DOCUMENTED PATIENTS' JOURNEYS THROUGH AN EMERGENCY DEPARTMENT AS THE BASIS FOR A DISCRETE EVENT SIMULATION MODEL USING DATA FROM UNIVERSITY OF BENIN TEACHING HOSPITAL (NIGERIA) AND MANCHESTER ROYAL INFIRMARY (UNITED KINGDOM)

A THESIS SUBMITTED TO THE UNIVERSITY OF MANCHESTER FOR THE DEGREE OF

DOCTOR OF PHILOSOPHY

IN THE FACULTY OF ENGINEERING AND PHYSICAL SCIENCES

2015

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Final Word Count: 62,511

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ABSTRACT

This work compares the procedures used in the Emergency Departments in the University of Benin Teaching Hospital (UBTH) in Nigeria and in Manchester Royal Infirmary (MRI) in the UK. It goes on to develop a discrete event model of the latter in Rockwell Arena®.

Raw data from UBTH were obtained over a number of visits by interviewing senior administrators, clinicians and nursing staff and by tracking patients over a period of 2 months between 1 July and 29 August, 2011. Information from MRI was supplied through an approved ethical protocol to the National Research Ethics committee (REC Reference 13/NN/0175, IRAS ID 124168, dated March 4, 2013). This embraced patient journeys, locations, investigations and tests for the 98236 patients who attended the ED between April 2012 and March 2013. These (anonymised) data were obtained as spreadsheets from the original Symphony® records, which were then manipulated and analysed using the computer language, R. Anecdotal information on ED operations, patient flow and procedure duration times were also obtained from ED staff.

All of this information identified similarities and differences between patient journeys in the two hospitals and were used to generate appropriate process maps. Proposals were made to improve the recoding and maintenance of patients' records in UBTH.

In the case of MRI, each patient's journey was expressed as a journey-string, which was an ordered list of locations and milestones derived from the time-stamps recorded in the original spreadsheets. A large transition matrix (168 by 168) was generated from the set of journey strings and established the probability of a patient going from one location to any another. This reflects all the decisions which were made at each step of the patient's journey. The number of destinations from a particular source reflects the options available at a particular instant in time, while the size of each probability reflects the preferred destination. The transition matrix together with the duration and resource requirement of the process associated with the destination is the key to the generation of a process map for each journey through the system. This methodology is original and can be applied generally. This was used as a basis for the journey-path model.

In the final MRI model the 4h deadline was not included since the mechanism for its actual implementation was somewhat vague. Instead some isolated models based on patients' priorities and resource re-allocation were described. From these it was inferred that changing the priority of a patient may not in itself be sufficient to alter the journey profile and in order to do so resources must be re-allocated. The only alternative would appear to be the fast-tracking of patients.

DECLARATION

No portion of the work referred to in this thesis has been submitted in support of an application for another degree or qualification of this or any other university or other institute of learning.

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DEDICATION

I dedicate this work to my hardworking mother (***Rose Ugbi***), wonderful father (***Bernard Ugbi***) and loving husband (***Beluolisa Anene Okonkwo***).

Above all, I dedicate this thesis to the Almighty God, who made its accomplishment possible.

ACKNOWLEDGEMENTS

Without the support of some amazing people, this work would not have been completed. Firstly, I wish to express my profound gratitude to Dr Jim Methven, who not only served as my supervisor, but also challenged and encouraged me throughout my academic program at the University. This research would not have been completed without his continuous guidance.

Special thanks to The Schlumberger Faculty for the Future Foundation who solely sponsored my PhD and made it possible financially. I also wish to appreciate Regina Hand of the Foundation for her role in ensuring proficient funding to complete this work. I also wish to thank Dr Richard Body, Ian Baskerville and Jonathan Smith (Manchester Royal Infirmary), as well as Dr Pius Irigbhogbe (University of Benin Teaching Hospital) for providing data and information for this work. I am grateful to Engr. Peter Olagbegi (University of Benin, Nigeria) and Prof Paul Mativenga (University of Manchester) for their academic advice, motivation and support during this research. I wish to thank Jon Santavy of Rockwell's Arena Simulation Products and Services, and Gerbert Heijkoop of Systems Navigator for providing the software used for building and simulation of the model. I thank Michelle Williams from Rockford Memorial Hospital for the guided tour around the emergency department of the hospital.

I specially appreciate my soul mate and precious husband for his infinite love, support, inspirational counsel, understanding and prayers. Even when I was stressed he constantly found a way to make me feel better and put a smile of my face. I appreciate my lovely parents and sisters; Ifunanya, Oghenekome, Victoria, Oghogho and Grace, and extended family for their undying love and prayers throughout this study. I am grateful to my inspiring mother-in-law (Ifeyinwa Okonkwo), father-in-law (Samuel Okonkwo), amazing sister-in-law (Amalachuckwu Ibeneme) and wonderful brothers-in-law (Oseloka and Obumneme Okonkwo) for their consistent support, motivational counsel and prayers. I wish to particularly thank Oseloka for his role in the successful visit to Rockford Memorial Hospital. I appreciate Chukwunonso Ugwu for his prayers and messages. May God continually bless you.

I also thank Dr Ekenedilichukwu Illechie for her assistance during data collection at University of Benin Teaching Hospital. I wish to thank my friends and colleagues; Jennifer Cook, Awo King-Hans, Saran Toure, Nneamaka Ofime, Awajiokiche Ujile, Nike Adeyemi, Christine Mwangi, Leila Abouba, Happiness Daher-Ebhohon, Afokeoghene Afimoni, Ifeanyi Maria Oduah, Farah Aboubakar, Mariam Nuhu, Elizabeth Chike, Blessing Bassey, Adetokunbo Bakenne, Dr Roland Ukor, Tina Nzekwe, Dr Vincent Balogun and Omonigho Otanocha for the different roles they played during the course of this research.

Finally, I wish to thank my lovely Illinois families, especially Angela Olieh, Sue and Dan Rotzoll, Mary Agasi, Osa Basil Kunume Onwueme, and Sandra Ibe for their motivational messages, prayers and for also playing roles in making my write-up period enjoyable.

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She also gained her master's degree at the University of Manchester in Advanced Manufacturing and Systems Management. Her dissertation was on the Simulation of the Extrusion plant of a manufacturing company - Quantum Profile Systems Limited (QPSL), located in Oldham Manchester. This project used Rockwell Arena® software to create a discrete event model of a First-In-First-Out operation taking account of the order arrival times, profile shapes, colours, purge time, tool-change time, and order quantity. She gave recommendation for better efficiency of the plant. During her master's degree, she was a Student Representative at the University.

Her undergraduate degree was in Production Engineering from The University of Benin, Nigeria. Her degree project was on the Experimental Sanding Sealer Formulation using Locally Sourced Raw Materials.

CHAPTER 1 INTRODUCTION

1.0 Outline of the Research

The emergency department (ED) is the "*shop window*" of acute hospitals and is part of the hospital most closely in contact with the public as it offers the most informal access (Sakr and Wardrope, 2000). There are no pre-booked appointments and patients present randomly at discrete times. There are many compounding factors involved with treatments in emergency departments and its daily running involves the coordination of machines, people and resources.

With increasing population and increasing demands for medical care, Emergency Departments (EDs) worldwide have seen immense increase in patients visits over the past decade (HSCIC, 2013). This increase has led to issues such as Emergency Department (ED) overcrowding, long waiting time, long length of stay (LOS), insufficient staff, and patients leaving without being seen due to long queues (reneging) or long waiting times (balking) (George et al., 2006). There is therefore a need for comparative studies both locally and internationally to account for avoidable areas of delay in the care of emergency patients, harness these perplexing problems, and hence improve the overall quality of healthcare (Elkum et al., 2011). This has led to significant investigations by healthcare professionals and academics, in an attempt to reduce the problems and strive for possible solutions. The performance measures of an emergency department are tightly bonded and dependent of each other. A positive change in one is obtained only by a negative change in one or both of the others; this is known as the "Iron Triangle" (Roberts, 2011). Yet, the UK NHS has set standards which include 95% of patients not spending more than 4-hours from arrival to discharge, cost minimisation, a minimum of 28 days for re-admission after discharge, patients satisfaction and quality of care (Department of Health, 2013, NHS England, 2013); all of which emergency departments must meet.

The original intention of this research was to gather information from the Emergency Departments at four hospitals in order to create discrete event simulation (DES) models. These were Manchester Royal Infirmary (MRI) in the UK, The University of Benin Teaching Hospital (UBTH), Lagos University Teaching Hospital (LUTH), both of which are in Nigeria, and The Rockford Memorial Hospital (RMH) in Illinois, USA. It soon became apparent that information from LUTH (following a visit) and RMH would be difficult to obtain and hence the study focussed on UBTH and MRI.

Insufficient and poor data from UBTH made the generation of a DES model impossible, although enough information was provided for the generation of an informed comparison with MRI (Chapter 4). The data which were acquired are discussed in detail in Chapter 5.

Much of the research was devoted to the analysis of the data from the ED at MRI. The main reason for this was the desire to generate a model which was evidence-based rather than one which relied on anecdotal information from clinicians and other medical staff. The analysis of the data is described in detail in Chapter 6. A DES model of the ED at MRI was generated (Chapter 7). The 4 hour deadline is considered separately in Chapter 8.

In Nigeria, Emergency Department (ED) is known as the Accident and Emergency (A&E) department while in the UK, rather the term A&E is gradually phasing out and Emergency Department is being used. Consequently, the words “Emergency Department” and “Accident and Emergency Department” will be used interchangeably throughout this thesis.

1.1 Aim and Objectives

This work sets out to document and to compare the procedures that are used in the emergency departments of University of Benin Teaching Hospital (UBTH) and Manchester Royal Infirmary (MRI) using primarily historic (documented) data from the hospitals. These data were gathered directly by the author by tracking patients in UBTH, and made available as spreadsheets from MRI. In both facilities, information on resources, staffing, locations, etc. were provided by medical staff. Anecdotal information from emergency department (ED) staff was also gathered.

The raw data from MRI was manipulated in R and used to create a discrete event simulation (Rockwell Arena®) model. The model focuses on the activities, throughputs and resource utilization in the ED of Manchester Royal Infirmary. The target is to make this an evidenced-based model, with minimal reliance on anecdotal data from staff. To the knowledge of the author, this work is the first study of the ED at MRI and indeed some of the findings from the analysis of the data obtained from MRI were new to ED staff. The aim of this research is achieved based on the following objectives:

I. Carry out extensive literature survey on the healthcare systems – United Kingdom and Nigeria specifically, with comparison to overseas in some context.
II. Visit and observe the emergency department of Manchester Royal Infirmary
III. Conduct relevant interviews with staff of Manchester Royal Infirmary
IV. Collect recorded data from the emergency department of Manchester Royal Infirmary (MRI)

V. Carry out comprehensive analysis of obtained data using R studio and compare with the data reported by Hospital Episode Statistics (HES) (which is a UK government's data warehouse)
VI. Create a discrete-event model based on the real data collected from Manchester Royal Infirmary (MRI)
VII. Visit and observe the emergency department of University of Benin Teaching Hospital (UBTH)
VIII. Conduct interviews with staff in the ED of UBTH
IX. Collect data from UBTH and carry out analysis
X. Carry out a comparative report on information obtained from both UBTH and MRI

1.2 Scope of the research

A walk-in centre is situated in the ED of MRI known as the Primary Care Emergency Centre (PCEC). The PCEC is not considered to be part of the emergency department and therefore is not included in the model. The scope of this study considers the time period from arrival to exit of each patient. Here, "exit" means exit from ED (when the clock stops).

1.3 Simulation of Discrete Systems

Generally, simulation is simply the imitation of a system in an attempt to improve the functionality of that system without affecting the system in real life. As the name implies, a computer simulation is the act of doing simulation on a computer by creating models using one or more simulation tools[1]. Sanchez (2007) described a system as a set of elements that interact or interrelate in some fashion. Simulation can be categorized in terms of system states as dynamic, discrete, deterministic or stochastic (Goldsman, 2007b). Dynamic simulation is when the state of a system changes over time, while in discrete simulation, the state of the system changes due to discrete events (Goldsman, 2007a). This research is focussed on discrete event simulation (DES). Two other simulation techniques currently being exploited in healthcare are System Dynamics (SD) and Agent-based Simulation (ABS). Another growing technique is the combination of two or more simulation techniques in ED problem solving. More details on these three simulation techniques as applied to healthcare systems are discussed in *Chapter 2*. However, since the emphasis here is on DES, for better understanding, a brief general description on this technique is given here.

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[1] *See Chapter 2*

Discrete event simulation is broadly used in industries, businesses, and government organizations (Allen, 2011). The term "discrete event" defines the fact that the system only changes at discrete times, rather than continuously (Altiok and Melamed, 2007). In very general terms, a DES can be used to model a sequence of operations that results in the transformation of an input entity into a (changed) output entity (Kelton et al., 2006). Typically, the sequence involves one or more processes that are performed on the entity as it passes through the system. Each process demands a unique set of resources (people and equipment) and has a particular duration. According to the available number of resources and the rate of arrival of the input entities, queues may form at the various points through the system (Vangheluwe and Naghdy, 1997). The simulation allows the overall transformation to be quantified by calculating the transit time of the entity through the system, the queue parameters and the usage of the resources.

In a typical model, the arrival rate of the input entity is probabilistic as are the durations of each operation and this means that the model has to be run many times (replications) in order to establish statistically robust values for the various outputs (Kelton et al., 2006). For example, this work has shown that the arrival times are non-stationary over time and that using a single distribution is inaccurate (Banks, 1998).

By running different scenarios (input parameters) a robust DES model is a highly effective tool for optimising the use of resources and manipulating queues. DES models are used widely to complement analytical models in manufacturing, assembly, healthcare and logistics (Banks, 1998). Queues are generally formed in discrete systems as entities have to compete for limited resource. Typical examples of a discrete system include a call centre, manufacturing plant and hospital (Banks, 1998). These systems are made up of entities which have one or various attributes and resources.

In a call centre for example (Kelton et al., 2006), the customers' calls are the entities and the operators are resources. Here, customers call at discrete times and each call utilizes one from a finite number of operators. If all the operators are busy, subsequent customers' calls will be placed in a queue until an operator is free. The first customer on the queue will then be served and so on. This is similar in typical manufacturing plant. For example, an extrusion plant, the raw material represents the entity while the extruder is the resource. Assuming that the raw materials are in three sets (which could be based on their colour attribute; say, green, black and white). Raw material is fed into the extruder, one set at a time, while the others wait until the extruder is free. In this example, the extruder is not the only resource; an operator could also be a resource, if the extruder is not automated. In the case of the call centre example above, the trunk line (through which the call reaches the operator) could also be a resource. In both examples, the queue only decreases when an entity leaves the system, which happens at discrete times.

In an emergency department (Altiok and Melamed, 2007), the various elements that make up the chain of patient arrival (input) – diagnosis/treatment (processes) – discharge (output) can be treated as a paradigm to a typical manufacturing chain which can be represented by raw materials (input) – transformation procedures (processes) – final products (output). In the current study, DES is used to model a sequence of processes that transforms an input entity into an output entity. The sequence involves one or more processes that are carried out on entities (patients) as they flow through the system where each process demands a unique set of resources (staff and equipment) and has a particular duration. Queues may be formed at various processes depending on the arrival rate of input entities and number of resources available. The emergency department is similar to manufacturing system in other ways. For instance, when there is mass casualty from an accident, all available doctors in the emergency department will be required hands-on to treat the patients involved. To do this, they may have to leave the current patient being attended to. This can be associated with the breakdown of machines in a manufacturing system whereby all other jobs are altered (Banks, 1998). A great deal of insight achieved by modelling the chain of processes using DES In the context of manufacture and manufacturing techniques has also been applied with some success in solving healthcare problems (Dickson et al., 2009b, Johnston, 2009, Bowers and Mould, 2005). One significantly increasing technique is the application of operation research tools such as Lean, Six Sigma and Just-in-Time, in solving ED problems (Dickson et al., 2009a, Mandahawi et al., 2010).

