ABMS has not been widely used in healthcare systems might be attributed to different factors. First, ABMS may be computationally demanding. The growth in computer power is bringing new opportunities for ABMS modelling; however, running a model with high levels of detail and a large number of agents may consume a considerable amount of time. Second, mastering ABMS software is not straightforward because most of its use requires high programming skills as well as a global understanding of ABMS theory. Third, the data collection process may be complicated. Sometimes the existing data sources do not include the information required for a detailed ABMS model, and it might be necessary to collect data from direct observation. Moreover, the data cleaning process or error collection might be hard to perform and is time-consuming work.

3.8 Summary

This chapter has reviewed the use of different simulation modelling techniques in healthcare. The most common simulation techniques used in healthcare are discrete event simulation (DES), system dynamics (SD) and agent-based modelling and simulation (ABMS). Of these, discrete event simulation is the most popular, system dynamics the second most frequently used and agent-based modelling and simulation the least used simulation technique in healthcare. In particular, this chapter has reviewed the use of ABMS in healthcare. It can be seen that most of the previous ABMS models in the healthcare area have focused on representing patients' behaviour rather than staff. It will be discussed later how staff behaviour can be modelled in ABMS models and how that behaviour can be linked to waiting time performance in an A&E department.

The next chapter will discuss how human behaviour has been modelled in healthcare. It will review some important aspects of human behaviour that need to be considered in simulation models, and it will also present the advantages of the use of agent-based modelling and simulation as a tool for modelling human behaviour. Finally, it will introduce two main human behaviour frameworks commonly used in simulation modelling.

CHAPTER 4: MODELLING HUMAN BEHAVIOUR

4.1 Introduction

Chapter two discussed the effects of performance measurements in public systems. Specifically, it showed how the literature had offered different points of view of the effects of the NHS performance measurement framework in the UK. It has been argued that despite improvements in waiting times after the introduction of targets in England (Bevan, 2009; Lewis & Appleby, 2006; Triggle, 2005), they may have distorted the quality of care and clinical priorities in healthcare service delivery (Bevan, 2009; Kelman & Friedman, 2009; Mason et al., 2012). Hence, it may be beneficial to develop simulation tools that incorporate human behaviour in healthcare settings in order to understand how these affect performance against system performance targets. In this way, simulation models may enable a better understanding of the balancing of clinical priorities with waiting times.

Therefore, it may be beneficial to use a tool that represents how people behave within the NHS under the current performance system and that allows the evaluation of different alternatives for improvement that balance clinical priorities with other performance measurements, such as waiting times.

As discussed earlier, simulation models have been widely used in healthcare for different purposes. Chapter three reviewed the use of simulation in healthcare. It was found that discrete event simulation has been commonly used to support decision- making at the tactical and operational level and also for system planning or system resource utilisation. Applications in healthcare include staff scheduling, patient flows, resource utilisation, and waiting time issues.

SD, on the other hand, has more often been used to support decision-making at a strategic or policy level and to help people understand how different aspects of the structure of the healthcare systems affect their overall behaviour. Most of applications in healthcare include models for evaluating public health policies and for studying different aspects of the infrastructure of the healthcare systems.

ABMS has been mainly used as decision support systems and to model some aspects of human behaviour in healthcare. The majority of the work in this area emphasises aspects of the behaviour of patients rather than that of clinicians in different healthcare units such as Emergency

Departments. There is also no evidence in the literature of studies of models of the effects of targets on hospital performance using ABMS.

Since the primary purpose of healthcare systems is to provide healthcare services to people, it is crucial to include the modelling of healthcare systems some aspects of the people's behaviour. Representing human behaviour in healthcare models is not easy because of the complexity and the characteristics of both the healthcare and human systems.

This chapter will start by reviewing how human behaviour has been included in simulation models. It will then present some relevant aspects and theories of human behaviour, and finally, it will introduce agent-based modelling and simulation and two popular agent frameworks that have been used to model human behaviour.

4.2 Simulation of human behaviour

As the study of human behaviour is a complex topic, it, therefore, follows that the modelling of human behaviour is not an easy task. It seems all commentators agree that the behaviour of human beings does not follow the same reliable laws followed by physical systems such as the climate or an electrical power distribution system. Moreover, the data about human behaviour is scarce since the behaviour of people can be difficult to measure and quantify; and in some cases, human behaviour is not suitable for experimental control or manipulation.

However, sometimes there are some aspects of human behaviour that need to be captured in simulation models but do not require a detailed representation, for instance, the models that are built to help understand how the structure of a healthcare system affects its behaviour, such as models used to understand the impact of the increase in hospital bed capacity on patients waiting times. In this case, it might be necessary to model patients' arrival and discharge rates, but without focusing on individual behaviour. Another example can be the models that are used for system planning or system resource utilisation, for instance, the models that are used to study scheduling of staff to reduce bottlenecks. In that case, although staff scheduling requires representing individual nurses and doctors, these are models that may not need a detailed representation of human behaviour.

On the other hand, there are some models that need to include individual characteristics and individual decision-making processes of the people involved in the system that is being modelled, for example, models of healthcare systems where performance may affect people's behaviour, such as accident and emergency departments where the four-hour waiting time target may influence staffs' decision- making processes within an accident and emergency department. Other examples include disease models, in which individual health tendencies affect the spread of a virus, and models for the prevention of a disease that depends on individual patient habits.

The next sections will briefly discuss how system dynamics, discrete event simulation and agent-based modelling and simulation have incorporated human behaviour in healthcare models.

4.2.1 System dynamics and human behaviour

System dynamics assumes that behaviour emerges from the structure of the system rather than from the personality of the people in the system (Sterman, 2000). Structure is composed of interconnected feedback loops and nonlinearities created by stock and flow networks, information flows and the decision-making processes of the people acting in the system.

Sterman (2000, pp. 28) argues: "when we attribute behaviour to personality, we lose sight of how the structure of the system shaped our choices" and that when behaviour is attributed to people rather than system structure, management intervention is usually focused on blaming people rather than on the design of organizations. Sterman (1989) reports on experiments in which participants were given complete and perfect knowledge of a system structure within which they were required to operate. He found that the performance of participants was poor and their learning was slow and rather limited because they seemed unable to make correct inferences about the dynamics of a system, even though they understood its static structure. Thus, he believed that it is often unreasonable to blame people, especially when an improved system structure would support improved performance.

As discussed in the previous chapter, generally SD use has more often been at a strategic or policy level than at a tactical level. Applications of system dynamics in healthcare human behaviour modelling include models to examine the consequences of government policies on different healthcare sectors, to assess the management of hospitals and management of waiting list for elective patients, and to study healthcare reforms, HMO planning, patient flows, performance assessment, public health emergencies and public health planning (Coyle, 1984; Lane et al., 2000; Milstein & Homer, 2005; Royston et al., 1999; Van Ackere & Smith, 1997, 1999; Wolstenholme, 1993). That is, SD has not been employed to understand the interaction of individual human behaviour with system structure.

4.2.2 Discrete event simulation and human behaviour

Unlike system dynamics, discrete event simulation allows the representation of individuals in the model. A DES model typically includes two sets of dynamic objects: entities and resources. Entities are individuals whose behaviour is tracked in detail, and resources are countable items, and their behaviour is not tracked in the model (Pidd, 2004). The focus of DES is on the detailed rules that drive the interactions of the entities in the model (Pidd, 2004).

It was seen in chapter 3 that DES use had been mainly at operational or tactical levels, commonly used to model patient flows and to identify and eliminate bottlenecks in a healthcare unit such as a clinic, a ward or a hospital department. Some factors of human behaviour have been included in DES models; however, most of these models represent human behaviour as resources with multiple parameters as attributes. Garnett and Bedford (2004) report that there are four main factors of human behaviour incorporated on DES models, each with some limitations:

1. *Human factors* such as human workload capacity, multi-tasking and attention span. The limitation in modelling these factors is that most of the work done in this category focus on the structure of the job rather than on the person that performs the job.
2. *Physiological and environmental factors* such as age, time of the day, light, temperature or noise. The main limitation of this factor is that representations are usually shown as variations in the time scale rather than based on how the human factors interact with performance.
3. *Decision-making processes* are included in models in different ways. They range from simple 'either/or' rules to rules that allows evaluation of different strategies to linking the DES model with an expert system.
4. *Human psychology factors* such as motivation, emotion, cognition and social status. In this aspect, they reviewed the work of Schmidt and Brailsford (2003) and concluded that the limitation of their approach is that modelling psychological factors in DES should not be as simple as linear, parametric models.

Those four factors have been reported in previous DES studies in healthcare. For instance, Brailsford and Schmidt (2003) described a model that considers *human psychological factors*, since the model captures a patient's motivation to attend for screening for diabetic retinopathy when invited on a given occasion. The model was based on a previous study of DES for screening for diabetic retinopathy in a group of patients with a specific condition, where the probability of attendance was constant for every patient (Davies, Brailsford, Roderick, Canning, & Crabbe, 2000).

The motivation of patients to attend was implemented in the model by adding more fields for the attributes to the patient’s record. Those attributes considered physical, emotional, cognitive and social aspects of the patients. That model shows the potential of including human behaviour on DES models and offers a more accurate way of modelling attendances for screening. However, the patients’ behaviour modelling ignores interactions with other members of the healthcare professional staff.

Another example is the work done by Günal and Pidd (2006), where *Human factors*, *Physiological and environmental factors, and Decision-making processes* are considered in a DES model. Human factors include multitasking behaviour and workload capacity of medical staff. In this case, the workload triggers the multitasking behaviour of doctors who can multitask at all times. Although this is a good example of representing human behaviour and decision-making processes in one model, one of the limitations of this method is that it ignores any other possible factors that may affect multitasking behaviour. Those factors may depend, for example, on the doctors’ interactions with the patients, other medical staff and the environment of the work.

In summary, most DES applications have been widely used for modelling hospital performance. One of the most common areas of applications of DES in healthcare is A&E departments; however, some essential features of human behaviour that may affect hospital performance have been ignored in most of the reported DES models. For example, simulation models of A&E departments may need to consider not only simple human, physiological and environmental factors but also a more sophisticated way to represent the individual’s decision-making process which in turn may depend on psychological aspects of the individuals who make decisions within the department. That will be discussed later in this chapter.

4.2.3 Agent-based modelling and simulation and human behaviour

As discrete event simulation, agent-based modelling and simulation also allow the modelling of individual behaviour, the main components in an ABMS are the agents, the agents’ behaviour and the environment (Gilbert & Terna, 2000; North & Macal, 2007).

As discussed in chapter 3, ABMS is one of several agent technologies used in healthcare but is not as popular as others, such as Multi-Agent systems, agent software or artificial intelligence. The most common applications of agent technologies in healthcare are at operational and tactical levels with the purpose of use for aiming at decision automation and routine decision support. Applications at this level include (Isern et al., 2010):

- *Medical and data management systems*: to record and process medical data.
- *Decision support systems:* to assist with different healthcare processes like treatment and diagnosis.
- *Planning and resource allocation*: to coordinate and schedule different human and material resources.
- *Remote care*: to remotely monitor a patient's status.
- C*omposite systems*: to combine different aspects to provide complete and integrated solutions for healthcare management.

A few applications of ABMS have been made at strategy and policy level to support investigation of human behaviour within the systems. Applications at this level include a model to study effects of fluctuations in workload and economic forces on patient safety, a model to help understand some important questions about people's behaviour in an emergency department and a model to study cooperative policies for ambulance diversion (Hagtvedt et al., 2009; Kanagarajah et al., 2006; Stainsby et al., 2010; M. Taboada, Cabrera, & Luque, 2011).

Human behaviour can be represented in ABMS using decision rules that range from simple reactive behaviour to a more complex decision system (North and Macal, 2007). It should be noted from the above literature review that studies on the use of ABMS for Emergency Departments demonstrated that the majority of human behaviour that was included in those models is mainly reactive, and there is little evidence of research about complex human decision making in ABMS applied to Emergency Departments. For instance, most of these studies use if/then rules to define simple behaviours such as:

- Movement: usually agents decide to move when they are informed that an activity can begin or has finished.
- Queuing: patients join the queues when there are no available resources to start an activity. Patients are organized in the queues based either on their attributes (for instance, the severity of their condition) or on their waiting times, for instance, priorities can be updated when patients spend more than specific time in a department.
- Interacting: Usually, patients interact with other patients in the queues or with staff in the activities. These interactions commonly governed by events driven by time and rarely involve any decision making.
- Patients' abandonment: Patients abandon the department before being seen usually motivated by long waits and interactions with other patients.

- Fast-track treatment: Doctors can speed up a service when they perceive long queues.
- Staff scheduling: generally, staff scheduling it is not modelled as human behaviour, but as global data (resource scheduling), that affects Emergency Department global performance.

In summary, this section has discussed how SD, DES and ABMS have been used to model human behaviour in different ways. System dynamics looks beyond separate events and decisions to see the system structure underlying decisions and their combined effects on system performance. Discrete event simulation focuses on the events and the consequent decisions that are triggered by those events. Agent-based modelling and simulation represents people as agents and looks for the relationship between people, and between people and their environment, and how those relationships affect their behaviour.

The next section explores two main theories of human behaviour: normative and descriptive. It will then discuss some aspects of human behaviour that need to be considered when representing people in simulation models.

4.3 Human behaviour perspectives

In many complex systems, human beings are essential components and are fundamental to the operation of those systems; for example, a healthcare system includes different people such as regulators, providers and patients. Each person involved in this system has a particular role, and specific objectives and the interactions among them and their changing environment define the operation and behaviour of the system.

A large and growing body of literature has investigated human behaviour from different disciplines such as biology, psychology, sociology, economics and management but this is too vast a literature to cover here in anything like its entirety. There are many different ways of describing and theorising about human behaviour, but all are concerned with the factors that affect or influence the way people do things.

In the context of this research, theories of human behaviour study can be divided into two main groups: normative and descriptive. *Normative theories* attempt to determine, under specific circumstances, how people *should* behave in order to achieve specific goals. By contrast, *descriptive theories* aim to describe how people *actually* behave in order to achieve those goals (Simon, 1972). Traditionally, the aim of the researchers of the normative perspective has been mainly to identify the rules or principles that define what it is to behave or reason correctly

(Samuels, Stich, & Faucher, 2004), whereas the aim of the descriptive view has been to characterize how people actually reason and to determine the psychological mechanisms and processes that drive the observed types of reasoning (Samuels et al., 2004).

There are different views of which perspective is followed by research in different areas. In the past, it was believed that the normative perspective was commonly used by economists and the descriptive perspective was mainly a subject for psychologists and anthropologists. Currently, both normative and descriptive theories are the subject of study of academics from different areas of knowledge such as psychology, economics, and biology, that are used for normative or descriptive purposes. For instance, behavioural economics theory applies concepts from both psychology and economics. That is, it combines the commonly used descriptive theories of cognitive processes studied in psychology with the traditional economic, normative models of rationality studied in economy.

Management scientists use models to support decision-making and control in organisations (Pidd, 2009). As discussed in Section 3.2, simulation models can have different modes of use, as proposed by Pidd (2009). Those modes could be associated with the two theories of human behaviour that are considered here. The *normative view* may include the models that are intended to be used for decision automation and routine decision support. The *descriptive* view may include the models that are intended to be used for system investigation and improvement, for providing insight about a system's behaviour and for providing insights for debate and for generating hypothesis and theories about the system's behaviour. Simulation models could be useful tools to study different perspectives on human behaviour.

The next sections discuss the ideas of rationality and other factors that drive human behaviour differently from reason.

4.4 Rational behaviour

Rationality refers to the way humans behave in order to achieve specific goals under given circumstances. Economists have used the concept of rationality to explain human behaviour; the classical view of rationality has been widely studied to explain different concepts of economic theories.

According to (Simon, 1955, pp.99), this theory assumes that a person:

1. *has knowledge of the relevant aspects of his environment which, if not absolutely complete, are at least impressively clear and voluminous*
2. *has a well-organised and stable system of preferences*
3. *has computational capabilities that enable him/her to calculate the value of each alternative course of action that is available and to compare these, so as to reach the highest attainable point of his preference scale.*

That classical view of rationality has been an object of considerable debate, particularly of its limitations and critiques. Simon (1972) proposed a variation to the classical theory, known as bounded rationality, in which one or more than one of the assumptions of the classical rationality are relaxed.

Simon's idea of bounded rationality assumes that human rationality has its limits: man has partial knowledge about reality, time and information constraints, and, among other limitations, limited computing capabilities. The classical model of rationality may be appropriate if behaviour is goal-oriented under defined given constraints and conditions, and if the rational choice is the one that best leads to the goal. Bounded rationality assumes behaviour that results from some adequate deliberative process of thinking, in which the decision-maker has control over a person's actions. The focus is on the decision-making process, and the aim is to develop mechanisms for making better decisions.

Simon's ideas of bounded rationality correspond more or less to modes of use 2 and 3 of the simulation models proposed by Pidd (2009). These cover models that are used for system investigation and improvement, and for providing insight into a system's behaviour. The latter aim is to provide insights for debate and for generating hypothesis and theories about the system's behaviour.

4.5 Other aspects of human behaviour

Psychological, philosophical and biological theories have different perspectives on the factors that guide people's judgment and behaviour. The concepts of rationality and bounded rationality have been widely studied by researchers in different areas such as economics and psychology. The ideas of misperception of feedback and intuitive and emotional behaviour will be discussed in the next sections.

4.5.1 Misperception of feedback processes

Sterman (2000), in his discussion about *dynamic complex systems,* suggests that there are two main consequences of bounded rationality that limit our ability to learn from experience: misperception of the feedback structure of the environment and faulty mental models.

Sterman (2000, pp.21-22) argues that *dynamic complex systems* have the following characteristics:

- ***Dynamic:*** *Systems change over time*
- ***Tightly coupled:*** *Actors on the system interact with each other and with their environment*
- ***Governed by feedback:*** *Decisions made by people have impacts on the state of the real world driving other people's actions and in turn modifying the conditions to make new decisions.*
- ***Nonlinear:*** *The effect of the decisions is not always proportional to their cause. Multiple factors are interacting in the decision-making processes.*
- ***History-dependent:*** *Many actions are irreversible.*
- ***Self-organising:*** *The internal structure of the system defines the dynamics of the system.*
- ***Adaptive:*** *The capabilities and decision rules of the agents change over time. People can learn from experience.*
- ***Counterintuitive:*** *Cause and effect are distant in time and space.*
- ***Policy resistant:*** *The complexity of the systems in which we are embedded overwhelms our ability to understand them.*
- ***Characterised by trade-offs:*** *Time delays in feedback channels mean the long-run response of a system to an intervention is often different from its short-run response.*

When people make decisions, those decisions have a direct or indirect effect on their environment. In dynamically complex systems, people often develop and use mental models to guide their decision-making processes. However, those models are usually dynamically deficient. Frequently there are misperceptions of the feedback processes that limit the potential for learning and therefore limit knowledge about the real world (Sterman, 2000).

Figure 4-1 shows an example to illustrate an example of the feedback process in an A&E department. A high number of patients in an A&E department can lead doctors to employ strategies to avoid long waits, which may include multitasking or reducing the time spent with each patient. These may cause the doctor to pay less attention to each patient, which may reduce the quality of the doctor's assessment of a patient. Reducing the quality of patient assessment can cause diagnostic errors which can lead patients to re-visit the department, which in turn increases the level of occupancy of the department; the whole loop then starts again.

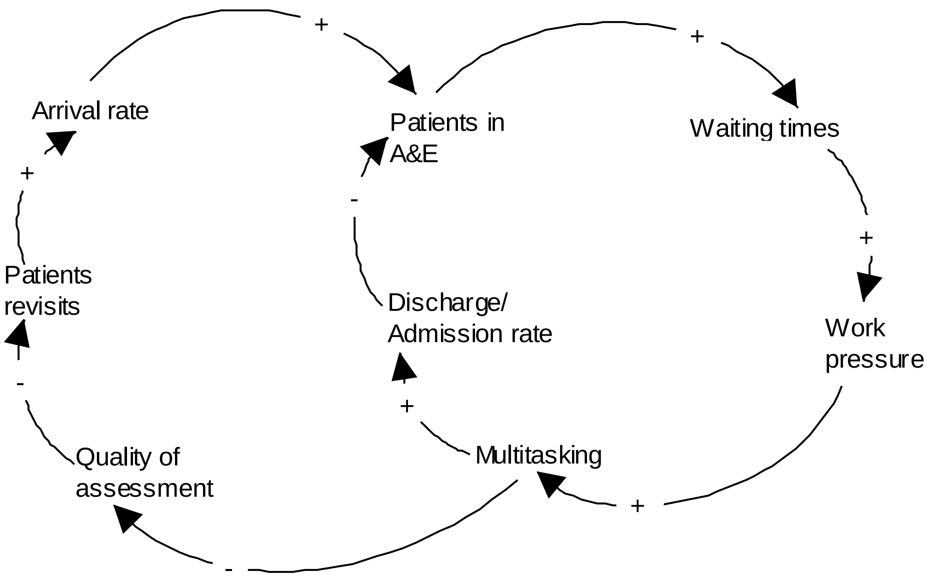


Figure 4-1. Misperceptions of Feedback processes

Therefore, the environment in which the individual is immersed and the conditions of choice may be affected directly or indirectly by individuals' past actions (Sterman, 1989). That means that there are key dynamic and feedback processes that should be considered when attempting an adequate representation of human decision processes.

4.5.2 Intuitive behaviour

In recent years, a large body of literature has been published about the idea that human beings employ two different kinds of reasoning and it has been proposed that there are two different cognitive systems that underpin reasoning; this is often called dual-process theory (Evans & Stanovich, 2013; D. Kahneman, 2003; D. Kahneman & Frederick, 2002; Stanovich, 1999).

Kahneman (2003) reports on investigations into the relationship between intuition and decision making, based on dual-process theory. The main idea of his theory is that cognitive tasks occur in two different ways: a fast and intuitive process of thinking and a slow and reflective process (Evans & Stanovich, 2013).

Kahneman argues that classically rational models are psychologically non-realistic, and has demonstrated that many judgements and choices are made intuitively. He follows the notation proposed by Stanovich (1999) and Stanovich and West (2000) who proposed the name for the two different types of reasoning as *System 1* and *System 2*. Kahneman (2003, pp. 1451) provides a concise description of his view of these two systems as follows:

- *In system 1, the operations are governed by habits and are fast, automatic, effortless, associative and often emotionally charged. This type of system is difficult to control or modify.*
- *In system 2, the operations are slower, serial, effortful and deliberatively controlled. They are also relatively flexible and potentially rule-governed.*

System 1 is a perceptual system in which intuitive operations reflect impressions obtained from the objects; this system corresponds to the part of "thinking fast" of the title of Kahneman's (2011) work – *Thinking Fast and Slow*. System 2 is based on reasoning, following a deliberative process in which judgments are explicit and intentional; this system corresponds to the part of "thinking slow".

Kahneman's view of the predominance of intuition in judgments and choice does not imply that people do not use system 2 or that they always act intuitively. He believes that system 2 is present in the situations that require it, but that a central characteristic of humans is that they often act intuitively and that their behaviour is often driven by what they see at a given moment, rather than by what they are able to compute.

4.5.3 People's emotions

Although most of the interpretation of bounded rationality relies on the assumption that rationality is bounded by human cognitive limitations, some views consider that emotional factors also influence bounded rationality. That is, they believe that a different perspective on behaviour includes the belief that humans are essentially emotional or emotional-social beings, without ignoring the importance of the cognitive-intellectual processes in determining human behaviour. In other words, the acquisition of knowledge through experiences may be as important or more important than learning through theories or facts (Izard, 1991).

Some researchers have emphasised the role of emotions in cognition and behaviour and studied how emotions can fit into the theory of bounded rationality (Damasio, 2006). Simon, in his book "Reason in human affairs" agrees that sometimes people use intuition when finding solutions to problems (Simon, 1990). He believes that correct intuitive decisions occur only to people who have appropriate knowledge and that, in most problem situations, people use intuition and deliberation to search for solutions. Moreover, he recognises that one of the essential characteristics of intuitive processes is the role of the emotion in those processes. Thus, he argues that "*in order to have anything like a complete theory of human rationality, we have to understand what role emotions play in it*" (Simon, 1990, pp. 29)

Despite the vast amount of literature published on emotions, there are still ambiguities in the language of emotion and some inconsistencies in definitions of the concept of emotion (Plutchik, 2003). The concept of emotion proposed by Izard (1991, pp.14) is simple and clear enough to describe how emotions guide behaviour. Izard states that an emotion can be experienced as a "feeling that motivates, organises and guides perception, thought, and action". That feeling is produced by evaluating events and situations.

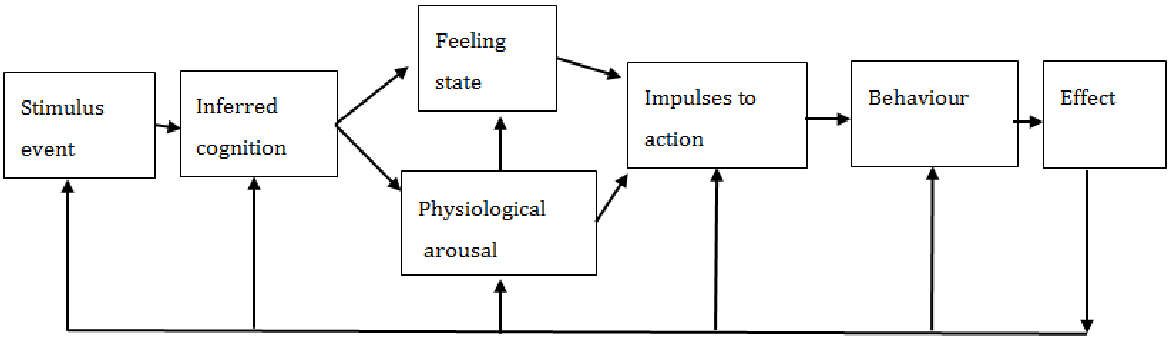


Figure 4-2. Chain of events defining an emotion Plutchik (2003, pp. 108)

Similarly, Plutchik (2003) describes the chains of events that define an emotion (Figure 4-2), based on evolutionary theories of emotions. The assumption is that a stimulus event triggers the process of emotion. For example, he explains that one stimulus event could be a threat by a predator; the interpretation of that stimulus is "danger", which causes a feeling of "fear" and physiological or physical activations. The feeling state of fear tends to trigger an action, in this case, an impulse to escape from the predator, so the behaviour selected is running away, and the effect is safety. A feeling of safety causes the person to stop running because he perceives there is no danger, and the threat is reduced.

4.5.4 The role of intuition, emotion, cognition and feedback processes in human behaviour modelling

According to Reiss (2004), the reasons people have for performing voluntary behaviour are regarded as *motives,* which usually affect peoples' perception, emotion, cognition and behaviour. He identifies the basic motives, known as drives (Woodworth, 1918), that are necessary for ensuring people's survival (e.g. eating and sleeping) and other intrinsic motivations such as curiosity and autonomy.

Other factors that may affect human behaviour are related to an individual's characteristics. Kennedy (2012) identifies four main factors related to an individual's personality that affect human behaviour:

- *Human sensory capabilities*: humans obtain information from their environment using their senses and process that information based on the characteristics of their personality. Personality may affect thoughts, behaviours and emotions.
- *Human Motivations*: different motivational theories in psychology explain some aspects of human behaviour.
- *Human Emotions*: Emotions may affect rational decision making because they affect the perception that a person has about the environment.
- *Human Sociability*: The behaviour of a person may be influenced by others' behaviour and the perception a person has about others' future behaviour.

When developing any model, it is essential to define the purpose of the model and to determine the level of detail to include in it. Specifically, models that include human behaviour require a specification of which aspect of human behaviour is necessary to include in the models.

Suppose, for example, there is a manager of Textile Company who is interested in studying how to increase daily production without incurring high costs, subject to some capacity constraints, and simulation is a suitable tool to deal with the problem. Obviously, it is necessary to consider the workforce, represented by the workers employed in the textile production process, when developing the model.

The representation of the workforce, though, may require the inclusion of human factors such as workload capacity, multitasking and efficiency. However, a detailed representation of the personality of the agents may not be necessary, which may mean that human psychological factors such as emotions are not relevant to the model. In this case, human behaviour can represent the behaviour of groups of people with similar characteristics. Most of the decisions that operatives make in the textile company may not require a slow and deliberative process of thinking. Hence, that means that the system 1 discussed by Kahneman, in which habits govern the operations, might be the main influence on the decisions considered in this type of model.

However, assuming a different situation in which a manager of a healthcare unit (such as an A&E department) wished to study how to reduce the waiting times of patients in the system, the level of detail of the representation of human behaviour may be much higher than the one considered of the operatives in the Textile company model. That is because there are many interactions among the people involved (such as doctors, nurses and patients), which implies they engage in some social behaviour. The decisions that one person makes may influence directly or indirectly the behaviour of other people. For instance, a junior doctor with minimal experience may need to consult other doctors about different patients' conditions or require more tests or investigation than a doctor with more experience. That could delay the length of stay of the patient, which in turn may affect the performance of the department. Therefore, the ideas of misperception of feedback, intuition and emotion may be necessary when designing a model to study this particular situation. That situation suggests that the type of reasoning of the people involved may be grouped in the system 2 discussed by Kahneman (2003) since there is a deliberative process of thinking influenced by individual judgments.

4.6 Agent-based modelling and simulation of human behaviour

Chapter 3 presented a general background and concepts of agent-based modelling and simulation. In particular, it placed the concept of "agent" in different areas of study such as computer science, social science and management science. It was shown that although there is not a precise and general accepted definition of what an agent is, there are several common characteristics that an agent should have:

- Social abilities: communication, cooperation, competition
- Initiative: acting proactively
- Goal-orientation: pursuing their own objectives and behaving to attain them

- Autonomy: to make decisions and perform actions
- Reactiveness: ability to react to perceptions or information from outside

In general terms, it can be said that anything capable of making decisions in a system can be represented as an agent. In particular, in the field of complex systems where human beings form an essential part of the systems, the use of an agent framework can help in representing essential characteristics of people. In agent-based modelling and simulation, an agent is an entity with attributes and behaviours.

4.6.1 Agent attributes

The attributes are characteristics that belong to an agent and are closely related to the agent's personality. The agent's personality affects the perception, reasoning and the cognition that an agent has of the real world either directly or indirectly. The agent's personality also influences the drives, emotions and intuition of an agent. Perception and cognition interact with each other and are influenced by motives (drives, emotions and intuition) and reason.

There are some attributes (e.g. age and gender) that can be represented in a simple form, and there are some others (such as preferences and experience) that are affected by other factors (multifactorial) and require a different level of representation. The multifactorial attributes can change over time as a result of an agent's past actions or experiences (North & Macal, 2007)

4.6.2 Agent behaviour

The agent's behaviour is represented in an agent-based model by decision rules. According to North & Macal (2007), there are two main levels of agent rules that allow agents to communicate and interact with each other and to interact with their environment:

- Base-level rules: activated by routine events
- Rules that change the base-level rules: provide adaptation that allows the base-level rules to change over time

Gilbert and Terna (2000) consider two techniques for defining agents' behaviour: production systems and learning.

On the one hand, a modeller might define simple behaviour using production system techniques. In general, a production system is composed of three elements:

1: *a set of rules, each of which has two components: a condition that indicates when to execute the rule and an action which is the consequence of executing the rule.*

2: *working memory: some rules may include actions that insert facts in the working memory; others include conditions that assess the state of the working memory.*

3: *a rule interpreter, which considers each rule and executes the ones that have a true condition and performs the actions related to those rules and repeats the cycle indefinitely.*

The production system technique supports the straightforward creation of reactive agents (Figure 4-3), that is, the agents who respond to the stimulus of the environment (as in system 1) through specific actions and whose responses are not modified as a result of the experience acquired from the environment (Gilbert & Terna, 2000).

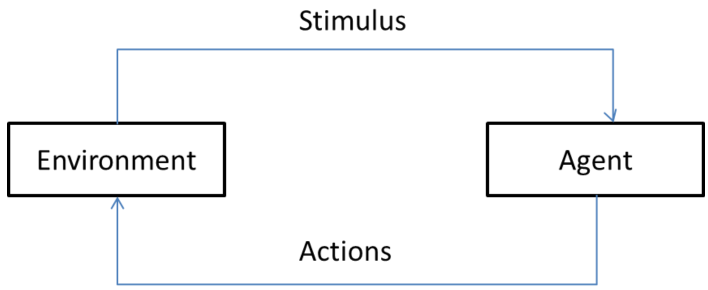


Figure 4-3. Agent's reactive behaviour

On the other hand, a modeller can include agents that can learn and consider adaptation on the internal structure and process of the agents. Two common techniques used for modelling adaptation are neural networks and evolutionary algorithms. However, these techniques are not being evaluated in this research, so they will not be considered further.

4.7 Human behaviour modelling frameworks

Previous sections discussed some theories of human behaviour. The normative approach deals with determining under given circumstances how people *should* act, under certain assumptions, in order to meet their goals, while the descriptive approach focusses on describing how people actually behave in order to achieve those goals.

Some studies have implemented human behaviour frameworks in simulation models such as BDI (Belief-Desire-Intention), PECS (Physics, Emotion, Cognition, Social status) and SAMPLE (Situation Awareness Model for Person-in-the-Loop Evaluation), OCEAN, among others (Elkosantini, 2015).This section discusses the two first frameworks for modelling human behaviour, BDI and PECS, because they appear to be suitable to model generic aspects of human behaviour within Emergency Departments. The BDI agent framework is compatible with the normative view, while PECS relates more to a descriptive view.

4.7.1 BDI agent framework

BDI is a framework that assumes that the mental attitudes of Belief, Desire and Intention (BDI) define the behaviour of a rational agent (Rao & Georgeff, 1995). Salamon (2011) summarises the main components of this framework:

- *Beliefs constitute the agent's knowledge of the world. The world includes the environment, other agents and itself. They are called beliefs because the agent uses a perception system to generate an understanding of the world that can be different from the real world. It means the agent's perception of the world is just a representation (set of beliefs) of that world.*
- *Desires are the agent's goals. Those goals can be short-term or long-term goals, realistic or unrealistic goals, and they can even be contradictory goals. These goals turn into intentions when the agent selects the most important ones or the ones that can be achieved.*
- *Intentions could be seen as a subset of goals or as a set of plans to meet the desires (or goals).*

The BDI framework was developed by Bratman (1987), who views human intention as a key factor of behaviour (action) of a rational agent. The theory consists of three main components: reflectiveness, planfulness and a concept of temporally extended agency.

Reflectiveness assumes that people are capable of assessing and reflecting on their desires and inclinations that are factors that guide their deliberation, motivations and conduct. *Planfulness* assumes that people do not merely act (instinctively), but that they act based on a pre-defined plan of action which serves as a support of the organisation and coordination of their activities over time. *Temporally extended agency* assumes that people understand their behaviour in a temporal dimension, that is, they see their actions at a current time based on the actions they have had in the past, and the ones they will have in the future.

The BDI framework assumes rational agents that are continually deliberating about the best course of action to follow based on a particular situation. The behaviour of the agents and the selection of the best course of action is determined by primary mental attitudes of Beliefs, Desires and Intentions that represents the information, motivational and deliberative state of the agents (Kahneman & Frederick, 2002). The general ideas of the BDI framework include the ideas presented by Kahneman (2003) in system 2, but ignore the presence of system 1 in an agent's reasoning process.

Rao and Georgeff (1995) discussed the applicability of the BDI agent framework and highlighted two main criticisms that the BDI framework has received. Rao and Georgeff (1995) found that the first group included people who question the need for either having three attitudes or the convenience of having only three. The second group included the people who questioned the relevance of BDI in practice because they considered it was too restrictive.

However, the idea of defining these three factors for rational behaviour may be useful for those models in which the rationality of an agent may not be affected by emotions and intuition such as the models of systems in which human interactions are very few (such as automation systems or manufacturing systems) or for those models in which the intended mode of use does not require a detailed representation of human behaviour.

For those systems in which there are many human interactions (as in social systems), or in which the model is intended to be used for system investigation, improvement and for providing insight about the system's behaviour or for providing insights for debate and for generating hypothesis and theories about the system's behaviour, the BDI framework may be too restrictive.

4.7.2 BDI applications

The BDI is one of the most widely accepted and used framework to model an agent's decision making. It is prevalent to find BDI applications in the area of artificial intelligence, specifically in multi-agent systems, to represent agents' behaviour (Rao & Georgeff, 1995).

By using the Web of Science, a search in the topic of the strings *("BDI" AND "Agents")* retrieved 778 hits on July 2019. Table 4-1 shows that more than 64% of the applications of BDI are in the area of artificial intelligence, and other areas such as information systems and software engineering have more than 30% of the applications.

Table 4-1. Areas of application of BDI framework.

Web of Science Categories	**records**	**% of records out of 778**	**records including social/ human behaviour**	**% of records including social/ human behaviour per category**
COMPUTER SCIENCE ARTIFICIAL INTELLIGENCE	500	64.267	62	12.400
COMPUTER SCIENCE THEORY METHODS	179	23.008	26	14.525
COMPUTER SCIENCE INFORMATION SYSTEMS	152	19.537	21	13.816
ENGINEERING ELECTRICAL ELECTRONIC	128	16.452	16	12.500
COMPUTER SCIENCE SOFTWARE ENGINEERING	101	12.982	13	12.871
AUTOMATION CONTROL SYSTEMS	82	10.54	7	8.537
COMPUTER SCIENCE INTERDISCIPLINARY APPLICATIONS	60	7.712	6	10.000
ROBOTICS	51	6.555	5	9.804
TELECOMMUNICATIONS	43	5.527	5	11.628
COMPUTER SCIENCE HARDWARE ARCHITECTURE	32	4.113	3	9.375

In order to check for specific applications in the area of interest, another filter was included in the original search, adding the strings ("social" OR "human behavior" OR "human behaviour"). The resulting records were also included in Table 4-1. Note that the number of studies in the area of interest, compared with the global data, is relatively small and that the proportion of records including social and human behaviour in each category is similar.