1.4 Rockwell's Arena Software

There are other DES software in existence; however Rockwell's Arena version 14.0 is used for this work because it is one of the most widely used and efficient in the context of healthcare (Rojas and Herrera, 2008). Arena simulation software is effective in identifying bottlenecks in processes or systems such as over- or under-utilization of resources and build-ups of queue (Kelton et al., 2006). It also helps to predict the performance of a system based on its parameters such as cycle time, throughput, costs and resource utilization (Altiok and Melamed, 2007). Therefore it can help in the planning of staff, equipment and/or material requirements. Simulation modelling using Arena is popularly done in many industries and manufacturing systems. Also, its application in healthcare simulation has been widely discussed (Altiok and Melamed, 2007, Kelton et al., 2006, Rojas and Herrera, 2008). Arena is widely used because it enables the users design and creates models of a system's processes, simulate these models and test or run the simulations (Allen-

Bradley, 2012). It allows the users visualize a system's operation with dynamic animation graphics. It possess 3D animation graphics ability in the recent version 14.0 (Allen-Bradley, 2012). Arena also has the ability to combine visual (Visual basic application) and textual programming, and has debugging capabilities. It also provides accelerated real-time video re-enactment of simulation over a specified period of time. It also has computationally-efficient input and output analysis capability. It is necessary that a significant number of replication is carried out for each simulation run. This increases the robustness of the output result, such that each replication generates a value for a target output such as a journey time through the system. According to the central limit theorem[2], these averages are distributed normally[3] about a mean (the average of the averages) and their chances can be extracted by the spread of their means (Kelton et al., 2006). The limits of the estimation of the target parameter can then be calculated from these parameters for a given confidence level. Arena reports these limits as the "half-width" in its output and will provide values only if there are enough replications available. It is essential that this half-width is finite; otherwise the results will be misleading.

1.5 Thesis road map

This thesis is structured in eight chapters including this introductory one (*Chapter 1*) which contains the general introduction, aim and objectives of this study, descriptions of discrete event systems, Arena and limitations to this study. One important aspect of this research is the use of simulation and modelling to improve the emergency department. *Chapter 2* presents an extensive literature survey on Simulation and Modelling in healthcare systems. The implementation and benefits of healthcare simulation, especially in emergency departments, is discussed. The three major simulation modelling methods namely; Discrete Event Simulation (DES), System Dynamic (SD) and Agent-based simulation (ABS) are also reviewed. Tools for carrying out successful simulation are also highlighted. A healthcare system constitutes an emergency department, thus it is important to carry out a review on the healthcare systems under study and relate them to healthcare systems in other parts of the world. *Chapter 3* discusses the background and literature review of healthcare system in the UK and Nigeria, with comparison to overseas countries such as the United States of America, Canada, Australia, China, Hong Kong, South Africa, India, Namibia, Madagascar and South Korea. *Chapter 4* gives a comparison between the EDs at UBTH and MRI including the structure and mode of operation based on the data collected and anecdotal

[2] *The central limit theorem explains that for a set of random variables, taking the mean of the samples and plotting the frequencies of the means (averages), gives a normal distribution. See Appendix A for more details.*
[3] *The Student t-distribution can also be used providing the number of degrees of freedom is known*

information. The recorded data and information obtained from UBTH and MRI are parsed using R and presented in *Chapter 5* and *Chapter 6* respectively. Particular issues with the data are also discussed. *Chapter 7* describes the two models; anecdotal-based (called the “Base” model) and evidence-based (known as “Journey-path” model) of Manchester Royal Infirmary using the analysed data from Chapter 6. The 4-hour deadline was not incorporated in the models in Chapter 7, however detailed description on how it can be modelled is provided in *Chapter 8*. *Chapter 9* presents and analyses the outputs from the model. Important details of the thesis is discussed and concluded in *Chapter 10*. Recommended future works are also outlined in this final Chapter.

CHAPTER 2 SIMULATION AND MODELING IN HEALTHCARE – A REVIEW

2.0 Introduction

Simulation modelling is a common paradigm for analysing complex systems (Altiok and Melamed, 2007) and most people are familiar with it. It is used to solve problems that are too expensive, dangerous and complex to solve analytically (Ingalls, 2002). It also provides a means for carrying out analysis of uncertainty (sensitivity analysis) by making changes to the input parameters and measuring the change in output. This gives useful details on what part of a system requires improvement before implementation is carried out in real life. Simulation has many benefits; however its pitfalls are enormous as well which will be summarized later in this chapter.

This Chapter reviews simulation modelling in healthcare systems. It is divided into six sections excluding this introductory one. Section 2.1 reviews literatures on simulation modelling in general with more focus on healthcare systems. Section 2.2 describes the three most popular simulation methods namely; System Dynamics (SD), Discrete-Event Simulation (DES) and Agent-based Simulation (ABS), and their implementation in solving healthcare problems. The combination of these three methods in healthcare is also reviewed. Other techniques exploited for the betterment of healthcare systems is briefly discussed. Section 2.3 outlines some available tools for carrying out simulation studies. The application of simulation studies in emergency departments is examined in Section 2.4. A range of the benefits and challenges of simulation modelling is evident in literatures (Brailsford, 2007, Moscardini and Fletcher, 1991, Parks et al., 2011). These benefits and challenges are summarized in Section 2.5, with reference to personal encounter during this study. Additional note on an analysis result from a short survey carried out by the author in Nigeria on the knowledge and implementation of simulation modelling is described in Section 2.6. The survey was done using a questionnaire which was completed by engineering students of the University of Benin, and medical students and staff of the University of Benin Teaching Hospital (UBTH).

2.1 Simulation and Modelling in Healthcare systems

There is agreement (Banks, 1998, Owen and Jones, 1994) that the word simulation means imitation of a process or system over time. Simulation is done to analyse present and future performance of a system, to understand complex relationship and identify opportunities for improvement. Modelling is the process of creating a simple representation of a complex system in order to be able to predict the system's performance measures in the most optimum way (Altiok and Melamed, 2007).

A simulation model can describe patient flow, medical care delivery process, imitate the process and enable predictions for the purpose of improving the performances of hospitals. It helps healthcare management carry out "what if" analyses and evaluation of the efficiency of the system currently being used (Kelton et al., 2006). Simulation has been widely used for many years in many contexts and this is rapidly increasing. It is now rare to imagine an accredited institution which does not carry out some "kind of" simulation education (Huang et al., 2012). Over 30 years ago, simulation was introduced as a technique for solving healthcare problems and the past few decades have seen a prominent increase of its use in the healthcare sector (Fone et al., 2003).

Proudlove et al (2007) , Goldsmith and Siegel (2012), Barado (2012), Cooper et al. (2007), Brailsford and Harper (2007), Mustafee et al. (2010), Persson and Persson (2010), Roberts (2011) have analysed the application of simulation modelling to healthcare systems. These studies cover healthcare systems design, patient flow, layout & capacity planning, healthcare operations management, ambulance services, emergency services, surgical procedure modelling, epidemic modelling, transplant management, radiology, cancer care, mental health and public health. Roberts (2011) outlined some qualities of simulation that makes it attractive in healthcare systems which include:

- *The uncertain nature of healthcare systems makes simulation able to integrate variability by its handling of random variables and probabilistic outcomes.*
- *Healthcare systems are complex and simulation possesses the ability to simplify this complexity and solving issues relating to it.*
- *The ability to make relevant assumptions where necessary but as minimal as possible.*
- *Its ability to carry out "what-if" analysis. People in healthcare like to experiment and simulation can help them do this.*

Many ongoing simulation conferences, workshops and meetings in healthcare exist and are continually increasing. Conferences include the Winter, Summer, Spring & Autumn Simulation Conferences, SIMULTECH, and Principles of Advanced Discrete Simulation (PADS) Conference, to mention a few. These conferences are mainly organized by simulation societies. Many developed Simulation Societies[4] include the Society for Simulation in Healthcare (SSiH) , INFORMS Simulation Society, The Society for Modelling and Simulation International (SCS) , International Paediatric Simulation Society (IPSS) , The International Society for Human Simulation (ISHS) , Society in Europe for Simulation Applied to Medicine (SESAM) and Dutch Society for Simulation in

[4] *See reference for webpage of each society*

Healthcare (DSSH) . Another forum for improving healthcare is the Cumberland Initiative (The Cumberland Initiative, 2012); which is a combination of academics and medical professionals specializing in simulation, modelling and systems thinking for the purpose of greatly impacting healthcare.

Despite the increasing use of simulation and modelling in healthcare services, the implementation and adoption of simulation to optimize healthcare systems is scant (Brailsford et al., 2009b, Fone et al., 2003). This is due to various barriers associated with it such as lack of simulation awareness, high simulation project costs, lack of skills and expertise, organizational obstacles and technical limitations (Eldabi et al., 2002, van Lent et al., 2012). Kirchhof and Meseth (2012) carried out a survey of these barriers to the adoption of healthcare simulation via an empirical assessment. They found the fundamental one to be the lack of awareness of the benefits of simulation as a method to help in making decision and planning processes[5]. Jahangirian et al. (2010b) proposed a 2-by-2 matrix framework to demonstrate the cost-effectiveness of simulation modelling associated with the three main aspects of healthcare systems; logistics, training and physical design. Their study showed that healthcare logistics costs demonstrated the highest cost-effectiveness, hence could be a source for minimising cost in simulation modelling projects than in the other sectors. Another interesting barrier is the problem of gaining access to stakeholders in healthcare, although identifying who they are, is the key issue (Brailsford et al., 2009a). Ways of overcoming these barriers to improve implementation of recommendations from simulation studies have been reviewed in literatures (van Lent et al., 2012, Brailsford, 2005, McHaney and Cronan, 2000, McHaney et al., 2002).

Other barriers that are rarely acknowledged to the adoption of simulation and modelling in healthcare are the lack of ease in accessing data and lack of complete data. Obtaining complete data for creating the model was a huge challenge during this research. In particular, this is key to the outcome of the model and discussed in more details in Chapter 6. It is surprising that studies in literature that applies computer modelling to healthcare do not contain the data used in carrying out the simulation.

2.2 Simulation Methods

Klein et al. (1993) carried out an extensive literature survey on simulation methods, software reviews, vendor surveys, list of recent simulation text books, operational healthcare systems applications, medical decision-making applications and systems dynamics models. Various

[5] *This study was restricted to the German healthcare institutions and may not apply to other countries*

methods have been used to carry out simulations in healthcare systems, however, the three major methods associated with healthcare are Discrete-Event Simulation (DES), System Dynamics (SD) and Agent-based Simulation (ABS) (Forsberg et al., 2011). The earlier two are said to be the most effective due to their ability to model the high complexity and variability associated with healthcare systems (Banks, 1998). These methods are briefly described below; more detailed descriptions can be found in Banks (1998).

2.2.1 Discrete-Event Simulation (DES)

A discrete-event simulation imitates the behaviour of a system whose state changes at discrete points in time (Banks, 1998). Ingalls (2002) explained the structural components of discrete-event simulation which includes; entities, activities and events, resources, global variables, random number generator, event calendar, system state variables and statistics collectors. A wide range of literature review on the use of Discrete-event simulation modelling in healthcare systems have been carried out (Günal and Pidd, 2010). Discrete-event simulations are arranged according to several paradigms: scheduled events, interacting processes and activity scans (Balci, 1988).

DES models are computer programs that model the logical flow of complex processes occurring at discrete times and use random numbers to mimic the inherent variability in them (for example arrival and service times) (Banks, 1998). Model validation is performed by modelling processing times with real data, and by checking that the model outputs reasonably match actual system inputs. With a validated DES model, healthcare decision makers can conduct a variety of “what-if” analyses (Kelton et al., 2006). This will enable them to examine how their process might react to changes which may be too costly, time consuming, or dangerous to test with a trial-and-error approach in real life. An example of a discrete-event system is the one under study (the emergency department of Manchester Royal Infirmary). Here, the system consists of discrete unit of traffic (patients) that compete with each other for the use of limited resources (doctors, nurses, bed space) while flowing (patient-flow) from one point to the other within the system (emergency department).

DES allows scenarios involving different resources or procedures to be modelled with little cost and no risk, since modelling will be done on a computer rather than in real life. This is made possible by representing the operation of a system as a chronological sequence of events which occurs at an instant in time and marks a change in the system (Robinson, 2004). Several health care administrators have used discrete-event simulation as an effective tool for allocating scarce resources to improve patient flow, while minimizing health care delivery costs and increasing patient satisfaction (Robinson, 2004). The rapid growth in DES software technology has created many opportunities for new application, including more sophisticated implementations, as well as combining optimization and simulation for complex integrated facilities (Jun et al., 1999).

DES has become a powerful tool that has been applied to many other industries including manufacturing, banking, transportation, and call centres, as well as natural systems in physics, chemistry, biology, and economics (Werker et al., 2009). DES is without doubt the most widely used simulation method, especially in complex systems such as the healthcare system, due to its stochastic element (Werker et al., 2009). It is said to be the foundation for agent-based modelling, although, the accuracy of discrete event simulations can often be misleading considering the level of assumption-making that is normally required for model building (Allen, 2011). A wide application of discrete event simulations have been discussed in many literatures (Ceglowski et al., 2007, Knight et al., 2012, Zhu et al., 2012, Parks et al., 2011) as well as Winter Simulation Conference (WSC) proceedings (See References). McHaney and White (1998) proposed a theoretical structure of assumptions, principles and rules for DES software selection profiling. The study indicates a number of factors relevant to a decision on which type of software tool might be selected to conduct a given project. More detail on DES and its software packages are discussed in section 2.3.

2.2.2 System Dynamics (SD)

System dynamics is a popular method for modelling continuous systems (Gunal, 2012). Professor Jay Forrester of the Massachusetts Institute of Technology is known as the “father” of system dynamics (Forrester, 1989). SD is *the study of information-feedback characteristics of industrial activity to show how organizational structure, amplification , and time delays interact to influence the success of the enterprise* (Borshchev and Filippov, 2004). Feedback-loop concept is an important feature of system dynamics and is represented by casual relationships; which can be positive or negative. For example, it can be said that “specialty ward” affects “bed occupancy” positively (Gunal, 2012).

SD utilizes deterministic approach to study the behaviour of complex systems and evaluates the cause-and-effect relationship in a system, thus helping to understand how systems change over time (Gunal, 2012). The main concept of SD is to observe and understand the entities and variables in a system, which usually have strong interactions with each other. System dynamics is common in Automation/Systems/Control engineering, economic and ecological systems (Karnopp et al., 2000). Most SD models in healthcare are either used for persuasion purposes or for providing a framework for evaluation; thus are appropriate for studying the inter-relationship between elements of healthcare systems (Gunal, 2012).

As noted by Brailsford et al. (2010), SD models tend to look at strategic-level problems, whereas DES is used for operational-level problems. Researchers in healthcare have combined systems dynamic with discrete-event model for simulation but it has never been used as a stand-alone method. The hybrid of these two methods has been discussed briefly in section 2.2.4. For more detailed description see (Brailsford, 2008, Roberts et al., 1983, Moscardini and Fletcher, 1991)

2.2.3 Agent-based Simulation Modelling (ABSM)

Macal and North (2011) presented an introductory tutorial on ABSM at the 2011 Winter Simulation Conference held in Phoenix, Arizona. They defined ABSM as a method used to construct computational devices, known as agents (with some attributes or properties), which are then simulated in parallel. Agents are like entities in a DES model; however here, they are social and interact with others, live in an environment, and their next actions are based on the current state of the environment (Gunal, 2012). According to Allen (2011), three ideas central to agent-based models are social agents as objects, emergence, and complexity. Thus, the entities in the system are not merely passive objects, but active learning interactive agents. Agent-based models, therefore, are particularly useful for assessing when equilibriums are likely to expire, what transient behaviour can then be expected, what trigger events are likely to promote stability or instability, and how robust the system is likely to be (Macal and North, 2005).

Examples of applications range as far as the spread of epidemics, the threat of bio-warfare, the growth and decline of ancient civilizations, social networks, word-of-mouth effects in marketing, supply chain management, large-scale evacuations, and organizational decision-making (Macal and North, 2009). ABSM is also recently receiving a great deal of attention in the healthcare sector (especially the emergency department) as proven by many recent studies (Rateb et al., 2003, Escudero-Marin and Pidd, 2011, Laskowski et al., 2011, Leykum et al., 2012, Stainsby et al., 2010). Cabrera et al (2012) carried out a study to obtain the optimum staff configuration that will minimize the length of stay of patients in an emergency department (ED) using agent-based modelling. Taboada et al (2011a) proposed an agent-based model (used as a decision support system) as an effective decision making tool to aid ED managers carry out “what if” analysis, using Net Logo. Agent-based modelling offers interesting opportunities but also poses challenges in both debugging and validation due to the complexity of the interactions (Taboada et al., 2011b, Stainsby et al., 2010). Other areas of agent-based simulation application include National security, logistics, transportation, and distribution.

2.2.4 Combining Simulation Modelling Methods

The creation of a model to enable the hybrid of discrete-event simulation (DES) and system dynamics (SD), known as the “holy grail”, is beginning to gain huge attention in healthcare systems simulation (Martin and Raffo, 2001, Brailsford et al., 2010, Venkateswaran and Son, 2005, Chahal and Eldabi, 2008). Brailsford et al. (2010) described the “holy grail” as a simulation method which combines the benefits and virtues of both the continuous approach of SD method and the probabilistic approach of DES method in one model. The advantage of this is to develop a genuine model that will cater for every detail, even the tiniest one, of a system for improved and enhanced decision making process. Pidd (2012) argued that combining other methods with DES should be the norm and not seen as unusual.

Chahal et al (2013) proposed a conceptual framework for hybrid (discrete-event (DE) and system dynamics (SD)) simulation in the healthcare domain. Alzraiee et al (2012) proposed a novel method for synchronizing DE and SD simulation methods on a single platform. Zulkepli et al (2012) also applied both methods to an integrated healthcare system. Agent-based modelling and System dynamics have also been integrated in studies. For instance, Djanatliev et al (2012) combined ABSM and SD to carry out Prospective Health Technology Assessment (ProHTA). Zhang (1999) created a model using both DES technique and System Dynamic approach for the Emergency department (ED) of a National Health Service (NHS) hospital in Northwest England. His model sought to reduce the queuing length of patients. His proposal after this study was the addition of “enough” special nurses, however the cost of staffing was not considered. Is the hospital supposed to employ “more” nurses at any cost? This is where the “Iron Triangle” described by Roberts (2011) comes to play. The development of a hybrid for DES and ABSM is an interesting recommendation for future study.

2.2.5 Other Techniques used for modelling healthcare systems

Besides the use of simulation modelling, studies (Young et al., 2004, Dickson et al., 2009a, Hoot et al., 2008, Mandahawi et al., 2010, Dickson et al., 2009b) have discussed the potential for adopting operation research tools such as six-sigma, lean thinking, forecasting , Linear Programming and theory of constraints in the context of healthcare systems improvement. For instance, Lean thinking, which is a manufacturing approach to identify and minimize waste has been said to be promising for improving quality of care (Johnston, 2009, Young, 2005). The adoption of Lean principles was shown to improve the value of care delivered and significantly increase patient-flow without increasing length of stay (LOS) and as such show an increase in patient satisfaction (Dickson et al., 2009b, Dickson et al., 2009a). Young et al (2004) illustrated the application of three approaches namely; lean thinking, theory of constraints and six sigma. They suggested that the three approaches could minimize waiting time and work environment stress in healthcare systems. LeBaron et al. (2010) suggested a system called "BEQK" (Bedside Registration, Bed-ahead Program, Electronic medical record and Quick Triage Program) as a means to reduce patients' wait time, patients who balked or reneged, and significantly improve patient satisfaction in an emergency department.

2.3 Simulation Tools

Many simulations are carried out using Simulation Programming Languages (SPLs). This includes discrete event simulation languages, agent based and Monte Carlo. Over the past years, many simulation language software have been introduced including Simio, Simul8, Rockwell's Arena, Lanner Witness, ProModel, Any-Logic and FlexSim which are currently used in the simulation of healthcare services (Borshchev and Filippov, 2004). Any-Logic provides for all three major approaches (DES, SD and ABS)[6] while Witness can provide for two (DES and SD) within one model. Net Logo and MASON are agent-based modelling tools. VenSim, PowerSim and iThink serve as SD only Tools while Rockwell's Arena, Simul8, Tortuga and ProModel is used for only DES models (Brailsford et al., 2010). However, Arena allows the exploration of agent-based modelling essentials by assigning rules for specific interactions and entities attributes (properties) (Jajo and Matawie, 2014).

2.4 Simulations applied to Emergency Department (ED)

The emergency department encompasses variability and system interactions. It is therefore very difficult to understand how changes would affect the system without using simulation. Simulation has been used as a method to justify basis for proposing and making change in Emergency services (Johnston, 2009). It is also important in order to identify opportunities to improve patient flow and help identify and observe bottlenecks as well as study ways to reduce them. Recent studies have attempted to use simulation models to reduce patient waiting time, allocate resources, analyse patient flow and improve the overall efficiency of EDs worldwide. Rojas and Herrera (2008) applied Arena 10.0 simulation software to optimize human resource distribution and analyse emergency hospitalization process. Zeng *et al.* (2011) used SIMUL8 to carry out a

[6] *This is said to be the reason for its name: "Any"-Logic*

study to improve the quality of emergency care of a community hospital. Hung *et al.* (2007) used Arena discrete event simulation to model the patient flow in the Paediatric emergency department of the British Columbia Children Hospital (BCCH). Werker *et al.* (2009) applied discrete event simulation modelling to reduce the variability and length of oncologist-related delays, thus improving the planning time for radio-therapy (RT) process. Martin *et al.* (2011) utilized Unified Modelling Language (UML) to model the patient flow of an Australian ED. Sinreich and Marmor (2005) laid a foundation to develop a flexible, easy-to-use simulation tool for analysing general ED performance. The former health minister, Lord Norman Warner stated that NHS Trusts in London, Cardiff, Devon, Lincolnshire and Nottingham have applied computer modelling to tackle major Accident & Emergency department issues, and advised other trusts should follow suit, in using technology to improve healthcare services (The Cumberland Initiative, 2013). By contrast, in the ED, only time-stamps for arrival at each location are recorded, but there is no record of the duration of tasks such as consultation, evaluation, assessment and treatment which take place at these locations. No business could plan for the future, consider expansion or even survive using this approach, yet Government assumes there is sufficient knowledge in and control of ED systems for them to be able to meet targets which include cost minimisation, a total journey time which is less than a prescribed maximum, a minimum re-attendance rate within a prescribed period after discharge, and a satisfaction score that reflects the degree of stress experienced by patients on their journeys through the system (Foundation Trust Network, 2012, Department of Health, 2013).

Literatures have focused on using simulation models to address several issues associated with emergency departments such as long waiting time, overcrowding and quality of care. It is worth reviewing some of the outcomes of these literatures.

2.4.1 Waiting Time

When patient presents at the emergency department, they usually have to wait in a queue as described in Chapter 1. Specifically, as patients flow through the emergency department, for each process where there is a queue; patients have to wait for a period of time before undergoing that particular process. This is due to limited resource in the emergency department. Studies have attempted to reduce waiting time of patients in emergency departments (EDs) using various techniques such as agent-based models, queuing models and ED fast track systems (Lau and Leung, 1997, Laskowski et al., 2009, Mandahawi et al., 2010). Laskowski et al. (2009) applied both agent-based models and queuing models to investigate patient access and flow through an emergency department (ED) in order to reduce patient waiting time. Karve et al (2011) found that longer waiting time was associated with non-ambulance mode of arrival, urban hospitals, or non-emergency triage. They also suggested that long waiting time affects other performance measures such as quality of care, resource utilization and total throughput time. However, ED fast track systems have evolved to improve the management of patients with non-urgent complaints by decreasing waiting time, ED length of stay (LOS) and overcrowding (Quattrini and Swan, 2011), thereby increasing patient and staff satisfaction with quality ED care (Considine et al., 2010). Ardagh et al. (2002) also suggested that triaging trivial ED patients through a rapid assessment clinic will help improve waiting and flow time. In their study carried out in a South African hospital (Bruijns et al., 2008), it was found that an effective triage system helps to reduce waiting times in EDs. Clinical evidence show that a system to inform patients of expected waiting times is not in existence (for example, in MRI). Studies have shown that patients prefer to be routinely informed about their estimated waiting time, and this has a significant impact on their perception of the quality of care (Göransson and von Rosen, 2010, Krishel and Baraff, 1993). Still, the withholding of information is said to guard against patients in need of care leaving the ED before being seen, in response to being knowledgeable about the long wait ahead (Pich et al., 2011). It is therefore left at the discretion of individual triage nurses. In many cases, the operations of an emergency department (ED) are over-utilized due to compromises between competing priorities, however, best efforts are made to minimize patient waiting times and other patient care parameters (Laskowski et al., 2009).

2.4.2 Emergency Department (ED) Overcrowding

The utilization of emergency departments has increased over the years in countries all over the world, which has evidently led to ED overcrowding. In a national survey of ED directors, overcrowding has been defined as waiting more than 1 hour to see a physician which is likely to result in adverse outcomes (Lambe et al., 2003). Studies (Deo and Gurvich, 2011, Elkum et al., 2011, Migita et al., 2011) have shown that this is an increasing significant healthcare problem that contributes to the current healthcare crisis. From these studies, it is evident that increase in the number of ED attendees, changing demographics and altered patient expectations are all contributors to overcrowding. The problem has reached crisis level in a number of countries, with significant implications for patient safety, quality of care, staff 'burnout', and patient/staff satisfaction (Richardson et al., 2005). In the UK, a 4-hour target was introduced by the Department of Health in that 95% of patients who arrive at the ED should be seen, treated, discharged or admitted into hospital within four hours of arrival (Eatock et al., 2011). Emergency services must be able to provide fast, high quality and effective care to patients with serious medical issues. This becomes impossible if the ED is overcrowded resulting in long patient waiting time, delay in treatment, over-utilized staff, patients leaving before being seen by a doctor, low patient throughput and ambulance diversion (Hoot et al., 2008). It is therefore significantly important to reduce overcrowding in order to improve the efficiency of the ED.

Understanding the causes of overcrowding in emergency departments is a good starting point to address this problem. Studies have attempted to assess emergency departments in order to develop and initiate mechanisms to reduce overcrowding (Proudlove et al., 2003, Chatterjee et al., 2011, Richardson et al., 2005, Andrulis et al., 1991, Schull et al., 2007, Howard et al., 2005). Current evidence suggests that analysis of patient demographic data only may not be enough to predict patients overcrowding (Hung et al., 2007). Hoot and Aronsky (2008) carried out article reviews of ED overcrowding in the context of its causes, effects and solution. They found that common causes of ED crowding includes non-urgent visits, influenza season, inadequate staffing, inpatient boarding and hospital bed shortage; Common effects includes transport delays, patient mortality, treatment delays, ambulance diversion, patient elopement, and financial effect; Common solutions includes additional staff, hospital bed access, non-urgent referrals, observation units, ambulance diversion, destination control, crowding measures and queuing theory.

Delays in patient transfer due to long wait for hospital bed could also lead to ED overcrowding. Another cause of ED overcrowding is non-emergency case patients attending the emergency department (Durand et al., 2011). Evidence show that some patients who attend the emergency department are not accident or emergency cases and could have been dealt with by a general practitioner (GP) (Davison et al., 1983, Green and Dale, 1990). Flower et al. (2011) pointed out that the identification of non-emergency cases which could be dealt with outside the ED may improve its efficiency. In many countries, non-urgent patients are referred to primary care facilities; however this raises warning signals about patient satisfaction and patient safety (Lowthian et al., 2011, Oredsson, 2011). In most cases, nurses would need to redirect the patients to the appropriate department. Non-urgent patients are associated with a negligible increase in length of stay and waiting for the initial physical contact (Fernandes et al., 1997). Schull et al. (2007) identified that the extent to which patients attending the emergency departments with minor conditions contribute to delays and crowding is controversial. This is proven in a recent study (Land and Meredith, 2011) which suggests that 20% of ED attendees don't require ED treatment and 20-40% attendees are ignorant of the existence of Urgent Care Centres which are primarily used to treat patients who have an injury or illness that requires immediate care but not serious enough to warrant a visit to the emergency room. The accessibility to primary healthcare for the homeless and asylum seekers in the UK has been discussed in literatures (Riley et al., 2003, O'Donnell et al., 2007). While speaking with Dr Richard Body, a consultant at Manchester Royal Infirmary, he narrated his experience with a homeless man during winter. He stated that *some homeless people, out of “sheer desperation”, use the emergency departments as shelters to escape cold* (Body, 2004), thereby wasting doctor’s time and resources.

2.4.3 Quality of care

To adequately assess emergency department efficiency and quality, measures are required for use of emergency care, impact of care, identification of at-risk groups, patient satisfaction, quality of life, and cost-effectiveness (Kyriacou et al., 1999). The importance of quality assurance and improvement in emergency care processes have been identified by various authors (Ekelund et al., 2011, Mital, 2010, Muntlin et al., 2010). Patient satisfaction is key to quality of care in emergency departments (Boudreaux and O'Hea, 2004), however the most efficient way of improving it is unclear (Brown et al., 2005). This subject has attracted many research studies.

Taylor and Benger (2004) identified published evidence relating to patient satisfaction in emergency medicine. From their review, it was suggested that the three most frequently identified service factors are: interpersonal skills/staff attitudes, provision of information, explanation and perceived waiting times. Patient participation in the ED process is also important for quality care (Frank et al., 2009). Sheppard et al. (2010) suggested that the recruitment of experienced staff will help improve patient degree of satisfaction. Oluwadiya et al. (2010) carried out a study on the factors affecting patients’ satisfaction with emergency care in a University teaching hospital in the South-western region of Nigeria. He narrated that patients mentioned that they were being “shouted at” by ED staff, which was “surprising”. Although, he explained that due to the rowdiness of the ED, patients needed to be shouted at in order to be heard. It is therefore important for hospital staff to explain the reason for raising their voices when speaking to patients. Croskerry (2009) gave an overview of patient safety within health care in the context of the culture of safety, importance of teamwork, organizational change and specific guidelines on issues such as medication safety, procedural complications, and clinician fatigue, to ensure quality care in the emergency department.