The lack of applications including social or human behaviour suggests that most of the applications of BDI focus on agent systems such as robotics or expert systems where the aim is to develop a system that behaves appropriately in order to obtain an optimal performance. The main weakness of the BDI framework is that it assumes that the agents are entirely rational, which limits the use of some other factors of human behaviour such as intuition and emotions.

4.7.3 PECS framework

Schmidt (2005b) proposed a structure of the PECS framework that is claimed to be applicable to any system in which human beings are essential components. The PECS framework was developed as a replacement for the BDI framework, based on an argument that BDI is not suitable for the development of sophisticated models of real systems in which other human factors such as emotion or intuition are relevant (Schmidt, 2005b).

The PECS framework assumes that human behaviour can be influenced by physical, emotional, cognitive and social factors; therefore, this architecture allows modelling human behaviour considering those factors and the interactions among them (Schmidt, 2005a, pp. 1). PECS stands for Physical conditions, Emotional state, Cognitive capabilities and Social Status.

In the PECS framework, a person is perceived as "a psychosomatic unit with cognitive capacities embedded in a social environment" (Schmidt, 2000, pp. 1). The behaviour of people "is usually dependent on drives, needs or desires which can be regarded as motives. The strength or intensity of these motives is a function of the state variables. In this case, the state variables do not determine behaviour directly, but rather indirectly, via the motives belonging to them." (Schmidt, 2005a, pp. 5)

The agent world of the PECS reference model has three main parts: the agents, the environment that contains all the agents and the connector that represents the communication mechanisms that allow the interaction among agents and agents and their environment (Figure 4-4).

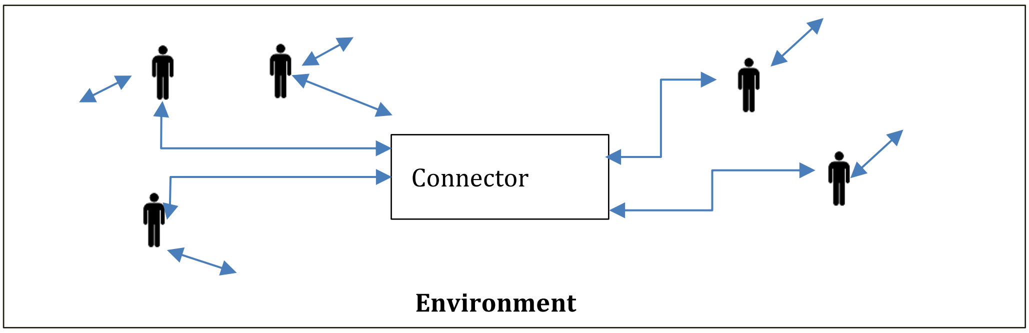


Figure 4-4. Structure of PECS adapted from (Schmidt, 2005b)

4.7.4 *Applications of PECS in different areas*

The PECS framework has not enjoyed the same popularity as the BDI framework, probably because PECS was developed later than BDI or perhaps because BDI has a broader scope of application since there is a significant number of studies of rational agents and rational behaviour.

The Web of knowledge retrieves 37 results when searching in the topic for ("PECS "and "AGENTS") on July 2019, but the majority of papers use PECS to refer to other terms such as "polyelectrolyte complexes" or "pulmonary endothelial cells". Therefore, the search was limited to the terms

("PECS" AND (" framework" OR "model") AND " agents"). The search retrieved 12 records, from which only four results were actually related to the PECS framework. Using Google Scholar, it was possible to find a few other papers that use PECS for agent-based modelling.

Some examples of the use of PECS in ABMS include Malleson, Heppenstall, & See (2010) who developed a simulation model of residential crime that considers human factors. The aim was to modify the social environment of the residential area in order to observe the impact of that change on the spatial and temporal dynamics of the crime occurrences. In this model, the agents are people that can be citizens and possible thieves, and the environment represents the city that consists of houses with individual characteristics. Each agent has to create wealth and sleep. The intensity of those needs is calculated based on the PECS framework. Similarly, Lacko et al. (2013) built an agent-based model of a riot in urban areas and modelled the behaviour of the protesters with PECS. Reger and Ohler (1999) used PECS for simulating role-play among children.

Additionally, Kaufman (1999) built a model to represent the behaviour of humans in a panic situation (such as evacuations) based on psychological theories and findings. The agents' primary state variable is *fear* which is modelled by differential equations that depend on the agent and its environment. The fear depends on the agent propensity to get anxious, the crowding and social forces and the agent's sensation of physical pressure in the environment.

Martínez-Miranda et al. (2005; 2003) proposed a model that represents a project manager who needs to select people to create a group for an engineering project. The model contains four main agents and includes personal, social and emotional characteristics of those agents to simulate group work. The PECS variables considered in their model were Cognition that represents technical knowledge of an agent, Emotion that represents basic emotions and personality and Social characteristics that represent interactions among members.

Ben Ammar et al. (2010) developed a platform to explore the possibility of integrating the communication of emotions into collaborative virtual environments. That platform responds to human emotions using a facial recognition system, and the decisions are taken based on the PECS framework.

It is important to notice that in the studies mentioned above, PECS was used to model deliberative behaviour, where agents update their internal states based on their own perceptions and information about the environment. Moreover, literature shows that PECS is adequate for modelling behaviour that is not strictly rational (in a classical sense), which seems suitable to represent the behaviour of doctors and clinicians within the A&E department considered in this thesis. Therefore, PECS seems to offer excellent opportunities to model deliberative complex behaviour within emergency departments.

The problem that is addressed in this thesis refers to a healthcare system where people's behaviour is a crucial component of the system's behaviour. The purpose is to identify the factors that lead to a particular kind of behaviour and to understand why some specific performance occurs within hospitals (descriptive behaviour), rather than to propose a model that offers an adequate course of action that leads to an optimal performance (rational behaviour). Therefore, the approach that will be followed here is descriptive rather than normative, which makes BDI inappropriate for this thesis; thus PECS is the framework chosen in this research, which is also found to be convenient to model the essential human behaviour within accident and emergency departments and to be simple to understand and to implement.

4.8 Simulation toolkits for modelling human behaviour

This section will review some simulation tools used to build ABMS and DES models. The focus is only on those two simulation methodologies because the research is concerned with the use of DES and ABMS for modelling human behaviour in A&E departments.

4.8.1 ABMS toolkits

There are several toolkits for implementing ABMS applications and a variety of software available for that purpose. Macal and North (2008) classify several approaches to building ABMS applications, considering the scale of the software that can be used. As with DES and SD, ABMS, models may be developed either using general-purpose software such as spreadsheets, particular ABMS software such as Netlogo or general computational mathematics systems. Large Scale Agent Development Environments suitable for ABMS include Repast, Swarm, Mason and Anylogic, which can be used to build sophisticated models including thousands of agents interacting in a complex environment. However, it is entirely possible to build even complex models using general programming languages such as Java or C++.

Several published surveys describe the various features of toolkits available for ABMS modelling. These surveys consider, among other factors, aspects such as the domain where the toolkit is intended to be used, the programming language required to build the model, the possibility of visual programming and whether the software is open source or not (Castle & Crooks, 2006; Nikolai & Madey, 2009; North, Collier, & Vos, 2006; North, Tatara, Collier, & Ozik, 2007; Serenko & Detlor, 2002; Shi, 2008). As mentioned earlier, most such ABMS toolkits used to model social interactions use Object Oriented Programming languages such as Java or C++ to express model logic and to form their environment (Nikolai & Madey, 2009). That fits in well with the notion (North and Macal, 2007) that in ABMS models, discrete entities are represented through *Objects* that are created from templates called classes. These classes specify the behaviour and properties of objects. Computer simulation environments used in large-scale agent-modelling require specific features to control the flow of time, to manage the communication among the agents, to specify how agents are connected within the model and to store and to display the state of the agents.

Some toolkits such as AgentSheets, Netlogo, Repast, Multiagent and Mason were developed with social science applications in mind. *Repast System* is the toolkit chosen to build the ABMS_A&E mode in this research. The Repast system is an open-source software framework for developing agent-based simulations using Java. The latest version of Repast is Repast Simphony (Repast S) which includes a new NetLogo model translation and Logo-like modelling capabilities called *Relogo*. It is based on a preconfigured Eclipse-based integrated development environment. Repast S includes a time scheduler that allows both time-step and next event scheduling. Repast S also includes a wide range of mechanisms to allow agents to communicate using different agent interaction topologies such as networks and grids and a full set of tools for displaying agents (North et al., 2007).

Repast S allows the development of an ABMS model either using the visual agent editor or using Java objects. That is, a user may choose to create the agent classes using the Java objects or the Repast visual agent editor (North et al., 2007). In Repast S, the model standard structure is based on Context and Projections. A Context is a simple container based on a set of semantics. Context creates an abstract environment that is the underlying infrastructure to create the population and to define interactions among the individuals of that population. Projections are related to the topology of the model and define a structure that describes how things are connected (Sourceforge, 2008). A topology describes how information is transferred from one agent to another.

Typical topologies include soups, networks and spatial grids (North & Macal, 2007). According to North & Macal (2007, pp. 198), soups (Figure 4-5-a) are simple connections where the agents have no specific spatial representation and with which interactions may occur by selecting a pair of agents randomly from the soup. Networks (Figure 4-5-b) are “point-to-point connections between agents” and allow the agents’ neighbourhood to have a more general definition. There are different types of spatial grids. The simplest grids are rectangular and common representations are

Von Neumann's neighbourhood consisting of four neighbours (Figure 4-5-c) and Moore neighbourhood consisting of eight neighbours (Figure 4-5-d) (Macal & North, 2010).

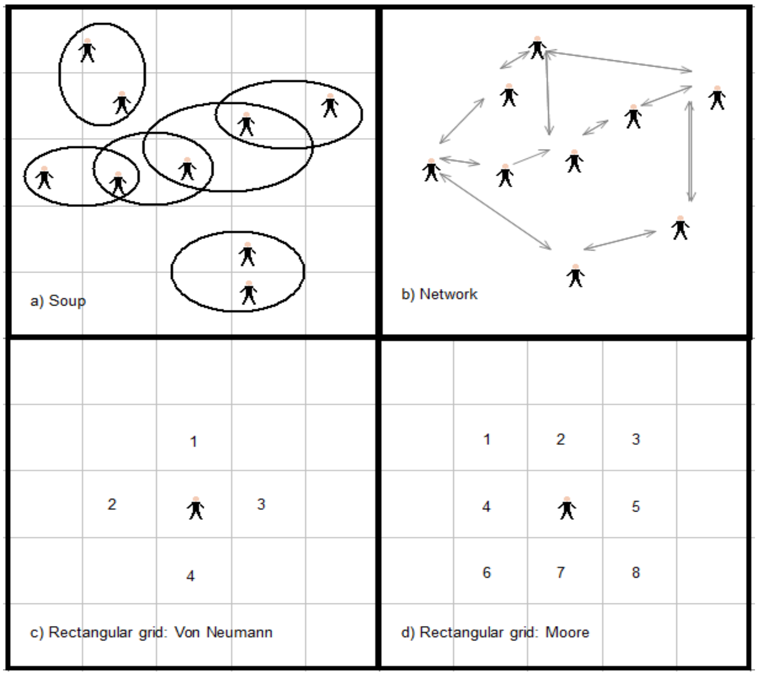


Figure 4-5. Common interaction topologies in ABMS. Adapted from North & Macal, (2007, pp. 198).

ABMS can be developed in general-purpose languages or specific simulation platforms. Repast Simphony was chosen in this research for different reasons. First, it is a robust tool that allows the inclusion of different levels of complexity in the simulation models; second, it is a free and open-source platform; third, it offers excellent support to users; four, its popularity among agent-based modellers; and five, because it is relatively easy to learn and use if you have knowledge in java programming. However, any other simulation platform would likely have served the same purpose for this research.

4.8.2 DES toolkits

There is a variety of DES specialist software that is flexible and easy to use. Some of the DES speciality packages commonly used are Promodel, Arena, Extend, Simul8, Witness, Simio, Microsaint Sharp. Many of DES software are similar in various aspects, for instance, they contain objects that represent entities, resources, activities, events and event lists, and simulation executive based on events management (Schriber, Brunner, & Smith, 2013).

The majority of DES models are visual interactive modelling systems (VIMS), where the model has a visual display (usually entities moving through the model and networks of queues and servers) that shows an animation while it runs (Robinson, 2004). With the VIMS it is possible to understand different aspects of the model, to perform verification and validation processes in a relatively simple way, to experiment with different alternatives very quickly, to obtain and understand the results of the model easily and to enable simple communication with the model user (Robinson, 2004).

There exist DES libraries in non-specialist software such as Java, C++ and Python, which can be used to manage the events and other aspects of DES models. However, in order to implement a DES model in those programming languages, the user needs to have sufficient experience in programming and to clearly understand how DES works in order to program from scratch all the logic of the model. There are different advantages of using those programming languages over specialist simulation software, but that is not relevant to this discussion. To learn more about this subject, see Robinson (2004); Schriber, Brunner, & Smith (2013) and (Pidd, 2004).

SIMUL8 is chosen in this thesis for implementing the DES_ABMS model for different reasons, first is that it is one of the most popular DES simulation tools, second it because it is easy to use, third I have more than 10 years in the use of it, and fourth because I obtained a sponsored SIMUL8 professional license for my PhD project.

4.9 Summary

In summary, modelling human behaviour in healthcare systems is essential because humans are at the heart of healthcare systems. Literature review demonstrated that most of the human behaviour that has been incorporated in OR/MS models involves patients' characteristics, such as virus transmission and demand factors; however, modelling the effects of performance frameworks on peoples´ behaviour, specifically of healthcare clinicians is a topic that has not been widely studied.

This chapter has explained different perspectives of human behaviour as well as the different mathematical models that have been used to represent it. There are two main approaches for modelling human behaviour: the normative and the descriptive. The normative defines how people should act in order to achieve some pre-established goals under specific circumstances; the descriptive describes how people actually behave.

The concepts of rationality, emotion and intuition were also presented. There are theories of rationality that use two main concepts: minimising (maximising) and satisfying. The classical rational theory looks at selecting the best option or determining the best course of action given some specific circumstances. The bounded rationality theory was introduced after the classical theory to relax some of the assumptions that were not always possible to meet in the classical theory. The bounded rationality theory assumes satisfying behaviour, rather than optimising.

The views of the role of emotion and intuition on human behaviour sometimes differ from the classical views of rationality. The idea is that there are factors that may affect human behaviour which are related to an individual's personality. For example, emotion is one of those factors and can be understood as a motive that guides people's behaviour. Intuition also plays an essential role in human behaviour, since it has been demonstrated that most of the judgments are done intuitively.

Two frameworks have been proved to be suitable to represent human behaviour. One (BDI) follows a normative view that considers rational agents, and the other one (PECS) considers emotions, intuition and deliberation of agents when choosing an action. PECS is the framework selected to model human behaviour in the ABMS_A&E and DES_A&E models, and its implementation is presented later in this thesis.

CHAPTER 5: ABMS MODEL DESIGN AND DEVELOPMENT PROCESS

5.1 Introduction

Chapter two argues that the imposition of targets may have influenced the measurement of waiting times used in assessing hospital performance. It might be the case that the reductions in waiting times occur when the risk of failing the targets is high, because more inpatients are admitted, or because more patients are discharged earlier in the case of A&E department departments. Chapters 3 and 4 focus on the importance of considering some aspects of human behaviour in healthcare modelling.

This research is concerned with the use of ABMS to represent human behaviour in an A&E department. Chapters 5 and 6 will demonstrate how different aspects of human behaviour within an A&E department can be represented in an ABMS model. Chapter 5 will focus on the conceptual modelling process, and chapter 6 will discuss the simulation modelling process. Later, Chapter 7 will demonstrate that DES can also be used to model human behaviour.

5.2 Agent-based Simulation modelling process

The model development process among the different simulation techniques (SD, DES and ABMS) is generally done following a similar iterative process approach (North & Macal, 2007; Pidd, 2009; Sterman, 2000). However, the pattern of iterations may differ from one technique to another (Pidd, 2004; Robinson, 2004; Tako & Robinson, 2009). A crucial common element of the simulation modelling process is a conceptualisation phase in which a conceptual model is created and continuously reviewed against the real world. That conceptual model is then translated into a computer model using whatever software is appropriate. Both the conceptual model and the computer model need to be verified and validated against the real world. The process continues with an experimentation phase in which the computer model is used to provide some insights and understanding of the real world. Finally, these findings from the use of the model can be implemented in the real world.

Developing and using a simulation model is an iterative process that generally involves three main steps: *Problem structuring, Modelling and Implementation* (Pidd, 2009). Specifically, speaking of agent-based modelling and simulation, Salamon (2011) proposes a methodology to develop an ABMS simulation model consisting of four phases as shown in Figure 5-1: *Requirements definition*, *Conceptual model*, *Platform-specific model* and *Simulation model*. Each phase is defined by several steps that constitute an iterative modelling process. Relating this methodology to the modelling process proposed by Robinson (2004), the phases 1 and 2 will be considered as part of the conceptual modelling process, whereas phases 3 and 4 will define the simulation process.

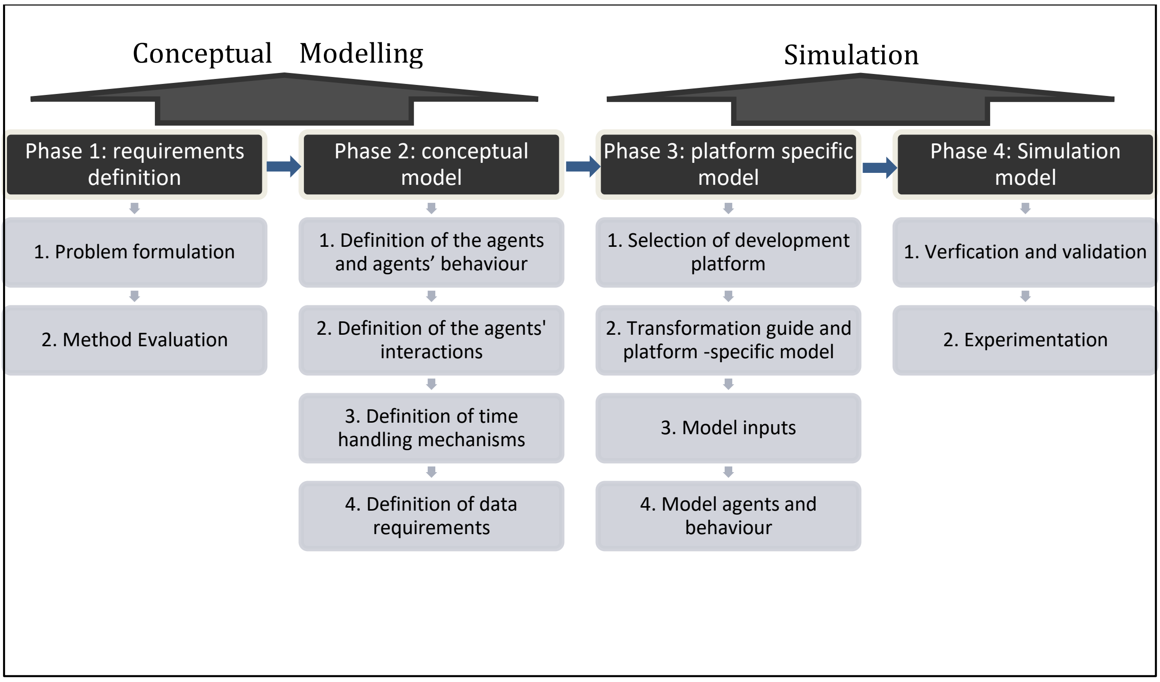


Figure 5-1. Modelling process (Adapted from Salamon (2011, pp. 107))

This chapter focuses on the conceptual modelling process by explaining the two first phases of the Salamon methodology. The simulation process will be discussed in chapter 6.

5.3 Phase 1: requirements definition

5.3.1 Step 1: problem formulation

The initial step in this phase is to describe the problem that is to be studied with ABMS independent from any software that will be used. In this step, it is important to consider six main topics (Salamon, 2011):

1. The problem: to provide an overall description of the problem.
2. The processes: to identify the processes
3. The entities: to describe the entities engaged in the processes, their characteristics, and to define what they want, what they do, and how they interact with each other.
4. The environment: to explain the characteristics of the environment and its interrelations with the entities.
5. The aim: to define the purpose of the study, what is to be measured, how it is to be measured and what questions are to be answered
6. Validation: how to evaluate and to test the developed model.

5.3.1.1 The problem

As was discussed in previous chapters, Emergency Departments are highly complex and dynamic systems. Emergency Departments in the UK are governed by a performance framework that has a set of performance standards that the departments must maintain. In particular, the four-hour standard originally stated that 98% of the patients being seen in an accident and emergency department should leave the department in less than four hours either because they are admitted as inpatients or because they are discharged from the department. Therefore, doctors and nurses need to make decisions that require balancing the patients' clinical priorities with the department's time performance standards. As a result, the decisions that clinical staff face are continuously affected by the different situations that are present in the healthcare provision process.

5.3.1.2 The process

Figure 5-2 shows the outline of the patient flows in an A&E department as a chain of activities. Patients arrive into the department via an ambulance or by the walk-in entrance. Patients arriving by ambulance are usually triaged and registered in route to the hospital before entering the department. Patients arriving by walk-in are first registered by a clerk and then are triaged by a nurse. The triage system considered here involves a colour and number coding scheme using red (number 5) to represent a patient who needs immediate attention, Orange (number 4) means very urgent, Yellow (number 3) means urgent, Green (number 2) standard, and Blue (number 1) non-urgent. Depending on the condition of the patient, the initial assessment that follows triage is done by a nurse or a doctor. Some patients may require tests at this stage, and some others may be discharged or immediately admitted as inpatients to the hospital. Those patients that require tests are usually treated by the same doctor who conducts the initial assessment.

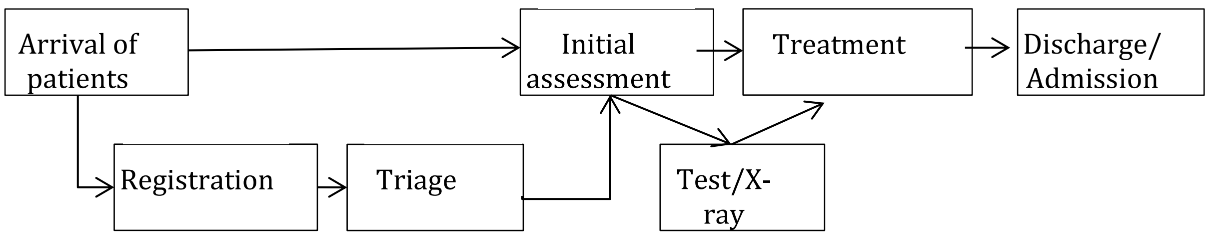


Figure 5-2. Patient flows in an A&E department

5.3.1.3 The entities

The different entities that participate in the process are:

- The patients who come to the department wish to be seen by the appropriate staff and to be diagnosed or treated within a reasonable time. They move from one process to another, queue when necessary, and leave when treatment is complete, or they are admitted to the hospital as inpatients.
- The clerk is in charge of registering the patients. The Clerks only task is to obtain necessary information from the patient to indicate them where to go next.
- The nurses are in charge of triaging the patients and in some cases of doing the first assessment and may accompany the doctors when necessary. Nurses wish to ensure that the patients are treated in the minimum possible time.

The doctors are in charge of doing the first assessment and the treatment of the patients. As with the nurses, the doctors wish to provide an excellent service within a reasonable time.

5.3.1.4 The environment

The environment in which they are acting is dynamic and uncertain. There are several sources of uncertainty in this environment, such as patient demand and the duration of the activities of the service process. This is a dynamic environment because the conditions of the environment change over time while the entities are making decisions. Three main characteristics make this environment dynamic. First is that the volume of patients that enter the department during the day changes with time; there are some busy periods and others that are quieter. Second, the number of tasks that a doctor or nurse can perform may vary depending on the conditions of the department at a particular time. A doctor, for example, could see more than one patient at a time if necessary. Third, the number of staff that work in the department changes over time: doctors, nurses and clerks have different working shifts.

5.3.1.5 The aim

The main purpose of the ABMS model is to gain insight into the overall value of including human behaviour into an A&E simulation. More specifically, this model aims to model how the four-hour target and other external factors may affect the behaviour of the clinical staff inside an A&E department. This model makes a simple representation of a typical A&E department, modelling some interactions among the patients coming to the department to be assessed and treated for their medical conditions, and the staff who are responsible for the provision of those services.

5.3.1.6 Validation

The ABMS model developed in this research does not intend to reproduce a real A&E department but to demonstrate how human behaviour can be incorporated in an ABMS model of an A&E department. The ABMS model is based on the DES model developed by Günal (2008). Therefore, the validation process will be done by comparing the ABMS model against the Günal model rather than comparing the ABMS model against the real world.

5.3.2 Step 2: method evaluation

The second step in this phase is to consider if Agent-Based methodologies are suitable to model the problem described in the previous phase. There is no single best way to determine which simulation method is more suitable than others to study a particular problem. However, some considerations may be taken into account when choosing a simulation method. Salamon (2011, p.p 112) suggests the following questions, which, if answered positively, can help determine whether agent-based methods are suitable for the problem of interest. These questions will be analysed according to the problem stated in this thesis.

1. **Are there entities that can make decisions?** In this simulation, there are patients, clerks, nurses and doctors that are continuously making decisions. For instance, after patients receive

information at each stage of the process, they may decide whether to continue the process in A&E or may quit and leave the department. Among other tasks, the doctors may decide the order in which the patients are seen, whether a patient needs any further investigation, and how to proceed with each patient.

2. **Are there many types of decision- making entities or many types of decisions?** In this model, there are four types of decision- making entities: patients, clerks, nurses and doctors. Each of them makes diverse types of decisions that range from the simplest (to walk) to the more complicated (e.g. Doctors change priority rules, see more or less patients and do more or less investigations)
3. **Does it look as if the system will have dynamic characteristics?** In this model, the agents have memory and information that affect their future behaviour.
4. **Do we feel a need to treat the overall behaviour of the whole system on a macro level**? The requirements of this model are oriented to the level of individuals. Each agent makes decisions based on its current and previous state and on the information and inputs it receives from the environment. For instance, the type of decisions that a doctor makes directly affect other specific agents (such as patients, other doctors and nurses)
5. **Is it difficult to describe the whole situation as a process (or activity) diagram or state transition diagram?** It is possible to describe some aspects of the problem being modelled using activity diagrams or process diagrams. However, as the decisions are taken at a micro (individual) level, the interactions and behaviour of the agents may not be fully captured in such types of diagrams.
6. **"Is it difficult to 'count-up' the entities into lump sums and then work solely with such amounts?** As there are different types of entities that make decisions, some of them could be grouped, for example, some patients could be called "red patients" and all such red patients may be treated in the same way. However, there are some individual characteristics (e.g. frustration) that affect the behaviour of the patients. Similarly, although there two main types of doctors: inexperienced doctors (junior) and experienced doctors (consultants), each doctor has particular characteristics, for example, energy, knowledge or stress level and makes decisions based on those characteristics.
7. **Are spatial factors of the environment important for the simulation?** The spatial characteristics are used only to create a layout of an A&E department for visual display purposes. That is, this model does not aim to improve the layout of the department.

Since the majority of the questions are answered positively, agent-based methodologies seem to be suitable to model the problem presented here.

5.4 Phase two: Conceptual model

Although there is no single accepted definition of conceptual modelling, it can be said that conceptual modelling deals with abstracting appropriate levels of simplification of a system (Pidd, 1994; Robinson, 2004). Robinson (2007, p.291) provides a conceptual modelling framework consisting of five iterative activities:

1. "understanding the problem situation",
2. "determining the modelling and general project objectives",
3. "determining the modelling outputs",
4. "identifying the model inputs",
5. "determining the model content (scope and level of detail), identifying any assumptions and simplifications".

These five activities relate more or less to the first two phases proposed by Salamon, of which activities 1 and 2 were included in the previous stage. This stage will include some of the processes defined in activities 3, 4 and 5.

Furthermore, Robinson (2007) suggests that it is crucial to represent the conceptual model so that it can be shared and understood by all the people involved in the simulation project. Onggo (2010) classifies conceptual model representations into three categories: textual representations, pictorial representations and multifaceted representations, suggesting that none of these is perfect, but all add some value. Within DES, common pictorial representations include Activity Cycle Diagrams, Process Flow Diagrams and Event Relationship Diagrams. Within SD, Causal Loop Diagrams or Stock and Flow diagrams (Sterman, 2000) are usually employed as pictorial representations. None of these pictorial schemes provides a complete representation for DES or SD, and there is no commonly used scheme for ABMS. Multifaceted representations contain both diagrams and a textual representation of different conceptual model components. One of the most common multifaceted representations used in software engineering is the Unified Modelling Language (UML).

ABMS is usually implemented in an object-oriented platform, for which UML is a generally accepted form of conceptual representation (Bauer & Odell, 2005). An advantage of using UML in modelling is that its symbols facilitate the verification and validation process; moreover, the use of an internationally standardised language can elicit common understanding among different stakeholders (Martin, Champion, Kinsman, & Masman, 2011).

UML 2.0 includes thirteen types of diagrams to represent static application structure, behaviour and interactions (Onggo, 2010) of which Use Case Diagrams, State Diagrams, Activity Diagrams, Class Diagrams, and Object Diagrams appear useful in ABMS (North & Macal, 2007). Onggo (2010) suggests, also, that Sequence Diagrams and Collaboration Diagrams can also be used to represent interactions of the model.

To explain the link between objects in object-oriented programming and agents in agent-based methodologies, Jennings and Wooldridge (1998) use an analogy between the concepts of autonomy in agents and encapsulations in objects. According to Jennings and Wooldridge (1998, p.4), in object-oriented programing, “an *object* encapsulates some state, and has some control over this state in that it can only be accessed or modified via the methods that the object provides”. Similarly, in agent-based modelling, the agents encapsulate some state in the same way that objects do, but additionally also encapsulate behaviour. That means that the agents have control over the execution of their methods and the selection of its actions (Jennings & Wooldridge, 1998).

Figure 5-3 is an example of a UML class diagram that allows representation of the main structure of an agent using object-oriented programming concepts (North & Macal, 2007). In Figure 5-3, classes are represented by boxes, and they define the properties and actions of the agents. The name of each class is at the top of the box; the attributes and methods are included below the name. Classes are organised into a hierarchical structure and are connected by inheriting the attributes and methods from other classes. A subclass inherits attributes from a superclass which is higher in the structure. From example, in a hospital model, patients, doctors, nurses and other medical staff could be subclasses of the class “GenericAgent”. “GenericAgent” contains the properties and methods that are common for all the agents within the model. Additionally, each subclass can have properties and methods that only belong to each subclass.

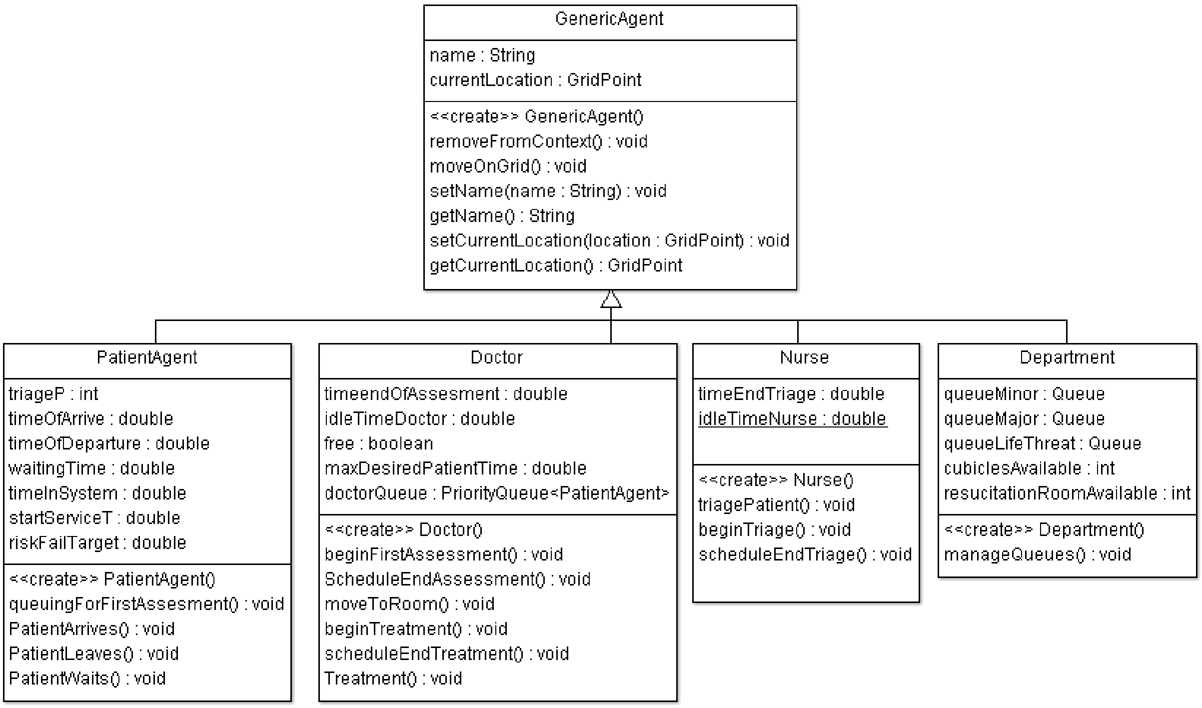


Figure 5-3. Example of a UML Class Diagram

In general, when developing ABMS, it is crucial to represent the two main parts of an agent-based model: agents and agent behaviours (North & Macal, 2007). Gilbert and Terna (2000) suggest that the modeller should first define the capabilities of the agents, the actions they can perform and the characteristics of the environment that surrounds them. They explain two different techniques to define agents and agents' behaviour and introduce a general framework to build an ABMS.

Gilbert and Terna consider two techniques for constructing agents. On the one hand, a modeller might include simple agents in their models using a production system technique. Here, agents respond to the stimulus of the environment through some actions; however, these responses are not modified as a result of the experience acquired from the environment. It means that the agents do not modify their behaviour, but react to different signals sent from the environment. In general, a production system is composed of a set of rules, working memory and rule interpreter. Rules have two components: a condition that indicates when to execute the rule and an action which is the consequence of executing the rule. Some rules may include actions that insert facts on the working memory, and others include conditions that assess the state of the working memory. The rule interpreter considers each rule and executes the ones that have a true condition, performs the actions related to those rules and repeats the cycle indefinitely.

On the other hand, it is possible to include some learning in the production systems, and the modeller might need to consider adaptation of the internal structure and process of the agents.

Two common methods used for modelling adaptation are neural networks and evolutionary algorithms.

The production system and learning techniques can be represented in a general scheme known as ERA (Environment-Rules_Agents). ERA contains three main parts: the environment, the agents and the agents' behaviour. The environment represents the context through rules, general data and the agents. A context can be just like a bucket that holds the agents of the model (Sourceforge, 2008). Agent behaviour is defined by two types of rules: master rules that represent the cognition of an agent (defined in the production system technique), and maker rules that modify the master rules (that involve learning).

For example, to model an A&E department using an agent-based model, the ERA scheme may be useful to represent the general structure of the model (Figure 5-4). Other concepts of an agent's behaviour will be discussed later. In this example, the environment contains the different agents which interact with each other using the environment: for example, Patients, Nurses, Doctors and the Department. Each agent has simple rules of behaviour. For instance, a particular doctor may choose a patient based on a set of specific master rules based on the condition of the patient and the time spent by that patient within the department. However, that doctor can adapt or learn from the system and modify those rules using a set of maker rules.

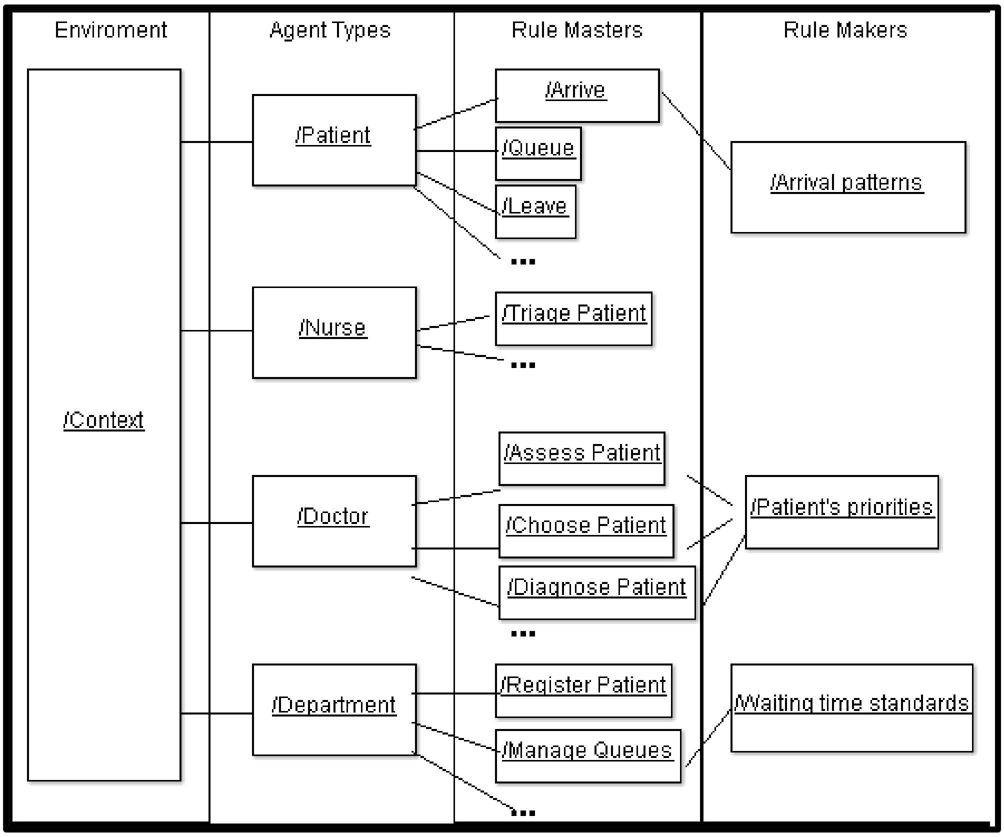


Figure 5-4. Example of an ABMS of an A&E department using ERA

5.4.1 Definition of the agents and agents' behaviour

In this step, it is necessary to define the two main parts of the model: *the agents and the agent's behaviour* (North & Macal, 2007). One of the features of agent-based models is ontological correspondence (Gilbert, 2007), which means that there can be a direct correspondence between the agents in the model and the entities in the real world (described in phase one).

Therefore, it is natural to consider four main agents in the model: the patients, the nurses, the doctors and the clerk. The behaviour of those agents may depend on the agent's capabilities, the actions they can perform and the characteristics of the environment that surrounds them (Gilbert & Terna, 2000).

The environment is the basic structure where agents act, and its function is to provide a mechanism for communication between agents (Gilbert, 2007). The environment of the A&E model contains the agents, the resources and the data required for the simulation.

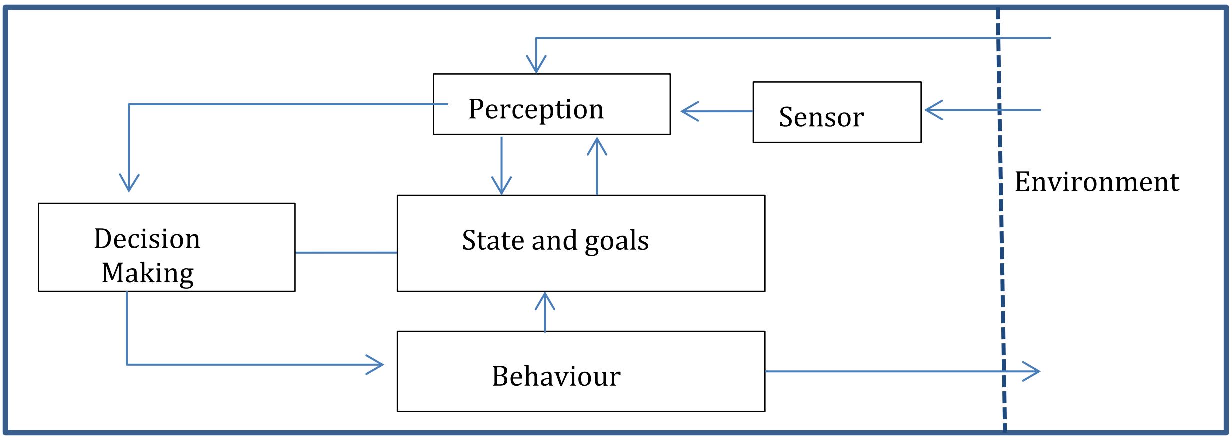


Figure 5-5. Agents' behaviour representation. Adapted from Schmidt (2000, pp. 2) and Salamon (2011, pp. 61)

Figure 5-5 shows a general representation of an agent's behaviour (adapted from Schmidt (2000, pp. 2) and Salamon (2011, pp. 61)). The agents can observe the environment using a sensor system and read information from the environment. Agents perceive the environment differently, depending on their current state and goals. The decision-making process can be reactive or deliberative. If the decision- making is deliberative, agents use perception and their internal state and goals to decide how to act, while if it is reactive, the agent behaviour is directly caused by the sensor. That means that his state and goals do not affect any of the behaviour process.

All the agents are capable of sensing and perceiving their environment, moving around the department, communicating with each other (by sending and receiving messages), interacting with the environment (by using the available resources), and selecting the behaviour to adopt. The ABMS_A&E model includes reactive and proactive behaviour. Reactive behaviour is defined as simple if/then rules and it is used to model the behaviour of the patients, nurses and clerks, who do not need to make complex decisions but have simple behaviour such as moving, engaging in activities, and changing their states. Therefore, the patient, nurse and clerk agents do not have a memory of the past and make decisions reactively based on the information they obtain (sense) from the environment, for instance, a patient will join a queue if there is not resources and staff available to start an activity.

However, doctor agents have a more complex behaviour, since they need to make decisions that depend not only on the state of the system, for instance waiting times, but also on the perception they have of it, which in turn affected by their internal states. For instance, they may need to speed up the attention of a patient if they perceive there is a high risk of failing to meet the target, which may be affected by their current level of stress or energy. Therefore, doctors in the ABMS_A&E model have proactive behaviour.

The following section will describe in more detail specific agents' behaviour.

5.4.2 Agents' interactions

This section describes the interactions between the different agents of the model using UML activity diagrams. Figure 5-6 shows the notation used in an activity diagram.

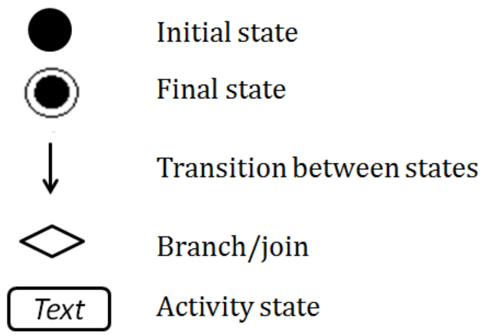


Figure 5-6. UML activity diagrams notation (North & Macal, 2007)

The first activity of the patient flow is registration. This activity involves the interaction between a patient and a clerk (Figure 5-7). When a new patient walks-in, enters the department and then walks towards registration. If any patients are queuing for registration or if there is no clerk available, this patient joins the queue for registration. Patients check if they are the only patient in the queue, and if that is the case, the patient moves to a specific place to be seen by the clerk. The clerk notices when a patient is ready for registering and if available, calls the patient to the cubicle. The patient walks towards the registration cubicle, and the clerk registers the patient and asks the patient to go to the waiting room until a nurse calls the patient's name. After registering the patient, the clerk becomes available and can start registering a new patient only if the working shift is not over.

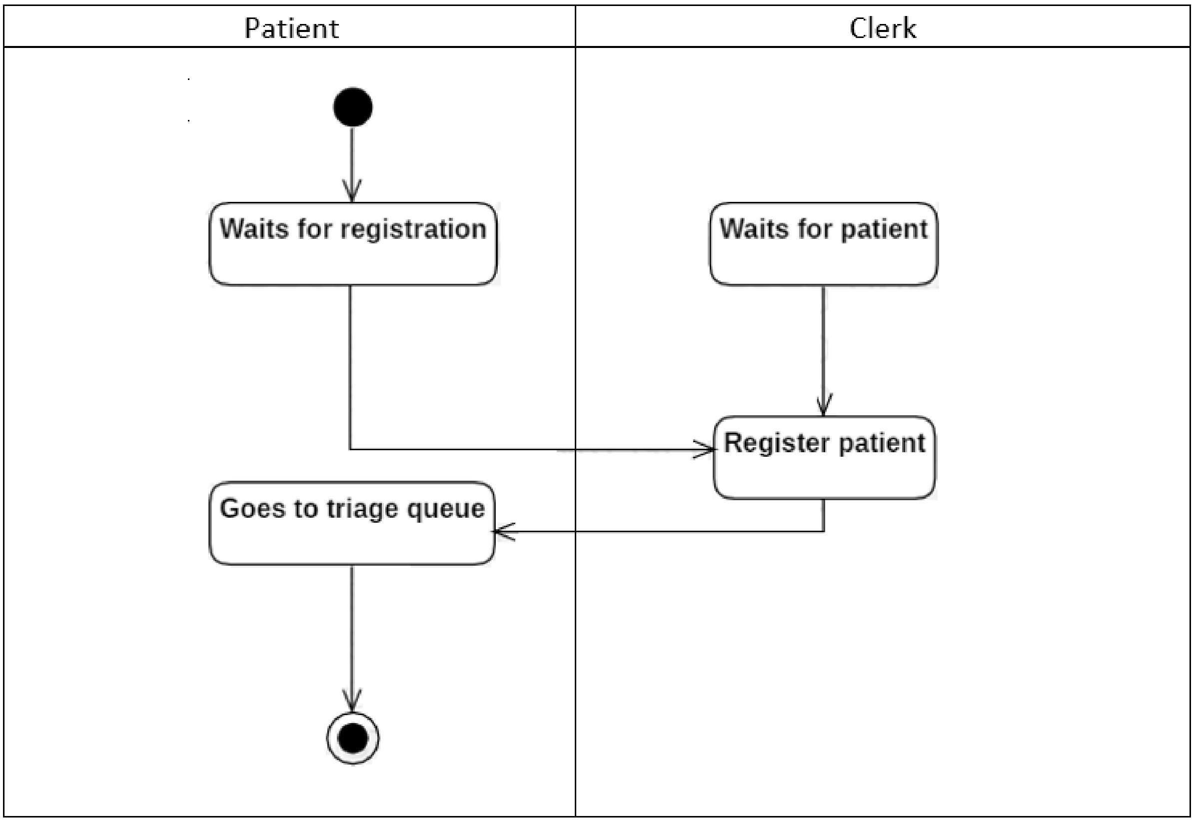


Figure 5-7. Activity Diagram for registration: Patient/Clerk

The nurse sees the patients waiting for triage and calls them if available. Then calls the patient to a cubicle and proceed with the patient's triage. A proportion of patients leave after triage; the rest of them stay for further evaluation. If the patient decides to stay, the nurse searches for available beds and asks the patient to wait there for the doctor’s assessment, if there are any available. This process can be seen in Figure 5-8.

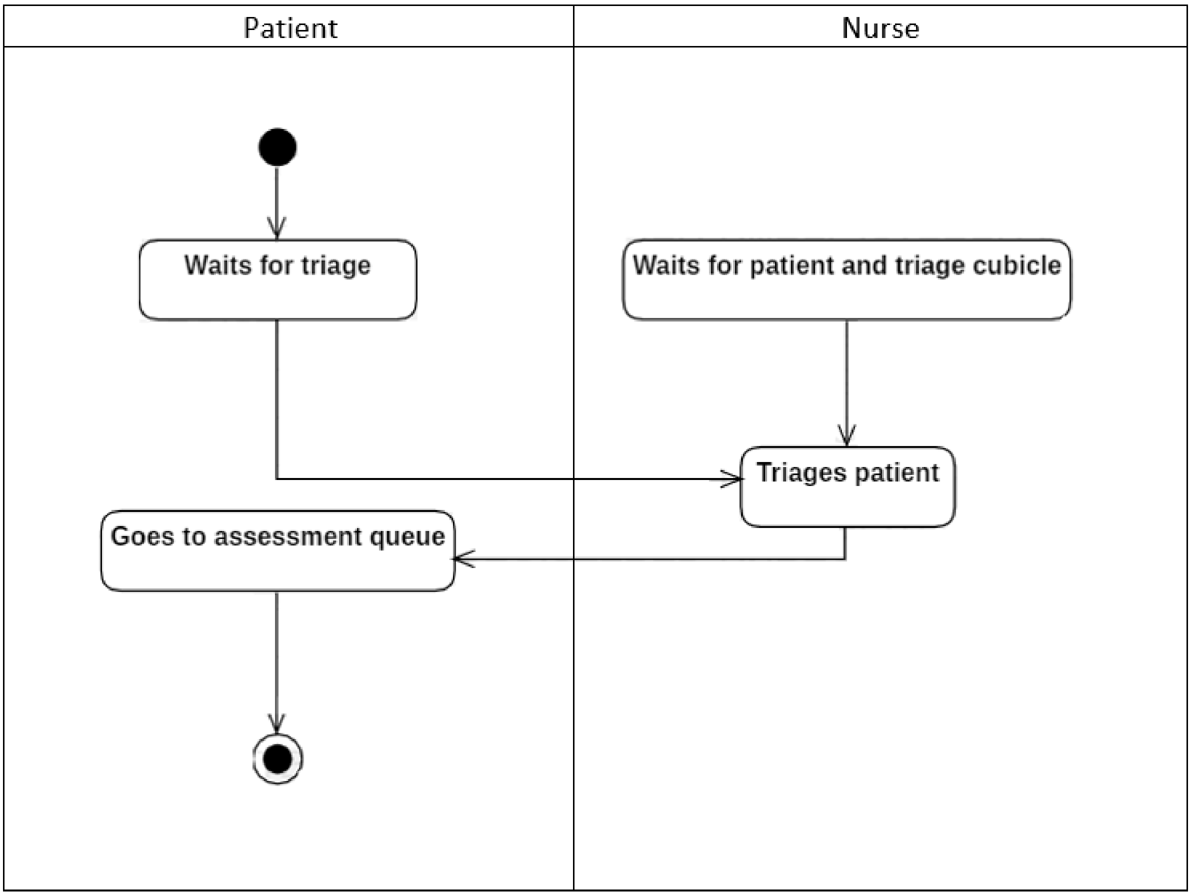


Figure 5-8. Activity Diagram for triage: Patient/Nurse

The doctors in the model have the objective of giving an accurate diagnosis to the patients and seeing them within four hours. The interactions between a doctor and a patient can be seen in Figure 5-9.

When a shift starts, doctors walk towards the doctors' area and decide what to do: if patients are waiting, they can either start an initial assessment with a patient or start a re-assessment. If they decide to start an initial assessment, they walk to the bed where the patient is. With a nurse's help, assesses the patient and decides if it is necessary to order any test.

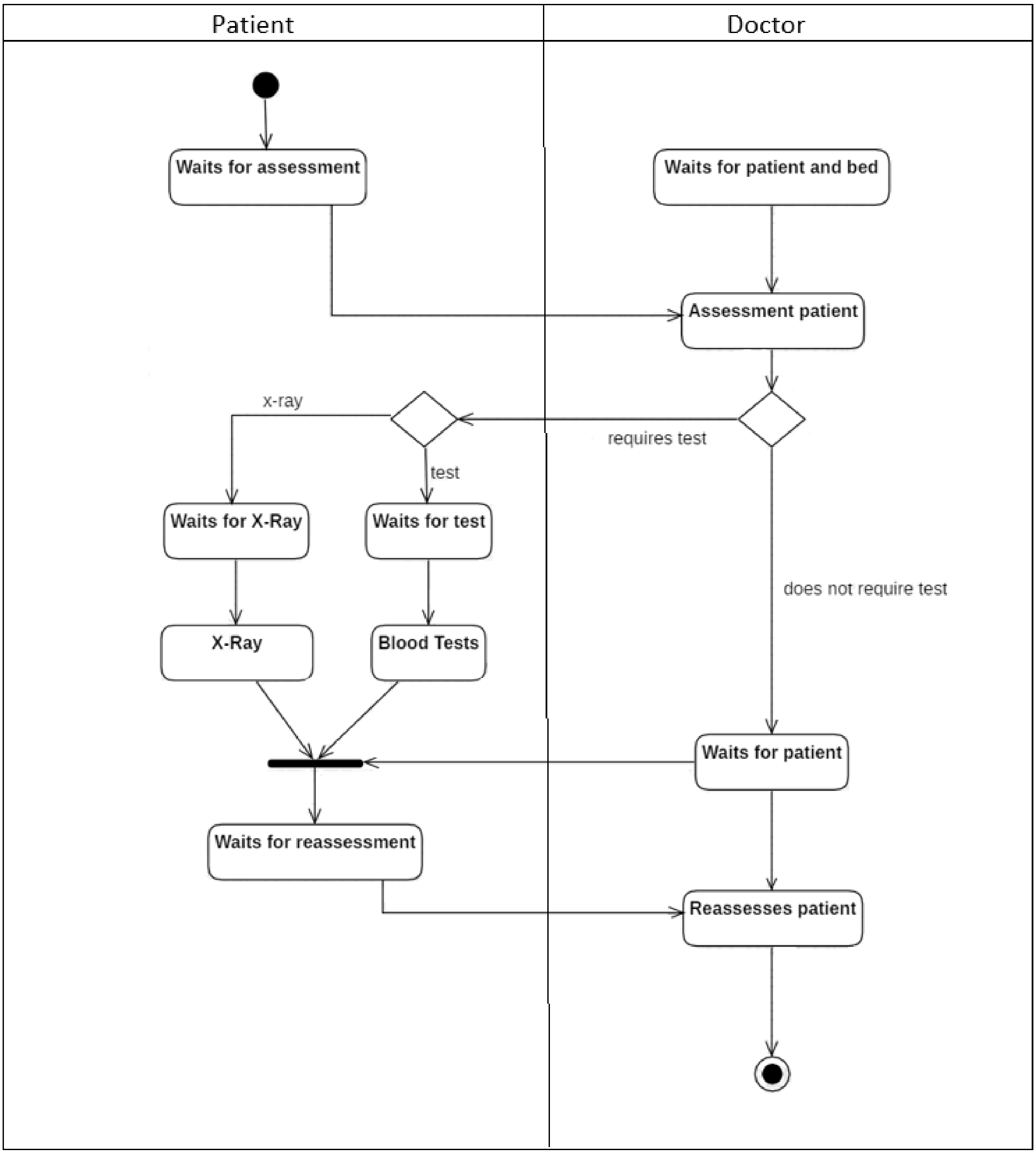


Figure 5-9: Activity Diagram for treatment: Patient/Doctor

If the patient requires an X-ray test, the doctor asks the patient to move to the X-Ray area, and the patient waits for the X-Ray to be taken. If the patient requires a blood test, the doctor orders the blood test. The patient can wait for the test results in the cubicle or somewhere else. When the doctor is ready for reassessment, a diagnosis is given to the patient and can then be discharged or admitted as an inpatient in the hospital.

5.4.3 Time handling

An important factor that may be considered before the model is implemented in a specific platform is time handling. In agent-based models, it is usual for the time-flow in the simulation to be handled in discrete time steps. That is, during every time step, the agents perform some actions until they have nothing else to do or they are removed from the simulation. The simulation model then moves on to the next time point.

However, several issues can arise when designing a simulation model that employs discrete time steps. (Gilbert, 2007) discusses three:

1. **Synchronicity**: That is, at a specific time (or step), some agents may be required to perform one action, and different agents may perform different actions. The order in which each action is called may be necessary for the execution of the model. For instance, at the beginning of the simulation, all the agents have to update their status and decide what action to perform, but if one agent updates his or her status and engages in an action with another agent before that agent updates his or her status, this may lead to an error causing the simulation to stop, because not all the conditions are fulfilled. There are different ways to deal with these problems:
    - Invoke the agents in a sequential order: that is call agents in order. For example, first call agent 1, then agent 2, and so on. That may work in the cases when the action of an agent does not directly affect the action of another agent at that time. For instance, let us suppose there are periods of low demand, which means that doctors are idle most of the time. If there is a method that is used to inform doctors when a new patient arrives, and there are six doctors, the method will invoke the doctors in a sequential order. In this case, it may happen that doctor 1 will work more than doctor 6.
    - Invoke the agents in a random order. In this case, the agents will execute the method in a random order
    - Invoke the agents in a convenient order, bearing in mind the order of the interactions among all the agents.

2. **Periods of inactivity**: There are periods where there is nothing to do in the simulation; that is, the agents have no actions to perform over several time steps. The simulation will then go from one step to another checking if there is anything to do but will do nothing. To avoid that, it might be better to consider the next event technique to handle those actions in the simulation.

3. **Calibrating time**: It is important to determine how simulation time matches real-time. Different questions may be considered; for instance, the modeller needs to think what the step of the simulation means in real-time? Or when the beginning or the zero time points are in both the simulated and the real world?

In this simulation, some events occur at regular intervals, such as at the beginning and the end of the working shifts. Those are events that occur once every day at a particular time, so they can be handled using the time-slicing technique. However, there may be periods of high activity and others of low activity, and the next event technique allows the time increment to adjust to each period.

In the ABMS model developed here, some events are handled using the time-slicing technique, such as the beginning and ending of a doctor's shift. Those are events that occur at regular intervals. Some other events related to the beginning and ending of other activities need to be scheduled using the next event technique.

5.4.4 Data requirement

The data for the development of this model was obtained from the Appendix of Günal's (2008) PhD thesis. This example describes a mid-size A&E department which deals with around 45000 patients per year. In this department, 75% of the patients arrive by walk-in, and the other 25% arrive by ambulance. Detailed information on the demand patterns by mode of arrival and hour of the day can be found in Günal and Pidd (2006, pp.448) and Günal (2008, pp.103).

5.4.4.1 Staff requirements

Günal and Pidd assumed that each member of a class of staff is identical in order to simplify according to the level of detail specified in their model. That means, for example, that there is not a significant difference in the service times between different doctors of the same category. In their model, they represent junior doctors (or inexperienced doctors) in one category and senior doctors (experienced doctors) in another category. The staff is treated in their model as countable resources; therefore, it was only necessary to determine how many doctors of each category were required by hour and day (see Table 5-1).

Table 5-1. Junior doctor's rotation

Time	Mon	Tue	Wed	Thu	Fri	Sat	Sun
00:00 - 00:59	3	2	3	3	3	3	3
01:00 - 01:59	1	1	2	2	2	2	2
02:00 - 02:59	1	1	1	1	1	2	2
03:00 - 03:59	1	1	1	1	1	1	1
04:00 - 04:59	1	1	1	1	1	1	1
05:00 - 05:59	1	1	1	1	1	1	1
06:00 - 06:59	1	1	1	1	1	1	1
07:00 - 07:59	2	2	2	2	1	2	2
08:00 - 08:59	2	2	2	2	2	2	2
09:00 - 09:59	2	2	4	3	4	3	3
10:00 - 10:59	2	3	4	3	4	3	3
11:00 - 11:59	3	3	4	3	4	4	3
12:00 - 12:59	4	3	4	4	5	4	4
13:00 - 13:59	4	3	4	2	5	4	4
14:00 - 14:59	4	4	7	3	5	5	5
15:00 - 15:59	4	5	8	4	5	5	5
16:00 - 16:59	4	5	7	3	3	6	6
17:00 - 17:59	3	3	4	3	3	4	3
18:00 - 18:59	3	4	3	3	3	4	3
19:00 - 19:59	3	4	3	4	3	4	4
20:00 - 20:59	4	4	4	4	3	4	4
21:00 - 21:59	3	4	4	3	3	3	3
22:00 - 22:59	2	3	3	3	3	3	3
23:00 - 23:59	2	3	3	3	3	3	3

In the DES_A&E model, the staff is not modelled as countable resources but as agents capable of making autonomous decisions. Thus, it might be necessary to define a shift pattern for each member of the staff that aligns to the department staff requirements.

Staff scheduling is a typical managerial problem. At this point, it is known from the data how many staff are required by every hour of each day. The question that may be asked is: how should that staff be scheduled? To answer that it might be necessary to use other operational research tools to obtain an optimal or satisfactory staff schedule. However, as the interest here is only on staff decision making, an arbitrary schedule was chosen to try to meet the constraints defined for resource scheduling in Günal's model. This schedule may be not convenient for doctors; however, since in this research I do not develop a fully realistic and detailed model, it is assumed that this scheduling is outside the scope of the project. Though, since the PECS framework is used to propose how to model human behaviour within A&E more realistically, it includes breaks on clinician shifts depending as part of their proactive behaviour.

For instance, it can be seen from Table 5-2 that on Monday at 00:00, it is necessary to have three doctors working, while at 12:00, it is necessary to have one more doctor. One possible method of scheduling for Monday is shown in Table 5-3.

By providing a similar arrangement for the rest of the week, it is possible to obtain a detailed schedule for the whole week and then, to assign each doctor a weekly shift schedule. The number of doctors required every day depends on the duration of the shifts and the doctor's requirements by hour. It is assumed that a doctor works less than 10 hours per day. If a doctor is required to work more than 10 hours per day, it may be possible to reduce the total number of doctors working in one day. Table 5-3 shows the detailed schedule for each doctor considered in this simulation.

5.5 Conclusions of the chapter

This chapter has explained the design process of the Agent-based model of an A&E department. The chapter aimed to structure the problem and develop a conceptual model of the A&E department, based on the first two phases of the methodology proposed by Salamon (2011).

The next chapter will describe the simulation process and will include phases 3 and 4 proposed by Salamon: selection of a development platform and the implementation and the validation processes.

Table 5-2. Monday's schedule of doctors.

Time	Doctors requirement	D1	D2	D3	D4	D5	D6	D7
00:00 - 00:59	3	x					x	x
01:00 - 01:59	1	x						
02:00 - 02:59	1	x						
03:00 - 03:59	1	x						
04:00 - 04:59	1	x						
05:00 - 05:59	1	x						
06:00 - 06:59	1	x						
07:00 - 07:59	2	x	x					
08:00 - 08:59	2	x	x					
09:00 - 09:59	2		x	x				
10:00 - 10:59	2		x	x				
11:00 - 11:59	3		x	x	x			
12:00 - 12:59	4		x	x	x	X		
13:00 - 13:59	4		x	x	x	X		
14:00 - 14:59	4		x	x	x	X		
15:00 - 15:59	4		x	x	x	X		
16:00 - 16:59	4			x	x		x	x
17:00 - 17:59	3				x		x	x
18:00 - 18:59	3				x		x	x
19:00 - 19:59	3					X	x	x
20:00 - 20:59	4				x	X	x	x
21:00 - 21:59	3					X	x	x
22:00 - 22:59	2						x	x
23:00 - 23:59	2						x	x

Table 5-3. Shift schedule for each doctor

	Doctor 1	Doctor 2	Doctor 3	Doctor 4	Doctor 5	Doctor 6	Doctor 7	Doctor 8	Doctor 9
Monday	00:00- 9:00	7:00-16:00	9:00-15:00	11:00-19:00 & 20:00-21:00	12:00-16:00 & 19:00-22:00	00:00-1:00 & 16:00-24:00	00:00-1:00 & 16:00-24:00	-	-
Tuesday	4:00- 9:00 & 10:00 -13:00	7:00-16:00	9:00-15:00	13:00-22:00	14:00-17:00 & 18:00-24:00	00:00-4:00 & 16:00-21:00	15:00-24:00	00:00-4:00 & 21:00-24:00	-
Wednesday	5:00 -11:00 & 14:00-17:00	7:00-16:00	9:00-15:00	14:00-22:00 & 23:00-24:00	15:00-17:00 & 18:00-24:00 & 00:00-1:00	9:00-18:00	14:00-23:00	00:00-5:00 & 20:00-24:00	00:00-2:00 & 11:00-17:00
Thursday	4:00-13:00	7:00-16:00	12:00-21:00	15:00-24:00	14:00-21:00 & 00:00-1:00	00:00-2:00 & 9:00-13:00 & 21:00-24:00	00:00-4:00 & 19:00-24:00	-	-
Friday	4:00-13:00	8:00-16:00	9:00-18:00	17:00-24:00	12:00-17:00 & 18:00-22:00	00:00-4:00 & 19:00-24:00	9:00-12:00 & 13:00-19:00	00:00-2:00 & 12:00-16:00 & 22:00-24:00	-
Saturday	4:00-13:00	12:00-21:00	7:00-12:00 & 13:00-17:00	16:00-24:00	14:00 -22:00	00:00-4:00 & 22:00-24:00	9:00-17:00	11:00-19:00	00:00-3:00 & 19:00-24:00
Sunday	4:00-12:00	12:00-20:00	9:00-17:00	16:00-24:00	14:00 -21:00	00:00-4:00 & 20:00-24:00	7:00-10:00 & 12:00-17:00	10:00-17:00	00:00-3:00 & 19:00-24:00

CHAPTER 6: ABMS MODEL IMPLEMENTATION AND SIMULATION

6.1 Introduction

Chapter 5 introduced the methodology proposed by Salamon (2011) for designing and process developing of ABMS models. It described the first two phases of the methodology (*Requirements definition*, *Conceptual model*) of the A&E department model proposed in this thesis. This chapter describes phases 3 and 4: *Platform-specific model* and *Simulation model*.

6.2 Phase 3: Platform Specific Model

6.2.1 Selection of development platform

Chapter 4 described some current toolkits available for implementing ABMS models; especially it explained the reasons for choosing the Repast Symphony as the simulation platform for implementing the ABMS_A&E model of this thesis. The ABMS_A&E model considers the operation of the A&E department for one year, and the time unit is in minutes.

6.2.2 Transformation guide

Most agent-based models are built under object-oriented paradigms. Most object-oriented software uses the same basic principles of object-oriented programming; therefore, there are standardised techniques to transform a conceptual model into a computer program (Salamon, 2011). However, agent-based models use more than object-oriented programming concepts; they include the concepts of agency, environment and interactions, which make it more challenging to have a standard method to transform an agent conceptual model into a computer simulation model.

The transformation guide described in this section aims to transform the conceptual model presented in chapter 5 into a computer simulation model. This process will be done first by describing the structure of the model using a UML class diagram. It will then describe each object of the simulation model and will finally explain the graphical user interface.

First, the class diagram of the ABMS_A&E model is presented in Figure 6-1; it shows all the classes used to build the model. Appendix B, Tables B1 and B2, present a brief description of each object in the simulation. The AEContextBuilder implements the Repast interface ContextBuilder<Object>, which builds the context by adding the agents and defining the projections (in this case a grid projection). The SimObject Class represents all the objects in the simulation: Agents, Resources, Queues, Entrance and Exit Doors, and an Administrator. All these objects are inherited from the SimObject class. The Agent class contains the Clerks, Doctors, Patients and Nurses. Doctor Class includes Consultant and Junior doctors.

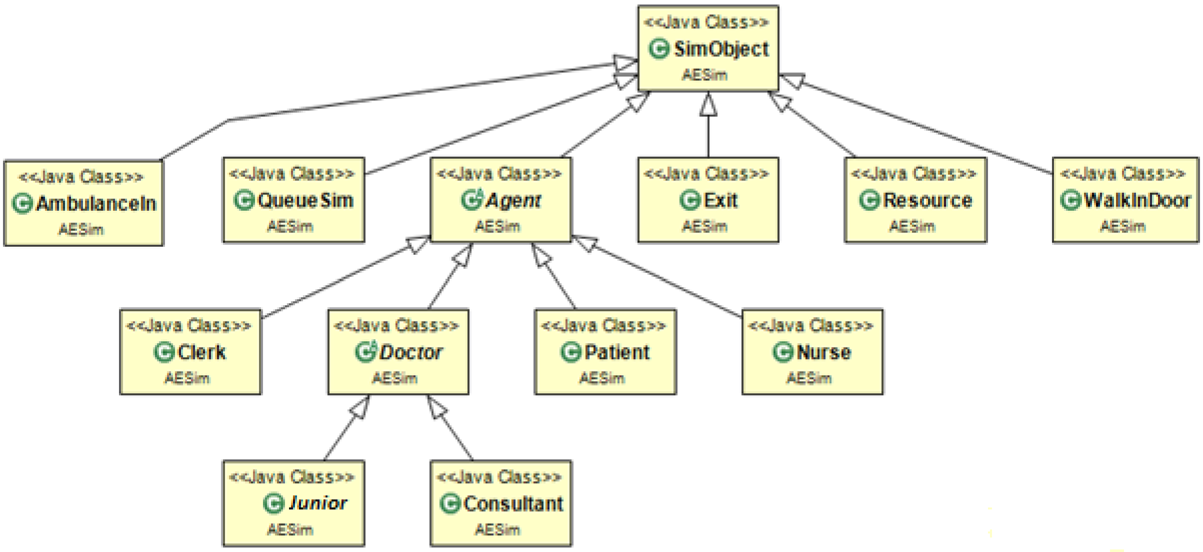


Figure 6-1. ABMS Model class diagram.

It is possible to run the model in a batch mode or a GUI (Graphical User Interface) mode. The batch mode runs the simulation in the background using a parameter sweep file defined by the user. The GUI mode allows user interaction in which it is possible to control the execution of the simulation, to manipulate the simulation parameters in a control panel, to access and view individual agents and to create data set and examine model outputs. Figure 6-2 shows the GUI of the A&E model.

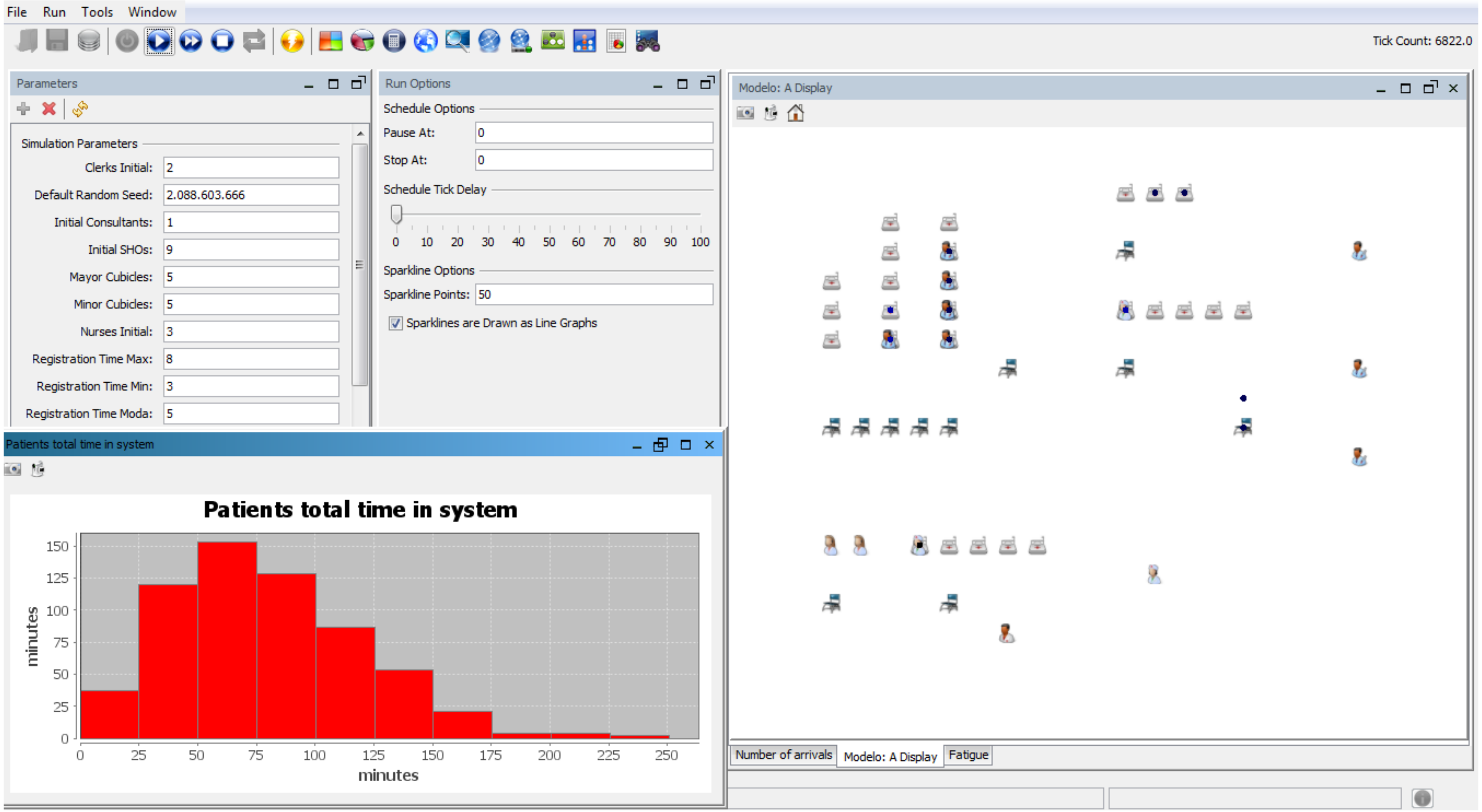


Figure 6-2. A&E model Graphical User Interface

6.2.3 Model inputs

Initial values and distributions were based on the DES model of the first study of an A&E department developed by Günal and Pidd (2006, 2009). Table 6-1 lists the number of resources and agents used to initialise the model.

Table 6-1. Number of objects within the simulation

Resources	No. of instances (base case)
Triage cubicles	5
Trolleys	10
Minor cubicles	5
Major cubicles	5
Resus cubicles	3
X-ray rooms	3
Test rooms	5

Agents	No. of instances (base case)
Doctors	9
Consultants	1
Patients	2
Nurses	5
Clerks	2

All the agents within the model have individual characteristics. Individual characteristics are related to individual personality. Appendix B, Table B2 presents the individual characteristics of the agents in the model with their respective values. Patient's attributes are related to the triage system explained in section 5.3.1.2, Doctor's attributes are related to the PECS variables, which will be explained later in this chapter.

6.2.4 Agents and agents' behaviour

The implementation of an agent's behaviour in the ABMS_A&E model was done in two steps. The first step considered the development of the A&E simulation model with simple behaviours. The agent's behaviour was assumed to be purely reactive in this step, which means the agents react to their current percepts and the information received from the environment. The second step included some deliberative behaviour of the agents implemented using PECS framework.

6.2.4.1 ABMS using simple reactive behaviour

This section will describe the first step of reactive behaviour. In the previous section, it was seen that all agents are subclasses of the “Agent” class. It can be seen from Appendix B, Table B1 that the class *Agent* has one method which is inherited by each agent: *moveTo (GridPoint). This* method receives a location in the grid and moves the agent to that point in the grid. Other methods do not define the agent’s behaviour but are used to obtain information about the agents and the environment. For instance, the class agent has a method called *getMyResource(),* which returns to the resource where an agent is at a particular time. For instance, let us suppose that a Nurse is seeing a Patient in a triage cubicle, then the method nurse.*getMyResource() and* patient.*getMyResource()* will return the location of the triage cubicle of the nurse and the patient.

There is some behaviour which is specific to each type of agent. Appendix B, Table B2, presents a description of the agents in the model and their respective variables. The *Patient* agent, besides moving, has two additional methods that define their behaviour: joinQueue(Queue) that defines the way a patient joins a particular queue and decideWhereToGo() that allows the patients to decide if they should continue in the department until the end of the treatment or leave at any point of the process.

The staff represents the clerks, nurses and doctors, each of whom has a specific working shift, and that defines when to start or end work. The methods *scheduleWorkShift(), startShift()* and *endShift()* define when to start and finish a shift. The methods *engageWithPatient()* and *releaseFromPatient(),* define what staff need to do when they interact with patients. The method findCubicle(), allows the staff to search specific cubicles, and the method *decideWhatToDo()* allows the staff to decide what to do at the end of any activity.