2.5 Comments and Conclusion

This Chapter has reviewed the implementation and barriers associated with simulation modelling in healthcare. The three major methods associated with healthcare; Discrete-Event Simulation, System Dynamics and Agent-based Simulation were discussed. Studies on key emergency department (ED) performance measures such as waiting time, overcrowding and quality of care were reviewed. The benefits and pitfalls of carrying out simulation modelling were summarized. Major simulation tools and other techniques for improving healthcare systems were outlined.

Simulation helps to understand the true capacity of the emergency department (capacity planning) (Bowers and Mould, 2005), manage resource utilization and optimize schedules. The use of simulation modelling to solve complex problems in healthcare is rapidly increasing. It helps identify means to reduce patients waiting time and plan for future growth strategy as well as enable the study of the effect of variability of the emergency department (ED) and how the processes can be controlled. Overall, simulation can be used to confidently make the right decisions during the design process. It is therefore not surprising that simulation has greatly progressed (Cellier, 1982). However, Simulation is not usually implemented in healthcare systems due to lack of simulation awareness, high simulation project costs, lack of skills and expertise, organizational obstacles and technical limitations. It is important that healthcare managers should be open to the implementation of simulation and modelling to improve the healthcare system. The following list identifies the key benefits and pitfalls of simulation in healthcare as described in literature (Brailsford, 2007, Parks et al., 2011), and as related to the current study.

Benefits

The ability to;

- Understand the system by creating a model to depict it and observing its operation in real time
- Study how the system reacts with the different operations and resources thus being able to alter the system's model and observe how those changes will affect it without disruption in real time
- Identify bottlenecks; which is the drive to solutions (eliminating them)
- Identify variability that affect key performance measures and how they relate with each other
- Use multiple performance metrics to carry out sensitivity analysis of the system

Pitfalls

- *It is difficult to obtain an exact replica of a system; especially a complex one*: It is important to determine which element of a system must be included in the model and which may be ignored. For example, in this study, the location data obtained from Manchester Royal

Infirmary slightly contradicted the description of the real-life operations in the emergency department[7].

- *Deciding which appropriate modelling technique and software package to use*: At the start of this work, there were various discrete-event simulation software tools to choose from such as Simio. Yet, the author chose Arena because of previous experience.
- *Erroneous and undocumented assumptions*: It is necessary to make assumptions, especially for complex systems such as emergency department, however it is important to avoid making unnecessary assumptions as this may lead to inaccurate conclusions. Nevertheless, assumptions are inevitable in such studies.
- Sometimes the simulation objectives, methodology and protocols are not clear in advance
- *The use of inaccurate probability distribution*: This is one of the popular issues against the adoption of simulation.
- *Simulation program bugs*: Arena has good error debugging capability so did not experience bugs. It can also check for errors before simulation run.
- Not carrying out multiple replications could lead to bias results: It is also important to decide the appropriate number of replications to do. In this study, this was achieved by carrying out checks on different numbers of replications until an optimal is reached.
- *Statistically analysing the output data*: This is time consuming and involves a lot of work.
- Difficulties with obtaining input data (as described in Chapter 6).
- Identifying stakeholders for data collection
- Lengthy application for ethical approval. This took 6 months during this study and could take up to 18 months in the UK (see more details in Chapter 4).
- Having an in-depth understanding of the software package to be used

2.6 Additional Observation

For completeness, the knowledge of simulation and modelling is very deficient in Nigeria and should be improved. It was found that in Nigeria, Higher Education emphasizes more on the theoretical and technical part of simulation but ignore the practical aspect. In a survey carried out to understand the awareness and implementation rate of simulation by 500 individuals including; medical professionals and medical students of UBTH, and University of Benin (penultimate and final year) Engineering students in Edo state, Nigeria, it was found that 76% of medical staff/students and 72% of engineering students had no in-depth knowledge of simulation and its use. About two-third of medical staff/students had never previously heard about simulation.

[7] *More details can be found in Chapter 5*

Although, there was great enthusiasm to learn about simulation in both cases, only 2% believed it will ever be implemented in Nigeria. It is important that educational institutions find the right balance between theoretical, technical and practical context of simulation in Nigeria.

CHAPTER 3 BACKGROUND, REVIEW AND CURRENT TREND OF HEALTHCARE SYSTEMS

3.0 Introduction

Hospitals or health care systems vary across different countries and their profession usually have a different national history, culture, fundamental beliefs and codes of practice (Poz et al., 2007). Every healthcare system is structured to provide diagnosis and treatment for people's health issues and comprises a healthcare workforce, practice settings and organizations responsible for workforce training, research and system management[8] (Goldsteen and Goldsteen, 2012). Emergency care is an important branch of any healthcare system as this is the part that is most accessible to the public (Sakr and Wardrope, 2000).

This research was majorly carried out in Manchester Royal Infirmary (United Kingdom) and investigations were done in University of Benin Teaching Hospital (Nigeria). It is imperative to investigate the background of healthcare systems in both countries. Therefore the primary focus will be on the two countries with some comparison to other countries such as Australia, Canada, Germany, New Zealand and the United States.

This chapter will review the background of healthcare systems in the United Kingdom and Nigeria, as well as some current trends. The chapter is divided into three major sections: 3.1, 3.2, and 3.3. Sections 3.1 and 3.3 are each subsequently divided into four sub-sections. Section 3.1 will discuss the healthcare system in the UK in terms of its structure, changes made over the past years as well as crises currently faced across the nation, especially in emergency departments. Triage process differentiates emergency department from other hospital departments. In Section 3.2, the context of emergency medicine and Triage is discussed and compared with systems in some overseas countries. These countries include United States of America, Norway, Sweden, Denmark, Finland, Canada, Ireland, Australia, New Zealand, Japan, Taiwan, South Korea, Israel, Germany, France, Hong Kong, Singapore, South Korea, China, Nicaragua, India, Thailand, South Africa, Namibia, Madagascar, Lebanon and Jordan. Section 3.3 covers the background, organizational and financial structure of Nigeria's healthcare system. This section also takes a look at the adoption and current issues with emergency medicine in Nigeria. Literature on Nigeria's healthcare system is currently lacking. Consequently, most information on Nigeria's health system was obtained from online resources such as media reports, seminars, newspapers and magazines, as well as personal experience, interviews and through personal observation. Section 3.4 summarizes the chapter.

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[8] *This includes administration, regulation, planning and evaluation of healthcare systems*

3.1 The United Kingdom's healthcare system

3.1.1 Background

The United Kingdom (UK) is made up of four countries; England, Scotland, Wales and Northern Island. According to national statistics, the total population of the UK in mid-2012 was estimated at 63.7 million with 53.5 million people in England, 5.3 million in Scotland, 3.1 million in Wales and 1.8 million in Northern Ireland[9] (Office for National Statistics, 2013). Healthcare in the UK is regulated by the National Health Service (NHS) of the UK government. The NHS, which is the largest employer in Europe, was formed on 5th July 1948 (Brailsford and Vissers, 2011) . Hospital Episode Statistics (HES, 2014b) recorded an average income before tax for combined GPs (contract and salaried) across the UK as approximately £92,900 in 2012 - 2013. NHS has evolved to be one of the largest healthcare systems in the world (Grosios et al., 2010). It came into existence after the second world war, after the then minister of health, Aneurin Bevan (who was a former miner), presented the National Health Service Bill to the parliament in 1946 (Delamothe, 2008b). The aim of the NHS was to make healthcare services universal, equitable, comprehensive, high quality, centrally funded, and free at the point of delivery (Delamothe, 2008c). According to Aneurin Bevan's biographer, Michael Foot, NHS is "the greatest socialist achievement of the Labour Government", which eventually became Bevan's legacy (Delamothe, 2008b).

Although the NHS's founding principle was to make healthcare services free to all, there are still a range of healthcare services that are not met by them (Delamothe, 2008a). Based on scores of health system performance from the collated data by the Commonwealth Fund between 2004 and 2006, the UK was ranked highest in the overall score ahead of Australia, Canada, Germany, New Zealand and the United States; however, it was ranked low on patient centred care, access, and healthy lives (Delamothe, 2008c). Nonetheless, a recent health reform has been implemented to curb this low healthcare system performance measure which will be discussed in Section 3.1.2. Now, the structure of UK's healthcare system will be described.

3.1.2 The organization of United Kingdom's healthcare services

Jeremy Hunt (the Secretary of State for Health in England), Alex Neil (the Secretary for Health and Wellbeing in Scotland), Mark Drakeford (the Minister for Health and Social Services in Wales) and Edwin Poots (the Minister for Health, Social Services and Public Safety in Northern Ireland) are responsible for the provision and development of healthcare services in England, Scotland, Wales and Northern Ireland respectively (Harker, 2012). They are supported by the Department of

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[9] *These are the latest estimate figures released.*

Health in England, the Scottish Executive Department of Health in Scotland, the NHS Directorate in Wales and the Department of Health, Social Services and Public Safety in Northern Ireland respectively (Harker, 2012). The Department of Health is responsible for the overall performance of the NHS and adult personal social services, and for setting the direction on promoting and protecting the public's health (National Audit Office, 2013). As described by the National Audit Office reports (Morse, 2012) in each country, the health services in England, Scotland, Wales and Northern Ireland are structured as follows:

England

Before 1 April 2013, the structure of the NHS England was as shown in Figure 3.1. However, concerns about cost containment, quality, and accessibility to health services prompted calls for health-care reform. Consequently, NHS England was restructured under the Health and Social Care Act 2012 in 1 April 2013. The 10 strategic health authorities and 151 Primary Care Trusts were abolished and replace by the NHS commissioning board and 211 Clinical Commissioning Groups, and local authorities became responsible for public health (Morse, 2012). This was the "most wide-ranging and complex" transition since the inception of the NHS (The Comptroller and Auditor General (National Audit Office), 2013). The new structure from 1 April 2013 is shown in Figure 3.2. According to a report by the National Audit Office(2013) the reformed structure gave birth to the following:

- *Redundancy of 10,094 full time NHS staff*
- *211 Clinical Commissioning Groups*
- *The closing down of 170 organizations and establishment of 240 new ones*
- *Estimated saving of £2.4 billion in administration costs*

Although the reform is said to have generated savings in administration costs, there was an increase in the burdening of NHS staff. Many GPs are worried that this dramatic extension of their power could also damage their relationship of trust with patients because they have become responsible for rationing care, which will generate inevitable tension. They also worry that they now have to do both their jobs (delivery) and that of management (finance), for which they are not specially trained[10].

[10] *Based on recent BBC news broadcast (April 2013)*

Figure 3.1: The organization of NHS England before the reform before April 2013 (Morse, 2012)

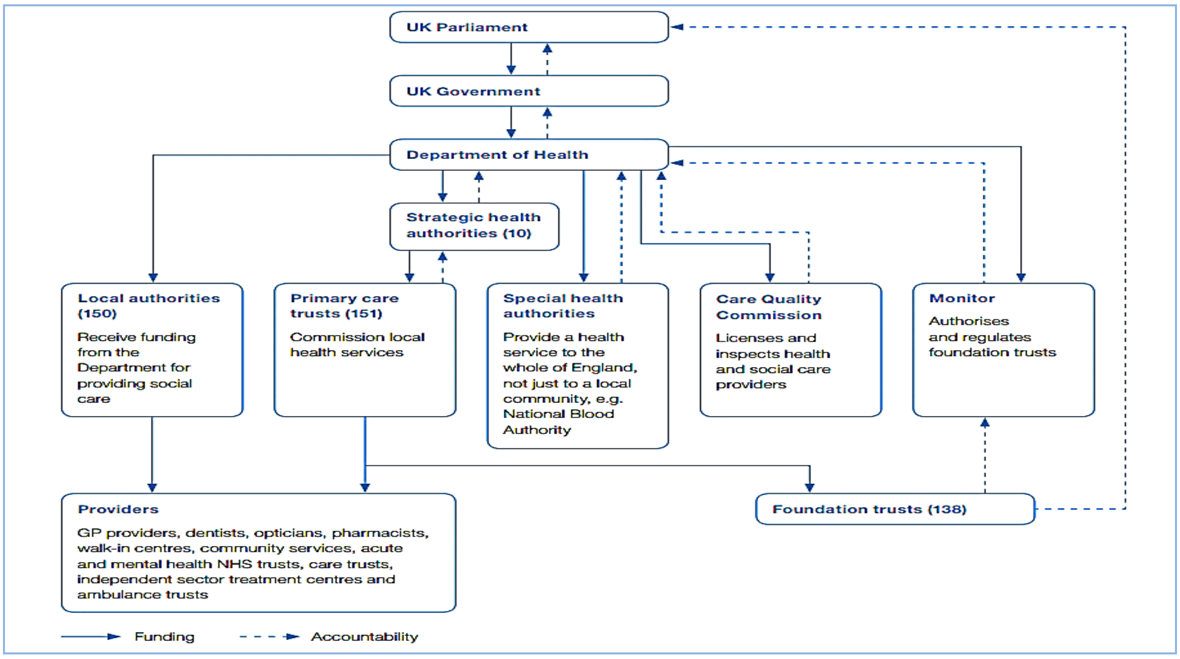
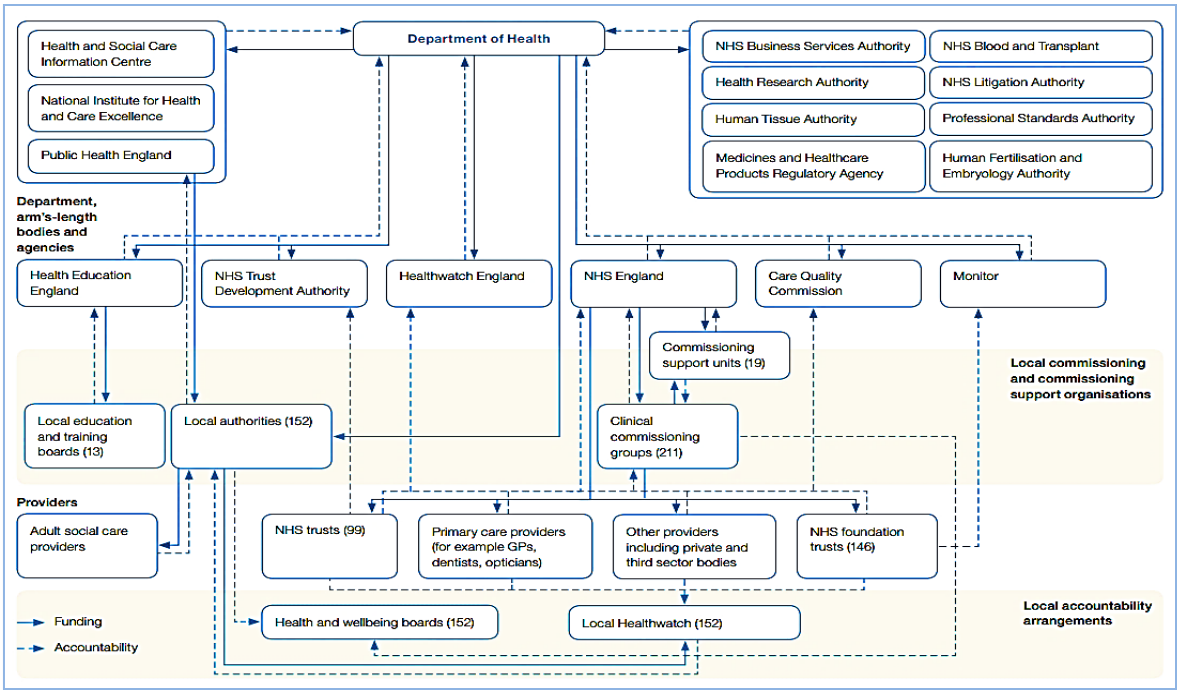
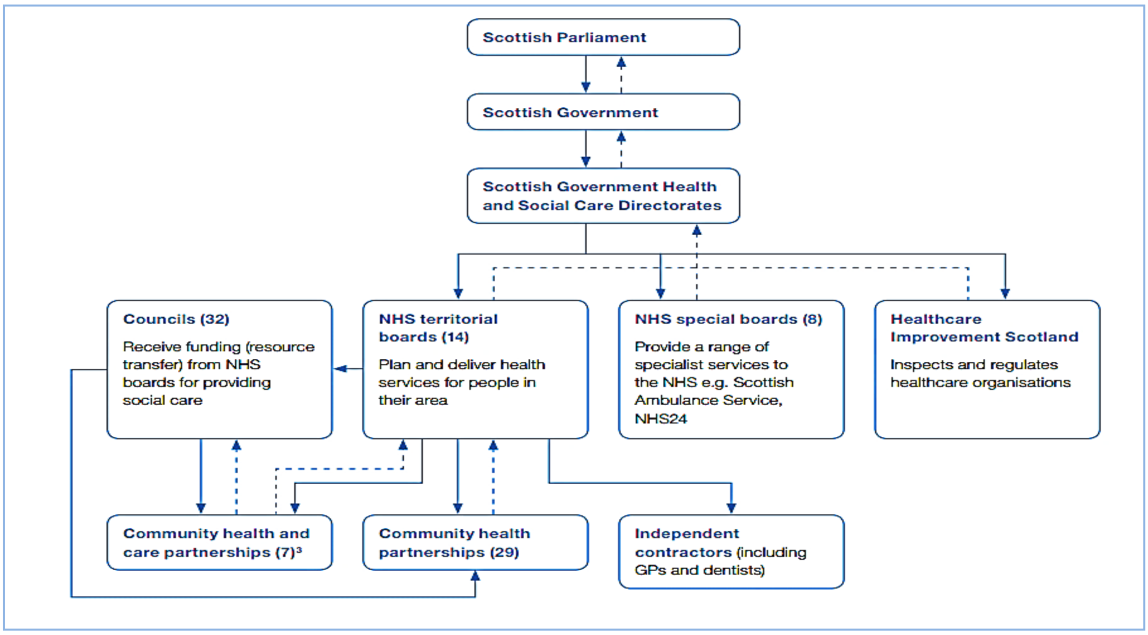