Each member of staff has the responsibility for seeing patients in different processes. Clerks register patients, nurses can triage patients or stay with them during the treatment process, and doctors treat patients.

6.2.4.2 ABMS using deliberative behaviour

It was mention in chapter 5 that if agents have deliberative behaviour, they use a more complex decision-making process where they need to use a perception system that depends on agents’ internal states and goals. Deliberative behaviour here is done by implementing the PECS framework. The following section will explain this framework and how it is implemented to model doctors’ behaviour in the ABMS_A&E model.

6.3 PECS framework

As introduced in chapter 4, PECS is a Multi-purpose reference model that considers human beings as "psychosomatic units with cognitive facilities embedded in a social environment" (Urban and Schmidt,2001; Brailsford & Schmidt, 2003; Schmidt, 2005b), in which behaviour needs to be defined considering four state dimensions: Physical conditions (Physis), Emotional state, Cognitive capabilities and Social status.

The PECS agent architecture consists in three different layers in an extension of an input:output framework (Urban and Schmidt, 2001) as shown in Figure 6-3. The *input layer* is defined by a *sensor* component that receives the information from the environment and sends it to the *perception* component. The information in the input layer is processed by the perception component and transferred by a set of *functions* represented by *F* to the *internal layer*, which contains the set of the PECS state variables represented by *Z*. The *actor and behaviour components define the output layer*. The behaviour can be reactive or goal-directed, and the actors are responsible for executing the actions ordered by the behaviour component.

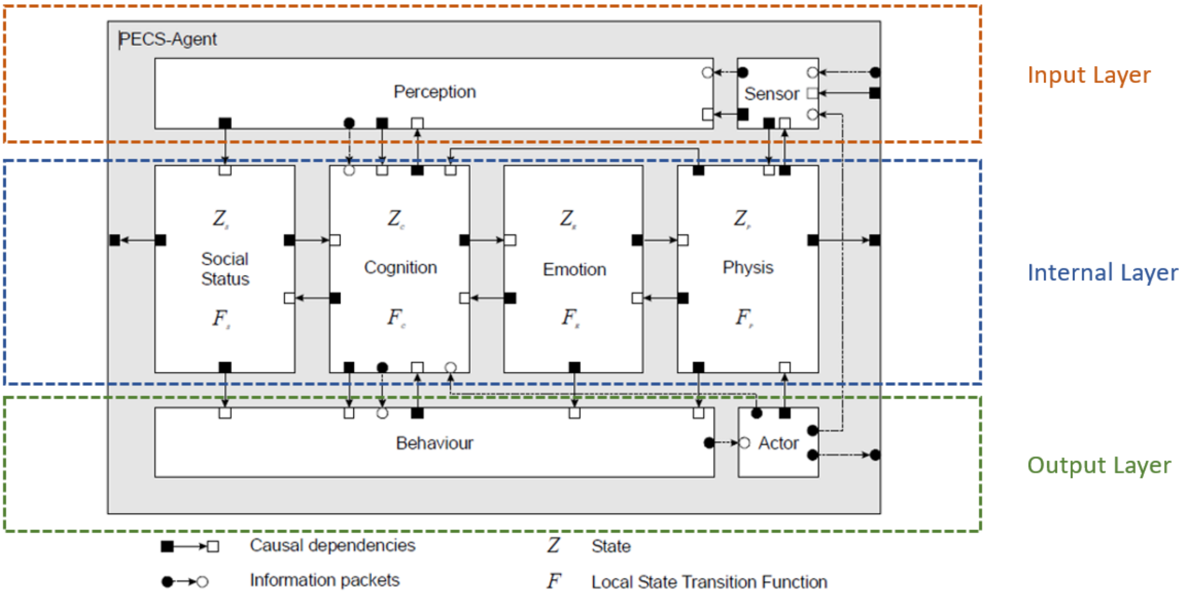


Figure 6-3. PECS architecture (Urban and Schmidt, 2001, pp.2)

In order to implement PECS framework in simulation models developed in this thesis, it is necessary to define for each entity or agent that makes decisions the functions that allow the transformation from the information received by the input layer to the actions defined by the actor component. Figure 6-4 shows a Pictorial representation of the implementation of PECS in the simulation model and the variables are defined below.

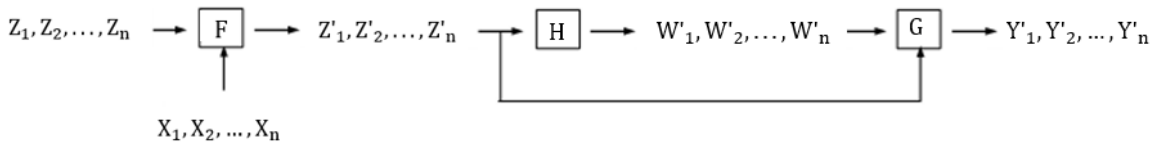


Figure 6-4. Pictorial representation of the implementation of PECS in simulation models

Firstly, at a time t, each agent or entity receives information from the sensor in the form of the input variables $X_1, X_2, \ldots, X_m$ and from the internal layer receives the values of the state variables $Z_1, Z_2, \ldots, Z_n$ at the same time. **F** represents the set of functions $F_1, F_2, \ldots, F_n$ in the perception layer that transform the input and state variables in time t to the state variables $Z'_1, Z'_2, \ldots, Z'_n$ at time $t' = t + \Delta t$, as shown in Equation 6-1. That is, F is the state transition function that transforms the state variables at time t into subsequent state at time t' as a result of inputs.

$$F: STATES \times INPUTS \rightarrow STATE.$$

$$F((Z_1, Z, \ldots, Z_n), (X_1, X_2, \ldots, X_m)) = (Z'_1, Z'_2, \ldots, Z'_n) \qquad \text{Equation 6-1}$$

Behaviour is not directly trigged by state variables Z. Schmidt defines other variables, known as dependent variables represented by W, that are responsible for an agent's behaviour. The dependent variables in this research represent the intensity of each state variable, so it is possible to compare all dependent variables and define the possible behaviour for each agent or entity. The relationship between state variables Z and dependent variables W can be defined by a set of functions represented by H. The H functions transform the state variables $Z'_1, Z'_2, \ldots, Z'_n$ at time t' into dependent intensity variables $W'_1, W'_2, \ldots, W'_n$ at t', as shown in Equation 6-2.

$$H: STATES \rightarrow DEPENDENT.$$

$$H(Z'_1, Z'_2, \ldots, Z'_n) = (W'_1, W'_2, \ldots, W'_n) \qquad \text{Equation 6-2}$$

Finally, the actor component is responsible for executing the actions ordered by the behaviour component through a G function as presented in Equation 6-3. G is the output function, that transforms the state variables and the dependent variables at time t' into the outputs or observable behaviour $Y'_1, Y'_2, \ldots, Y'_n$ at the same time.

$$G: STATES \times DEPENDENT \rightarrow OUTPUTS$$

$$G((Z'_1, Z'_2, \ldots Z'_n), (W'_1, W'_2, \ldots, W'_n)) = (Y'_1, Y'_2, \ldots, Y'_n) \qquad \text{Equation 6-3}$$

Schmidt suggests that the adaptation of this structure to specific cases can be made by defining the parameters, the specific state variables and the functions F, H and G. The assignation of the parameters of the functions defines the personality of the agents.

6.4 PECS framework for doctors

Although the behaviour of all the people that take part of an A&E process affect its performance, in order to demonstrate how human behaviour can be included in simulation models of A&E departments PECS framework will be implemented to model doctors' behaviour in the ABMS_A&E model. As it was stated in the research design, the A&E models built in this thesis do not attempt to realistic simulations instead to gain insight into how human behaviour can be incorporated into those models.

The assumption considered in the PECS framework is that a human being can be represented as a system and therefore, the system-theoretical principles apply to define the structure of an agent. In this framework, each agent behaves accordingly to the intensity of motives which depend on the state of the PECS variables. Although for many years, researchers have tried to measure different factors of human behaviour such as fatigue, emotions, learning and social status, there is no universal approach to measure those factors (Ajzen & Fishbein, 1980; Beurskens et al., 2000; Chang, 1998; Conrad & Kellar-Guenther, 2006; Lee, Dziadkowiec, & Meek, 2014; Maytum, Heiman, & Garwick, 2004; Perlovsky, 2014; Sterman, 2000).

Previously, it was mentioned that in the PECS framework, behaviour needs to be defined considering four state dimensions: Physical conditions (Physis), Emotional state, Cognitive capabilities and Social status. In this research, the physical condition (P) will be defined later by a state variable that represents doctor's energy level, the emotional state (E) will be defined by state variable that represents doctor's calmness level, the knowledge level (C) will be defined by a state variable that represents the level of knowledge that a doctor has about a patient and the social status (S) will be defined by two state variables one represent doctor's level of experience and the other doctor's reputation. As mentioned earlier, the behaviour is not directly trigged by state variables but by the dependent variables. The dependent variables are calculated through the state variables, and they can drive to an output that defines the agents' behaviour.

6.4.1 Logistic curves to represent PECS behaviour

The underlying assumption in PECS is that the state transfer functions (F) and the intensity function (H) define the agent's personality. Different forms of the functions F and H can be implemented in

PECS; however, in this thesis, Logistic Functions (S-shaped functions) are chosen to model most of the F and all the H functions.

The state and dependent variables considered in the PECS framework are variables that cannot grow or decline forever. Although there might be different curves that can represent well the behaviour of those variables, in this context, it makes sense that a S-shape (Figure 6-5) can be considered as a possible form of their behaviour.

S-shaped behaviour is a commonly observed mode of behaviour in dynamic systems, in which constraints limit the values of the variables, for instance, minimum and maximum possible values can constrain a variable.

Moreover, in an S-shaped curve, growth is non-linear, it grows exponentially at first but then slows gradually until the value of variable approaches its maximum (Sterman, 2000). For instance, the cognition of a doctor represented by a Knowledge variable seems to exhibit such behaviour, it starts from zero when a doctor meets a patient, and the speed of learning is higher at the beginning when he or she starts discovering more about patient's condition and slow down when he or she is approaching the maximum possible knowledge of the patient's condition. Something similar seems to happen with other PECS variables such as Stress (Emotional dimension) and Reputation (Social Dimension).

Additionally, literature shows that S-shaped functions have been used to model some aspects related to the dimensions considered in the PECS framework. S-shaped curves have proved to be suitable for modelling learning in different areas (Murre, 2014; Kucharavy and De Guio, 2011) which suggest that the Knowledge that represents the Cognition dimension in the PECS framework may exhibit such shape. Moreover, S-shapes have been commonly used to study the relationship between physical stimuli and sensations, cognitive development and human behaviour (Tong, Ellsworth, & Bishop, 2009). One example is Tong (2009) who investigated the nature of the relationships between emotions and appraisals, and he found that there are s-shaped relationships between emotions and behaviour. These functions have a *baseline* that represents the minimum level of the emotion, an *asymptote* that represents the maximum level of the emotion and a *slope* that represents the intensity of the relationships between behaviour and emotions. As for the Knowledge dimension, the Emotional dimension represented by the variable Stress could also display an S-shaped form.

S-shaped growth processes can be approximated by a Logistic Function, as shown in Figure 6-5 and defined by Equation 6-4. A Logistic Function is a smooth bounded function that monotonically increases (or decreases) at non-constant rate. In an increasing function as the one shown in Figure 6-5, the growth is close to zero when the value of the function is close to zero then it starts growing exponentially up to it reaches the half of the maximum value of the function (which means that the growth rate is maximum when $x = c$, where occurs the inflexion point of the function) and then starts slowing up to zero until the function approaches its maximum value (M).

$$f(x) = \frac{M}{1 + e^{-\alpha(x-c)}} \qquad \text{Equation 6-4}$$

Where:

M: is the asymptotic maximum value of f(x).

α: is the logistic growth rate (affects the steepness or width of the curve: that is, as α increases, the curve approaches M faster)

c: is the value of x when the curve has its maximum growth (c also means the value of X at which the curve reaches the 50% of M)

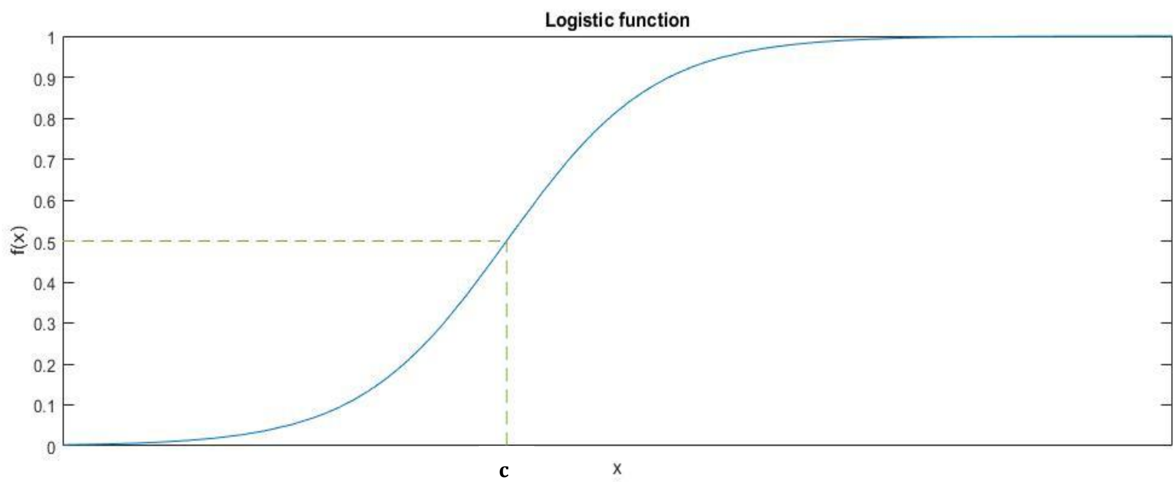


Figure 6-5. Logistic function

In conclusion, in this research, Logistic Functions are selected to model PECS state and dependent variables for different reasons. First, they exhibit an S-shape form, which seems adequate for representing the behaviour of the PECS variables considered in this research. Second, these curves allow the modelling of processes on which stimulus triggers behaviour. Third, they are flexible functions which parameters are easy to understand and to modify.

6.4.2 PECS state variables for doctors

In this research, it is assumed that each of the PECS factors (Physical, Emotional, Cognitive and Social) is represented by the variables and parameters used for the PECS framework in Table 6-2.

Table 6-2. PECS variables and parameters

X_1:	is an input variable that represents the number of patients seen at time t
X_2:	is an input variable that represents a Doctor's total working time (hours) at time t
X_3:	is an input variable that represents the maximum triage number among all the patients being seen by a doctor at time t.
X_4:	is an input variable that represents the average time in the system (hours) among all the patients being seen by a doctor at time t.
X_5:	is an input variable that expresses the ratio between the number of tests ordered for a patient at time t and the maximum number of tests that a patient can have.
X_6:	is an input variable that represents the time a doctor has worked in the A&E department (in weeks)
X_7:	is an input variable that represents the maximum time in the system (hours) of the patients being seen by a doctor
Z_1:	is a state variable that represents the energy level of a doctor at a specific time t (dimensionless). The physical condition (P) is defined by this state variable.
Z_2:	is a state variable that represents the emotional state (E) is defined by this state variable that represents the calmness level of a doctor at a specific time t (dimensionless).
Z_3:	is a state variable that represents the knowledge that a doctor has about a patient at a specific time t. The knowledge level (C) is defined by this state variable (dimensionless).
Z_4:	is a state variable that represents the level of experience the doctor has gained at time t (dimensionless). This state variable defines the social status (S)
Z_5:	is a state variable that represents the reputation of a doctor at a specific time t respectively(dimensionless). This variable, along with $Z_{4,}$ defines the social status (S)
W_1:	is a dependent intensity variable(dimensionless) that represents the fatigue as a function of the energy state (Z_1).
W_2:	is a dependent intensity variable that represents stress as a function of the calmness state (Z_2)
W_3:	is a dependent intensity variable(dimensionless) that represents the need of knowledge as a function of knowledge about a patient (Z_3)
W_4:	is a dependent intensity variable (dimensionless) that represents social desire as a function of reputation (Z_4)
c_1:	is a parameter for the Energy function that represents the maximum number of patients a doctor is capable of seeing in one hour
c_2:	is a parameter for the Energy function that represents the duration of a doctor's shift (hours)
c_3:	is a parameter for the Calmness function that represents the maximum time in the system (hours) over all the patients being seen by a doctor at which the doctor loses 50% of their calm.
c_4:	is a parameter for the Knowledge function that represents the time that doctors need to obtain 50% of the knowledge (hours) about each of their patients.
c_5:	is a parameter for the Experience function that represents the time (in weeks) when a doctor reaches 50% of the maximum experience.
α_3:	Is a parameter for the Experience function that represents the growth rate of the function. This value gives a measure of the speed with which doctors gain experience.

To explore differences in the behaviour of the doctors, here we consider there three levels of expertise (based on their clinical training) of doctors. There are doctors with low levels of expertise, doctors with medium levels of expertise, and doctors with high levels of expertise.

Since it is assumed that the level of expertise is based on doctor's clinical training, it makes sense to think that doctors with low levels of expertise are younger and they tend to get tired slower than the ones with higher levels of expertise. However, doctors with lower levels of expertise could get stressed quicker than doctors with higher levels of expertise. That is because the less expert they are, the higher levels of uncertainty they perceive when facing challenging situations.

In the ABMS_A&E and DES_A&E models, it is considered that 9 doctors are working along the day; they are categorised by their level of expertise as follows:

- Low level of expertise: Doctor 1, Doctor 2, and Doctor 9
- Medium level of expertise: Doctor 3, Doctor 4 and Doctor 5.
- High level of expertise: Doctor 6, Doctor 7 and Doctor

Table 6-3 shows the value of the parameters of the PECS state variables for each doctor. The following section explains in more detail the PECS variables.

Table 6-3. Doctors' parameters of the PECS state variables

	c_1	c_2	c_3	c_4	c_5	c_6	α_3
D1	4	9	1	0,5	200	1,167	0,0075
D2	4	9	1	0,5	200	1,167	0,0075
D3	4	8	1	0,5	50	1,5	0,0125
D4	4	9	1,33	0,5	50	1,5	0,0125
D5	4	7	1,33	0,5	50	1,5	0,0125
D6	4	9	2	0,5	0	2,167	0,0175
D7	4	9	2	0,5	0	2,167	0,0175
D8	4	9	2	0,5	0	2,167	0,0175
D9	4	9	1	0,5	200	1,167	0,0075

6.4.3 Physical condition (P)

The physical condition (P) is defined by the state variable Z_1 that represents the energy level of a doctor at a specific time t. For instance, assuming that the energy level of an agent depends on the number of hours worked in a day, the energy state (physical condition) is expected to decrease when the time work increases. One mathematical function that shows this type of behaviour is a rational function. For instance, let us consider the following rational function: $Y(x) = \frac{c}{c+x}$, where c is a constant and x is the independent variable. When x increases $Y(x)$ decreases exponentially until zero.

For this research, it seems reasonable to assume that the relative energy level of a doctor is affected by both the time worked (X_1) and the number of patients seen (X_2); hence, the function includes both X_1 and X_2. The function includes its product because the function has to emphasise their joint effect. So, the Energy state variable for each doctor in the time $t + \Delta t$ (Z_1') is modelled using the rational function shown in Equation 6-5:

$$Z'_1(X_1, X_2) = \frac{c_1 c_2}{c_1 c_2 + X_1 X_2} \qquad \text{Equation 6-5}$$

Using Wolfram Mathematica 10 ®, we obtain the graph in Figure 6-6. It can be seen from this graphic that the energy decreases as the number of patients and the working time increase.

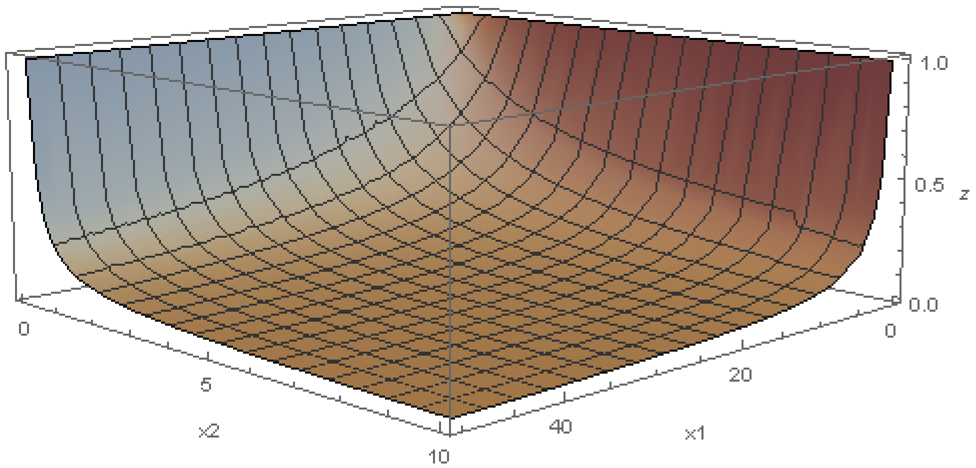


Figure 6-6. Example of a function of the variable P: Energy

6.4.4 Emotional state (E)

The emotional state (E) is defined by the state variable Z_2 that represents the calmness (lack of stress) level of a doctor at a specific time t. For instance, if a doctor is seeing several patients and the average time in the system of all those patients is close to the target, the doctor will be less calm than if that average is much smaller. As mentioned earlier, the Logistic Function is used here to model the Calmness Variable. In this case, the F function that transforms the input and dependent variables in time t into state variable Z'_1 in time $t + \Delta t$ will have an S-shaped form as shown in Equation 6-6:

$$Z'_2(X_3, X_4, Z_1) = \frac{1}{1 + e^{X_3(1-Z_1)(X_4-c_3)}} \qquad \text{Equation 6-6}$$

Notice that in this function, the factor $X_3(1 - Z_1)$ multiplies the factor $(X_4 - c_3)$, which in the logistic function (Equation 6-6) means that $X_3(1 - Z_1)$ represents steepness or width of the curve, while c_3 means the value X_4 at which the Calmness reaches the 50% of its maximum value (in this case the maximum value is 1).

Table 6-2 shows that X_3 represents the maximum triage number among all the patients being seen by a doctor, Z_1 represents a doctor's energy level, X_4 represents the average time in the system among all the patients being seen by a doctor, and c_3 represents the maximum time in the system (hours) over all the patients being seen by a doctor at which the doctor loses 50% of their calm. In this context, that means several things. First, it means that the higher the values of the patient's triage (more critical patients) and the less value of a doctor's energy, the faster a doctor loses his or her calm. Second, it can be seen from Table 6-3 that the values of the parameter c_3 are different for each type of doctor. Doctors with low level of expertise, lose their 50% of the calm when their patients have been waiting around 1 hour, doctors with medium level of expertise when their patients have been waiting around 1.33 hours (around 80 minutes), and doctors with high level of expertise when their patients have been waiting around 2 hours. That is because they perceive the risk of failing the 4-hour target differently depending on their experience; it is natural to assume that the inexperienced doctor gets stressed sooner than the more experienced ones.

Figure 6-7 shows an example of how the behaviour of the variable Calmness would be for the three types of doctors when they have different values of the triage. The graphic confirms that the doctors that have higher experience working in A&E departments may know better how to deal with critical patients (Figure 6-7-e) than less experienced doctors; therefore, they lose their calm much slower than inexperienced doctors. It is also possible to see from the graphic, that when doctors are low experienced, they lose their calm sooner because of patients' waiting times than doctors that are more experienced.

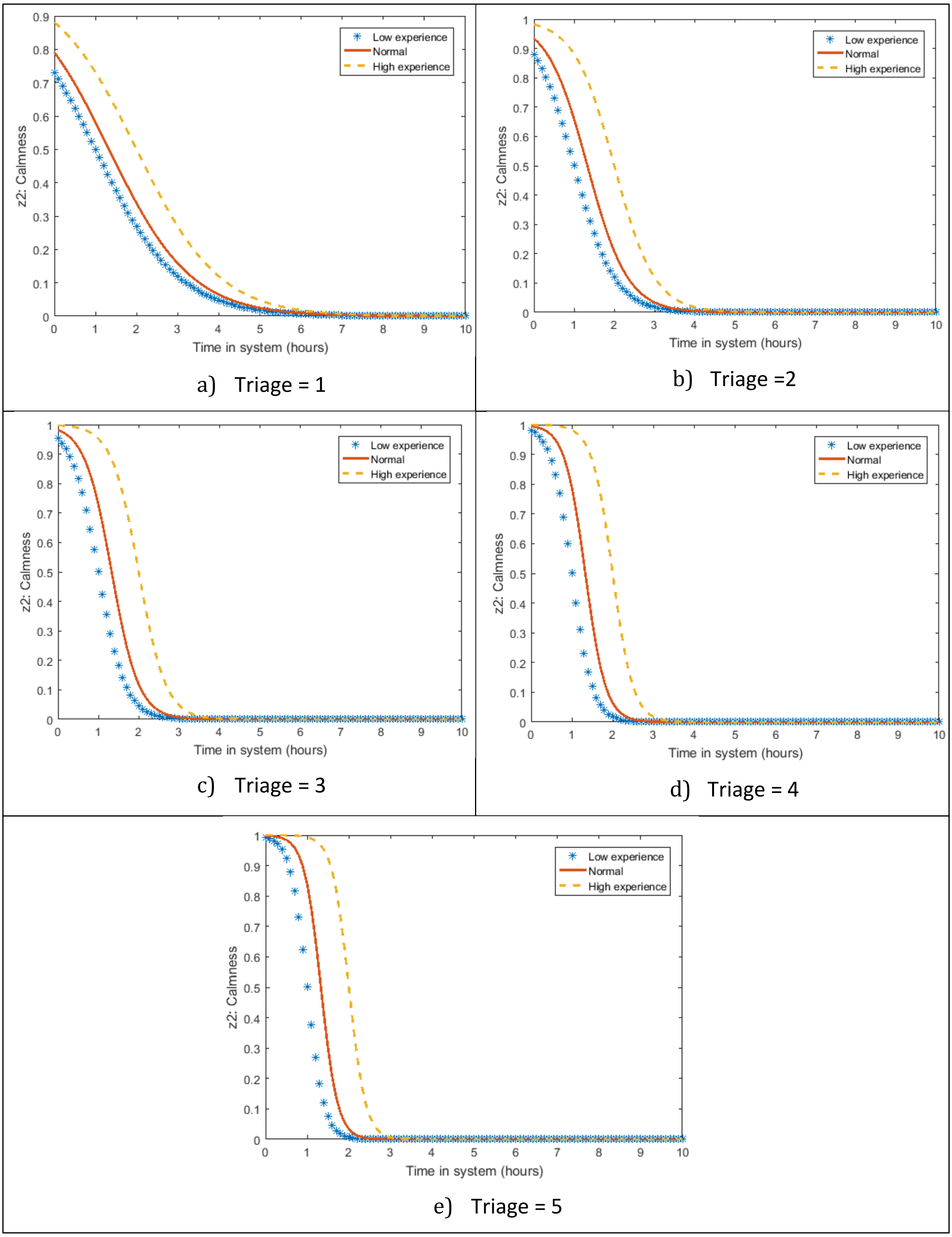


Figure 6-7. Example of a function of the variable E: Calmness

6.4.5 *The knowledge level (C)*

The knowledge level (C) is defined by the state variable Z_3 that represents the knowledge that a doctor has about a patient at a specific time t. As discussed earlier, the F function that transforms the input and dependent variables in time t into state variable Z'_3 in time $t + \Delta t$ also has a logistic shape, as shown in Equation 6-7:

$$Z'_3(X_4, X_5, Z_4) = \frac{1}{1 + e^{-(X_5+Z_4)(X_4-c_4)}} \qquad \text{Equation 6-7}$$

Table 6-2 shows that c_4 represents the time that doctors need to obtain 50% of the knowledge about each of their patients, X_4 is the average time in the system of all the patients being seen by a doctor, X_5 is the ratio between the number of tests ordered for a patient and the maximum number of tests that a patient can have, Z_4 is the value of the level of experience of a doctor, which is the job experience that a doctor gains by working continually in the department.

Similar to the calmness function, the steepness or width of the knowledge curve is affected by a factor that considers an input variable and a state variable: X_5+Z_4. That means that the more level of experience the doctors have or, the more tests they order to a patient, the faster doctors will get the maximum knowledge of a patient's condition (they will be confident with their diagnoses).

Figure 6-8 shows different curves of the variable Knowledge. The graphics demonstrates that the more experience doctors have, the faster they learn about a patient's condition. Similarly, the more information doctors gain from their patients (defined by the number of tests ordered) the faster doctors increase their knowledge of their patient's condition.

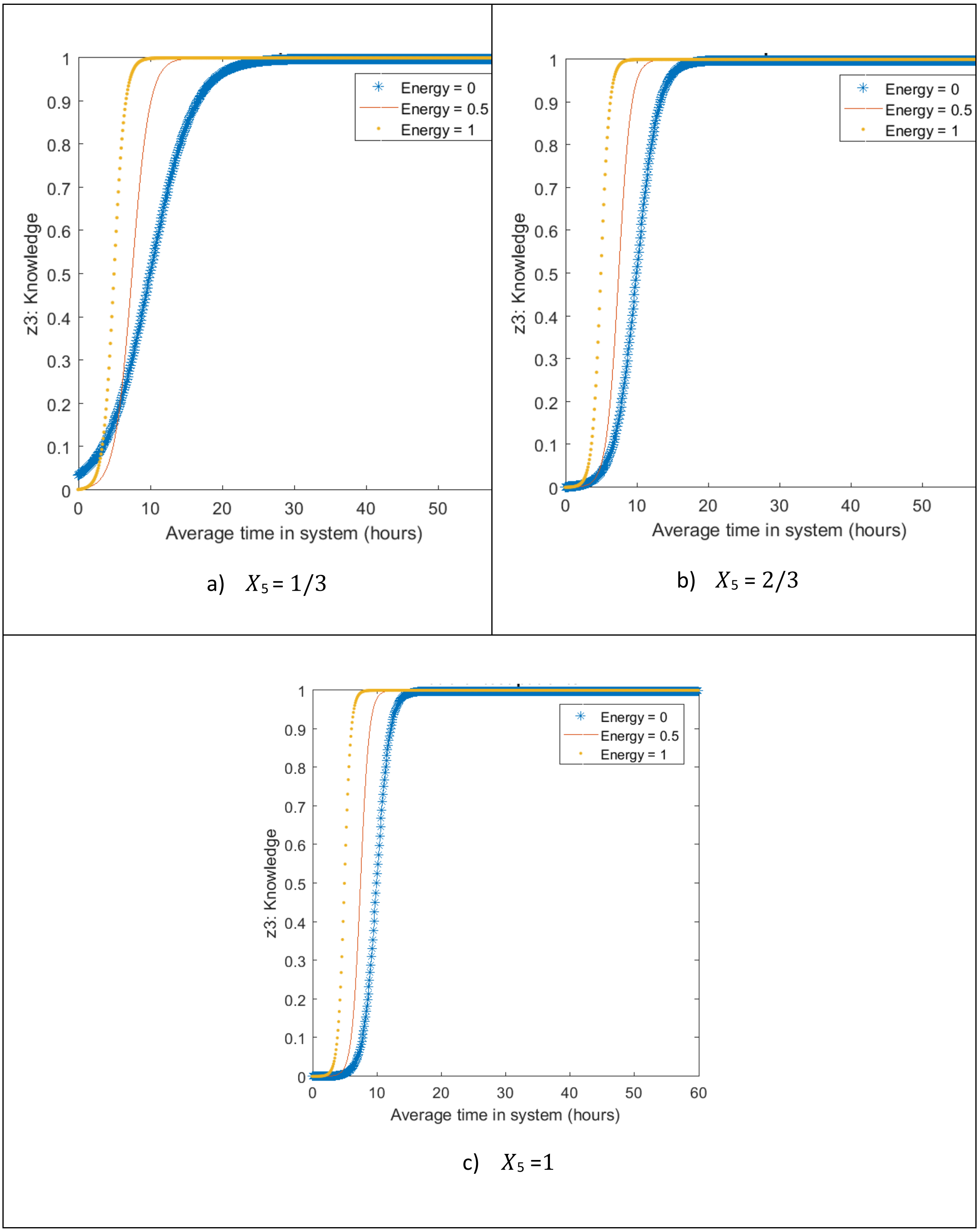


Figure 6-8. Example of a function of the variable C: Knowledge

6.4.6 The social status (S)

In this research, it is assumed that the Social Status can be represented by doctors' Experience and doctor's Reputation because we believe that both are related to how well doctor have been doing their jobs over time and that directly influence the good opinions their colleagues may have about them. Therefore, the social status (S) is defined here by the state variables Z_4 and Z_5 that represent how the experience and reputation of a doctor change over time, respectively.

The Experience and Reputation state variables are also modelled with a Logistic Function that provides an S-shaped curve. The level of experience of doctors at time t+Δt is represented by Equation 6-8.

$$Z'_4(x_6) = \frac{1}{1 + e^{-\alpha_3(X_6 - c_5)}} \qquad \text{Equation 6-8}$$

From Table 6-2 it can be seen that α_3 is the growth rate of the function, X_6 is the time a doctor has worked in the A&E department, and c_5 is the time when a doctor reaches 50% of the maximum possible experience.

Figure 6-9 shows the level of experience by each type of doctor (see Table 6-3). It is important to notice that the level of experience is related to the skills a doctor gains while working in the A&E department while the level of expertise is an attribute that does not change over time and refers to a doctor's seniority. The figure shows that doctors with a higher level of expertise reach the maximum experience sooner and quicker than doctors with low levels. That is because the value of α_3 is higher for doctors with higher expertise, meaning that the Experience curve for them is steeper than for the others. Also, as the value of c_5 is smaller for doctors with higher expertise, the more expert doctors will reach 50% of the maximum Experience sooner than the others. Table 6-3 shows that doctors with low level of expertise reach the 50% of the maximum experience at 200 weeks (approximately 4 years after the simulation stats), doctors with medium level at 50 weeks (around 1 year) while doctors with high level reach the 50% of the maximum experience at the beginning of the simulation. In the ABMS_A&E and DES_A&E, the Experience does not change significantly during a run because that variable is updated weekly, and therefore a significant increase in its level can only be seen over the years.

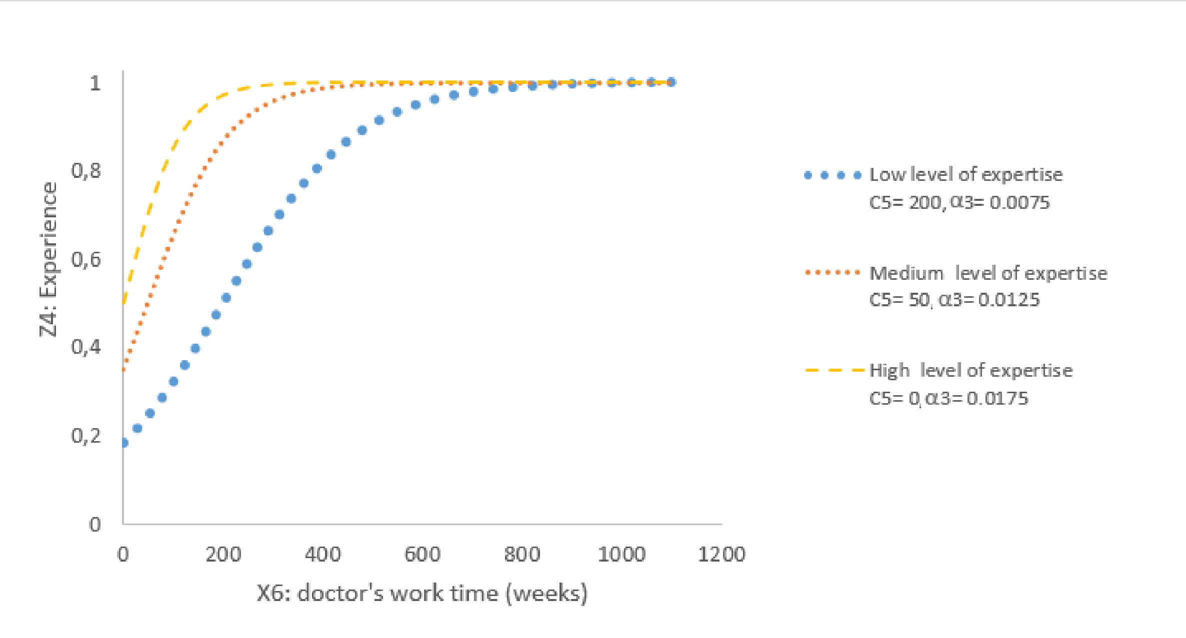


Figure 6-9. Example of a function of the variable S: Experience by type of doctor

The level of Reputation of doctors at time t+Δt is represented by Equation 6-9.

$$Z'_5(X_7) = \frac{1}{1 + e^{\alpha_4(X_7 - c_6)}} \qquad \text{Equation 6-9}$$

Here it is considered that reputation is understood as how well a doctor manages to meet the 4-hour target, that is the doctor maintains a good reputation if he or she manages to attend his or her patients within 4 hours, the more time a doctor's patients stay in the department, the less reputation the doctor will have. Therefore, as the Reputation depends on the maximum time in the system of a doctor's patients, reputation is 1 when the patients' times in the system are zero, and then begins to decrease until it approaches zero as waiting times approach the four-hour target.

From Table 6-2 it can be seen that X_7 is the maximum time in the system (hours) a doctor's patients, c_6 is the time when a doctor loses 50% of the maximum reputation (hours). In the Logistic Function, α_4 is the growth rate of the Reputation, here α_4 is defined as a function of the experience (α_4= 1+Z_4), that is because it is assumed that the higher the experience, the steeper the Reputation function should be.

From Table 6-3 it is possible to see that low experienced doctors lose their 50% of the maximum reputation when patients' times in system approach 1.167 hours (around 70 minutes), medium experienced doctors at 1.5 hours (around 90 minutes) and, highly experienced doctors at 2.167 hours (around 130 minutes). Those values were chosen arbitrarily to establish that the doctors with higher expertise are more likely to handle well patients with long waits than inexperienced doctors, then the more experienced doctors lose the 50% of their maximum reputation later than inexperienced doctors. Figure 6-10 shows the level of Reputation by each type of doctor. Assuming that a particular time, the value of experience of a low experienced doctor is Z_4= 0.2, for medium experienced doctors Z_4= 0.4, and for highly experienced doctors Z_4=0.6, the Figure 6-10 shows that as the patients' time in the system increases, the low experienced doctors lose their reputation, slower than the more experienced ones. That can be explained because we assume that it is more likely that inexperienced doctors make mistakes than experienced ones.

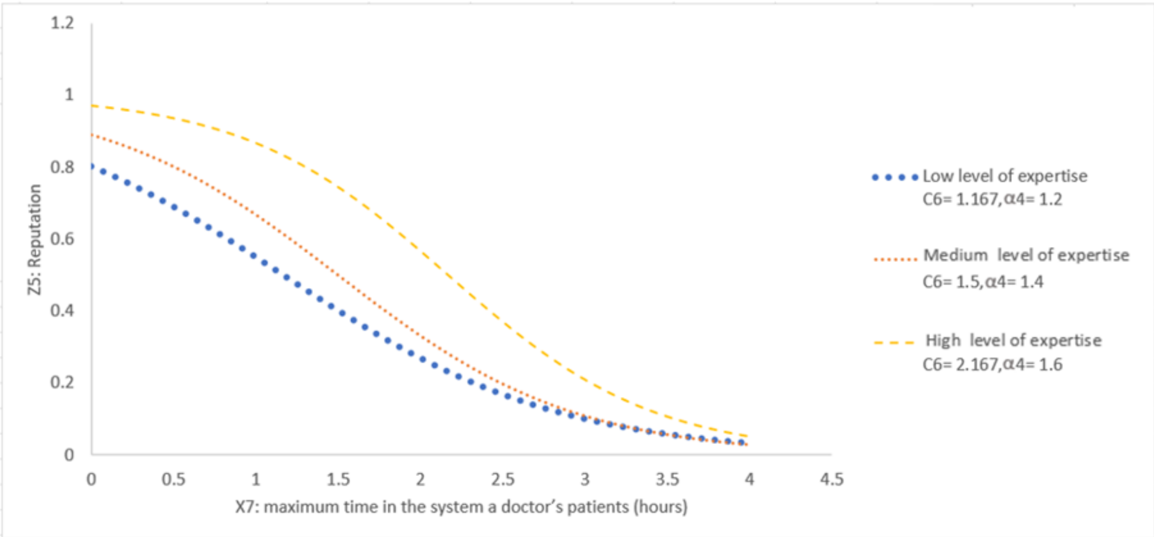


Figure 6-10. Example of a function of the variable Reputation

6.4.7 Dependent variables (intensity variables)

As said before, according to Schmidt (2005a, pp. 5) the behaviour of the people in the PECS framework "*is usually dependent on drives, needs or desires which can be regarded as motives. The strength or intensity of these motives is a function of the state variables. In this case, the state variables do not determine behaviour directly, but rather indirectly, via the motives belonging to them.*". That is, in the PECS framework, the behaviour is not directly trigged by state variables but by the dependent variables, which represent the motives. It was also said before that the dependent variables are calculated using the state variables, and they can drive to an output that defines the agents' behaviour.

The dependent variables give an idea of how important it is to satisfy a need depending on a state variable. For instance, when the level of energy decreases, fatigue increases, and when fatigue approaches the maximum value, the doctor needs to take any action that allows the energy level to refill. It makes sense to think that as the energy decreases the fatigue increases, but that relationship is not necessarily a linear one. Intuitively one can think that decreasing the level of energy from 1 to 0.9 might not cause the same fatigue than moving from 0.7 to 0.6 (as in Figure 6-11-a). For example, when doing exercise, it seems that the fatigue a person feels after jogging for 10 minutes at the beginning of the activity is not the same fatigue that person feels when running for 10 minutes after exercising for two hours. In other words, it seems that the relationship between the energy and the fatigue is non-linear.

Although there might be different functions that can model the relationship between dependent variables and state variables in the PECS framework, here it is assumed that a Logistic Function is suitable for modelling that relationship since it not only has excellent mathematical properties (see section 6.4.1) but also it provides a shape that intuitively corresponds to the relationship between dependent variables and state variables.

The dependent variables of this model are W_1 that represents fatigue as a function of the energy state variable; W_2 represents stress as a function of the calmness state variable; W_3 represents the need of knowledge as a function of knowledge state variable, and W_4 represents social desire as a function of reputation state variable.

As explained before, H is an intensity function that transforms the state variables Z' at time t + Δt into dependent variables W' at time t + Δt.

$$H: STATES \rightarrow DEPENDENT.$$

$$H(Z'_1, Z'_2, \dots, Z'_n) = (W'_1, W'_2, \dots, W'_n)$$

In this case, H will have the form of a logistic function, as shown in Equation 6-10:

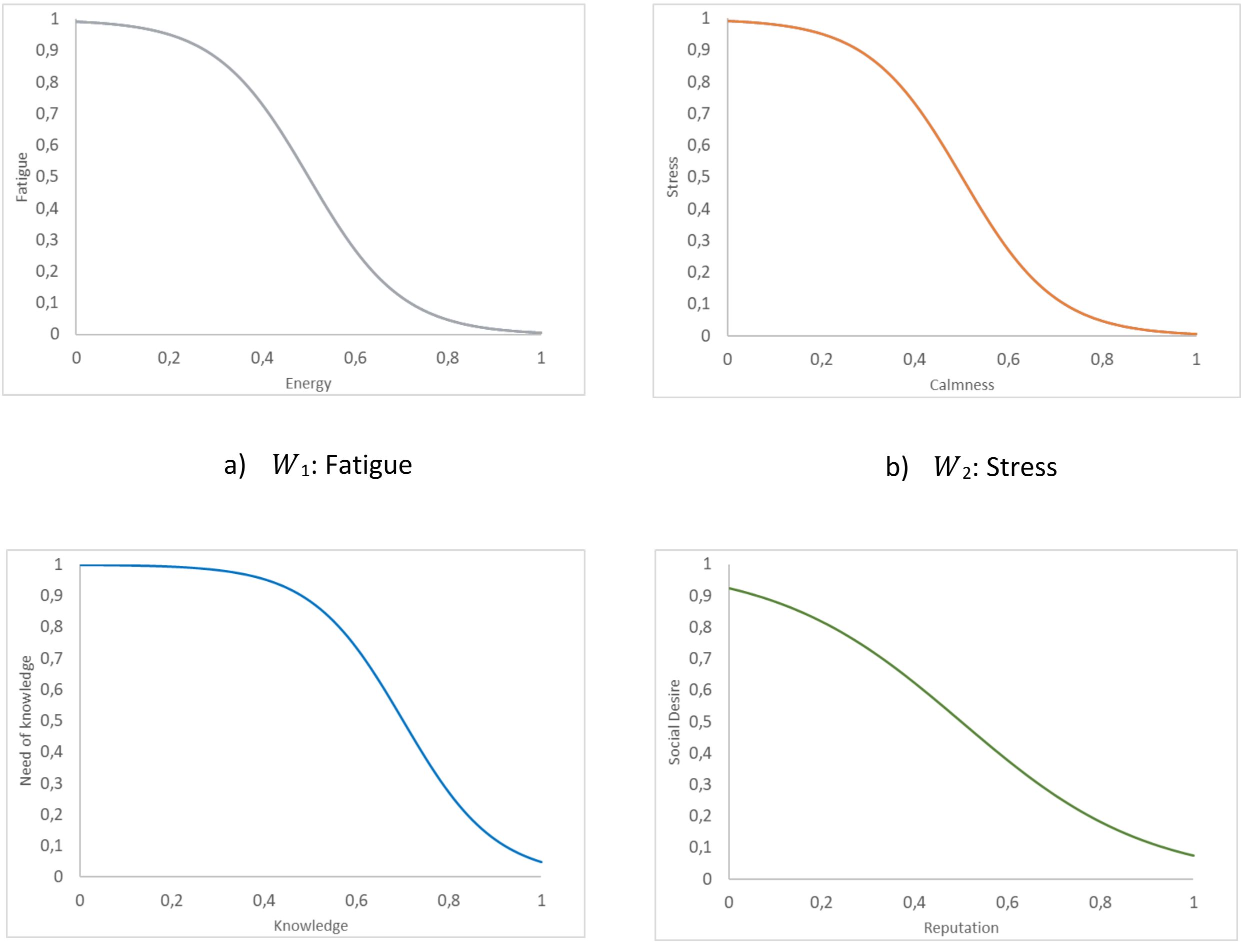
$$W'_i = \frac{1}{1 + e^{\alpha_i(Z'_i - c_i)}} \qquad for\ i = 1,2, \dots n \qquad \text{Equation 6-10}$$

Where α_i and c_i are constants.

Table 6-4 shows the value of the parameters of the PECS dependent variables and Figure 6-11 presents the dependent variables as a function of the state variables.

Table 6-4. Doctors' parameters of the PECS dependent variables

W_i	α_i	c_i
W_1	10	0,5
W_2	10	0,5
W_3	10	0,7
W_4	5	0,5



a) W_1: Fatigue

b) W_2: Stress

c) W_3: Need of knowledge

d) W_4: Social desire

Figure 6-11. PECS's dependent variables

6.4.8 Outputs (behaviour)

As discussed in previous sections, the output layer of the PECS architecture shown in Figure 6-3, includes the Actor, which contains the possible actions that an agent can perform. Those actions are guided by the motives represented by the dependent variables. The dependent variables are changing continuously over time, and when an agent, in this case, a doctor, needs to decide, he or she compares all the levels of the dependent variables and the higher one becomes the action-guiding motive and defines the action the agent needs to perform (Schmidt, 2000).

There are different points of time at which a doctor needs to make decisions. In the simulation, these are the times when doctors need to compare the values of their dependent variables to choose the most appropriated action for each situation:

1. At the beginning of the shift
2. At the end of a service (first assessment or re-assessment)
3. When finishing his or her shift

Every moment the four state variables (W_1, W_2, W_3, W_4) are compared. Each variable drives a specific action:

- If the Fatigue (W_1) is the strongest motive, the doctor takes a break to refill the energy.
- If the Stress (W_2) is the strongest motive, the doctor checks what the most stressful situation is. If the stress is caused by the severity of a patient's condition, the doctor uses a priority system is based on the triage, while if stress is caused by long patients' waiting times, the doctor changes the queues' priority system by increasing priorities of the patients that are close to breaching the 4-hour target. Doing that, the doctor increases their calmness levels.
- If the Need of Knowledge (W_3) is the strongest motive, the doctor orders more tests to be more confident about his or her diagnoses and avoids multitasking (seen more than one patient at a time).
- If the Social Desire (W_4) is the strongest motive, the doctor reduces the service times and increases his or her multitasking in order to avoid failing to meet the target

6.5 Phase 4: Simulation

The purpose of the ABMS_A&E model is to demonstrate general principles of modelling human behaviour in an A&E department using ABMS. The development of the ABMS_A&E model was based on the DES model of an A&E department built by Günal (2008); however, the ABMS_A&E is not an exact replication of Günal's model but an equivalent simulation. Therefore, the ABMS_A&E model is not intended to be an accurate replication of an A&E department.

The ABMS_A&E model is implemented in Repast Simphony. Repast has a Scheduler to control the flow of time. This Scheduler acts as the heart of a simulation engine and allows synchronisation of the activities carried by the agents over time (North and Macal, 2007). Three approaches are used in the ABMS_A&E to schedule the activities in an ABM simulation.

The A&E patient flow is modelled in Repast using java programming. Some data structures, such as arrays and lists, are used to represent the patients' queuing process, the schedulers previously mentioned are used to define the execution of actions related to activities.

First, some actions are modelled using time-step scheduling using Java Annotations. Annotations, in java, "*are bits of metadata which can be attached to classes, methods or fields that are available at runtime to give the system more information an integer counter to update and evaluate the model*" (Repast, 2019). Second, some actions are scheduled using a discrete-event approach by implementing a Repast IAction interface. Third, some actions are triggered by a change in an agent's state. Those actions use java annotation based on watchers. A watcher "*allows an agent to be notified of a state change in another agent and schedule an event to occur as a result. The watcher is set up using an annotation (like above), but instead of using static times for the schedule parameters, the user specifies a query defining whom to watch and a query defining a trigger condition that must be met to execute the action*" (Repast, 2019).

This ABMS model of an A&E department considers human behaviour in a more detailed way than the DES model developed by Günal. Table 6-5 presents a comparison of different aspects of the representation of the behaviour of the A&E department staff in the Günal's DES model and the ABMS_A&E model. The model representation of staff in Günal's model is made under the assumption that each member of the staff is identical, which means that they behave the same under the same circumstances. Therefore, staff are modelled as countable resources, which means that it is not necessary to track individual staff behaviour in the simulation. In the ABMS_A&E

model, each member of staff is modelled individually as an agent whose behaviour is tracked in the simulation.

Staff multitasking behaviour in the Günal's model includes multiple representations of each type of staff by fragmenting them into several "mini-doctors" and "mini-nurses". In ABMS, the multitasking behaviour is represented by task switching, for example, a clinician (e.g. a doctor) can switch from one task to another if the number of patients being seen simultaneously is less than the multitasking factor. The staff's availability in Günal's model takes into consideration the number of each type of staff available per hour, whereas, in ABMS_A&E, the availability depends on individual working shifts. It is assumed that the work shift duration is between 7 and 9 hours. The scheduling of the work was made heuristically considering requirement of doctors each hour and the maximum duration of work shifts for each member of the staff.

Staff individual behaviour is not represented in Günal's model. In the ABMS_A&E model, each member of the staff arrives in the department at the time specified by their shift. If they have completed all the necessary services at the end of their shift, they leave the department; otherwise, finish all the services they have before leaving. When doctors are seeing patients, who are waiting for test results when their shift ends, they search for an available doctor to take over their patients and then leave. If the doctor who assessed the patient for the first time is available when the patient gets the results of the test, the doctor reassesses the patient. Otherwise, if there is another available doctor, that doctor sees the patient.

Table 6-5. Representation of staff's behaviour in the Günal's model and ABMS_A&E

<table>
<tr><th>Aspects of Staff behaviour</th><th>Günal's DES_A&E</th><th>ABMS_A&E</th></tr>
<tr><td>Staff type</td><td>Nurses, Consultant and junior doctors.</td><td>Nurses, Consultant and junior doctors.</td></tr>
<tr><td rowspan="3">Assumptions</td><td>Each member of a type of staff is identical.</td><td>Each member of the staff is modelled individually in the model.</td></tr>
<tr><td rowspan="2">"Mini-doctors"/ "mini-nurses" represent multitasking behaviour</td><td>Staff availability represents multitasking behaviour.</td></tr>
<tr><td>The shifts length is between 7 and 9 hours.</td></tr>
</table>

Aspects of Staff behaviour	Günal's DES_A&E	ABMS_A&E
Model representation	Countable variables (resources/ resident entities)	Agents
Availability	Number of each type of staff available per hour	Individual work shifts
Behaviour	No.	Each staff member meets their work schedule.
		Doctors are responsible for their own patients; they do not leave the department if there is any unfinished work.
		Each doctor decides how to reassess patients.

The model can be run in a batch run and non-batch run mode. In the batch-run mode, the model's parameters are read from a parameter file and, the simulation does not require user interaction to start running. On the contrary, using non-batch run mode requires the user interaction through a graphical interface not only to provide the initial parameters of the model but also to control and manipulate the simulation (Sourceforge, 2008).

6.5.1 Verification process

Verification and validation processes are important processes in any simulation project since it builds confidence in the simulation results. According to Robinson (2004, pp.210), verification aims to "ensure that the model is sufficiently accurate". Robinson considers that accuracy in verification refers to the transformation of the conceptual model into a computer model, while with validation the idea is to ensure that the model is sufficiently accurate to the purpose for which the model is intended to be used.   Therefore, the concept of accuracy in simulation is linked to the purpose of the model, which may have been defined at the beginning of the simulation study. Robinson summarizes the methods of verification and validation in six categories: conceptual model validation; data validation; verification and white-box validation; black-box validation; experimentation validation and solution validation. The first five methods will be considered here.

It is important to note that validation in ABMS can be a challenge, especially when the behaviour of humans is an essential element of the system being modelled. Onggo, B. & Karatas, M. (2016) summarise common challenges faces in ABMS model validation. One challenge is obtaining information about the behaviour of social, intelligent agents, mainly when their behaviour is not easy to observe. Also, they found that it is also a challenge to validate if the rules used in the model to define agents' behaviour represent the rules of the agents that act on the real world and if the heterogeneity of the agents is accurately represented in the model. A second challenge they identified is validating an ABMS model at a macro or system-level based only on the information of individuals' behaviour, that is to validate that the interactions between agents cause emergent behaviour. The last challenge is obtaining qualitative data on the behaviour of heterogeneous agents.

The conceptual model validation and the data validation were based on the MicroSaint sharp® DES model proposed and developed by Günal (2008). The process consisted of ensuring that the logic of the DES model was included in the ABMS model in some form. Some parts of the Günal's model remained unchanged in the ABMS model; for example, the patient's arrival process in the ABMS_A&E is the same as in Günal's model. The data used in the ABMS model is the same data used in Günal's model for the A&E-1 example (Günal, 2008, pp. 73 - 109).

The white-box validation was developed basically considering that the logic of the model represented the behaviour of the A&E department with two main purposes: first that the model represented the patient flow process as it was represented in the DES model; second that the behaviour of the agents corresponded to the decision rules that were written in the code. In order to do this, the model was debugged at each step of the development process, and the graphical interface of the model allowed for checking the behaviour of the model in each part of the development process.

In black-box validation, the overall behaviour of the model is considered. The approach here is to compare the ABMS model against the DES model rather than to compare the ABMS model against the real world. The DES model was run 50 times for 52 weeks. Initially, the AMBS model took approximately 24 hours to make a single run of 52 weeks, so it was necessary to run the model in several computers to obtain a sufficient amount of data to analyse the results. Later for the experiments, the code was cleaned, and the length of the run was reduced to improve the speed of the run. Figure 6-12 shows a comparison of the proportion of patients that waited more than four hours between the ABMS model, the DES model, and the actual performance of the real A&E. The ABMS displayed considerable variations in comparison to the DES model; however, the global shape of the histogram was captured in the ABMS model.

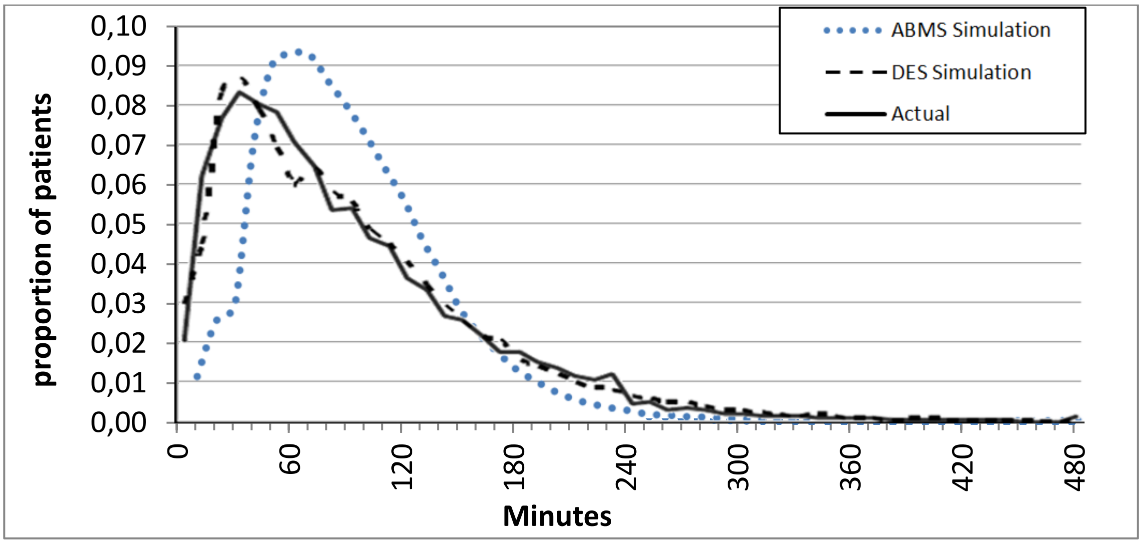


Figure 6-12. ABMS results- total time in the A&E department

Table 6-6 shows that the mean of the proportion of patients who waited more than four hours obtained from the ABMS model is close to the actual proportion; however, the variability among the runs in the ABMS is higher than the DES model.

Table 6-6. Proportion of patients that wait more than four hours

ABMS Proportion of patients t>240	
Run 1	0.0540
Run 2	0.0523
Run 3	0.0154
Run 4	0.0232
Run 5	0.0520
Run 6	0.0443
Run 7	0.0279
Run 8	0.0488
Run 9	0.0284
Run 10	0.0269
Run 11	0.0280
Run 12	0.0187

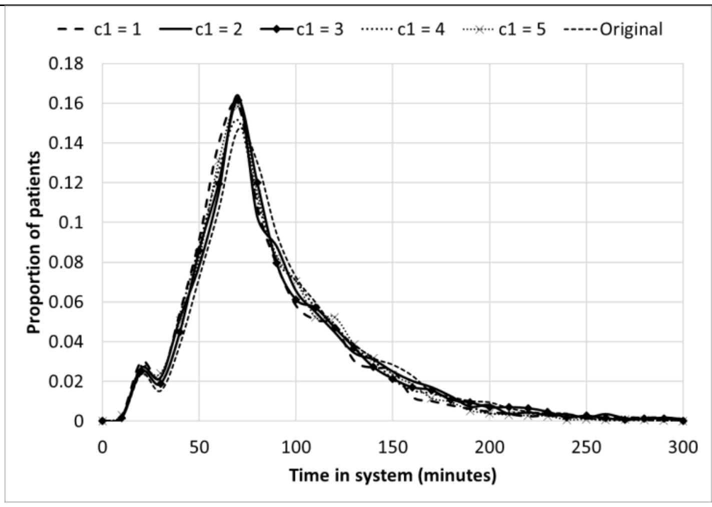
	ABMS model	**DES model**	**Actual**
Mean	0.0350	0.0049	**0.036**
Median	0.0282	0.047	
Min	0.0154	0.032	
Max	0.0540	0.071	

6.5.2 Sensitivity analysis for the ABMS_A&E model

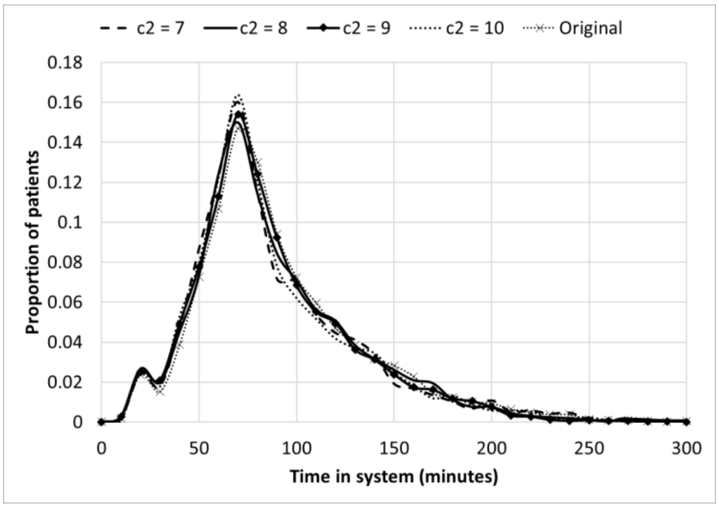
A parametric sensitivity analysis is necessary here to test the effect of the uncertainty of the PECS parameters on the distribution of the patients' total time in the system. As previously described, the ABMS_A&E model considers that doctors have different levels of expertise (low, medium and high). However, in order to reduce the number of possible combinations for the sensitivity analysis, and to obtain a better insight of the effect of each parameter, it is assumed here that all doctors have a low level of expertise, and a parametric sensitivity analysis is done by varying each PECS parameter simultaneously on all the doctors.

Figure 6-13 shows the sensitivity analysis on the parameters C of the Logistic Functions of some PECS' state variables. Figure 6-13 a) shows the impact of changes in the parameter c_1 that represents the maximum number of patients a doctor is capable of seeing in one hour on the distribution of the patients' total time in the system. It means that for example if a doctor is capable of seeing maximum one patient per hour and the system is not too empty, he or she will be seeing more patients in one hour than he or she normally sees and he or she will get tired faster. It is important to notice that c_1 affects the state variable Energy, it means that the smaller the value of c_1, the higher might be the doctor's fatigue. Also, the state variable Energy also affects the doctor's calm and therefore, the doctor's stress. It can be seen from the graphic that c_1 does not significantly affect the distribution of times in the system.

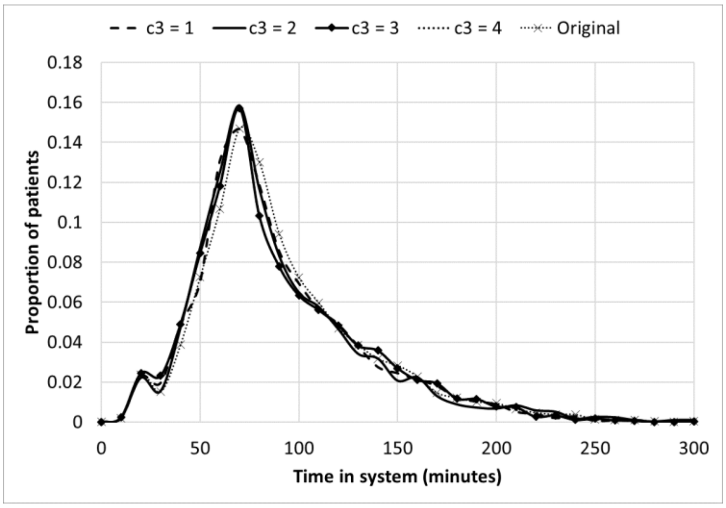
Similarly, Figure 6-13 b) and Figure 6-13 c) show that changes in the parameter c_2, which represents the expected duration of a doctor's shift (hours), parameter c_3, maximum time in the system at which the doctor loses 50% of calm, do not significantly affect the distribution of times in the system. Appendix C shows the sensitivity analysis for the rest of the PECS parameters. None of the PECS parameters significantly influences the distribution of times in the system.



a) C_1: a doctor's maximum number of patients seen per hour



b) C_2: expected duration of a doctor's shift (hours)



c) C_3: maximum time in the system (hours) at which the doctor loses 50% of calm

Figure 6-13. Sensitivity analysis for parameter C of Logistic Functions

6.5.3 *Experimentation: PECS Framework*

The key output of the ABMS model developed here is the distribution of the time spent by patients in an A&E department. Before implementing PECS in the ABMS model, a doctor agent had very simple reactive rules of behaviour:

- If time is due, then starts a shift
- If another doctor is leaving who still has patients, takes over the patients or else walks to the doctor's area
- If the doctor has patients waiting for reassessment then does reassessment or else checks if there are patients for first assessment
- If patients are waiting for the first assessment, then chooses the one with the highest triage and does the first assessment
- If the patient requires tests, then orders tests
- If the shift has ended and has patients in test then looks for another doctor, hands over the patients and then leaves

6.5.3.1 *Results of the Base case scenario*

The base case scenario after implementing PECS assumes that each doctor agent has some variables associated with four attributes: energy, stress, knowledge and social desire. At the end of any action, the doctor agent compares the state of the four variables and decides what to do next.

- If the intensity of the energy is the highest, then schedules a rest as soon as an action is finished
- If the intensity of the stress is the highest and the stress is caused by the risk of failing to meet the department target, then chooses the patients with the highest time for first assessment and modifies the multitasking factor associated
- If the intensity of the need of knowledge is the highest, then decides to order more tests for the patients
- If the intensity of the social desire is the highest, then does not modify the initial behaviour

The base case scenario showed that 98% of the patients meet the 4-hour target. Therefore, the effect of the implementation of the PECS framework is not significant at this point; however, in more extreme conditions it might be possible to see how using PECS for modelling agents' behaviour may produce a different overall behaviour and therefore have an impact on the department's performance. Figure 6-14 shows the results of this scenario. It can be seen that the proportion of patients that are close to the four-hour target increases.

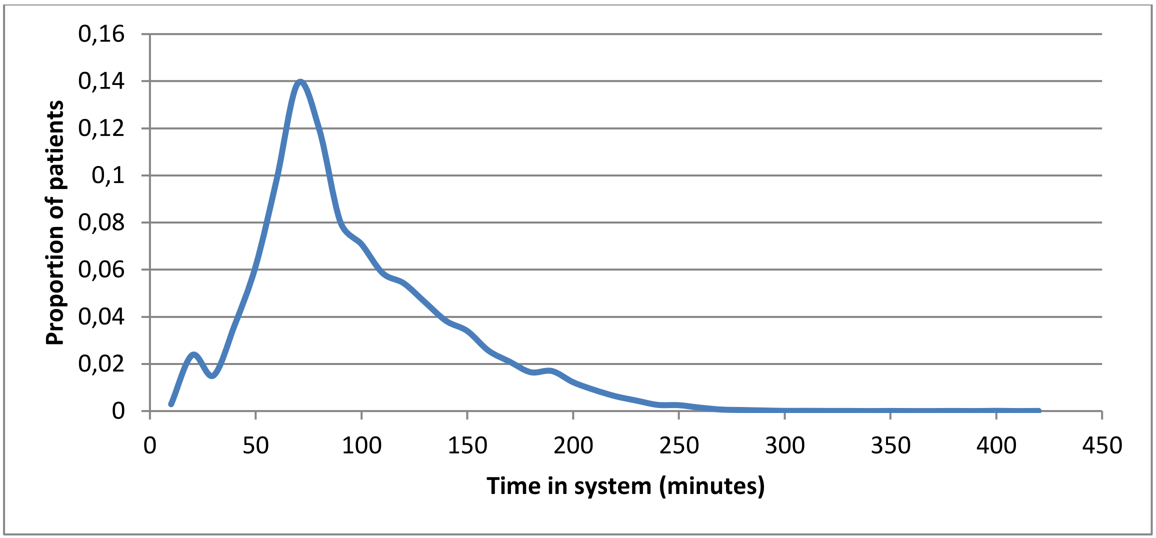


Figure 6-14. Total time in an A&E department (base case).

6.5.3.2 Scenario 2: 20% increase in the demand

In this scenario, the inter-arrival times of both Walk-in and Ambulance patients is reduced by 20%. This model was run ten times for 7 weeks each run, and the distribution of the patients' time in the system is shown in Figure 6-15. In this figure, the effect of the four-hour target is more evident than in the base case scenario.

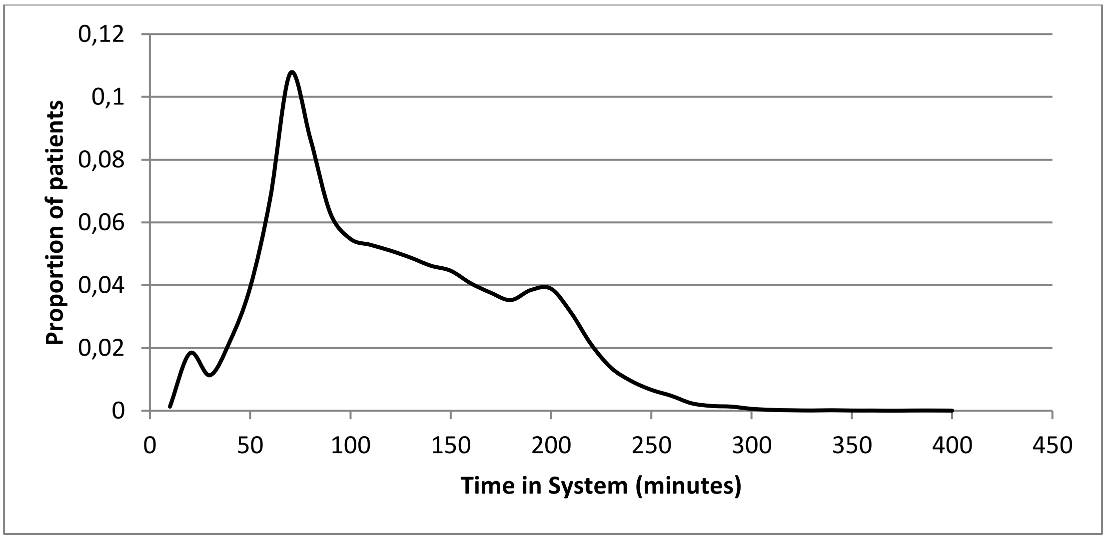


Figure 6-15. Total time in the A&E department in scenario 2

6.5.3.3 Scenario 3: 30% and 40% increase in the demand

In this scenario, the mean inter-arrival times of the distributions from which both Walk-in and Ambulance patients are drawn are reduced by 30% and 40% and the distribution of the patients' time in the system is shown in Figure 6-16. In this figure, it is possible to see that substantial growth in demand has a substantial impact on patients' waiting times, and it is much more evident the effect of the four-hour target on the A&E waiting time performance. The figure shows that when the demand is increased by 30%, the proportion of patients leaving the department before four hours is higher than when the demand is increased by 40%.

The differences in the distribution of the patient's time in the system may be explained not only by the relation between demand and capacity but also by the effect of the PECS framework. The PECS framework defines that at busy periods, doctors get more stressed and need to maintain a high reputation, so they tend to speed up the service and increase multitasking which leads to release patients as sooner as possible, this can be seen in the figure because the two higher peaks in the graphs occur sooner when the increase in the demand is 40% than when it is 30%. That is when the demand is increased in 40% the higher proportion of patients leave the department around 60 minutes, whereas when the demand is increased in 30%, the higher proportion of patients leave the department around 70 minutes.

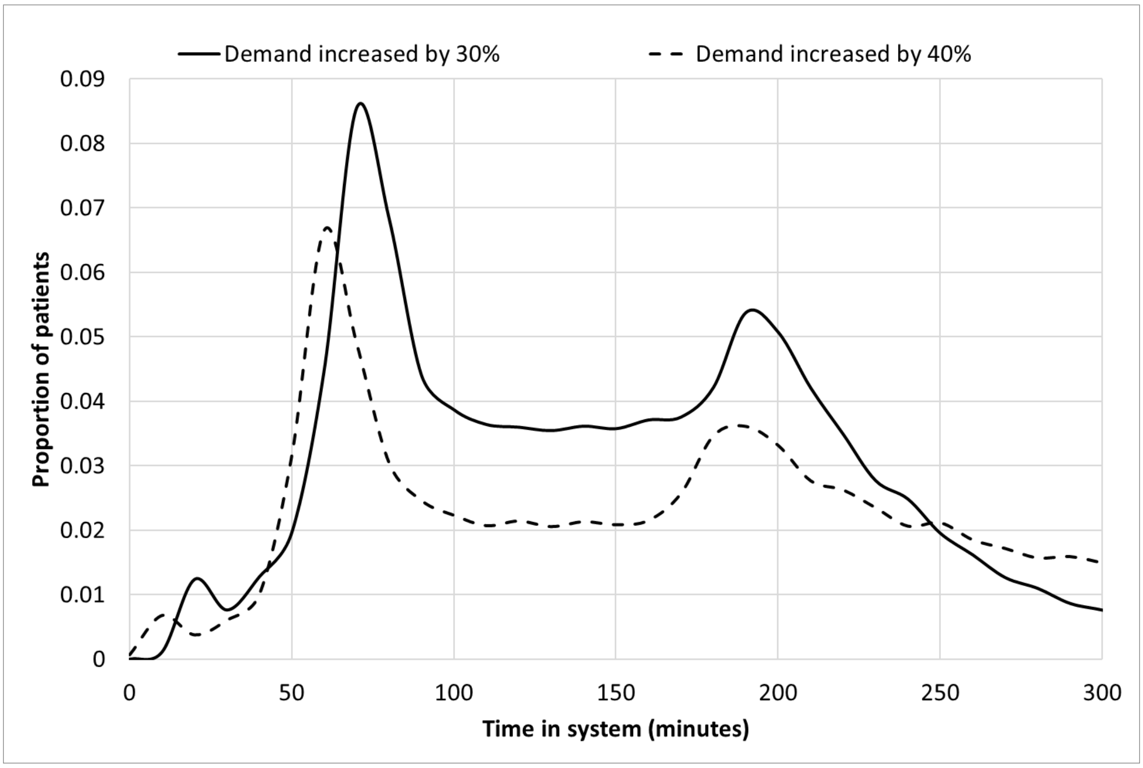


Figure 6-16. Total time in the A&E department in scenario 3

In order to understand how PECS affects each doctor's decision, it is important to consider the periods of highest demand. It can be seen from Figure 6-17 that the busiest periods are between 10:00 a.m. and 1:00 a.m.

Section 6.4.2 presented the distribution of doctors by level of expertise, where doctors 1, 2, 9 have a low level of expertise, doctors 3, 4 and 5 have a medium level of expertise, and doctors 6, 7 and 8 have a high level of expertise. Additionally, in Chapter 6 it was shown that there are different shift patterns for each doctor, as shown in Table 5-3. From Table 5-3, it can be noticed that for example on Mondays, doctor 1 (D1) works in a period when there are not many patients, while doctors 2,3,4,5,6 and 7 work in the busiest periods.