Figure 3.2: The current reformed structure of NHS England (The Comptroller and Auditor General (National Audit Office), 2013)



Scotland

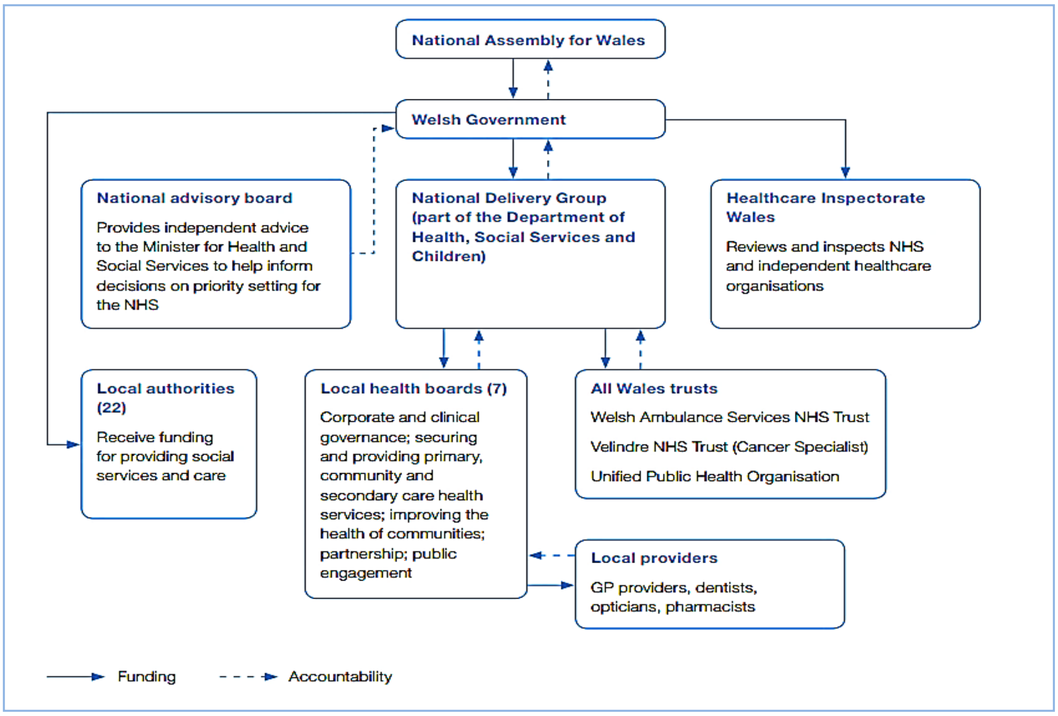
Figure 3.3: The structure of NHS Scotland (Morse, 2012)



The Scottish government has recently announced plans to integrate adult health and social care services

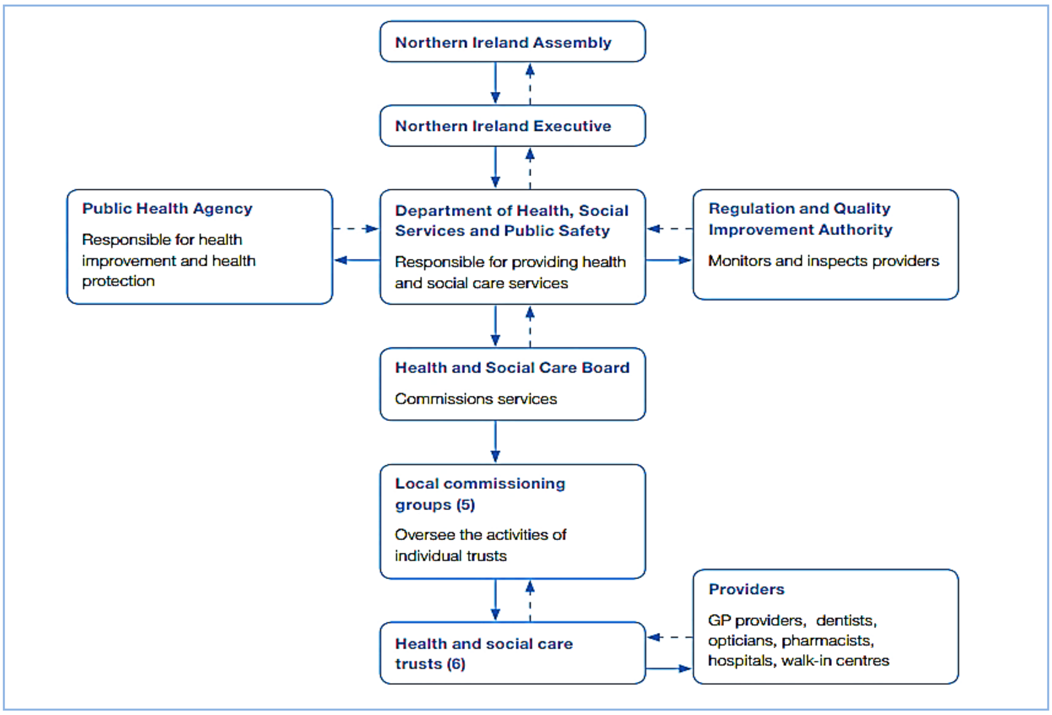
Wales

Figure 3.4: The organization of NHS Wales (Morse, 2012)



Northern Ireland

Figure 3.5: The structure of NHS Northern Ireland (Morse, 2012)



General Practitioners (GPs) in Northern Ireland are contracted directly by the Health and Social Care Board and so they receive funding from, and are directly accountable to the board rather than the Health and social care trusts (Morse, 2012).

3.1.3 Emergency service in the United Kingdom

Emergency medicine (EM) is thriving internationally and varies with different countries. This is not surprising as countries have different mode of operation; economically, medically, culturally, politically and ethically. As stated by Halpern *et al.* (2004), "*National differences in culture, economy, medical economics, medical tradition, and geo-political reality may necessitate the implementation of different solutions to the same problems, and emergency medicine development in each jurisdiction across the globe will reflect this reality*". The United States of America, Canada, Australia, and the United Kingdom (UK) pioneered the efforts to distinguish emergency medicine among other branches of medicine, and it was officially recognized and accepted as a distinct discipline in the 1970s (Halpern et al., 2004). Now almost every country in the world, both developed and under-developed has a recognizable specialty of emergency medicine, or is working to introduce it (Benger and Hassan, 2007).

The UK's emergency departments operate on a twenty-four- hour, seven-days-a-week and 365-days-a-year basis by specialist emergency medical and nursing staff. Over the years, EDs across the UK has seen rapid increase in attendance rate. According to Hospital Episodes Statistics reports, 18.3 million attendees were seen in EDs across the UK between April 2012 and March 2013 (HES, 2014a). This figure has increased by 4% (2011 to 2012) and by 12% (2010 to 2011) reports (HES, 2013). In order to provide efficient care and services, the emergency department is dependent on a variety of services provided by its hospital for the successful treatment of patients. Emergency medicine in the UK has remained dependent on inpatient specialties to help it provide a comprehensive service (Leaman, 2007). Beattie and Mackway-Jones (2004) identified 36 potential indicators of good quality of care in the emergency departments in the UK. It could be said that emergency service in the UK is progressing effectively. However, in the last couple of years, there have been a lot of crisis in emergency departments across England, which required the system to be restructured. More details will be discussed in Section 3.1.4.

Emergency service in the UK has previously undergone some changes, one of which includes the issue of rebranding. This involved changing the name from Accident and Emergency department to Emergency Department. The aim of rebranding was to deter the attendance of "inappropriate" patients (patients with trivial complaints or injuries) at emergency departments. This has been debated on by researchers. Benger and Hassan thought "*rebranding was not such a bad id*ea", while Revil (2003) believed the governement was obsessed with "*image*". Leaman (2007) suggested that changing "Accident and Emergency department" to Emergency Department will result in confusion on its purpose in his statement: "*the term ''A&E'' was widely understood by the public and emphasized the ability to manage all types of emergency, while the term ''emergency medicine'' means little to the public, fails to indicate the ability to manage all types of emergency and risks confusion with acute medicine".* This is the third alteration over the past four decades. It was known as "casualty service" in the sixties and seventies, then the term "Accident and Emergency" was introduced in the eighties after Sir Harry Platt, the chairman of the Accident and Emergency Sub-Committee of the Standing Medical Advisory Committee , produced the Platt Report in 1962, as shown in Figure 3.6 (Sakr and Wardrope, 2000).

However, the terminology "Accident and Emergency" (A&E) is still commonly known and used in some hospitals across the UK and most people still refer to it as the "A&E" across the nation. In this thesis, both terms: Emergency Department and A&E Department will be used interchangeably.

Figure 3.6: Platt Report (Sakr and Wardrope, 2000)

The Platt Report

- The name "casualty service" should be altered to "accident and emergency service."
- Every major accident and emergency unit should have three consultant surgeons (orthopaedic) devoting substantial part of their time to the unit, and be supported by adequate number of intermediate and junior medical staff.
- The department should receive all undiagnosed medical emergencies as well as accident victims.
- Injured patients should be taken to the department that is staffed and equipped to deal efficiently with the type and severity of their injuries, not to the nearest one.
- The departments should be purpose built.
- Separate provision must be made for treatment of minor non-traumatic conditions however this should not interfere with care of seriously ill. This could be provided in hospitals with non-designated departments.
- The care of accident patients should be in general hospitals where all specialities are available.
- Minor cases could be reduced by the provision of GP services.
- Rotation of the medical staff between A/E and general surgical work is valuable particularly at registrar level.
- There should be adequate nursing staff, radiographers, secretarial, receptionists and other supporting services.
- The number of the departments should be reduced. Each unit should not normally serve a population of less than 150 000.

3.1.4 Criticism on the United Kingdom's emergency department

The UK Government has been frustrated that thousands of patients wait for long hours in emergency departments (EDs). A decade ago, a four-hour target was introduced by the Department of Health in that 95% of patients who arrive at the ED should be seen, treated, discharged or admitted into hospital within four hours of arrival (NHS England, 2013). In the first trimester of 2013, from January to March, the number of patients who waited more than four hours increased by 39% in emergency departments across England (Hughes, 2013). Currently, most NHS hospitals in the UK have breached this four-hour target (Triggle, 2013b). This is due to long term issues such as 50% increase in emergency department attendances, changes to GP out of hours care, aging population, leading to pressure on the emergency departments (Hughes, 2013). Williams (2013) reported that some NHS managers and hospital trusts have been manipulating statistical data in order to meet the four-hour target, thus being disingenuous. He also highlighted that the government has flagged this as a criminal offence and is on the move to instigate penalties which could include seven-figure fines and jail terms, in order to instil honesty and accountability in hospital trusts. Triggle (2013a) suggested that the ability to triage patients efficiently means that patients who are most able to cope with delays will wait longest. This suggests that although long wait time is very uncomfortable, for the less severe cases, there is no threat to their lives.

Over the past year, there have been many reports on the issues in emergency departments across England. Today reporter, Tom Bateman (2013), reported that patients were left on trolleys and ambulances were unable to unload sick and injured patients. He also stated that the increase in patients' attendances due to an ageing population, winter illness, changes to GP out-of-hours services, confusion over the NHS helpline and pressure on community service are the reasons for this crisis. When there is delay in admitting patients into the hospital due to bed unavailability, the emergency department has to look after the patient, causing more burden on the department (Hughes, 2013). This delay could also be due to people who are not supposed to be in the hospital occupying hospital beds because the doctors are unable to discharge them into the social system (Triggle, 2013b). Consequently, staff are massively overworked, leading to compromise in patient safety and workforce crisis in the emergency department (BBC News Health, 2013). A senior executive who represents health trusts stated that the emergency department may collapse within a year unless "money is freed up and available to improve A&E services"(Bateman, 2013); therefore stating "funding" as a second key issue. It is anticipated that the new reform will solve these issues.

3.2 Emergency medicine in other Nations (Sakr and Wardrope, 2000)

Emergency clinicians worldwide strive to provide excellent emergency care. According to Sakr and Wardrope (2000), emergency care is categorized into two main models in developed countries namely: Anglo-American and Franco-German model. This model is sometimes referred to as "Scoop and Run" versus "Stay and Play" (Cameron, 2014).

1. The *Anglo-American model*: Emergency care is provided by trained specialist hospital based doctors who deliver different services for all patients who present at the emergency department. Emergency medicine is practiced as an independent specialty and there are structured training and recognized qualifications. Also, paramedics are utilized for pre-hospital emergency medical service (Fleischmann and Fulde, 2007), and relies heavily on land ambulance and less on aero-medical evacuation or coastal ambulance (Al-Shaqsi, 2010). This model is practised in USA, Ireland, Australia, New Zealand, Canada, Japan, Taiwan, South Korea and Israel.
2. The *Franco-German model*: Contradictory to the Anglo-American model, in the Franco-German model, emergency medicine is not practiced as an autonomous specialty from

general medicine, but this is rapidly changing (Fleischmann and Fulde, 2007). Here, hospital is brought to patients requiring emergency care. The attending emergency doctors in the field have the authority to make complex clinical judgement and treat patients in their homes or at the scene; thus resulting in many users being treated at the site of incident and less being transported to hospitals (Al-Shaqsi, 2010). This is practiced in countries such as Germany, Belgium, Czech Republic, Estonia, Hungary, Italy, Poland, Romania, Slovenia, France, Greece, Malta, Austria and the United Kingdom (Al-Shaqsi, 2010, Fleischmann and Fulde, 2007).

In Asian-Pacific countries such as Hong Kong, Japan, Turkey, United Arab Emirates (UAE), Malaysia, Taiwan, Singapore, South Korea, China and Nicaragua, there is no one model that fits and the different hospitals in each country operate on diverse priorities(Sakr and Wardrope, 2000 pg.317). Emergency Medical Service (EMS) here are underdeveloped, however many countries have recently begun to recognise the importance of emergency medicine. This has led to the creation of the Pan Asian Resuscitation Outcomes Study (PAROS) to address issues in EMS care, and standardise terms and definitions used to allow cross-national, among other objectives (Ong et al., 2013). According to them, the situation is different in developing countries such as India, Thailand, South Africa, Namibia, Madagascar, Lebanon and Jordan as shown below;

Country	**Ways of Operation**
India	Emergency Medicine is not operated as a specialty. Emergency service is provided in "Casualty Centres" staffed by physicians who have no postgraduate qualifications. The position is temporary in most circumstances. Ambulances are privately owned and operate on a fee for service basis.
Thailand	Emergency departments are poorly staffed, especially in rural areas (young staff and obsolete equipment).
South Africa	Emergency medicine is not a specialty. Doctors working in the emergency departments are called "Casualty Officers" and most of them have never had specialty training. A new specialty diploma has been introduced but most of those who hold the diploma prefer to work in private hospitals.
Namibia, Madagascar, Lebanon and Jordan	Emergency department post is temporary. On-call staff/physicians are summoned when required.

Triage

Triage is an important part of the Emergency department and varies worldwide. It is the process of quickly identifying and prioritizing the urgency of a patient's need for medical care. Here are literatures on Triage systems practised overseas.

The term triage is not new and has been explored in many literature (Debbie, 1999, Fernandes and Christenson, 1995, Fernandes et al., 1999, Lyons et al., 2007, FitzGerald et al., 2010, Farrohknia et al., 2011, Derlet et al., 1992, Oredsson, 2011). An ideal triage system should prioritize patient ailment by severity, and care should be delivered within a reasonable time frame (Elkum et al., 2011). Emergency departments worldwide use different triage systems to assess the severity of conditions of arriving patients and assign treatment priorities. Questions on who should efficiently conduct triage have been discussed in various studies. In a study done in France (Durand et al., 2011), triage conducted by nurses was inconsistent due to their inability to identify non-urgent patients. Subash et al. (2004) suggested that combined doctor and nurse triage (team-triage) would reduce waiting time of patients and subsequently improve emergency department efficiency; this idea is not new. Choi et al. (2006) described this system as Triage Rapid Initial Assessment by Doctor (TRIAD), while Cooke et al. (2003) described it as "See and Treat". Here, a senior experienced clinician is required at triage stage to allow the treatment of minor issues in one step. Thus, allowing for a large number of patients to be discharged after one single contact - at triage.

The popular triage systems are (Lee et al., 2011, Elkum et al., 2011, Cronin, 2003, Kantonen et al., 2012, Bruijns et al., 2008):

- the Canadian Triage and Acuity Scale (CTAS)
- the Australasian Triage Scale (ATS)
- the Manchester Triage Score (MTS)
- Cape Triage Score (CTS)
- Emergency Severity Index (ESI)
- the ABCDE triage

The Canadian Triage and Acuity Scale (CTAS) is a well-recognized and validated system of triage in Canada (Elkum et al., 2011). There are five CTAS levels which are designed such that level 1 represents the sickest patients and level 5 represents the least ill ones (Beveridge et al., 2013). Studies have attempted to validate the CTAS system outside the Canadian healthcare system (Lee et al., 2011, Jiménez et al., 2003). For example in a recent study (Elkum et al., 2011), CTAS was adopted at a major tertiary care institution in Saudi Arabia and was proven to be very effective. The authors suggested its usage in hospitals outside Canada.

Most emergency department across Australia have been using the Australasian Triage Scale (ATS), which was initially known as National Triage Scale, since 1993 (Considine et al., 2004). The ATS is a 5-point triage scale with category 1 to 5; 1 being the life-threatening situation and 5, the non-urgent one (Considine et al., 2000).

The Manchester Triage Score (MTS) is predominantly used throughout the UK's NHS Trusts (Cronin, 2003) , including the Manchester Royal Infirmary. The MTS uses colour codes which defines required time targets for patients to be seen. The colour codes are as follows Red (critical and seen immediately), Amber (serious and seen within 15 minutes), Yellow (significant problems and seen within 1 hour), Green (minor problems/injuries and seen within 2hours) and Blue (illness/injuries longer than 7 days and seen within 4hours). The UK system also assesses the patient based on their ability to walk, their respiratory rate and heart rate (Horne et al., 2011) and assigns the accurate colour code based on this assessment. Note that based on data from MRI, these target times are not implemented in practice as will be shown in Chapter 6 of this thesis.

Zeng *et al*.(2011) describes the Emergency Severity Index (ESI) as a five level triage system where patients are assigned as critical, emergent, urgent, non-urgent and minor. They also added that the most serious (acuity level 1) are the critical/trauma patients. They have the highest priority, whereas minor patients have acuity level 5 and are often "clinic-type" patients. ESI is popular in the United States of America and similar to the triage process in Lagos University Teaching hospital. The implementation of ESI is described in the handbook published by the Agency for Healthcare Research and Quality, USA (Gilboy et al., 2012) .

The first draft of the Cape Triage Score (CTS) was produced by June 2004, and the tool was finalized in 2005(Bruijns et al., 2008). The CTS is mainly utilized in South Africa. The CTS prioritizes patients using colour codes as follows: (1) red (immediate care needed); (2) orange (very urgent care needed); (3) yellow (urgent care needed); (4) green (routine care needed); and (5) blue (dead). Based on the author's observation, this is almost similar to the system used in Manchester Royal Infirmary (except the "blue" means the patient is "trivial" not "dead") and University of Benin Teaching Hospital[11] (except the "blue" is replaced by "black").

[11] *See detailed description in Chapter 4*

The ABCDE triage is developed for the use of primary health care emergency departments and is different from other hospital oriented triage systems (ATS, CTAS, MTS and ESI). In ABCDE triage system, A-group patients go straight into secondary care, B patients are to be examined within 10 minutes, C-group patients must be seen within 1 hour, D patients are to be examined within 2 hours and E-group patients do not require urgent treatment and are taken care of by the nurses(Kantonen et al., 2010). Kantonen et al.(2012) compared these 5 triage scale as presented in Appendix C. This method of triage is used in Finland.

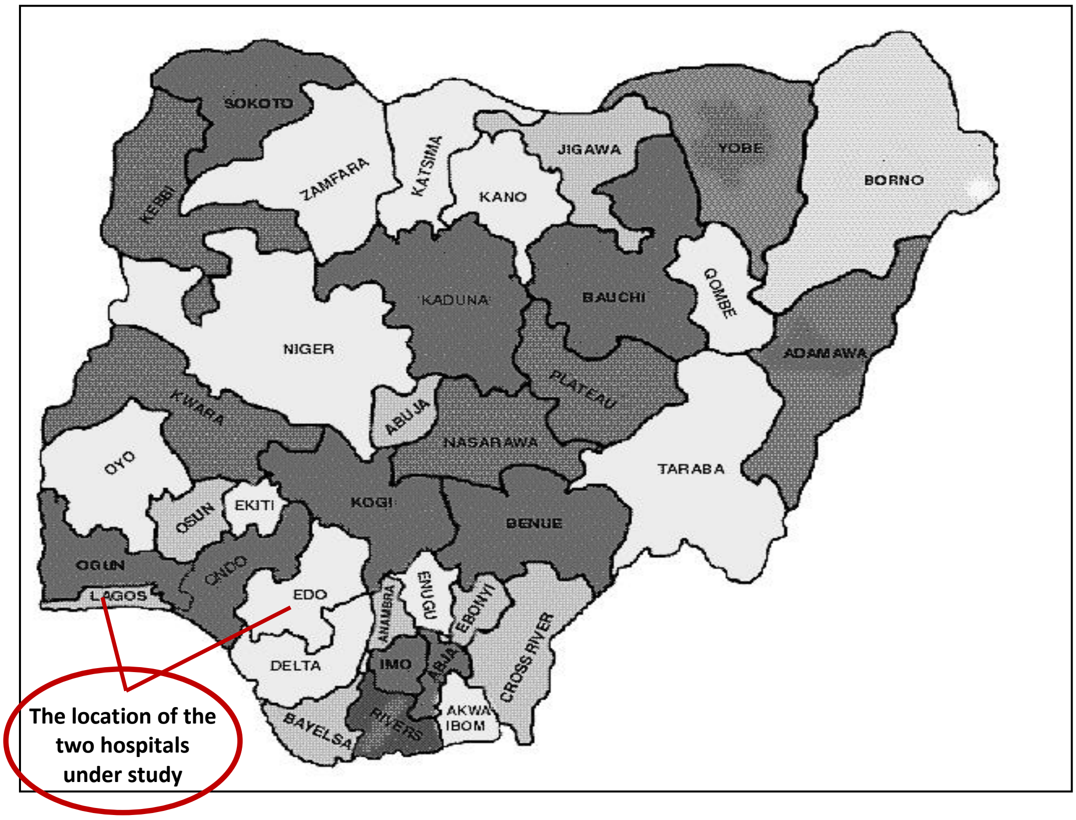
There is no doubt that the above described triage systems have similarities. They are all designed in 5 levels, with 1 being the most critical and 5, the least critical. Also, they have the same principal mission of evaluating and prioritising patients based on urgency of care.

3.3 The Nigerian healthcare system

Nigeria is the most populous country in the African continent, with about 160 million people (BBC News Africa, 2012). Nigeria is one of the world's top oil-producing countries and the fifth-larger supplier to the United States (Paulson, 2001), with a Gross Domestic Product (GDP) of $522.6 billion (World Bank, 2014). However, its wealth is not evident in its healthcare sector. Figure 3.7 shows the map of Nigeria with its 36 contiguous states and the Federal Capital Territory, Abuja, highlighting the locations of the two hospitals investigated.

In Nigeria, there are three tiers of government namely; the Local, State and Federal Governments, and each manages the three categories of healthcare systems. The healthcare organizational levels are described in section 3.3.1 of this chapter. The three categories of healthcare systems are the primary, secondary and tertiary healthcare schemes. The primary healthcare scheme consists of health centres (which are meant to provide healthcare in rural areas), dispensaries (for small communities), and clinics. The secondary healthcare sector consists of the General (public) hospitals. There are also private specialist hospitals which are privately owned and operated by individuals or organizational bodies. The tertiary healthcare scheme includes the University Teaching hospitals and Federal Medical Centres.

Figure 3.7: Map of Nigeria showing its 36 states (Umunna, 2013)



The two hospitals (University of Benin Teaching Hospital and Lagos University Teaching Hospital) observed are teaching hospitals. The teaching hospitals combine hospital services with medical research and teaching of medical students, thus it is required to be well equipped. This is not the case in most hospitals; it is instead a story of low infrastructural facilities and poor healthcare services. This is however currently being looked into by the current government and hopefully changes will be seen in coming years.

The organizational structure and management of the healthcare system as described in a World Health Organization report on Nigeria's health plan and delivery system is described in section 3.3.1.

3.3.1 The organization and management of Nigerian's healthcare system (World Health Organization, 2009)

I. The Federal Government level

Healthcare in Nigeria is controlled by the Federal Ministry of Health (FMOH) which is responsible for regulating policy and giving technical support to the overall healthcare system. This also includes support of inter-National Relations on health issues, the National Health Management

Information System and the provision of health services through the tertiary and teaching hospital as well as researches in national laboratories.

II. The State Government level

This government level is controlled by the State Ministry of Health (SMOH), who is responsible for secondary healthcare services. The SMOH also regulates and provide technical support for primary healthcare services.

III. The Local Government level

The Local government is responsible for Primary Health Care (PHC) services.

IV. The Community level

The community is the most important link in healthcare delivery and forms the support structure for the implementation of Primary Health Care (PHC) services.

V. Agencies and Departments

There are departments and agencies within the various levels described above in (I) to (IV). The National Council on Health (NCH) coordinates the activities of all stakeholders such as the Federal Ministry of Health (FMOH), agencies and State Ministry of Health (SMOH). Similarly, the State Council on Health (SCH) coordinates the SMOH and the Local government health authorities. Profit and non-profit private health Institutions are also regulated by the appropriate government body (depending on the level of operation).

It is also important to note that the organization of the healthcare system is usually not practised as depicted. This is due to duplication and confusion of roles and responsibilities among the different tiers of government.

3.3.2 Healthcare finance in Nigeria

The National Health Insurance Scheme (NHIS) in Nigeria was implemented in 2005 (World Health Organization, 2009). At inception, it was focused on Government employees at the time. Few years later, large private and international companies began to offer free or reduced healthcare cost to their employees as part of their remuneration package. Most Nigerians do not benefit from the scheme and have to pay for healthcare at the location of service. This restricts access to the majority of poor Nigerians who mostly require free healthcare. Welcome (2011) outlined the objectives of the NHIS as follows;

- Accessibility of good healthcare services for Nigerians
- Guidance against the financial burden of medical bills
- Minimization of healthcare cost
- Increased efficiency in healthcare services
- Equitable distribution of health care costs among different income groups and at all levels of healthcare
- Preservation of highly standardized healthcare delivery services within the scheme
- Improvement of private sector participation in the provision of healthcare services
- Adequate distribution of health facilities and infrastructure in Nigeria
- Availability of funds to the health sector for operational improvement.

The performance of a healthcare system can be evaluated on the quality of healthcare provided, the equity achieved in the provision of healthcare, and the efficiency with which healthcare is provided (Goldsteen and Goldsteen, 2012). The above outlined objectives of the NHIS have hardly reached its goal as health care delivery services in Nigeria continue to deteriorate. This is because it is limited, not equitable and does not meet the needs of the majority of Nigerian citizens (Welcome, 2011).

Nigeria's public healthcare system is funded by both the Federal and state Government of each state in the country and is administered by the National Health Service. However this fund is very limited and does not cater for the majority of the masses. Consequently, people have to pay for their medical cost on arrival at the hospital. During the visit to Lagos University Teaching Hospital (LUTH), it was observed that there was provision for a better health service at the emergency Spill-Over wards. However, an initial payment of 150,000 Nigerian Naira (an equivalent of £600) must be made before admission. This spill-over ward consists of thirty-six beds and patients are adequately catered for and given preferential treatment when compared to the main hospital wards.