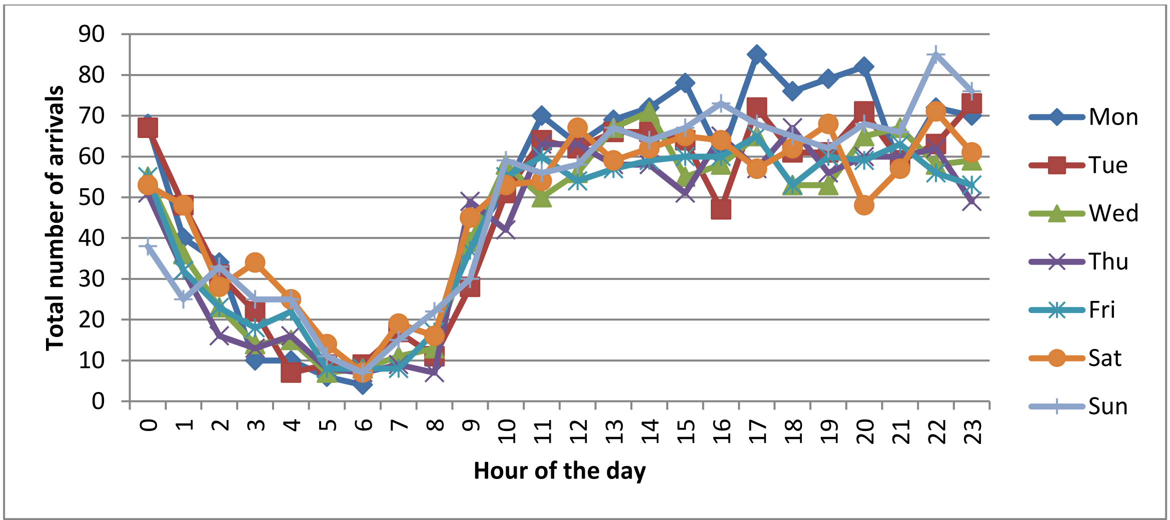


Figure 6-17. Number of arrivals in the A&E department

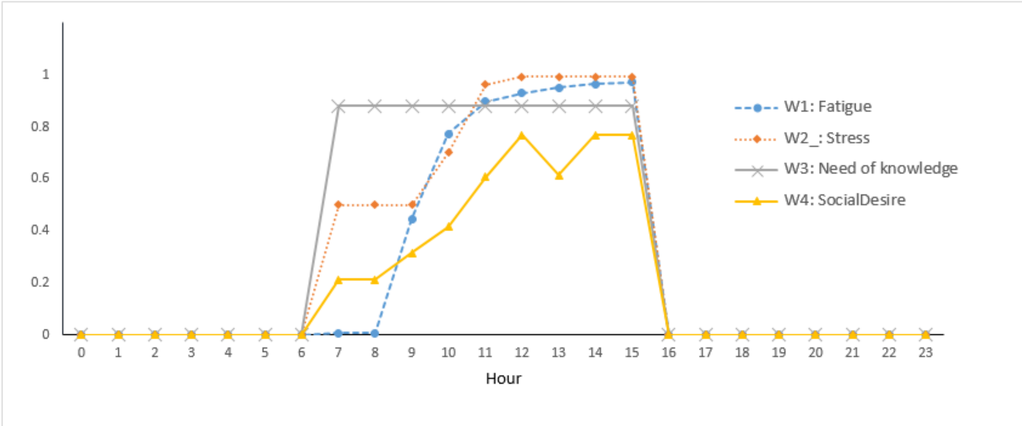
Let us consider the case of Doctor 2 who works Monday from 7:00 a.m. to 4:00 p.m. as shown in Table 5-3. It can be seen in Figure 6-18 a) that at the beginning of the shift, doctor 2 starts with around 50% of the level of stress. That is because of the patients received from doctor 1, who was leaving at the beginning of doctor 2's shift and therefore gained the stress associated with the doctor 1's patients.

Figure 6-18 b) shows that when the doctor 2 starts his or her shift, the maximum value of the triage of his or her patients is 3 and all of them have waited less than half an hour. Besides, Figure 6-18 a) shows that although fatigue increases very quickly, stress is higher most of the time, however, around 10:00 a.m. the fatigue is higher, and it seems that doctor 2 took a short break to recover his or her energy around that time, because as Figure 6-18 b) shows, that from 11:00 a.m. to 12:00 p.m. he or she does not increase the number of patients seen, also, it is possible to see that after the break the slope of the time worked curve is smaller than before.

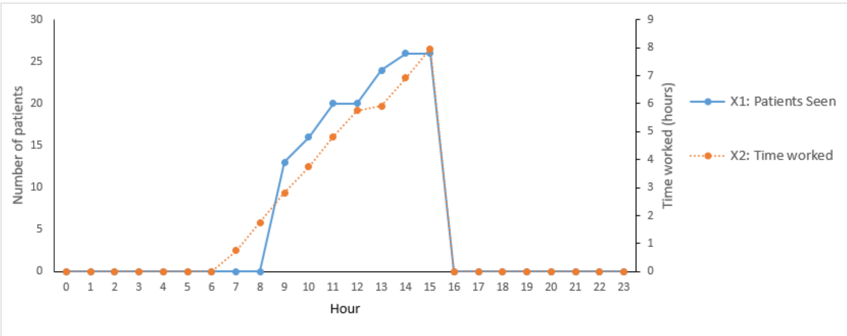
Furthermore, as doctor 2 has a low level of expertise, he or she tends to get stressed sooner and faster than the other doctors, that is probably why the stress is higher than the other dependent variables most of the time.

Another example considers the case of Doctor 6, who works on Wednesdays from 9:00 a.m. to 6:00 p.m. Although doctor 6 is working in a busy period, Figure 6-19 a) shows that his or her Stress is smaller than the Need of knowledge for the first three hours of his or her shift. That could be because first, Doctor 6 is a highly experienced doctor, and his or her stress increases at a slower rate than other doctors'; second, as shown Figure 6-19 c), the average time in system of his or her patients increases significantly after the first two hours of the doctor's shift, and third the maximum triage of his or her patients also is higher after the first two hours of the doctor's shift.

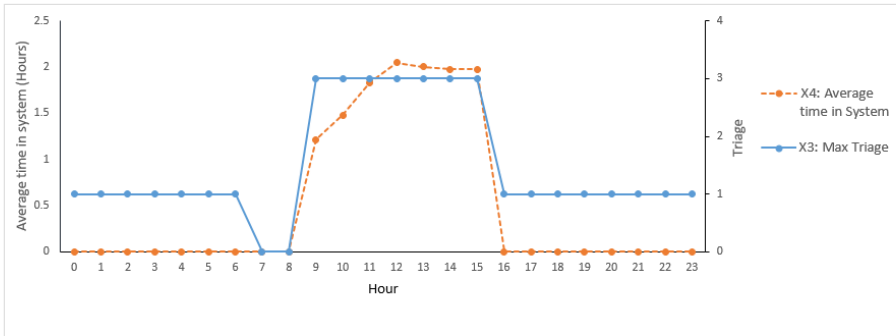
Results of the model in this scenario show that when demand increases, there is an increase in the level of stress of doctors. The more experienced doctors, for example, doctor 6, handle lower levels of stress than inexperienced ones, as in the case of doctor 2. In any case, it is possible to observe that when demand is higher than expected, doctors perceive more stress than fatigue, need of knowledge and social desire. That affects the decisions doctors make in the models resulting in an increase in the proportion of patients attended whose time in the system is close to the four-hour target. As it was explained earlier in this chapter, higher levels of stress affect the time a doctor spends with each patient, which affects patients' waiting times.



a) PECS dependent Variables

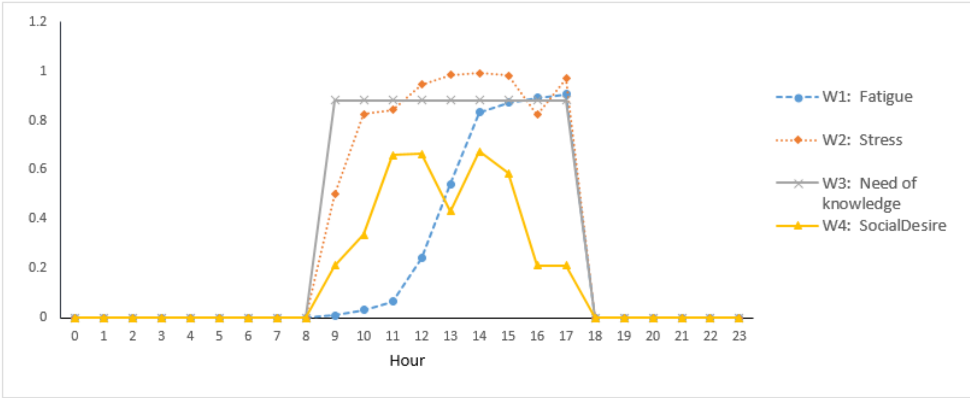


b) Input variables for Z_1

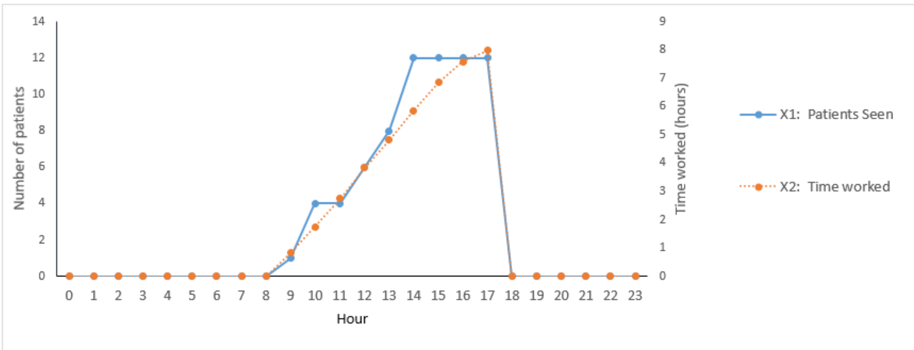


c) Input variables for Z_2

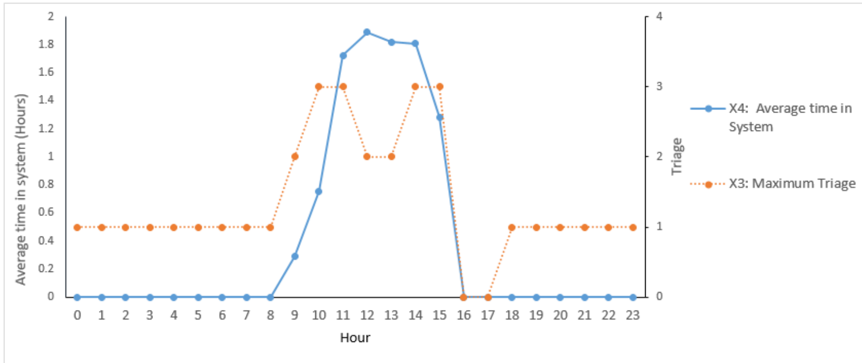
Figure 6-18. PECS variables for Doctor 2 on Monday



a) PECS dependent Variables



b) Input variables for Z_1



c) Input variables for Z_2

Figure 6-19. PECS variables for Doctor 6 on Wednesday

6.6 Conclusions of the chapter

The results in this chapter demonstrate how human behaviour can be included in an A&E simulation using ABMS. This chapter showed how to implement the PECS framework for including proactive behaviour in an A&E department and how to model the patients flow using java programming to define queuing structures and actions as well to make use of the properties of object-oriented programming to represent inheritance within agents' classes. Although ABMS offers good opportunities to include a more detailed and realistic behaviour in simulation models, the modelling of human behaviour is never simple, many factors influence the way we behave, and usually, those factors are difficult to measure and to validate.

CHAPTER 7: HUMAN BEHAVIOUR IN A DES MODEL OF AN A&E DEPARTMENT

7.1 Introduction

Previous chapters have discussed the use of simulation in healthcare. In particular, it was reported that DES has been mainly used to support decision-making processes at the operational or tactical level and for planning in specific units of a healthcare facility, commonly to study problems such as staff scheduling, resource utilisation and waiting time issues. However, human behaviour is rarely presented as an area of application in simulation models.

This chapter aims to demonstrate how human behaviour in the context of A&E departments can be modelled using DES and how it may offer opportunities to improve the level of decisions that can be made within DES models. Chapter six showed how clinician behaviour could be incorporated in an ABMS model using PECS; this chapter investigates whether the same can be done in DES.

7.2 Discrete event simulation modelling process

Much of the structure and the logic used in the DES model described in this chapter are based on the ABMS model presented in chapters 5 and 6, the modelling process described in this section will be less detailed than for the ABMS_A&E.

7.2.1 Model Content

- Patients: In the DES_A&E model, patients are the entities that flow through the activities. Each entity has attributes that define its behaviour. The main attribute of a patient in the ABMS_A&E was the Triage, as defined in Section 5.3.1.2. Here, besides considering the triage, other attributes such as the number of tests, doctor assigned, and the routes to be followed during the process are included.
- Staff: The staff considered in the DES_A&E model include doctors, nurses and clerks. The types of doctors included in the DES_A&E model are:
- Consultants: represent consultants or senior doctors. The model considers some global variables that track some of the states of the doctors. They have different shifts during the week.

- Junior doctors: The model considers some global variables that track some of the states of the doctors. They have different shifts during the week.

In the ABMS_A&E model, both types of doctor are represented as agents who make decisions at different moments during the simulation. In the DES_A&E, all doctors are represented as resources with some global variables through the use of a spreadsheet that keep information about their attributes.

In both models, doctors' behaviour is modelled through the PECS framework described in chapters 4 and 5. In the DES_A&E model. Each doctor has a table that keeps the information about the state variables that define their behaviour (by using the PECS framework). In ABMS, doctors' behaviour is defined by a set of rules that include the PECS framework.

The attributes assigned to each doctor are:

- the physical condition (*P*), defined by a state variable that represents the energy level of a doctor at a specific time *t*.
- the emotional state (*E*), defined by a state variable that represents the calmness level of a doctor at a specific time t.
- the knowledge level (*C*), defined by a state variable that represents the knowledge that a doctor has about a patient at a specific time t.
- the social status (*S*), defined by a state variable that represents the experience the doctor has gained at time t and the reputation of a doctor at a specific time t respectively.
- the Level of experience: All doctors have different levels of experience, which reveal diversities of individual characteristics
- the Multitasking factor:Depending on the level of experience, doctors can see a different number of patients at the same time
- the Maximum number of patients expected per hour: Depending on the level of experience, doctors expect to see a different number of patients per hour

The rest of the staff of the A&E department studied here includes clerks and nurses. Here, clerks and nurses are modelled as resources. Although in ABMS, they are agents, their behaviour is modelled as reactive behaviour, and they have attributes for identification and location.

Queues represent the places where entities wait for service. There are two main ways in which queues are modelled here. First, there are the queues for the processes of registration, triage, X-ray and test. In those cases, there is a single queue for each process, no matter how many resources are required to do the activities.

- Queue for registration: is modelled as a single queue with infinite capacity and no maximum waiting time constraint.
- Queue for triage: is modelled as a single queue with infinite capacity and no maximum waiting time constraint.
- Queues for treatment: each queue is modelled as a single queue with infinite capacity and no maximum waiting time constraint.
- Queues for resuscitation: each queue is modelled as a single queue with infinite capacity and no maximum waiting time constraint.
- Queue for X-ray: is modelled as a single queue with infinite capacity and no maximum waiting time constraint.
- Queue for test: is modelled as a single queue with infinite capacity and no maximum waiting time constraint.

Activities represent the places where a service is provided. They represent the interaction between entities and resources.

- Registration: is performed by a clerk. An input distribution defines its duration.
- Triage: is performed by a nurse. An input distribution defines its duration.
- First assessment (treatment room): is performed by a Consultant or junior doctor. Its duration is defined by an input distribution that depends on the patient's triage and on the type of doctor that performs the activity. It requires a minor or major room.
- First assessment (resuscitation room): is performed by a Consultant or a junior doctor. Its duration is defined by an input distribution that depends on the patient's triage and on the type of doctor that performs the activity. It requires a resuscitation cubicle.
- Re-assessment (treatment room): is performed by a Consultant or a junior doctor. Its duration is defined by an input distribution that depends on the patient's triage and on the type of doctor that performs the activity. It requires a minor or major room.
- Re- assessment (resuscitation room): is performed by a Consultant or a junior doctor. Its duration is defined by an input distribution that depends on the patient's triage and on the type of doctor that performs the activity. It requires a resuscitation cubicle.
- X-ray: requires an X-ray cubicle and its duration is defined by an input distribution. It is modelled as a work centre with three replicates.

- Tests: requires a cubicle and its duration is defined by an input distribution

Resources are objects that are required at activities in order to provide a service.

- Minor rooms: represent the rooms where minor patients are seen.
- Major rooms: represent the rooms where major patients are seen.
- Resuscitation cubicles: represent the rooms where patients that have a life-threatening condition are seen
- X-Ray cubicles: represent the rooms where X-rays are done.

In ABMS, each agent has information about the pathway that should follow within the model based on the decision rules and the communication interaction mechanism defined in the model.

Decision rules define the behaviour of the agents of the model. In the DES_A&E model, doctors have two main goals: to give an accurate diagnosis to their patients and to release them within a 4-hour time period. The patients' objectives are to obtain proper treatment for their condition within a reasonable time. The decision rules of each entity vary from one activity to another and depend on the current state of the system.

7.2.2 Selection of development platform

In order to implement a model of an accident and emergency department inside a DES language it is necessary:

1: to define the entities and their attributes: usually, the patients are the main entities of the model, and their attributes often are triage, mode of entry, health status, and waiting time.

2: to draw the entities' pathways in the model using the simulation objects available (this can be done using statecharts, activity diagrams, process diagrams among others); a standard accident and emergency department include arrival, registration, triage, service and discharge.

3: to define the input variables (using distributions, databases, spreadsheets): usually, the input variables are such factors as arrival times, service times for all the activities, the time between stops or breaks, duration of the break and efficiency.

4: to define the resources, which are the objects that are seized by the entities immediately before the start of an activity: commonly the resources represent beds, cubicles, rooms, and staff (clerks, nurses and doctors). The resources may be scheduled based on shifts and may have different states such as available, occupied, blocked or stopped. In DES, traditionally the staff is modelled as resources. It does not mean that they cannot be modelled as entities, but it is not always possible (or at least simple) to do it in all commercial software.

5: to define and calculate the output variables of the model. Sometimes the most common output variables are defined and calculated directly by the software. In other cases, it may be necessary to define and calculate those variables in the software. In both cases, obtaining this data is straightforward because, in any DES model of an accident and emergency department, the output variables are usually the same, and the performance of the departments is usually measured in terms of waiting times, resource usage and staff occupation.

6: to set the initial conditions or warm-up period and to define the number of replications to be performed.

7.2.3 Model development

In chapter 4 it was said that although there is a variety of DES specialist software that is flexible and easy to use, SIMUL8 is chosen here for implementing the DES_ABMS model mainly because of its popularity, my good knowledge of it and the possibility to use a professional license and specialist support. The development of the DES model starts by representing the flow of patients in the department and then the specific behaviour of doctors is added based on the PECS framework described in previous chapters.

7.2.3.1 Simulation main Objects

Generally, systems are modelled in a simulation by adding simulation objects to the model and defining the logic of the model either by using some menus or writing a piece of code. Simulation objects are used to collect information (data and behaviour) of the objects that are being simulated. The main objects of the DES_A&E model are entities, resources, queues, and activities.

It is important to note that the use of the concepts of entities and resources described here is based on the software SIMUL8 used to model the accident and emergency department. Other software may use the concepts of resources and entities differently. There are two main objects represented in the DES_A&E model: physical resources and humans. Physical resources include all the beds and cubicles required for the activities. Humans on the model are the patients and the staff.

In Simul8, resources are objects required for activities before they can start, but their behaviour is not explicitly tracked in the model. The resources are seized by the entities in order to start an activity. In the model developed in this chapter, physical resources are represented as resources.

Humans in the model play two primary roles. One is to provide a service, and the other is to being served. The ones to provide a service are clerks, nurses and doctors. The ones that need attention are the patients.

Clerks, nurses and doctors are modelled as resources in Simul8. However, doctors are given some characteristics that allow them to decide how to engage with patients in the model. The characteristics given to doctors represent the PECS variables described in chapters five and six. In the ABMS model developed earlier, doctors were modelled as agents, and the PECS variables represented doctors' attributes in the model. In the DES_A&E model, the PECS variables cannot be represented as attributes because doctors are not active entities, and in Simul8, there is no direct way to assign attributes to resources. However, global variables were used to represent the different PECS for each doctor and are stored in a table (in Simul8 tables are spreadsheets). In total, there were 36 global variables, one for each of the PECS variables for the nine doctors considered in the model. The Simul8 model layout is shown in Figure 7-2.

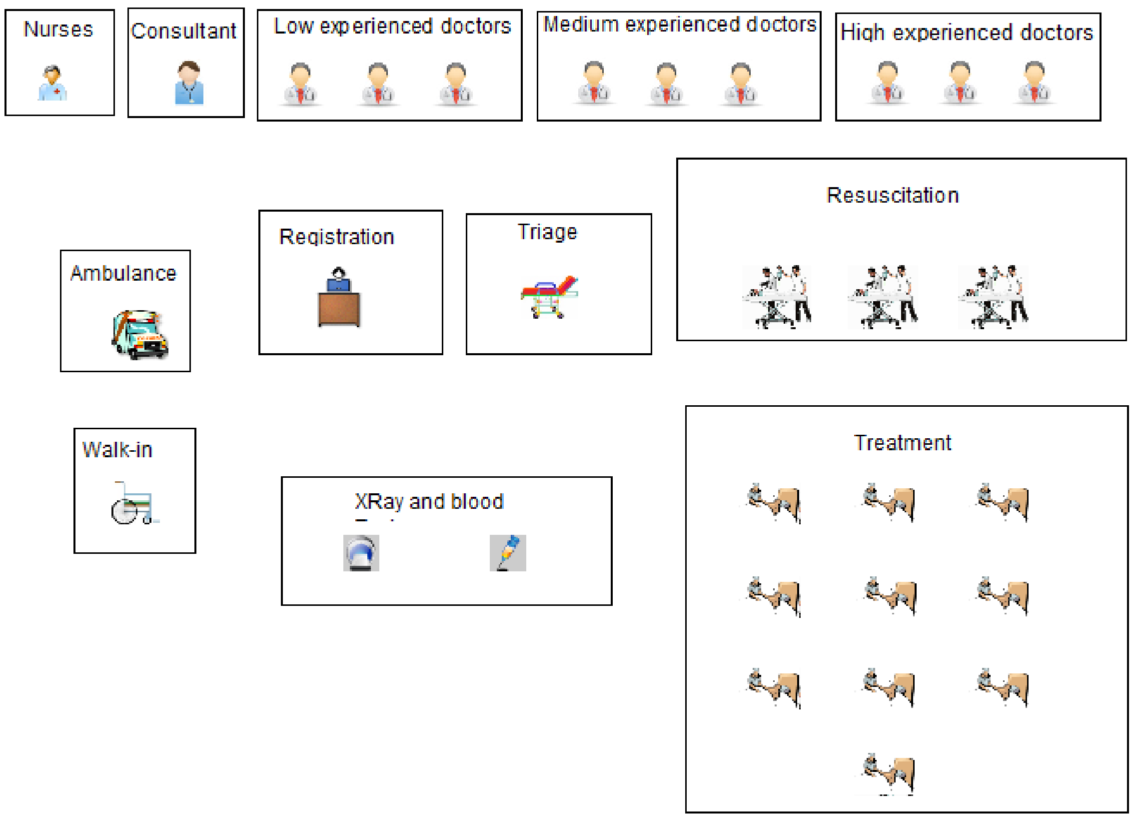


Figure 7-2. Simul8 model layout

7.2.3.2 PECS framework in a DES model

As described in chapter five, the PECS framework proposed by Urban and Schmidt (2001) assumes that human behaviour may be defined based on four main state variables: Physical conditions (Physis), Emotional state, Cognitive capabilities and Social status (see section 4.7.3). Each entity receives information from the environment through a sensor component. The sensor component within the DES model is not specific for each doctor but is represented as all the global information available in the model at any time. That is, a doctor can access, for instance, the information related to patients' waiting time at any time.

In this framework, the sensor component sends the information received from the environment to the perception component. The perception component processes that information based on a filtering process (that depends on the internal state of the entity) and updates that internal state by updating the four PECS variables. In the DES model, each doctor interprets the information from the environment based on the state of the PECS variables. For example, a doctor that has more experience can perceive high waiting times differently than another more inexperienced doctor because the cognition state variable is for this doctor is higher than the junior doctors. That is, for junior doctors, high waiting times can have a higher effect on the emotional state (stress) than for experienced doctors.

The behaviour component chooses from the possible actions of the entity when an activity is triggered. In the DES model, a doctor may take diverse types of decisions (actions). For instance, if the level of stress of a doctor is low (because, for example, there is not an imminent risk of failing meeting the four-hour standard) but the level of the physis state variable is too high (for instance because the doctor is too tired), the doctor may decide to take a break instead of seeing another patient. In the DES model, this decision implies that the doctor (the resource) becomes unavailable for the duration of the break. The action of "taking a break" is executed by the actor component of the PECS framework.

As was mentioned in the previous section, in order to model the PECS state variables in the DES_A&E model, it was necessary to create four global variables that represent the physical, emotional, cognitive and social states for each doctor. Although it does not seem to be the best way to do it, there appeared to be no other way to model the four PECS states.

In Simul8, it is necessary to use the Visual Logic tool to update all the state variables of the doctors. As the state variables are changing during the simulation, it is necessary to keep the values of them on a spreadsheet that records every value after an activity has finished. That is, when the doctor resource is released from an activity, the doctor's state variables are updated on the spreadsheet based on the information that has been filtered by the perception component. Appendix E presents the Visual Logic (VL) code for one doctor.

As described in Chapter 5, the doctors' state variables are **the physical condition (P)**, which is defined by the state variable Z_1 that represents the energy level of a doctor at a specific time t; **the emotional state (E)**, which is defined by the state variable Z_2 that represents the calmness level of a doctor at a specific time t; **the knowledge level (C)**, which is defined by the state variable Z_3 that represents the knowledge that a doctor has about a patient at a specific time t and **the social status (S)**, which is defined by the state variables Z_4 and Z_5 that represent the experience the doctor has gained at time t and the reputation of a doctor at a specific time t respectively.

The same VL code is written for the rest of the doctors using different spreadsheets for each doctor to keep the values of their attributes. In total, the DES_A&E model uses 3116 lines of coding to implement not only the PECS behaviour but also all the Logic needed to make the SIMUL8 model. Every time a doctor sees a patient in an activity, the doctor updates his or her PECS variables for each patient. It means that the doctor calculates the values of z_1, z_2, z_3, z_4, w_1, w_2, w_3 y w_4 every time he or she interacts with a patient and decides what to do. It means that if the doctor is seeing several patients simultaneously, the doctor calculates PECS for each of them. The visual logic code of a doctor after being released from an activity can be summarized as follows:

1: to read the parameters of each PECS state functions from the input data

2: to obtain information about relevant variables of the environment and update the state variables: $(z_1, z_2 \dots z_n)$

3: to calculate the dependent variables: $w_1, w_2 \dots w_n$

4: to identify the variable with the highest intensity.

- If the highest intensity corresponds to the physical condition (P), the doctor starts a break: the availability of the doctor is set to zero, and the end of the break is scheduled based on the resting time.
- If the highest intensity corresponds to the emotional state (E), the doctor changes the priorities of the patients waiting for treatment based on the maximum waiting times.
- If the highest intensity corresponds to the cognitive state (C), the doctor sends more tests to the patient he or she is currently seeing.

- If the highest intensity corresponds to the social status (S), the doctor does not take any action but updates the emotional state.

7.2.3.3 Communication mechanisms and time handling

In DES, each event is programmed and executed by a central simulation object (simulation executive) defined by the software SIMUL8. There are two types of events considered in this model: the events related to the activities and the events programmed by the user. The events related to an activity include the beginning and ending of an activity driven by the simulation itself; however, there are some regular events not dependent on the activities which I managed with a time-slicing mechanism. In this case, the doctor's state variables are updated every 10 minutes; therefore, there is an event called every 10 minutes to update those variables.

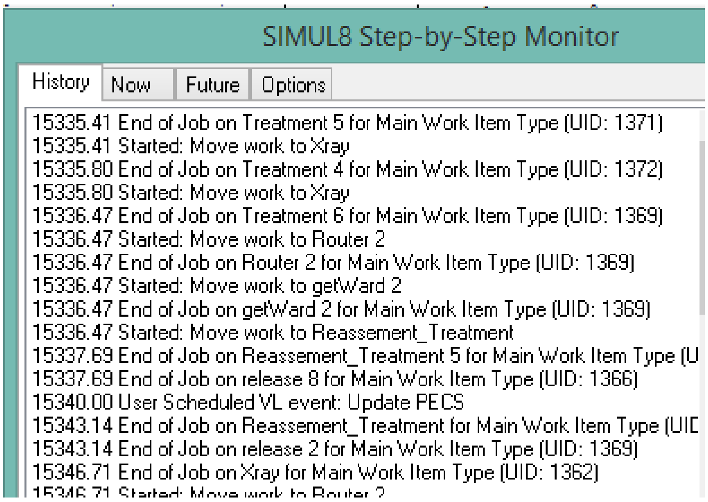


Figure 7-1. Simulation event list

Every time that an event occurs, the executive updates the simulation time; therefore, the time in the simulation progresses at irregular intervals. Once the event is being executed, all the different types of behaviour of the entities related to that event are executed.

The interactions between entities mostly occur in a queue (for example when an entity has a higher priority, it goes to the top of the queue) or during an activity (an entity can seize another entity). The entities do not interact directly with each other or with the environment; it is the simulation that pulls them through the process. Entities are typically located on a grid only for visual purposes, but the communication between entities does not necessarily depend on their specific location on the grid.

In an ABMS model, the time-flow in the simulation is usually handled in discrete time steps; that is, in every interval of time the agents perform actions until they have nothing else to do, or they are removed from the simulation. The simulation model then moves on to the next time point. In the ABMS model developed here, some events occur at regular intervals, such as the beginning and the ending of the working shifts. These are events that occur once every day at a particular time, so they can be handled using the time-slicing technique. However, as in the DES model, there are some events related to the beginning and end of an activity that requires a next-event technique approach.

7.2.4 Simulation results

As it was mentioned earlier, this research does not attempt to simulate a real department but to demonstrate how human behaviour can be modelled within a simulation model. Particularly, the DES_A&E model built in this chapter is aimed to implement a PECS framework and to model proactive behaviour of doctors within an A&E department. The DES_A&E model is based on Günal's model explained in chapter 6.

Initially, the DES_A&E model was run before implementing the PECS framework and then after its implementation. Before implementing PECS, the model was run for one year (525.600 minutes) and 36 replications. Table 7-1 shows that the proportion of patients that spent more than four hours in Günal's model is similar to the DES_A&E model.

Table 7-1: proportion of patients whose total waiting time is more than 4 hours

Performance indicator	**-95%**	**Average**	**95%**	Observed
Simul8 DES_A&E model	0.030	0.028	0.037	0.036
Günal's model	0.032	0.049	0.071	0.036

As described in chapter 6, The PECS variables used to represent doctors' attributes are:

- the physical condition (P) which represents the energy level of a doctor at a specific time
- the emotional state (E) which represents the calmness level of a doctor at a specific time
- the knowledge level (C) which represents the knowledge that a doctor has about a patient at a specific time
- the social status (S) which represents the experience the doctor has gained at time t and the reputation of a doctor at a specific time t respectively.

Doctors in the model were classified according to their experience:

- Low experience: it is supposed that low experienced doctors may be younger than doctors with medium and high experience; therefore, they get tired slower than experienced doctors. Moreover, the lack of experience of inexperienced doctors means they tend to get stressed faster than the others.

- Medium experience: medium experienced doctors are likely to be older and less experienced doctors. It is assumed that get tired and stressed at the same rate.
- High experience: the highly experienced doctors are likely to be older than the less experienced doctors; therefore, they get tired faster than the others, but they do not become stressed as quickly as them.

After implementing the PECS framework in the DES_A&E model, the simulation was also run for one year (525.600 minutes) and 36 replications. shows that doctors respond to long waiting times. It can be seen from Figure 7-2 that the distribution of the total time in the system for all the patients is steeper than the distribution of times before PECS implementation. However, the DES model does not capture the effect of the four-hour waiting time target on the proportion of patients that leave the system in the same detail as the ABMS model. From Figure 7-2, it can be seen that there is a slight increase in the proportion of patients that leave the department after around two hours, but this is less evident than in the ABMS results.

This may be because each type of doctor has a different perception of the risk of failing to meet the four-hour waiting time target. The perception of the risk of failing to meet the targets is related in this model to the PECS variables *Stress*. The stress variable is modelled as an S-shaped function, and for each doctor, there is a parameter that represents the point (time) at which the doctor losses 50% of the time. As described in chapter 6, Table 6-3 showed that doctors with low level of expertise, lose their 50% of the calm when their patients have been waiting around 1 hour, doctors with medium level of expertise when their patients have been waiting around 1.33 hours (around 80 minutes), and doctors with high level of expertise when their patients have been waiting around 2 hours. That is because they perceive the risk of failing the 4-hour target differently depending on their experience; it is natural to assume that the inexperienced doctor gets stressed sooner than the more experienced ones.

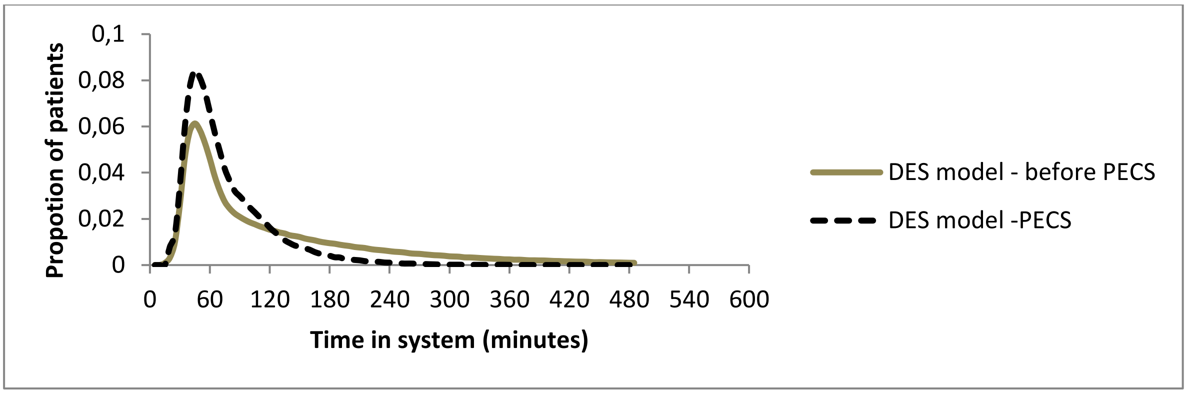


Figure 7-2. Total time in system in the A&E DES model

In order to analyse the behaviour of the doctors after implementing PECS, two types of doctors are selected: a low experienced doctor (doctor 1) and a highly experienced doctor (doctor 6). The behaviour of each doctor is tracked over one day, for instance, Wednesday. Figure 7-3 shows the demand for the A&E department by hour on a Wednesday. It can be seen from this figure that the period with highest demand is around 10:00 a.m. and stays relatively high until 9:00 p.m. On Wednesdays, Doctor 1 works from 5:00 a.m. to 11:00 a.m. and from 2:00 p.m. to 5:00 p.m., Doctor 6 works from 9:00 a.m. to 6:00 p.m.

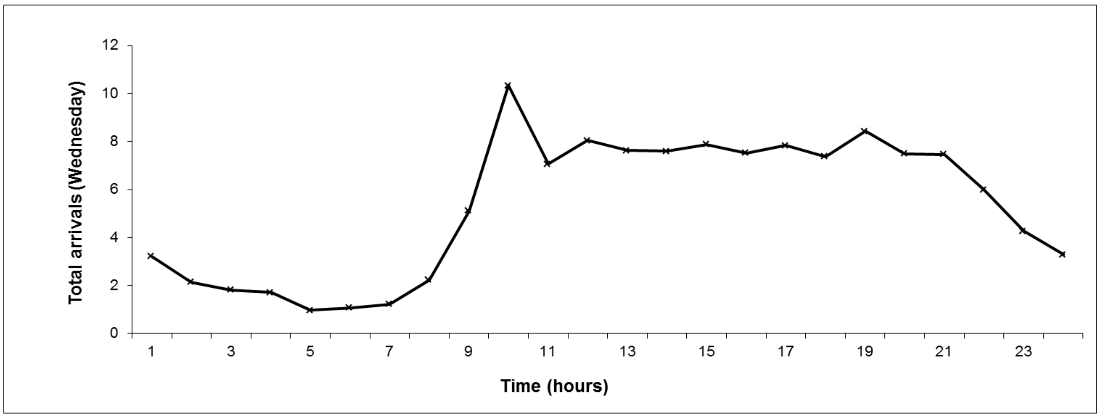


Figure 7-3. Demand per hour on Wednesday

Figures 7-5 and 7-6 show the behaviour of the PECS state variables of experienced and inexperienced doctors, respectively. At busiest periods an experienced doctor perceives a lower risk of failing to meet the target than an inexperienced doctor (as shown in the Emotion variable); therefore, the inexperienced doctor perceives more stress than an experienced one. At the same periods, experienced doctors are more willing to learn about the patient’s condition than inexperienced doctors (Cognitive variable).

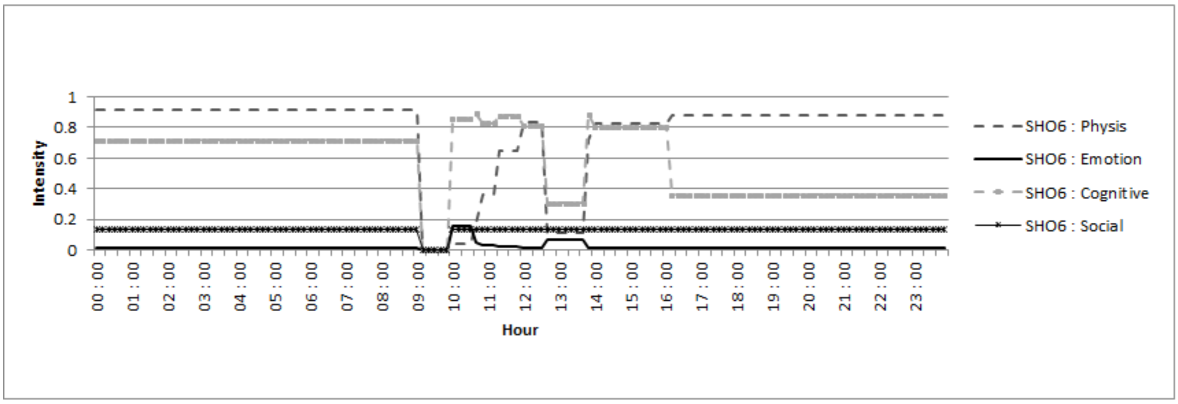


Figure 7-4. PECS variables for an experienced doctor by hour

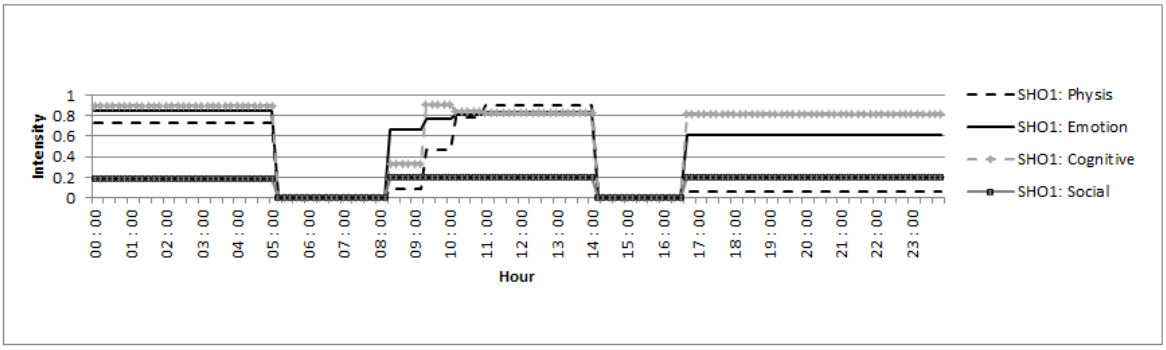


Figure 7-5. PECS variables for a low-experienced doctor by hour

7.2.5 Sensitivity Analysis

The parametric sensitivity analysis of the DES_A&E was done under the same assumptions that in the ABMS_A&E model, it is assumed here that all doctors have a low level of expertise, and the sensitivity analysis is done by varying each PECS parameter simultaneously on all the doctors.

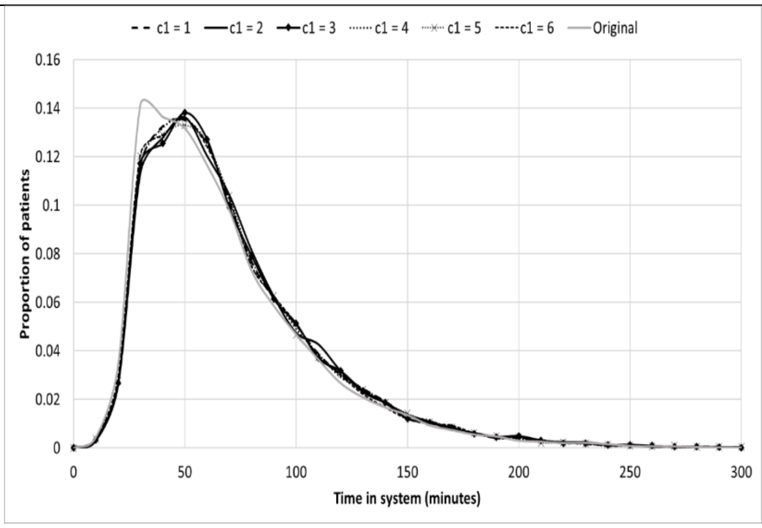
Figure 7-6 shows the impact of changes in the parameter c_1, c_2 and c_3 on the distribution of the patients' total time in the system. Chapter 6 presented the PECS variables and parameters, where it was defined that both c_1, which represent a doctor's maximum number of patients seen per hour, as c_2, which represents the expected duration of a doctor's shift, affect the state variable Energy, and that the parameter c_3 that represents the maximum time in the system among all patients at which the doctor loses 50% of calm is related to the state variable Calmness. It can be seen from

Figure 7-6 that there is not a significant impact of changes in c_1 and c_2 on the distribution of the patients' total time in the system.

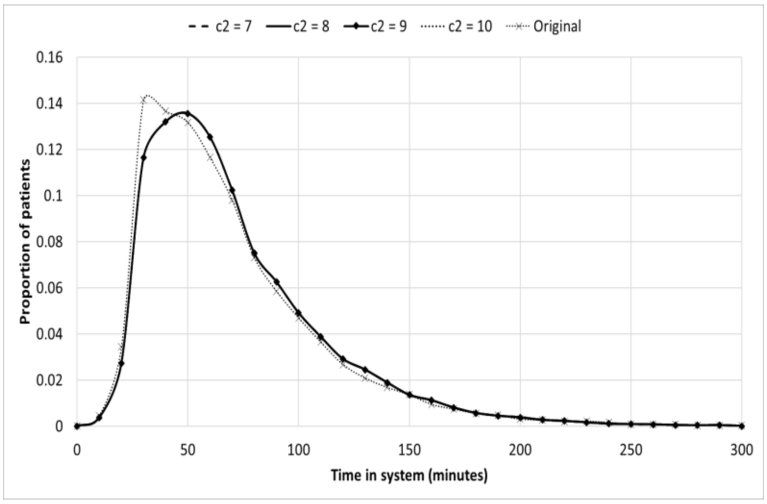
However, changes in the parameter c_3 have a notably impact on the output. The parameter C_3, which represent the time at which the doctors lose 50% of their calm, was varied between one and four. Figure 7-6-c) shows more significant differences between each of the runs, as the lines do not overlap until high values of patients' maximum time in system. When C_3 equals 1, there is a really tall peak when maximum times in system are around 30 minutes, meaning that when doctors stress sooner than usual, they try to release patients sooner. It can also be observed that the curves tend to get wider as C_3 grows, which means that when doctors stress later, the total patient time in system tends to increase. Appendix D presents an additional sensitivity analysis. Figure D1 shows the impact of running the simulation with all doctors having the same level of expertise. It can be seen from the figure that when all doctors have medium-level or high-level expertise, a higher proportion of patients leave the system around 50 minutes, while when doctors have low expertise, the highest proportion occurs around 30 minutes. It might be because low experienced doctors tend to get stress sooner and perceive the risk of failing to meet the four-hour target when times are shorter than more expert doctors.

Additionally, Figure D2 shows the impact of modelling the relationship between dependent variables and state variables in the PECS framework as linear functions instead of Logistic Functions. It means that the H function that transforms the state variables Z' at time $t + \Delta t$ into dependent variables W' at time $t + \Delta t$ is linear. It can be seen from the figure that keeping the same distribution of doctors (low, medium and high) when the H function is modelled as a linear function instead of a Logistic, the proportion of patients that leave the department approximately within 60 minutes is smaller than when using the Logistic Function; however, after that point the distribution show similar behaviour but the proportion of patients is higher using the linear function.

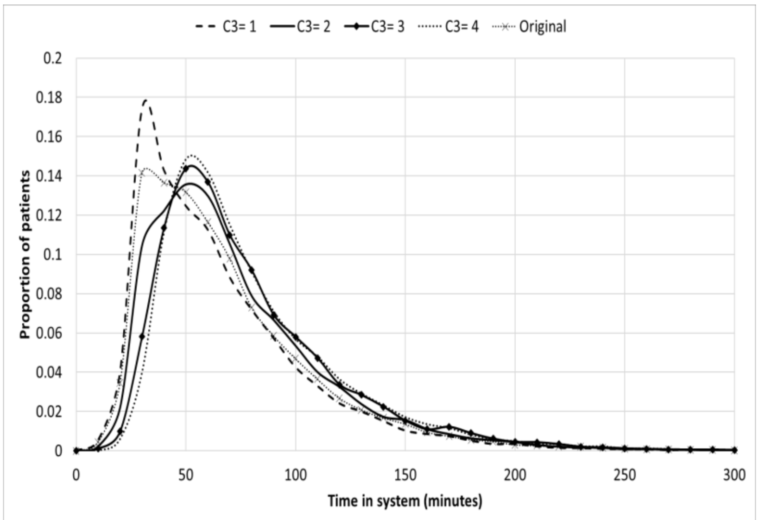
Comparing the sensitivity analysis of PECS parameters for ABMS_A&E and DES_A&E models, it can be seen that the DES_A&E model tends to be more sensitive to variation in PECS parameters than the ABMS_A&E model.



a) C_1: a doctor's maximum number of patients seen per hour



b) C_2: expected duration of a doctor's shift (hours)



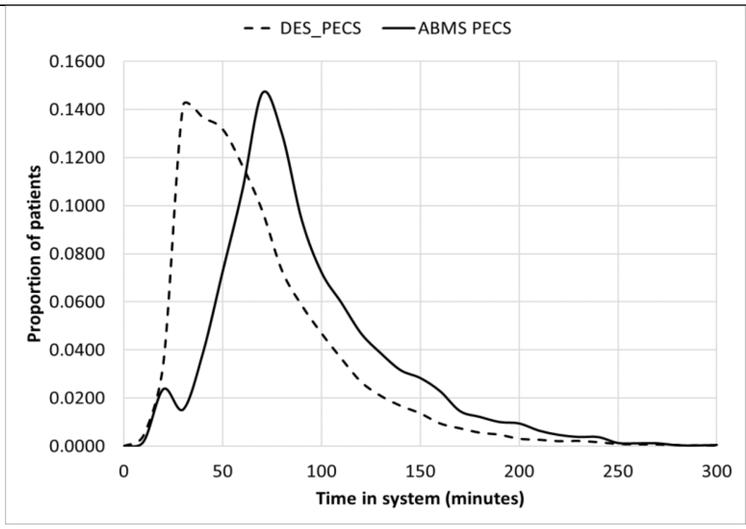
c) C_3: maximum time in the system (hours) at which the doctor loses 50% of calm

Figure 7-6. Sensitivity analysis for parameter C of Logistic Functions

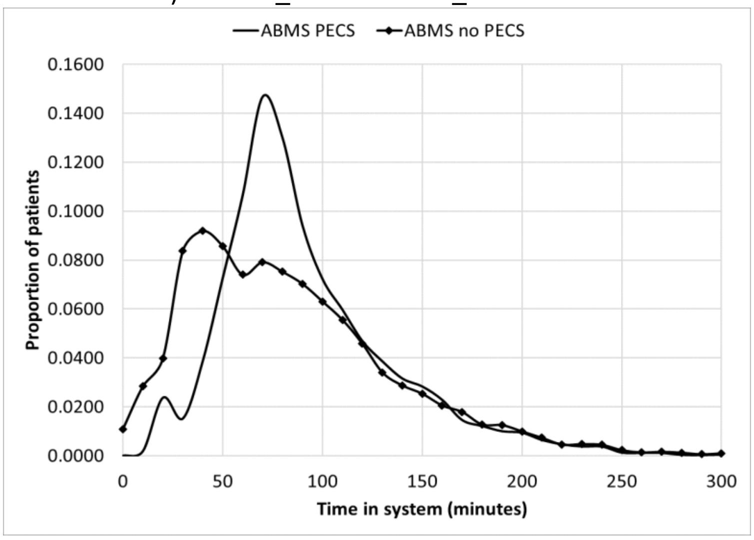
7.3 Modelling Human Behaviour using PECS in ABMS and DES

This chapter demonstrated how human behaviour in the context of A&E departments could be modelled using DES, and the previous chapter showed how the same could be done using ABMS. It is not possible to calibrate the ABMS model to match the DES model because the DES_A&E is not an exact replication of ABMS_A&E model but an equivalent simulation. Structurally both models are different, for instance, in the ABMS_A&E model was possible to give each agent a set of rules that allows them to respond to different stimuli by implementing PECS while in the DES_A&E doctors were modelled as resources with local variables that keep information about their states, and although it was possible to implement PECS to model proactive behaviour, DES is not as flexible as ABMS do to so.

Figure 7-7- a) shows that ABMS tends to represent better the effect of the four-hour target on the doctors' behaviour since there are small peaks around 150 minutes and 200 minutes, meaning that the proportion of patients seen seem to increase when the patients' time in the system gets close to the four-hour target, whereas the DES curve is smoother and there are no significant changes on the distribution of patients' waiting times. Additionally, it can be seen from Figure 7-7 that in the ABMS_A&E model after implementing PECS, there is a decrease in the proportion of patients leaving around 30 minutes. That might be caused for different reasons related to the PECS framework. For instance, before 30 minutes, the doctors have not lost much of either their calm (Figure 6-7) or of their reputation (Figure 6-10). Therefore, it is probable that the Fatigue and Need of Knowledge were higher at that time than Stress or Social Desire, which means that when patients' time in system is around 30 minutes, doctors tend to reduce multitasking or take brakes to keep the state variables Energy and Knowledge at high levels, that means that they tend to see less patients simultaneously with is reflected on the decrease of the proportion of patients that leave around 30 minutes.



a) AMBS_ A&E and DES_A&E with PECS



b) ABMS model with PECS VS AMBS model without PECS

Figure 7-7. Modelling human behaviour in an A&E using PECS

7.4 Conclusions of the chapter

The model developed in this chapter shows the value of DES to model human behaviour. I found several limitations in modelling behaviour in A&E Departments using DES. First, modelling human behaviour requires a higher level of detail, and the more detail that is added, the more complicated the model becomes. It is much more difficult to manipulate a model that deals with many operations and interactions than simpler ones. DES allows for increasing the level of decisions that can be modelled, but it comes with a cost related to the ease of use of the model.

Second, it may be necessary to use parallel computing or a powerful machine to run this type of model. This is because this model uses a considerable amount of data (inputs and outputs) and complex rules of interactions. Because of the stochastic nature of DES models, it is necessary to perform several runs and to perform long runs to obtain steady states.

Third, experimentation is not an easy process. On the one hand, there are multiple parameters involved in the model. Some are related to the distributions used in the model, others to the structure of the model and others still to the functions that define the behaviour of the entities. Therefore, sensitivity analysis and experimentation require multiple configurations. Besides, it also requires a great deal of computing capacity.

One of the motivations of this research was to investigate whether or not it was possible to represent human behaviour within an Emergency department more realistically in simulation models. It is natural to think of agent-based modelling and simulation to represent human behaviour because of its capability to represent micro-level behaviour based on decision rules that can range from elementary reactive behaviour to more complicated proactive behaviour. However, it is natural as well to think of discrete event simulation to model accident and emergency department aspects because of the operational nature of those departments. The process is easily observable; there are accumulations, delays, resources, events, and considerable experience in modelling accident and emergency departments.

DES has been widely used to model accident and emergency department aspects. The problem is not that DES is not satisfactory for modelling A&E departments; the issue is that there is a part of the A&E performance that has not been entirely explained by DES models, particularly the part when patients are reaching the 4-hour standard of maximum waiting time. It may be possible that micro-level behaviour can be explaining that part of the performance that traditional DES models cannot explain. The question is how to capture that micro-level behaviour in simulation models so the operational aspects can not only be represented but also more easily handled, but also that more realistic behaviour of the staff and patients within the departments can be included in the models.

This chapter has discussed the usual ways that DES work and has demonstrated that DES can be adapted to represent ABMS characteristics by adding more detail to the models. It is possible to give entities decision rules that depend not only on the state of the system but also on their internal state. It is possible to create functions to determine motives based on emotions (such as stress), or intentions based on beliefs and desires. It is possible to create an ABMS model within DES software or to create a DES model using ABMS characteristics. Of course, it is not very easy to add the necessary level of detail in DES models, but it is possible.

To model Emergency departments, especially if the purpose is to study waiting time performance, DES remains a better approach to tackle these problems. It is easier to add behaviour after all the process is modelled than to model all the process using individual behaviour. The benefit of using ABMS is in the flexibility to deploy human behaviour frameworks in a more natural way, which in DES is very difficult, but not impossible to do.

CHAPTER 8: DISCUSSION AND CONCLUSIONS

8.1 Introduction

Previous chapters included background, methodology and results chapters. Chapter 1 introduced two research questions that are addressed in the thesis:

1: How well suited is ABMS to modelling human behaviour in an accident and emergency department?

2: What benefit does ABMS bring to the study of waiting time performance in an accident and emergency department over DES?

Chapter two presented the context of the problem tackled in this research. It described the development process of the performance frameworks used in the UK since the creation of the NHS and showed that one of the most important areas in the UK Healthcare System is urgent and emergency care. The chapter presented some unintended consequences of the NHS performance framework, which have been the subject of intense debate in the UK. The literature in this context showed that one of the main unintended consequences within accident and emergency departments is that the performance measurements may have distorted the quality of care and clinical priorities in healthcare service delivery.

Chapter three discussed the use of simulation in healthcare. It was shown that the main simulation methodologies used in healthcare are Discrete Event Simulation (DES), System Dynamics (SD) and agent-based modelling and simulation (ABMS). DES appeared to be the most popular simulation methodology used in healthcare, which has been mainly used to support decision-making processes at the operational or tactical level and for planning in specific units of a healthcare facility. SD has been used mostly to study how different units of the healthcare systems relate to each other and to evaluate the impact of different strategies and policies on performance. ABMS has been mainly used in healthcare to model disease prevention and epidemiology problems. It was found that human behaviour is a rare area of application in simulation studies. Simulation studies that include human behaviour have mainly focussed on how changes in behaviour affect performance.

The literature review in chapter three demonstrated that simulation has been used for modelling several aspects of the complexity of accident and emergency departments. However, there is relatively little research on simulation modelling to study the relationships between human behaviour and the performance of accident and emergency departments, particularly the effects of waiting time performance on clinician's behaviour.

Chapter four discussed how human behaviour has been incorporated into simulation models and presented some frameworks and theories to model human behaviour. Human aspects have been usually included in DES models by using attributes to represent different factors such as gender, age, the severity of illness, workload capacity, multitasking and to model simple decision-making processes using "if-then" rules. However, human psychological factors are rarely included in DES models. Chapter four also introduced the PECS framework to model human behaviour. It was shown that a few DES models use PECS to model human factors. In healthcare, PECS has been mostly used in simulation models to represent patients' behaviour. Still, there is no evidence of the use of PECS for modelling the behaviour of staff within a hospital unit, particularly in accident and emergency departments.

Chapters five and six described the development of an ABMS model that represents some aspects of human behaviour within an accident and emergency department, with a focus on staff behaviour, rather than that of patients. Chapter seven demonstrated that DES could also be used to model the same aspects of human behaviour, though with some difficulty. Both models use the PECS framework to represent staff behaviour.

This chapter will discuss the main findings regards to the research questions and will draw general conclusions of this study. Furthermore, it will present the limitations and will propose recommendations for further research, and finally, it will give the contributions of this study.

8.2 Main findings

As stated previously, the purpose of this study was not to develop an entirely realistic and detailed model but to gain some insight into the overall value of including human behaviour in an A&E simulation and contrasting how it can be modelled with widely used DES and ABMS software. The PECS framework was used within both models to represent human behaviour to maintain some consistency. There are two main research questions in this thesis: 1. How well suited is ABMS to modelling human behaviour in an accident and emergency department? 2. What benefit does ABMS bring to the study of waiting time performance in an accident and emergency department over DES?

In order to answer the main research questions of this study, this thesis presented an exploratory study of the use of ABMS and DES to show how to model clinician's behaviour within an A&E department and how that behaviour is related to waiting time performance. In particular, it showed how the relationship between system performance and clinician behaviour could be modelled in a dynamic simulation of the activity in an A&E department.

8.2.1 Including human behaviour in A&E simulations

The first research question stated in Chapter 1 was "1: How well suited is ABMS to modelling human behaviour in an accident and emergency department?" Chapter two presented the evolution of the NHS, where it was possible to see that the performance of A&E departments has been highly affected by the waiting time targets or standards; and that people's behaviour plays an important role in healthcare performance. Therefore, including human behaviour in simulation models is essential to understand the relationship between performance measurement and people's behaviour.

The literature review demonstrated that the use of ABMS and DES for modelling A&E departments had included some aspects of human behaviour such as workload capacity, multitasking, workforce planning, patient flows and patients' priorities, mainly by using reactive behaviour rather than proactive behaviour. However, there has been little discussion on the value of including other aspects of human behaviour such as drives, motivations and emotions, and its relation to the A&E 4-hour target.

In the current study, human behaviour was implemented in the ABMS_A&E and DES_A&E models by including both reactive and proactive behaviour within the PECS framework. This allows not only multitasking, workforce planning and patient flows, which are topics usually covered in simulation models, but also includes some physical, emotional, cognitive and social aspects of doctors that drive their behaviour.

Reactive behaviour was represented in both models by using a series of simple if-then rules that apply to all agents and entities of those models. Proactive behaviour was also included in both models by using the PECS framework. The implementation of the PECS framework in the ABMS and DES models assumed that each doctor agent (in the ABMS_A&E model) or doctor entity (in the DES_A&E model) had four main attributes that defined their internal states: Energy (Physis); Calmness (Emotion); Knowledge (Cognition) and Reputation (Social status). The proactive behaviour considered that each doctor received input from the environment, and that input was interpreted by a perception system that was based on the doctors' internal PECS state variables and their own goals. The perception system determined the deliberative decision -making process that drove different actions and behaviours. This is not because of an assumption that only the behaviour of doctors affects A&E performance; here, we only considered doctors' proactive behaviour to show how human behaviour can be included in A&E simulations. Obviously, this ignores the behaviour of patients, nurses and clerks and is a limitation of this study than could be addressed in future research.

Considering the development platforms of each model (Simul8 and Repast), it was necessary to take different approaches to the implementation of PECS within them. First, and most obvious, is that it was much easier to implement PECS in the ABMS_A&E model than in the DES_A&E model. In the ABMS_A&E model, the PECS framework was programmed as a series of methods in a Doctor class, and each instance of the Doctor class inherited its behaviour. In the DES_A&E model, Doctors were represented as resources in Simul8, and the PECS framework had to be implemented for each doctor as a series of external programming codes because in Simul8 there is no direct way to assign attributes to resources. Therefore, it was necessary to use global variables which were stored for each doctor in spreadsheets to model each PECS function. All that made the DES_A&E model inflexible to manipulate and to change and hindered the process of implementing PECS. This limitation may not apply to all DES software, but it is a drawback of using the popular Simul8 package.

Another difference I found in the implementation process of PECS is that in the Repast implementation of ABMS, the PECS state variables of each doctor were updated every time that a doctor made a decision. By contrast, in the Simul8 implementation of DES, the decision-making process using PECS could only be triggered at an event time, because it is at event times that state variables are updated in a DES model. It was simpler and more convenient to update the PECS attributes within the ABMS model.

Therefore, one interesting finding on this research, is that is possible to include in both the ABMS and DES models different aspects of human behaviour related to motivation, emotion, cognition and social status and to model their effect on waiting time performance of an A&E department. For example, the ABMS_A&E and DES_A&E models showed that when patients' total waiting times were low, doctors used to have lower levels of stress and social desire while having higher levels of need of knowledge about their patient's condition. Therefore, doctors were likely to spend more time with their patients in order to increase their understanding of their condition by reducing multitasking and ordering more tests. It is important to notice that although the idea of growing doctors' knowledge is to improve the accuracy of their diagnosis, the diagnosis was not model here because that was not in the scope of this thesis. In addition, the ABMS_A&E and DES_A&E models also showed that when the department got more crowded and patients' total waiting times were higher, doctors tended to have higher levels of stress and social desire which led them to try to release patients with waiting times close to the four-hour target by increasing their multitasking, reducing service times and modifying patients' priorities based on time rather than on the severity of the condition. Though it was possible to implement these features in Repast and Simul8, to do so in Simul8, as an example of DES software, required much more work to program around its limitations.

All this leads to the answer to the first research question about how well suited ABMS is to modelling human behaviour in an A&E department. This research demonstrated that ABMS offers excellent options for modelling human behaviour in an Accident and Emergency Department and that including human behaviour in A&E simulations is valuable because it is possible to explain how that behaviour can be linked to waiting time performance in an A&E department.

8.2.2 Modelling waiting time performance of A&E departments

It is well known that in OR/MS, DES has been the most popular technique to model Emergency Departments; however, the literature showed that ABMS has started to gain popularity in healthcare and offers opportunities to study different aspects of Emergency Departments.

This study confirmed that DES is well suited for modelling patient flows in an Accident and Emergency Department. It also showed that it is possible to include different aspects of human behaviour in DES but that modelling those aspects in Simul8 can be challenging. In addition, this study found that ABMS is well suited to model human behaviour in an A&E Department but that it also supports modelling patient flows by using standard queuing structures and scheduling activities using different mechanisms. The results of this study demonstrated that ABMS is flexible enough to include various levels of detail and different types of behaviour in an A&E simulation model.

An important finding is that, though both ABMS and DES can be used for modelling human behaviour and its relationship with waiting time performance, it is much easier to do this using ABMS. That is, considering the development platforms used for the ABMS_A&E and DES_A&E models, ABMS allows observing the impact of the use of the PECS framework on global waiting times more clearly than DES. In general, it can be said that the ABMS model supports much more detailed modelling of individuals than the DES model. This is because generally, DES software such as Simul8 requires the aggregation of individual behaviours much more than in Repast, as an example of purpose-designed ABMS software. Therefore, representing individual decision making based on internal states in DES is not straightforward. In DES entities are pushed by a centralised event-driven mechanism, whereas in ABMS agents have no central control and each agent makes decisions autonomously.

In addition, the sensitivity analysis carried in both models showed the impact of the PECS variables on the distribution of the patient's total waiting times. Interestingly, sensitivity analysis of the Simul8 DES model showed a greater effect of the Stress variable on the distribution of waiting times than in the Repast, ABMS model. This result needs to be interpreted with caution because the most significant source of uncertainty in this research is related to the representation of the PECS variables within the two models. Neither model should be used to draw general conclusions about the effect of each PECS variable on a real A&E Department since there has been no attempt at full data validation against a real department in this research.

Thus, regarding the second research question about what benefit ABMS brings to the study of waiting time performance in an accident and emergency department over DES, this study found that the main the benefit of using ABMS over DES is in the flexibility to deploy human behaviour frameworks in a more natural way, which in DES is very difficult, but not impossible to do. This is perhaps unsurprising because Repast is aimed at easing the representation of proactive behaviour within a dynamic simulation model, whereas limitations in the Simul8 approach had to be programmed around.

8.3 Limitations of the study and recommendations for future work

One limitation of this work is that it focused on modelling human behaviour and its relation to a single standard related to waiting time performance, but it ignored its relationship to other aspects related to the quality of care. This study focused on a single performance indicator that is the total waiting times, and it did not consider other key performance indicators (KPI) such as average waiting times, waiting times segregated by the severity of conditions, waiting times in different points of the patients' pathways, but more importantly, it did not consider other important outcomes such as accuracy of diagnoses, patient satisfaction and overall quality of care.

Therefore, this research will serve as a base for future studies that can consider how human behaviour relates to other KPI's and outcomes beyond total waiting times. For instance, it might be useful to study how including human behaviour in A&E simulation can result in doctors ordering the right tests, giving a correct diagnosis, reducing readmissions or affecting other hospital's units. Also, it might be useful to consider how those outcomes could affect the doctors' behaviour by improving aspects such as reputation, or experience.

Another limitation of this research is that the models developed here are based on a hypothetical A&E department and are not based on a real situation. The data used for modelling the behaviour of doctors was assumed using some information found in the literature and using common sense. Therefore, although this study offers a scheme for including human behaviour in A&E simulations, the research findings on the actual effect of human behaviour in an A&E department and the validation of human behaviour modelling with a real system may be dangerous to generalise. However, it should be possible, with the cooperation of a real such department to attempt such validation. Therefore, future research might investigate how to model human behaviour based on real data or real situations. Particularly, there is ample room for further progress in collaborative work between OR/MS researchers and psychologists on the measuring and modelling of emotions in the context of A&E.

It should be noted that PECS is a relatively new framework for modelling human behaviour; therefore, there is not much information about how PECS variables should be modelled. Thus, considerably more work is necessary to make realistic estimates of the PECS variables. Real data should be obtained about the factors considered in PECS: physical, emotional, cognitive and social. That data could be obtained by direct observation or by gathering information from experts in the area. It is also recommended to use real data or information to define the individual decision-making rules of people in A&E departments. Future studies on the modelling of the PECS variables for doctors within an A&E are therefore recommended. Moreover, future research might consider modelling behaviour of other people involved in the A&E department process such as patients, nurses and managers. Moreover, it remains a question if other Human Behaviour frameworks could offer good opportunities for including human behaviour in healthcare units.

This work is also limited by the selection of the software used to build the ABMS and DES models. Repast is an excellent tool to implement Agent-Based models, but it requires excellent skills in java programming. In addition, to model A&E departments; it requires detailed knowledge of modelling queuing structures based on event-oriented systems. Simul8 is an excellent software for modelling Discrete Event Simulations. However, its focus on entities as objects that pass from station to station through is not flexible enough to model different types of behaviours of other active objects with the system, particularly of simulation objects such as doctors that process the objects flowing from station to station.

The ABMS and DES models could not be properly calibrated against each other, because they had significant structural differences due to the different modelling paradigms underpinning the two models. From the results of this study, some research questions are identified. Considering that this thesis showed that both ABMS and DES are robust methodologies for modelling Emergency Departments, where DES offers more flexibility for representing queue structures, processes and patients' pathways and ABMS is more flexible for implementing human behaviour frameworks; it seems wise to think that the strengths of each methodology could be enhanced through the development of hybrid simulations. Therefore, one research question that stems from that would be: what is the benefit of using hybrid simulations for modelling human behaviour within healthcare units over single DES and ABMS models? Though not widely used when this research started, there are now popular simulation packages such as AnyLogic that are intended to allow both ABMS and DES approaches. Hence it would be sensible for a further study to use such flexible software to permit closer calibration and comparison and hybrid approaches.

In addition, the literature review showed that human behaviour had been included in A&E simulation models with some limitations; therefore, more research on modelling human behaviour in healthcare units is needed. Further research could consider exploring topics such as human behaviour conceptual modelling, measuring and representing human behaviour and validating human behaviour models. Thus, an interesting research question resulting from that would be: how to develop realistic models of human aspects related to drives, motivations and emotions of people within healthcare units.

Finally, this research did not focus on the development of a detailed realistic model of an A&E department, and it would be interesting to explore the feasibility of developing generic A&E simulation models that include human aspects related to drives, motivations and emotions of people within healthcare units. A research question that could be asked include: to what extent is it possible to build a useful and generic A&E simulation model that includes human aspects related to drives, motivations and emotions of people?

8.4 Contributions

This research provides two main contributions:

First, this research compares and evaluates how suitable ABMS and DES are for modelling clinical behaviour and presents the strengths and limitations of ABMS and DES for modelling accident and emergency departments. It shows that this is possible in both ABMS and DES, but requires much more programming effort in DES packages such as Simul8.

Second, this research offers an approach to model the relationship between human behaviour and waiting time performance, considering four aspects of human behaviour (physical, emotional, cognitive and social) employed in PECS. The simulation models developed here allow modelling some human behaviour aspects within an A&E department to study how waiting time targets influence the doctor's behaviour within the department.

APPENDIX A: WINTER SIMULATION CONFERENCE PAPER

Proceedings of the 2011 Winter Simulation Conference
S. Jain, R.R. Creasey, J. Himmelspach, K.P. White, and M. Fu, eds.

USING ABMS TO SIMULATE EMERGENCY DEPARTMENTS

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ABSTRACT

Computer simulation methods have enjoyed widespread use in healthcare system investigation and improvement. Most reported applications use discrete event simulation, though there are also many reports of the use of system dynamics. There are few reports of the use of agent-based simulations (ABS). This is curious, because healthcare systems are based on human interactions and the ability of ABS to represent human intention and interaction makes it an appealing approach. Tools exist to support both conceptual modelling and model implementation in ABS and these are illustrated with a simple example from an emergency department.

1 HEALTHCARE SYSTEM SIMULATION MODELLING

Simulation methods have long been used to model elements of healthcare systems with a view to understanding and improvement. Literature reviews of simulation approaches in healthcare systems improvement include Fone (2003), Jun et al (1999) and Gűnal and Pidd (2005); and Brailsford (2007) discusses some of the challenges to be faced by those attempting such work. Brailsford follows Koelling and Schwand (2005) in dividing healthcare simulation applications into those concerned with the strategy and policy level, the tactical and operational level, and with disease prevention and epidemiology. Here we are concerned with the first two levels, which we capture under the general idea of healthcare system simulation.

1.1 Modes of model use

Becker et al (2005) argues that there are two intended uses of simulation models; descriptive models that are used for description, explanation and prediction; and normative models that are used for decision support purposes. However, this binary view seems too restrictive. Discussing OR/MS modelling in general, Pidd (2009) suggests four archetypal uses: decision automation, routine decision support, system investigation and improvement and providing insights for debate. Heath et al. (2009), focusing on agent-based simulation, suggests three different archetypal approaches to simulation modelling, based on the modeller's level of understanding of the system to be simulated. As shown in Figure 1, Heath et al argue that, when the level of understanding is high, a simulation can be used as a *predictor*; that is, as a machine that produces clear predictions about the system's behaviour under defined conditions. When the level of understanding is low, Heath et al suggests the use of a simulation model as a generator to support the generation of hypotheses and theories about system behaviour, but not in a precise manner. When the level of understanding is neither high nor low, Heath et al suggests that a simulation model be used as a *mediator*, which provides insight into the behaviour of the system without offering a complete representation of that behaviour. Clearly, these are three archetypal positions and many models will display characteristics that make them a mixture of predictor and mediator, or mediator and generator. These three tally, more or less, with the last three of the four types suggested by Pidd.

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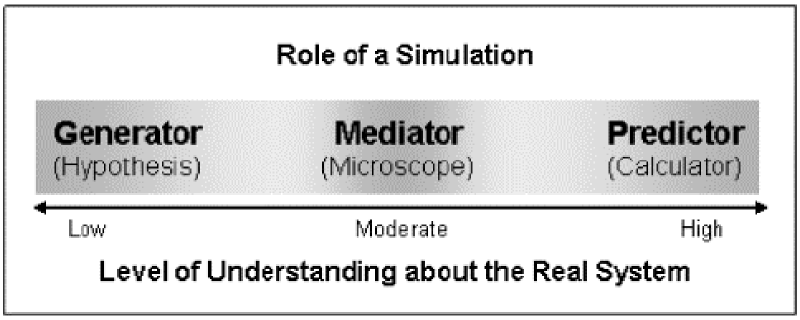

Figure 1: Roles of simulation models (from Heath et al 2009)

1.2 Simulation modelling approaches

Discrete event simulation (DES), system dynamics (SD) and agent-based simulation (ABS) are the main three approaches used when simulating healthcare systems. The typology of Heath et al, suggests that discrete event methods are best suited to use as predictors, or mediators, or somewhere between the two. Hence it should be no surprise that discrete event methods have enjoyed widespread use in healthcare modelling as documented in the literature reviews. Many SD models have also been developed (Brailsford 2007), though these seem to be fewer than DES models. SD models seem best suited to be used as generators; see Lane et al (2000) as an example of such an approach. What then of agent-based methods? Their use will be more formally considered later, but they seem best suited as mediators or, possibly, as generators. ABS models may offer ways to provide insight and to generate hypotheses about system behaviour by representing this as a result of the interaction of individual agents. However, the literature contains very few examples of ABS for healthcare system modelling, whatever the intended mode of use.

2 HUMAN PERFORMANCE MODELLING

In non-healthcare domains such as manufacturing, simulation methods have been used in human performance modelling (Kuljis, Paul, and Stergioulas 2007). Baines et al (2004) argues that errors in predicting performance in manufacturing system simulations are mainly due to inadequate representations of human behaviour in simulation models. Specifically, they suggest that it may be necessary for models to incorporate relationships between the performance of a person and the factors that affect that performance. In healthcare systems, perhaps even more than in manufacturing systems, the need for human discretion, contact and interaction suggest the importance of considering human behaviour. According to Kuljis, Paul, and Stergioulas (2007), performance metrics are taken seriously in healthcare as a way to monitor performance levels and quality of care. However, a single-dimensional focus on particular metrics, such as those related to waiting times for treatment of admission to hospital have often over-ridden reasonable clinical priorities. It seems that the performance measurement systems in place act as incentives to encourage particular aspects of performance. For example, from the mid-2000s to 2010, EDs in the UK NHS were set targets to complete the treatment of 98% of patients within 4 hours and some argued that this led to the distortion of clinical priorities. This suggests that the effect of incentives and other aspects of human performance are very important in healthcare. Therefore, in order to better understand the performance, it seems sensible to consider the inclusion of human performance factors in simulation models.

2.1 Human performance modelling in discrete event simulation

Some elements of human performance have long been included in DES models, usually by representing people as resources or as entities with multiple attributes that carry parameter values. The parameter values both define and are a result of human behaviour. Garnett and Bedford (2004) suggests that there are four main elements of human behaviour incorporated in DES models, albeit with limitations.

1. Human workload capacity, multi-tasking and attention span: usually focusing on the structure of a task, rather than on the person performing it.
2. Physiological and environmental factors such as age, time of the day, light, temperature or noise, which are usually outside a person's control.
3. Decision making processes: incorporated in different ways, ranging from simple 'either/or' rules to rules that allow evaluation of different strategies by linking the DES model with an expert system.
4. Human psychological factors such as motivation: including emotion, cognition and social status.

Within the healthcare system simulation literature, Brailsford and Schmidt (2003) describes a model that captures patient's motivation to attend for screening for diabetic retinopathy when offered an appointment. The model was based on a previous DES study of screening for diabetic retinopathy in a group of patients, in which the probability of attendance was constant for every patient (Davies et al. 2000). The motivation of patients to attend was implemented in the later model by adding more fields to the attributes of patient records to cover their physical, emotional, cognitive and social states. This example shows the potential for including human behaviour in DES models and leads to a more accurate way of modelling attendances for screening. However, this approach to modelling patient behaviour does not consider interactions with clinicians and others.