Since health insurance is very limited in Nigeria, most patients are admitted into the ED on emergency basis. On the visit to University of Benin Teaching Hospital (UBTH), it was observed that this happens more with accident victims since they are usually brought in by rescuers rather than people that actually know them. On an interview with the head of the emergency department, Dr Iribhogbe, he explained that the hospital admits these accident victims on the basis that when they are well enough, payments will be made by them or members of their family. Regrettably, some patients eventually abscond causing a potential loss to the hospital. Nonetheless, at UBTH, these are accounted for as part of research costs as they provide learning opportunities for their medical students; this also occurs in most teaching hospitals in Nigeria. Some patients are neither discharged nor moved to other relevant departments in the hospital because their bills have not been paid. They end up over-staying at the ED which is supposed to be a transit ward. As a result, non-emergency patients occupy bed-spaces which could be used for incoming emergency patients, thereby contributing to ED over-crowding. However incoming patients are still admitted since emergency department (EDs) are not allowed to reject patients; since dismissing ED patients without full assessment creates clinical risks that no health care organization is willing to accept (Benger and Hassan, 2007).

3.3.3 Emergency Medicine in Nigeria

Emergency care in Nigeria is not recognized as a specialty. Most doctors and nurses practising in the emergency departments come from other hospital departments. This is similar to the Franco-German model described in Section 3.2. In 1988, the Nigerian National Health Policy (NHP) was adopted to direct general health practice in Nigeria, however, no policy on emergency medicine was implemented (Aliyu, 2002). Recently, the National Emergency Management Association (NEMA) was introduced in Nigeria to administer emergency issues.

In 2005, an A&E department was incorporated as a standalone department in Lagos University Teaching Hospital. According to Dr Iribhogbe, emergency medicine as a specialty is currently not available in the curriculum of Nigeria's two medical training institutions; the National Postgraduate Medical College and the West African College of Physicians, which has led to deterioration in the efficiency of ED management across the country.

Medical emergency is a situation in which a patient needs immediate care and is unpredictable. Patients are required to be brought from the site to the emergency department within minimum possible time. Studies have shown that pre-hospital care exists in both developed countries such as United Kingdom, Germany, and United States of America (Schuster et al., 2010, Govindarajan et al., 2012, Morris et al., 2000) and under-developed countries such as China (Shao et al., 2009). One of the major issues with emergency medical service in Nigeria is the non-existence of pre-hospital care. Patients' conditions deteriorate over time; consequently pre-hospital care is required to transport patients to the ED in the most skilful manner. In most cases, ambulances used to bring emergency cases to the hospitals are fitted with medical amenities such as defibmonitors, syringe pumps, pulse-oxymeters and transport ventilators (Mital, 2010), for the purpose of carrying out pre-hospital care. Ambulances are usually accompanied by paramedics who are required to triage and provide necessary treatment to the patient, thus reducing the risk of patient dying on or before arrival at the hospital. However, this is not the case in most Nigerian hospitals. For instance, In UBTH, ambulances are owned by the hospital but are rarely used for the general public while in LUTH, ambulances (which are supposed to be owned by the hospital) are possessed by hospital managerial staff and rented to patients for their use.

In UBTH, patients from road accident scenes are usually brought into the ED by other means such as; the Police, Good Samaritans, Federal Road Safety Commission (FRSC) officer and SAVAN (Save Accident Victims Association of Nigeria) volunteers. This is inefficient, as the backbone of pre-hospital emergency care consists of emergency medical technician-staffed ambulances (EMTSA) or paramedics (Schuster et al., 2010). Therefore, compared to developed countries, there remains much room for improvement in emergency medical team building, scientific research, teaching or clinical and pre-hospital emergency management in Nigeria.

Some interviewed graduated paramedics at UBTH, showed high enthusiasm for the role. In the USA, Merlin et al. (2010) carried out a study on how to improve medical students' understanding of fundamentals in pre-hospital care by enforcing a mandatory fourth year emergency medicine clerkship, using a Likert five-point scale questionnaire. The fundamentals involved organizational structure, ground and air transport, on/off-line medical control, disaster management, future career opportunities, riding with advanced life support, critical care transport, physician response vehicles, attending pre-hospital/disaster medicine lectures and emergency medical dispatch (EMD). They found that this helped to significantly improve the understanding of pre-hospital care. Hopefully, if adopted in Nigerian hospitals, this will help improve pre-hospital care which will in turn improve the overall efficiency of emergency medical services in Nigeria.

3.3.4 Criticism on Nigeria's healthcare system

Nigerian healthcare status indicators are very poor with slow improvement in key health indicators (AHWO, 2010). Political instability and mismanagement have contributed to Nigeria's poor health indicators over the past three decades (Nigerian Tribune, 2013). Nigeria is the United States' largest trading partner in sub-Saharan Africa, however it is yet to develop effective measures to address corruption, poverty, ineffective social service systems and public mistrust of the government (U.S. Department of States, 2012).

Uffort (2010) argued that virtually all the teaching hospitals in major cities in Nigeria including Abuja (the capital city), which are designed to be centres of medical excellence are grappling with the problems of inadequate and obsolete equipment, lack of drugs, under funding, unreliable power supply and shortage of doctors to cater for patients who flock there daily for treatment. This lack of infrastructure in many hospitals across the country, especially the public ones, is caused by corruption and failure of successive governments to pay attention to the country's healthcare system (Obinna, 2011). Nigerian citizens blame the nation's poor healthcare delivery system on the inefficiency of government, through rising cost (the economy), limited financial resources, inefficient health systems, the huge burden of diseases, and changing social, technology and economic environment (Obinna, 2011). Nwangwu (2012) examined the problems of healthcare in Nigeria based on two crucial areas; quality of healthcare and accessibility to healthcare. He argued that the problems with quality of care include evaluation of the adequacy of healthcare facilities and systems, their operating procedure, knowledge of current world medical literature and level of care by medical practitioners; while problems with accessibility of care include the availability and distribution of healthcare facilities across the country, and the affordability and immediate access to these facilities by patients. Welcome (2011) proposed the use of a medical intelligence/surveillance model for a successful healthcare delivery system in Nigeria.

Nigeria's health workforce (per 10000 population) is 4 for physicians and 16.1 for nurses/midwives (World Health Organization, 2009). This is "poor" as the healthcare service of a country is greatly dependent on the size, skills and commitment of its healthcare workforce. Prospective medical doctors prefer to go abroad to practice medicine for career advancement. Thousands of Nigerian medical doctors practicing abroad are willing to return home and be of benefit to their nation but cannot do so due to the ill-equipped state of the hospitals. Over the past decades, Politicians and Government officials in Nigeria have spent millions of Naira travelling abroad for medical treatments (Uffort, 2010), rather than directing those funds into the improvement of hospital infrastructure and specialist trainings of medical staff.

3.4 Comments and Conclusion

This chapter reviews general healthcare systems with emphasis on the UK and Nigeria, with brief comparison to other overseas countries. From this review, it is evident that a high variation exists for healthcare systems worldwide. The UK healthcare system varies greatly to that of Nigeria as outlined below;

		United Kingdom	Nigeria
1.	Healthcare System Organization and Management	Practised Strategic Framework	Structured but not fully implemented in reality
2.	Emergency Medicine	A specialty	Not distinct from other medical practises
3.	Triage System	Mostly use Manchester Triage	No defined system of triage
4.	Healthcare Cost	Mostly Free for citizens	People pay out-of-pocket before treatment is provided
5.	Healthcare Delivery	Effective and striving to improve	Very poor and continues to deteriorate in some cases
6.	Pre-hospital Care	Equipped ambulance and helicopters are used accompanied by trained paramedics	Lack of functional ambulance and paramedic

Variation also exists between the two Nigerian hospitals; University of Benin Teaching Hospital (UBTH) and Lagos University Teaching Hospital (LUTH). UBTH is gradually introducing pre-hospital care by training paramedics, however implementation is slow. In a nutshell, it is clear that there is need for a great deal of improvement in Nigeria's healthcare system. More comparison in aspects such as the structure and triage details is described in Chapter 4.

Six popular triage systems used worldwide; the Canadian Triage and Acuity Scale (CTAS), the Australasian Triage Scale (ATS), the Manchester Triage Score (MTS), Cape Triage Score (CTS), Emergency Severity Index (ESI) and the ABCDE triage were described.

Two major models exist for emergency care;

- Anglo- American practiced in USA, Ireland, Australia, New Zealand, Canada, Japan, Taiwan, South Korea and Israel
- Franco-German practised in European countries including Russia.

Other countries operate in diverse ways and have no defined emergency care model.

CHAPTER 4 MANCHESTER ROYAL INFIRMARY VERSUS UNIVERSITY OF BENIN TEACHING HOSPITAL – A COMPARATIVE REPORT

4.0 Introduction

In chapter 3, a review on healthcare systems was carried out. It was highlighted that healthcare systems defer in nations worldwide, and so do their hospitals and emergency department systems. From branding to management to how they operate, there are various differences as well as similarities. In order to create a robust model and simulate an emergency department, preliminary explorations of the components of which the emergency department consist of and with which it must function are imperative.

As pointed out in Chapter 1, four hospitals were visited and investigated during the course of this research. To compare the healthcare system s in the various hospitals, it is important to harmonize the level of information available. Consequently, since more information was obtained from Manchester Royal Infirmary (MRI) and University of Benin Teaching Hospital (UBTH), than Lagos University Teaching Hospital (LUTH) and Rockford Memorial Hospital (RMH), only the former two are reviewed. This chapter provides an overview of what goes on in UBTH and MRI, and cites from figures obtained from each of the hospitals. More detailed analysis of data are described in chapter 5 and 6.

This comparative report is based on observation, personal experience of the author and interviews with hospital staff at the time of visits. Topics discussed include the ethical approval procedures, time spent during field work, structure and process maps of operations in each hospital. Some useful strategies for improving data recording process and information required for robust model building are highlighted.

4.1 Ethical Approval

In the UK NHS, it is imperative to obtain ethical approval from the National Research Ethics Service (NRES) in order to carry out research in hospitals. For the MRI investigation, the procedures were described by Dr Richard Body, one of the ED consultants.

The first step required the submission of an Integrated Research Application System (IRAS) form together with a Research Protocol to the National Research Ethics Service (NRES). The Proportionate Review Sub-committee of the NRES committee North-West Greater Manchester reviewed the application on 1 March 2013. The Committee is constituted in accordance with the Governance Arrangements of Research Ethics Committees and complies fully with the standard operating procedures of the research ethics committees in the UK. The Sub-committee was made up of two lay members, one consultant (chair of the committee) and one co-ordinator. They were of the view that the project did not require NHS Research Ethics Committee review since only anonymised data and information would be utilized during the study. Therefore, a favourable ethical opinion was granted for the duration of the research subject to the condition that management permission or approval must be obtained from MRI prior to the start of the study. Figure 4.1 shows the process map for ethical approval at MRI for this study. Note that the application process can be lengthy and time consuming depending on the research, especially in studies requiring more than one approval (Yong, 2010). For this research, only one approval was required, therefore it took lesser time. It will be helpful for future researchers if the processing time for ethical approval is reduced in the UK.

Figure 4.1: Process map for ethical approval at MRI

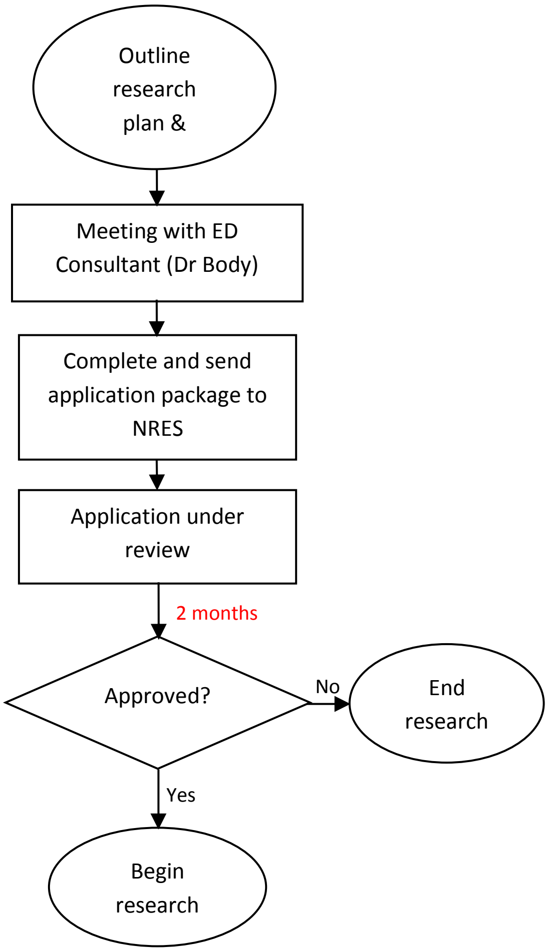
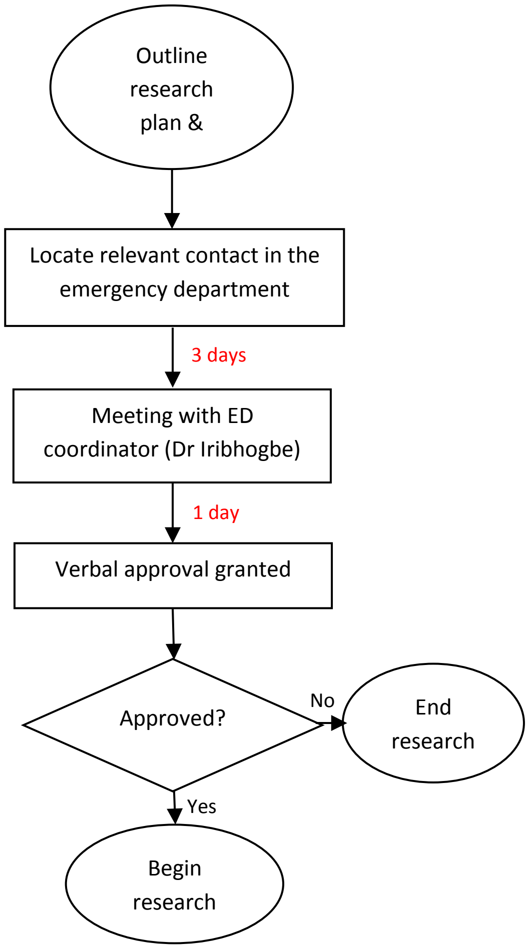


Figure 4.2: Process map for ethical approval at UBTH



In UBTH, obtaining approval to carry out this study was considerably quicker since there is no formal procedures to be followed (Figure 4.2). In effect, permission for the study was granted after a meeting with the ED coordinator, Dr Pius Irigbhogbe. Note that there is no data protection policy in place at UBTH but this is not the case for all hospitals in Nigeria.

4.2 Dates of Visits

After the ethical approval, MRI was visited approximately once a week for 4 hours between 9 April 2013 and 4 April 2014, which is a total of 208 hours.

The author spent three months in UBTH between 6 June and 31 August 2011. The working day was from 10.00am to 6pm from Monday to Saturday. With the scheduled two 1- hour breaks per day the total time spent in UBTH was roughly 450 hours.

4.3 Structure and Community served by the hospitals

MRI was formed in 1752, while UBTH was established in 1973, and both are University Teaching Hospitals. Both hospitals are the largest hospitals in the cities where they are located and they operate 24 hours daily. MRI is located in Manchester which had a population estimate of 514,417 in 2013 (Office for National Statistics, 2014), while UBTH is located in Benin city and serves the Edo state community with a population of approximately 3,233,366 based on the 2006 census (National Population Commission, 2009).