Another example is Günal and Pidd (2006), which describes a DES model of the process flow of patients through an A&E department. The model represents the multitasking behaviour of medical staff by fragmenting each doctor and nurse into M parts so that the workload triggers multitasking behaviour. Although this is a good example of representing human behaviour and decision making processes in a model, one of the limitations of this method is that it ignores any other possible factors that may affect the multitasking behaviour. These factors may depend, for example, on the doctors' interactions with patients, other medical staff and their working environment.

2.2 Human performance modelling in system dynamics

Though system dynamics (SD) applications in healthcare are not as common as DES (Brailsford and Harper 2008), there is a considerable literature in this area (Bayer et al. 2007; De Vries and Beekman 1998; Gonzales-Busto and García 1999; Lattimer et al. 2004; Leischow and Milstein 2006; Sardiwal 2007). Several studies investigate the relationship between healthcare demand, healthcare capacity and waiting times under different scenarios and incorporate behavioural assumptions (Brailsford et al. 2004; Lane et al. 2000; Royston et al. 1999; Van Ackere and Smith 1999; Wolstenholme 1993, 1999).

In 1995, the OR Group of the UK Department of Health (Royston et al. 1999) began to use system dynamics to understand and improve the performance of Emergency Departments. The initial aim was to expose the structure of the UK healthcare system by considering the interactions among its different parts. The idea was to help different healthcare stakeholders develop their understanding of system behaviour resulting from system structure. This work demonstrated important relationships among different sectors of the healthcare system, such as the observation that longer waiting times in GP consultations tend to elevate the number of arrivals at emergency departments. Another important finding in this model is that behaviour changes (e.g. willingness to admit) have a greater effect than changes in capacity.

Lane et al (2000) describes the use of SD to understand the different factors contributing to the long delays for unplanned, urgent admission to acute hospitals in the UK and to explore the dynamics of the system of which the emergency department is one element. The model considers interactions between the demand pattern, ED resource deployment, other hospital processes and bed capacity. The main finding is that although some delays in the patient's pathway are inevitable, a selected augmentation of A&E resources may lead to some reductions in those delays. Additionally, the study demonstrated that reductions in bed capacity have more impact on elective surgery cancelations than on waiting times for emergency admissions.

In summary, most SD applications have investigated the relationships between healthcare demand, healthcare capacity and within-hospital delays; others have investigated the interactions between different units of a hospital and other sectors of the healthcare system

3 AGENT BASED MODELLING AND SIMULATION

The term "agent" is used in different ways in different disciplines such as artificial intelligence, social science, complex science, game theory; however, there are several views about what an agent is (Borshcev and Filippov 2004). In general terms, an agent can be defined as an autonomous entity which makes decisions based on a set of rules (Bonabeau 2002). A broader definition considers an agent as an entity that possesses skills and resources and is capable of acting, perceiving and communicating, with behaviour driven by a set of tendencies (Ferber 1998). Although there are several different definitions of agent, there is some agreement: in complex adaptive systems, agents are the decision making components. That is, an agent can be seen as anything that makes choices in a system (North and Macal 2007). Moving beyond this general concept to consider agent-based modelling, an agent must be responsive, proactive and social (Wooldridge 2002). Thus agents must have attributes to make them uniquely identifiable individuals with behaviours that interact with one another to produce system behaviour. Additional characteristics such as adaptation, goal-direction and heterogeneity are often useful but not always required (Macal and North 2010).

In general, agent-based modelling and simulation (ABMS) is used to study complex systems that include agent entities whose dynamic behaviour is caused by and causes the state of the system (Shi and Brooks 2010). Although the term complexity may have different definitions, in general a complex system consists of interconnected components that work together in order to meet an objective and interchange resources and information with the environment (Tan, Wen, and Awad 2005). Therefore, in agent-based terms, a system is modelled as a set of heterogeneous agents that create overall behaviour through their interactions (Bonabeau 2002; Macal and North 2008; North and Macal 2007) . An agent-based simulation is a multi-agent system in which agent behaviours and interactions are simulated for a particular purpose (Van Dyke Parunak et al. 1998; Borshcev and Filippov 2004; Macal and North 2010).

3.1 ABMS tools

There are several software toolkits for building ABMS applications, including free implementations of very simple approaches such as NetLogo. Published surveys of toolkits available for ABMS modelling consider aspects such as the domain where the toolkit is intended to be used, the programming language required to build the model, the possibility for visual programming and whether the software is open source (Castle and Crooks 2006; Nikolai and Madey 2009; North et al. 2006; North and Macal 2007; Serenko and Detlor 2002; Shi 2008). The Repast System (North and Macal 2007) is a widely used, open source ABMS toolkit that supports the use of several programming languages. The electronic database of literature *Web of Science* shows a total of 110 records for the topic "repast". Repast toolkits include tutorials to support novice users and user support networks such as mailing lists, listservs, online forums and FAQs, a library of example models, a selection of references/publications on the toolkit (Nikolai and Madey 2009). Repast Simphony (also known as Repast S) was chosen for the ABMS work in this project, though that is the subject of another paper.

4 ABMS MODELLING OF EMERGENCY DEPARTMENTS

A large and growing body of literature describes the use of DES and SD models in Emergency Department (ED) studies. However there are few reports of the use of ABMS for this purpose. Kanagarajah et al.(2006) describes a hypothetical ABMS of an Emergency Department intended to demonstrate the effects of fluctuations in workload and economic forces on patient safety. The agents included are: patients, doctors, nurses, technicians, treatment rooms and managers, and all are programmed to aim for minimizing preventable adverse events while managing patient's outcomes. Patients are attended based on their condition, the time spent by medical staff with patients depends on demand pressures and patient characteristics, and doctors may work faster or in busy periods to clear excessive queues. The interactions among the agents within the model are defined by elementary rules of decision making, movement and action.

This is a clear illustration of the potential use of ABMS in modelling EDs. As in the non ABMS model of Günal (2008), medical staff modify their behaviour based on the workload. The behaviour of the doctors is represented by changes in the speed of the work but overlooks other aspects of doctor behaviour: such as the actions or decisions that staff can take. For example, a doctor might decide to ask for more investigations on a patient in order to give a more accurate diagnosis when not under pressure to discharge a patient soon and may not do so when very busy.

Stainsby et al.(2009) describes a preliminary conceptual ABMS model of an ED model with 5 classes of agent: patients, companions of patients, administrative staff, nurses and doctors.. The conceptual model shows patient flows and interactions among agents. Stainsby et al discuss the importance of modelling human factor in emergency departments based on the idea that humans are physiologically and psychologically complex and therefore interactions among people can get much more complex. The purpose of this model is to help understand some important questions about people's behaviour in an emergency department. For instance, they suggest that using the ABMS will support increased understanding of why some patients leave an emergency department while waiting for triage, or how the implementation of a fast track system affects the level of service as perceived by the patient. The general layout of the model shows agent interaction in each stage of the pathway. The rules of interactions between agents are based on the agent that starts the interaction; though it is not clear how these interactions may occur.

4.1 Issues to be faced in using ABMS to model emergency departments

One of the main challenges when developing simulation models is to keep a model as simple as possible whilst including the essential of the system needed to achieve the objectives of the simulation (Robinson 2004). A further complication is that different people may have different levels of understanding of a particular system, therefore designing a model that can be accepted by different people and that allows variations in levels of complexity is a real challenge for modellers (Onggo 2010). Although there is no single accepted definition of conceptual modelling, it can be said that conceptual modelling deals with abstracting appropriate levels of simplification of a system (Robinson 2004; Pidd 1994).

Onggo (2010) classifies conceptual models into three categories: textual representations, pictorial representations and multifaceted representations. Within DES, common pictorial representations include Activity Cycle Diagrams, Process Flow Diagrams and Event Relationship Diagrams. Within SD, Causal Loop Diagrams or Stock and Flow diagrams (Sterman 2000). There exists no single pictorial scheme that provides a complete conceptual representation of an Agent Based Model (Onggo 2010). *Multifaceted representations* contain both diagrams and a textual representation of different conceptual model components. One of the most common multifaceted representations used in software engineering is Unified Modelling Language (UML).

4.2 Conceptual modelling: agents and agent behaviour

When developing ABMS it is crucial to represent the two main parts of an agent-based model: agents and agent behaviours (North and Macal 2007). Gilbert and Terna (2000) suggests that the modeller should first define the capabilities of the agents, the actions they can perform and the characteristics of the environment that surrounds them. They introduce a general scheme to build ABMS: ERA, the Environment-Rules-Agents scheme, in which the environment represents the context through rules, general data and the agents. Agent behaviour is defined by two types of rules: master rules that represent the cognition of the agent called, and maker rules that modify the master rules.

The ERA scheme can be applied to represent a general ABMS of an ED in which the main actors may be patients, nurses, doctors and managers, each with basic tasks to perform. Patients arrive at the department and can stay or leave, most likely based on their own preferences or conditions. Those who decide to stay may need to wait at any point of the process if the for their service are not yet correct. Patients also engage in diverse activities, some of which involve other patients and many of which involve clinicians and department resources. Nurses triage patients and that triage depends on the condition of the patients, and may need to be present during treatment, assessment or reassessment. As with doctors, nurses may need to multi-task, seeing multiple patients at the same time. Doctors assess, treat and reassess patients, if necessary and these tasks may depend on factors such as: patient condition, time of the day, patient's time in the system, internal regulations and standards imposed by the department and personal attitudes. Therefore when doctor is choosing a patient to asses may consider not only the clinical priorities of patients but these other factors too. As with nurses, doctors may switch between patients to see multiple patients simultaneously.

4.3 Conceptual modelling: ABMS implementation

The context contains the different agents which interact to each other using the environment: for example Patients, Nurses, Doctors and the Department (which plays the role of manager). Each agent has simple rules of behaviour. For instance, a particular doctor may choose a patient based on a set of specific master rules based on the condition of the patient and the time spent by that patient within the department. However, that doctor can adapt or learn from the system and modify those rules using a set of maker rules. Figure 2 shows a simple ERA scheme for an Emergency Department model.

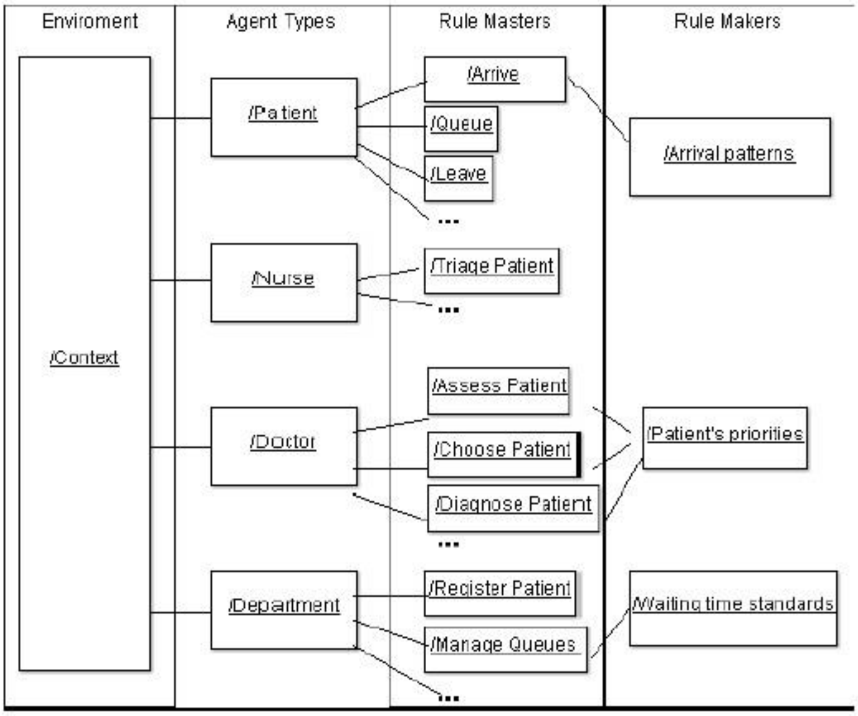

Figure 2: ERA scheme for an Emergency Department

Once the agents and their behaviour are defined, it is necessary to develop a model detailed conceptual representation that can form the basis for model coding. ABMS are usually implemented in an object-oriented platform, for which UML is a generally accepted form of conceptual representation. (Bauer and Odell 2005). An advantages of using UML in modelling is that its symbols facilitate the verification and validation process, moreover the use of an internationally standardized language can elicit common understanding among different stakeholders (Martin et al. 2011).

UML 2.0 includes thirteen types of diagrams to represent static application structure, behaviour and interactions (Onggo 2010) of which Use Case Diagrams, State Diagrams, Activity Diagrams, Class Diagrams, and Object Diagrams appears useful in ABMS (North and Macal 2007). Onggo (2010) suggests, in addition, that Sequence Diagrams and Collaboration Diagrams can be also used to represent interactions of the model.

Use Case Diagrams provide a specification of actions that agents can perform with outside actors (Odell, Van Dyke Parunak, and Bauer 2001) as shown in Figure 3.

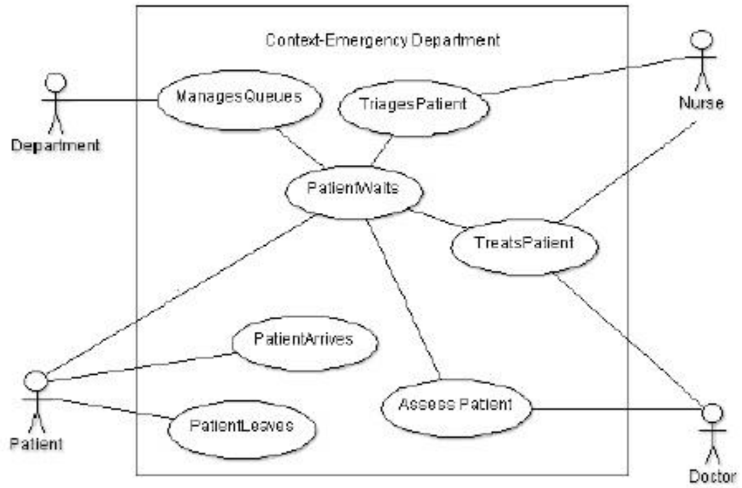

Figure 3: Example of a Use Case Diagram for an Emergency Department

A Class Diagram can be used to specify the available properties and potential behaviours of agents. This static structure, shows inheritance sources or super-classes. In this example there is a single super-class called *GenericAgent* that possesses general characteristics and methods that are inherited by the sub-classes: *PatientAgent, Doctor, Nurse and Department*. Those sub-classes also have their own properties and methods (See Figure **4**).

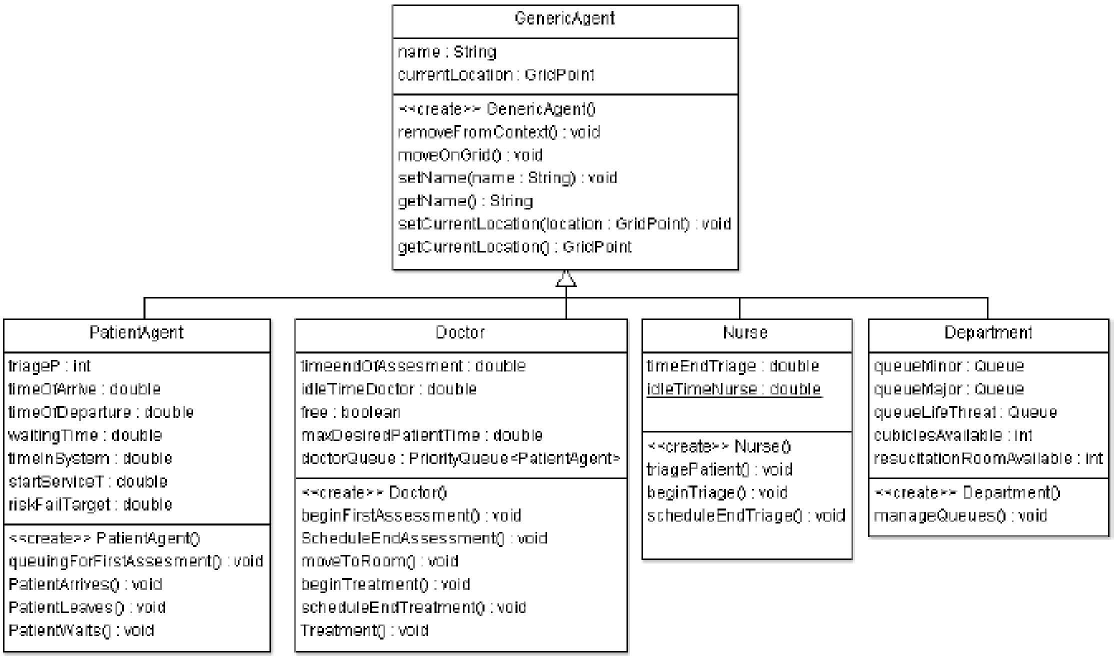

Figure 4: Example of a Class Diagram for an Emergency Department

5 CONCLUSIONS

It seems that there is considerable scope for the use of agent-based simulation approaches in healthcare system modelling, though there are very few reports of its use. Such models sit between the detail that is possible in a discrete event simulation and the broader treatment of system dynamics models. This paper has provided a general description of the possible potential of ABMS in healthcare, linking this to different modes of model use. Given the importance of human interaction and intention in emergency care, there is an opportunity for people skilled in agent-based modelling and simulation to make a contribution towards its improvement.

As with all approaches to computer simulation, before descending into model coding, it seems important to dwell on the conceptualisation of a model, though there is, as yet, no widely agreed approach to this for ABMS. As shown here, UML-based multi-facetted representations have much to commend them, given the somewhat complex interactions and behaviours to be represented in an ABS model and the need to link agent classes to their behaviours, whilst maintaining a conceptual distinction between the agents and their behaviours..

AMBS software support is continually improving, ranging from simple systems such as NetLogo and fully configured toolkits such as Repast Simphony. The latter includes some tools to support graphical model building, but these are nowhere near the level of sophistication and ease of use enjoyed by developers of discrete event and system dynamics simulations.

This suggests that more widespread use of agent-based approaches in healthcare system simulation will depend on the development of better and more widely adopted conceptualisation and implementation tools. It will also depend on the availability of trained modellers, though it seems likely that this will in turn depend, in part at least, on developments in conceptualisation and implementation.

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APPENDIX B: ABMS SIMULATION OBJECTS

Table B1. Description of the simulation objects

Classes	Superclass	Function	Variables
AEContextBuilder	Object	Creates the environment by adding a grid projection, the agents and initial model configuration.	
SimObject	Object	It is the superclass of all the objects of the simulation.	**protected** String id; **protected int** idNum; **protected** Grid<Object> grid; **protected** GridPoint loc; **protected** Context<Object> context; **protected static double** *minute*; **protected static int** *hour*; **protected static int** *day*; **protected static int** *week*;
Administrator	SimObject	It controls the time flow in the simulation, searches available resources and obtains information of all the patients at any time.	
Resource	SimObject	It defines the resources of the simulation such as triage, tests and treatment cubicles.	**private static int** *count*; **private boolean** available; **private** String resourceType; **private static int** *countTypeCubicle*; **private int** numAvailableXray; **private int** numAvailableTest;
Queue	SimObject	It defines the queues of the model.	**private** LinkedList<Patient> queue; **private int** maxInQueue; **private double** maxWaitTime; **private double** meanInQueue; **private double** meanWaitTime;

Classes	Superclass	Function	Variables
			private int totalInQueue; **private double** totalWaitTime;
AmbulanceIn	SimObject	Represents the entry point of the patients arriving by Ambulance.	
WalkInDoor	SimObject	Represents the entry point of the patients arriving by walking.	
Exit	SimObject	Represents the exit point of the patients.	
Agent	SimObject	It is the superclass of all the agents of the model. It defines the method : *moveTo(GridPoint);*	**protected** Resource myResource;

Table B2. Description of the agents.

Classes	Superclass	Function	Variables

Patient	Agent	The methods that represent their behaviour are:
		joinQueue(Queue);
		decideWhereToGo();
			private boolean needsTests;
			private int totalNumTest;
			private boolean wasInTest;
			private boolean wasInXray;
			private int totalProcesses;
			private Doctor myDoctor;
			private Nurse myNurse;
			private Resource myBedReassessment;
			private QueueSim currentQueue;
			private boolean waitInCublicle;
			private boolean backInBed;
			private String typeArrival;
			private int triageNum;
			private double queuingTime;
			private double timeInSystem;
			private boolean isInSystem;

Classes	Superclass	Function	Variables
			private boolean hasReachedtarget;

Staff	Agent	It is the superclass of the Clerk, Nurse and Doctor agents. The methods that represent all the agents' behaviour are:
		scheduleWorkShift();
		startShift();
		endShift();
		engageWithPatient();
		releaseFromPatient();
		findCubicle();
		decideWhatToDo();
			protected boolean available;
			protected int initPosX;
			protected int initPosY;
			protected int numAvailable;
			protected boolean inShift;
			protected double timeInitShift;
			protected float [][] myShiftMatrix;
			protected float [] durationOfShift;
			protected int requiredAtWork;
			protected double nextEndingTime;
			protected int multiTaskingFactor;
			protected int typeOfStaff;

Clerk	Staff	The clerk is in charge of registering the patients. Their behaviour is represented in the methods of its superclass and in the method: registerPatient();	
Nurse	Staff	The nurse is in charge of triaging the patients. Their behaviour is represented in the methods of its superclass and in the methods: triagePatient(); engageWithPatient();	
Doctor	Staff	Represents the doctors of the department. Their behaviour is represented in the methods of its superclass and in the method: searchWhoToHandOv er ();	**protected static final** LinkedList<Patient> *patientsForReassessment*; **protected** PriorityQueue<Patient> myPatientsInBed; **protected** LinkedList<Patient> myPatientsBackInBed; **protected** ArrayList<Patient> myPatientsInTests; **protected** ArrayList<Patient> allMyPatients;

Classes	Superclass	Function	Variables
			protected boolean isAtDoctorArea; **protected double** timeEnterSimulation; **protected** Patient myPatientCalling; **protected** Doctor doctorToHandOver;
Sho	Doctor	Represent the junior doctors. Their behaviour is represented in the methods of its superclass.	
Consultant	Doctor	Represent the Consultant. Their behaviour is represented in the methods of its superclass.	

APPENDIX C: SENSITIVITY ANALYSIS RESULTS FOR ABMS_A&E

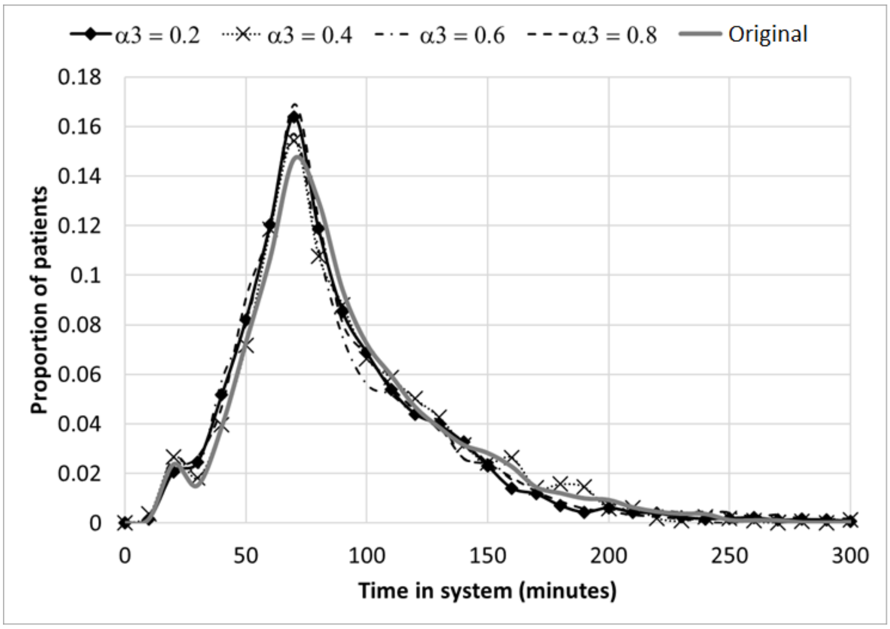

Figure C1. Results for sensitivity analysis on parameter $\alpha 3$.

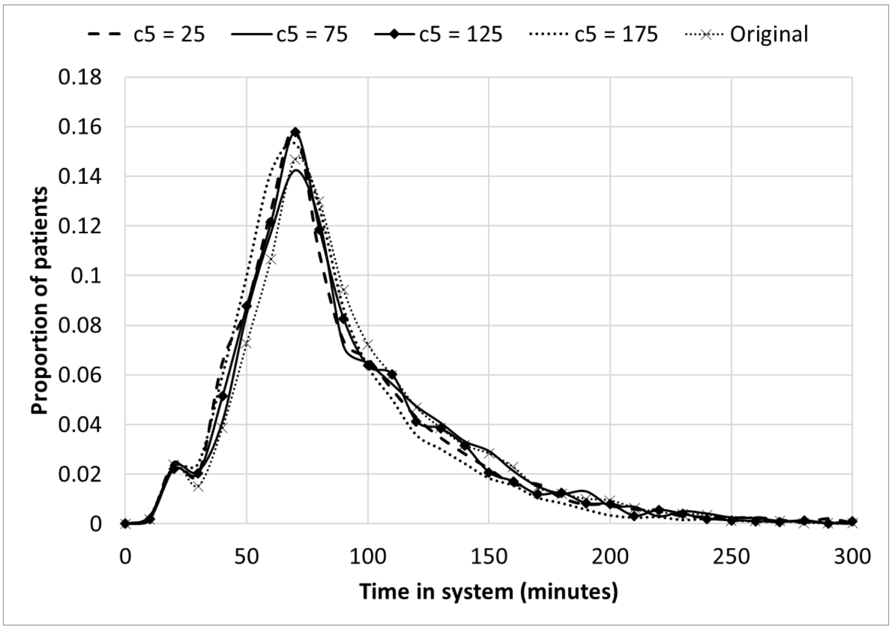

Figure C2. Results for sensitivity analysis on parameter c5.

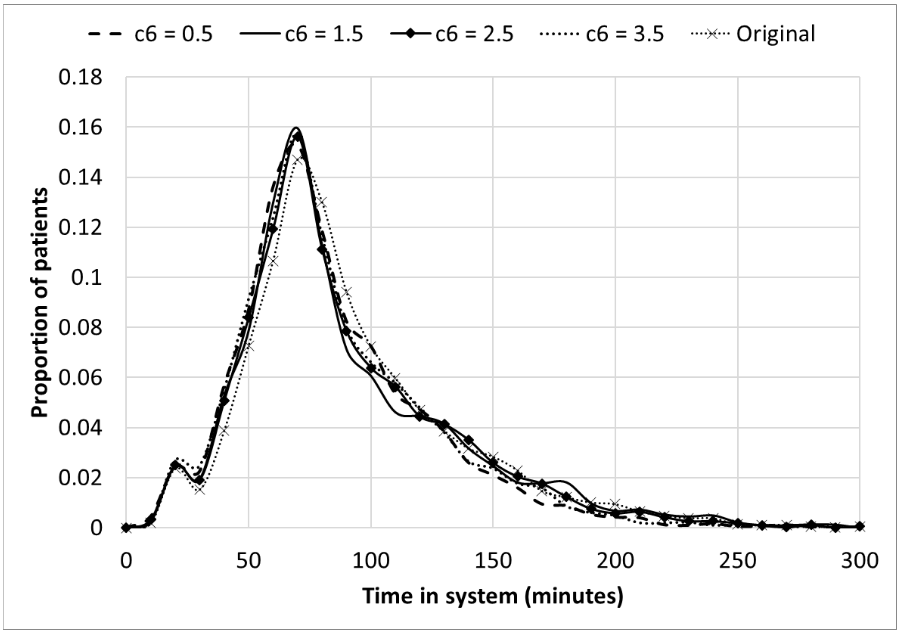

Figure C3. Results for sensitivity analysis for parameter c6.

APPENDIX D: SENSITIVITY ANALYSIS RESULTS FOR DES_A&E

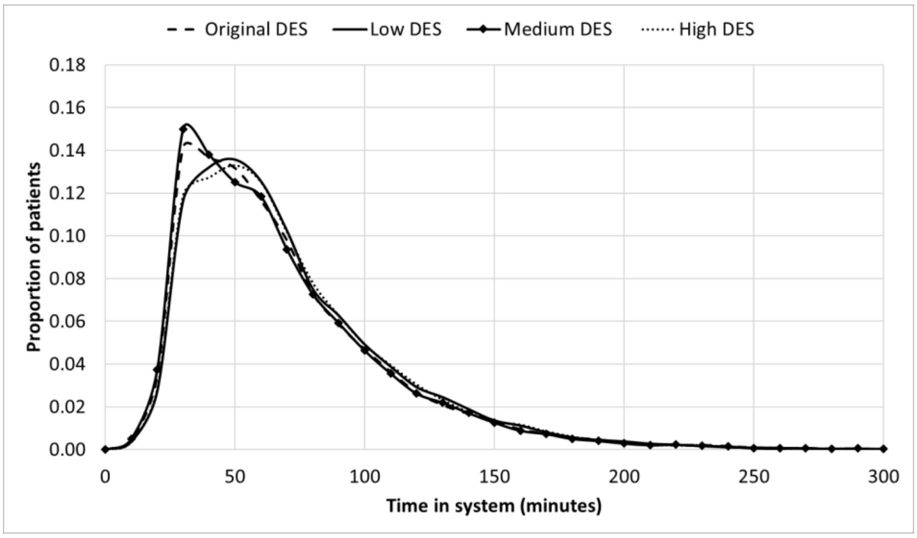

Figure D1. Results for sensitivity analysis of doctors' level of experience.

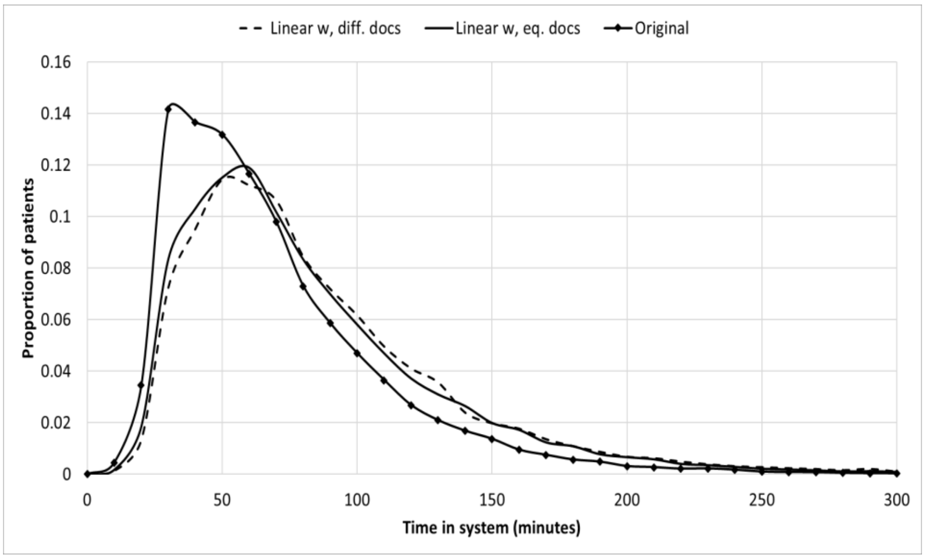

Figure D2. Impact of using linear functions on Dependent Variables.

APPENDIX E: VL SECTION DOCTOR1 ON RELEASE LOGIC

```
 'Setting PECS parameters
  SET P_C1  =  SS_DataDoctors[2,2]
  IF DAY[Simulation Time]  =  1
    SET P_C2  =  SS_ShiftsDurations[2,2]
  ELSE IF DAY[Simulation Time]  =  2
    SET P_C2  =  SS_ShiftsDurations[2,3]
  ELSE IF DAY[Simulation Time]  =  3
    SET P_C2  =  SS_ShiftsDurations[2,4]
  ELSE IF DAY[Simulation Time]  =  4
    SET P_C2  =  SS_ShiftsDurations[2,5]
  ELSE IF DAY[Simulation Time]  =  5
    SET P_C2  =  SS_ShiftsDurations[2,6]
  ELSE IF DAY[Simulation Time]  =  6
    SET P_C2  =  SS_ShiftsDurations[2,7]
  ELSE IF DAY[Simulation Time]  =  7
    SET P_C2  =  SS_ShiftsDurations[2,8]
  SET E_C3  =  SS_DataDoctors[2,4]
  SET C_C4  =  SS_DataDoctors[2,5]
  SET S_C5  =  SS_DataDoctors[2,6]
  SET S_C6  =  SS_DataDoctors[2,7]
  SET E_Alpha1  =  SS_DataDoctors[2,8]
  SET C_Alpha2  =  SS_DataDoctors[2,9]
  SET S_Alpha3  =  SS_DataDoctors[2,10]

'Calculate PECS variables
  SET P_X1SHO1  =  P_X1SHO1+1
  SET P_X2SHO1  =  [Simulation Time-VarStartShiftD1]/60
  IF At_Triage  >  E_X3SHO1
    SET E_X3SHO1  =  At_Triage
  SET PhysicalD1  =  [P_C1*P_C2]/[[P_C1*P_C2]+[P_X1SHO1*P_X2SHO1]]
  SET W1SHO1  =  1/[1+EXP[0+[AlphaZ1W1*[PhysicalD1-CZ1W1]]]]
  Find Maximum Value in Sheet Area   SS_Time[2,2] ,  1 ,  TotalPatients
,  Var_ColActivity ,  Var_RowActivity
  SET TimeQueue  =  SS_Time[Var_ColActivity,Var_RowActivity]
  SET EmotionalD1  =  1/[1+EXP[[E_X3SHO1*[1-PhysicalD1]]*[[TimeQueue/60]-
E_C3]]]
  SET W2SHO1  =  1/[1+EXP[0+[AlphaZ2W2*[EmotionalD1-CZ2W2]]]]
  SET C_X4SHO1  =  [Simulation Time-At_TimeEntry]/60
  SET C_X5SHO1  =  At_numberTest/2
  SET CognitiveD1  =  1/[1+EXP[0-[C_Alpha2*[C_X4SHO1-C_C4]]]]
  SET S_X6SHO1  =  Simulation Time/[[60*24]*7]
  SET SocialExpD1  =  1/[1+EXP[0-[S_Alpha3*[S_X6SHO1-S_C5]]]]
  SET   SocialRepD1     =     1/[1+EXP[0+[[1+SocialExpD1]*[TimeQueue/[60-
S_C6]]]]]
  SET W3SHO1  =  1/[1+EXP[AplhaZ3W3*[CognitiveD1-CZ3W3]]]
  SET W4SHO1  =  1/[1+EXP[0-[AplhaZ5W4*[SocialRepD1-CZ5W4]]]]

'Find maximum intensity -> Decision
  SET maxPECSD1  =  1
  IF W1SHO1  <  W2SHO1
```

```
    IF W3SHO1  <  W2SHO1
      IF W4SHO1  <  W2SHO1
        SET maxPECSD1  =  2
      ELSE
        SET maxPECSD1  =  4
    ELSE
      IF W4SHO1  <  W3SHO1
        SET maxPECSD1  =  3
      ELSE
        SET maxPECSD1  =  4
  ELSE IF W1SHO1  <  W3SHO1
    IF W4SHO1  <  W3SHO1
      SET maxPECSD1  =  3
    ELSE
      SET maxPECSD1  =  4
  ELSE IF W1SHO1  <  W4SHO1
    SET maxPECSD1  =  4
```

'Update behavior based on decision

```
  IF maxPECSD1  =  1
    Set Availability Percentage    SHO1 ,  0
    SET SHO1.Max Available  =  0
    Schedule Event    StopWorkD1 ,  5
    SET V_AvgTreatR  =  27
    SET V_ModTreatBG  =  20
    SET V_ModTreatYO  =  38
    SET V_SDTreatR  =  16
    SET V_maxTreatBG  =  55
    SET V_maxTreatYO  =  30
    SET V_minTreatBG  =  5
  ELSE IF maxPECSD1  =  2
    SET V_AvgTreatR  =  Data_Simulation[15,7]
    SET V_ModTreatBG  =  Data_Simulation[6,7]
    SET V_ModTreatYO  =  Data_Simulation[9,7]
    SET V_SDTreatR  =  Data_Simulation[16,7]
    SET V_maxTreatBG  =  Data_Simulation[4,7]
    SET V_maxTreatYO  =  Data_Simulation[10,7]
    SET V_minTreatBG  =  Data_Simulation[2,7]
```

Daemon actions

```
  SET SS_PECS_D1[1,1]  =  "SimulationTime"
  SET SS_PECS_D1[2,1]  =  " P"
  SET SS_PECS_D1[3,1]  =  " E"
  SET SS_PECS_D1[4,1]  =  " C"
  SET SS_PECS_D1[5,1]  =  " S"
  SET SS_PECS_D1[6,1]  =  " TimeInSys"
  SET SS_PECS_D1[7,1]  =  " w1"
  SET SS_PECS_D1[8,1]  =  " w2"
  SET SS_PECS_D1[9,1]  =  " w3"
  SET SS_PECS_D1[10,1]  =  " w4"
  SET Var_RowD1  =  Var_RowD1+1
  SET SS_PECS_D1[1,Var_RowD1+1]  =  Simulation Time
  SET SS_PECS_D1[2,Var_RowD1+1]  =  PhysicalD1
```

```
SET SS_PECS_D1[3,Var_RowD1+1]  =  EmotionalD1
SET SS_PECS_D1[4,Var_RowD1+1]  =  CognitiveD1
SET SS_PECS_D1[5,Var_RowD1+1]  =  SocialExpD1
SET SS_PECS_D1[6,Var_RowD1+1]  =  TimeQueue
SET SS_PECS_D1[7,Var_RowD1+1]  =  W1SHO1
SET SS_PECS_D1[8,Var_RowD1+1]  =  W2SHO1
SET SS_PECS_D1[9,Var_RowD1+1]  =  W3SHO1
SET SS_PECS_D1[10,Var_RowD1+1]  =  W4SHO1
```

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