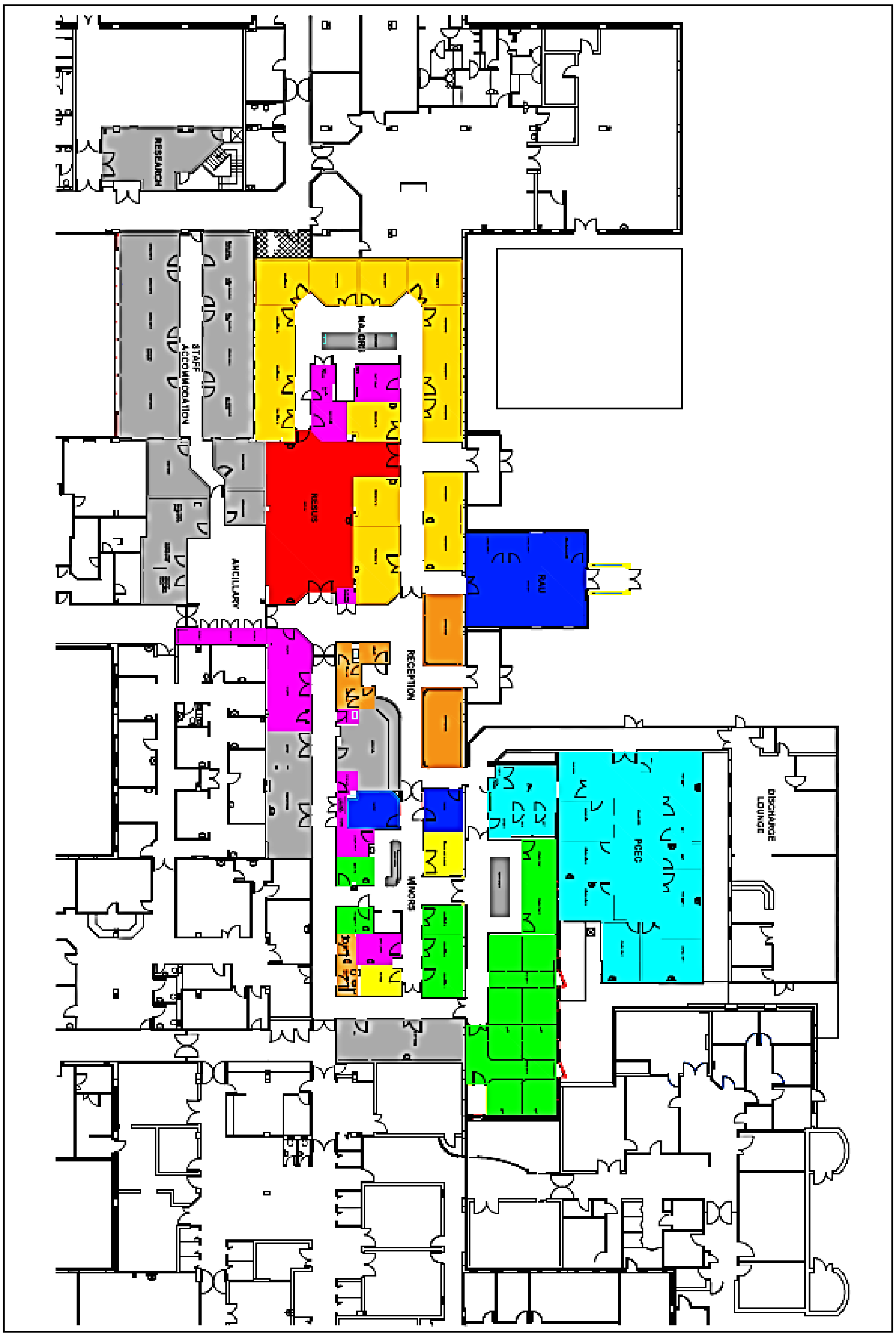
Both Manchester and Benin embrace large student communities (UBTH is surrounded by three Universities) but unlike Manchester, Benin itself has a high level of poverty and a high rate of illiteracy (Osiruemu, 2007).

Figure 4.3 shows the layout of the emergency department of MRI, as provided by Dr Richard Body (the ED consultant). No layout information was available for collection at UBTH during this study.

MRI as a whole has a bed capacity of around 800 while UBTH has 650. In the respective EDs, the bed capacities are 47 and 30. Although the MRI websites states that the emergency department sees around 145,000 patients annually, this study shows that approximately 100,000 patients attended the emergency department (ED) between April 2012 and March 2013. This is about nine times more than that of UBTH for the same period (11,000 patients; according to ED staff). Since MRI is located in a large student community, one would anticipate a lower attendance rate during the summer break or periods when the University is on holiday. However the analysis from this study show that there is no significant decrease in ED attendance for patients age between 18 and 23 during the summer break for the one year period (as shown in chapter 6). It will be interesting to investigate this further in the future using at least 10 years of historical data.

In very general terms some people shy away from attending the ED as a result of a fear of death that is linked to pain (Walsh, 1995). The pain creates a “fear of the unknown” which is identified with the uncertainty of the outcome of attending the ED, and to avoid this they would rather lean towards alternative treatments. McD Taylor et al. (2006) compared complementary and alternative medicines to prescription drugs from emergency patients' point of view. They found that the appeal of alternative medicines is that they are "drug free", "natural" and "safe", and that these characteristics outweigh any consideration of their efficacy.

Figure 4.3: Layout of Manchester Royal Infirmary (Provided by Dr Richard Body)



Based on personal experience with family and friends, observation and interviews with ED staff, these and other considerations including fear of death, ignorance, negligence, and religious beliefs (miracle cure) are indeed responsible to a greater or lesser degree for the low attendance rate at UBTH. As a result, many Nigerians cling to other means of treatment such as self-medication, unspecialized/specialized pharmacist/chemist, traditional/herbal means or spiritual beliefs.

However, the main reason for the difference in take up between MRI and UBTH is that of cost. In MRI, patients are treated free at the point of delivery, whereas in UBTH, they have to pay for treatment on arrival. The exceptions are patients who are unconscious on arrival such as road traffic accident victims and who are not accompanied by a family member or friend who can make the payment. Such patients are treated first and payment is made after resuscitation or is taken from a relative or friend when they become available.

As in MRI, emergency patients are treated in the ED until they are discharged or transferred to an appropriate department in the hospital. In UBTH the expected maximum time duration before discharge/transfer is 12 hours. However, a patient who has been treated in ED but is unable to pay for their treatment is in fact detained in the ED until payment is made and this can take more than 20 days in some cases, leading to significant overcrowding and bed shortages.

Against this background it is not surprising that those people who struggle for payment and have no wish to be incarcerated will seek cheaper (alternative) means of healthcare and avoid ED altogether or, at best, use it as a last resort. This in turn may account for the fact that many (more) patients arrive dead to the ED in UBTH because they have tried alternative (spiritual, traditional, herbal) medicines which have failed.

The use of alternative medicine can be minimized by raising awareness of its health risk among the community through healthcare seminars, workshops and especially through the media and social networks. Furthermore, the implementation of free healthcare, availability of adequate bed-space and staff can massively decrease the emergency department overcrowding and low attendance rate due to financial difficulties.

4.4 Systems of Operation

There are four main activities within both EDs: arrival, triage, treatment and outcome. These are illustrated in the process maps in Figures 4.5 and 4.6.

4.4.1 Arrival

In MRI, the actual means of arrival of each patient is recorded but arrivals are classified either as walk-in (those not delivered by ambulance) or by ambulance. Walk-in patients are registered (that is to say the clock starts) and are sent to the triage waiting area. In practice, registration and triage of patients who arrive by ambulance is carried in the ambulance itself and the records are then passed on to ED after they arrive.

On arrival in the ED at UBTH, patients are registered (personal details) and the reason for attendance is recorded. They are then sent to the triage waiting area.

In UBTH, patients arrive by foot, ambulance or other means such as private vehicles, good Samaritans vehicles, the police Hilux van and Federal Road Safety Corps (FRSC) ambulances or vans. Although there are three available ambulances in UBTH, they are rarely used as a means of transportation of patients attending ED. The reason given for this is that they are in a poor state of repair as a result of poor maintenance, and as a result of a lack of fuel. Maintenance and fuel are costs on UBTH which appear not to be fulfilled. Only about 16% of patients arrive at UBTH by ambulance, compared to 30% at MRI.

On arrival of a patient in UBTH the triage team (see next section) is summoned to the hospital entrance and transfers the patient to a trolley in order to check the patient's vital signs. In parallel with this payment is taken from the patient. If the patient is alive, they are moved to the triage area where treatment is started immediately by the physicians. According to the outcome of this initial examination a patient can be referred to either the trauma or medical team. If the patient is dead, they are pronounced "dead" and sent to the mortuary.

4.4.2 Triage

Triage (from the French word "trier" meaning to sort out) is a system which originated on the battlefield as a procedure for prioritising the treatment of wounded soldiers according to the severity of their injuries and which was practised against a background of limited resources. Nowadays it is used in the same general sense within ED to assign resources and procedures to a patient according to their condition (Göransson and von Rosen, 2010).

In MRI, triage is performed by assigning a priority to a patient according to the Manchester Triage Score (Mackway-Jones et al., 2006). This is measured by a triage nurse by observation, by measurement of vital signs, by questioning the patient and by assessing feedback from the patient. Triage assessment results in the patient being assigned a colour code and a care group classification. These in turn determine the units within ED to which the patients are directed. In

MRI, the units are Rapid Assessment Unit (RAU), major area (red and amber), minor area (Green and Green/MIU), and Primary Care Emergency Centre (PCEC). PCEC is also known as the blue area. About 1 in every 25 patients in the PCEC requires emergency treatment and is redirected back to the green area after initial treatment and evaluation. Figure 4.4 shows the triage information at MRI which is located on the wall of the ED; however, these target times are no longer practised. Table 4.1 shows the current triage practice in MRI as described by Dr Richard Body.

Figure 4.4: Poster showing Emergency Department information at Manchester Royal Infirmary highlighting the Triage Information

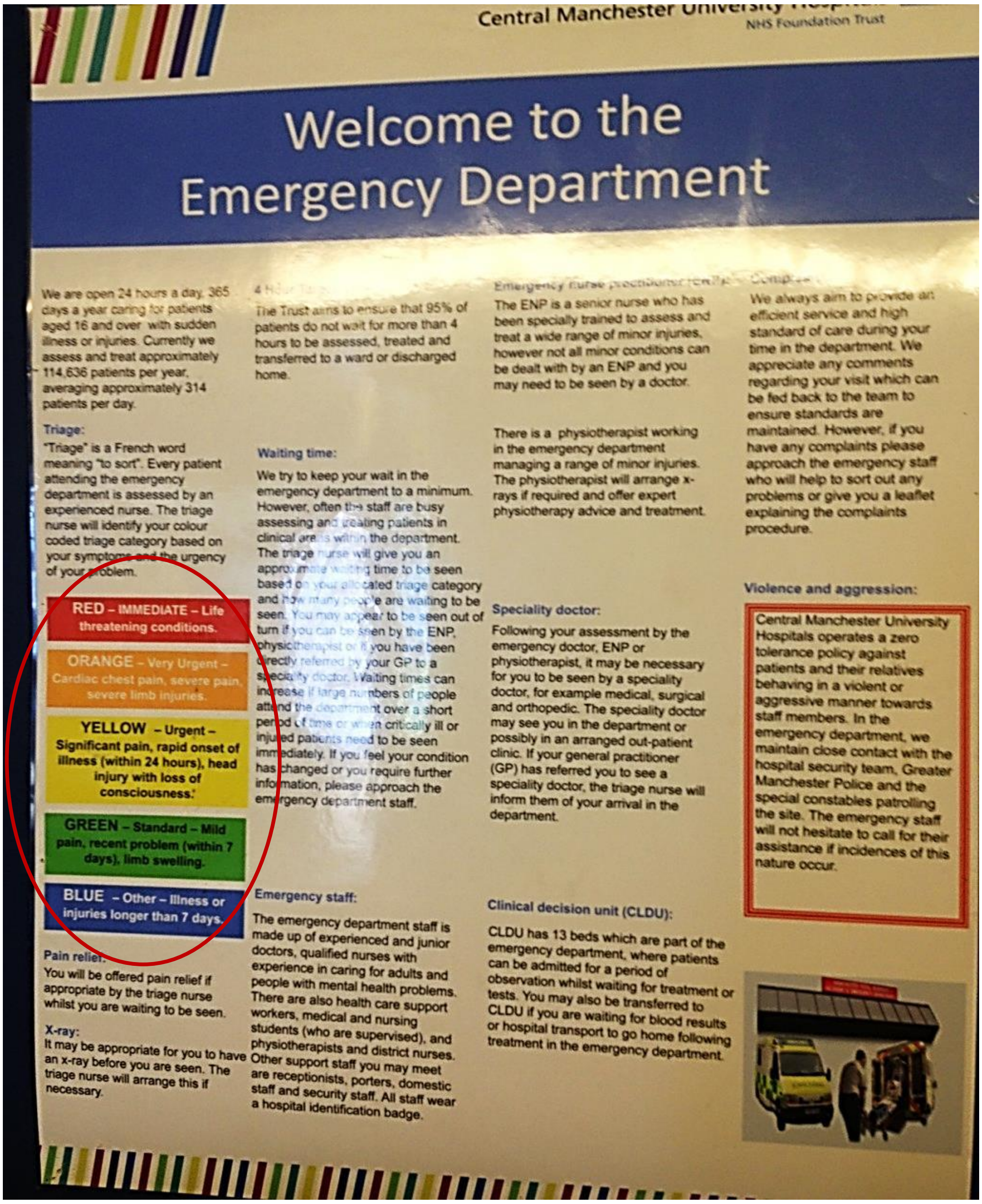


Table 4.1: MRI Triage code with target duration as described by Dr Richard Body

Triage severity	Triage colour code	Acuity Level	Examples	Target time to see Clinician
Critical	Red	1	Trauma	Immediately
Very serious	Amber	2	Cardiac chest pain	Within 15 minutes
Serious	Yellow	3	Significant chest pain/distress/broken leg	Within 1 hour
Good	Green	4	Recent recurring problem/minor injuries	Within 2 hours
Excellent	Blue	5	Illness/injuries longer than 7 days	Within 4 hours

The system of triage in UBTH is similar to that of MRI as shown in Table 4.2, except for the addition of "dead" category for patients who were brought in dead or died on arrival and non-emergency patients.

Table 4.2: UBTH Triage code with target duration as described by Dr Pius Iribhogbe

Triage severity	Triage colour code	Acuity Level	Target time to see Clinician
Dead	Black	1	Immediately
Critical	Red	2	Immediately
Urgent	Orange	3	Within 15 minutes
Serious	Yellow	4	Within 1 hour
Trivial	Green	5	Up to 6 hours

Here, triage nurses also determine which area of the ED the patient should go for appropriate care. If the patient is under 15 years old, the triage team refers the patient to the children's unit. Otherwise patients are directed to the three main areas; major, minor and GP clinic, according to the severity of their ailment. The GP clinic in UBTH is equivalent to the Primary Care Emergency Centre (PCEC) at MRI; which is where trivial patients are seen. Major patients are those seriously ill or injured such as trauma cases, road accident victims, serious burns and stroke patients. Minor patients are those with less serious injuries such as strains, sprains, cuts, bruises and less serious burns. Most minor patients arrive by themselves, especially by foot while major patients arrive by ambulance and other means. Note that there is no RAU and resuscitation is carried out in the Majors Area. Unlike in MRI, should any patient who was originally assigned to the GP clinic require more extensive treatment, they are sent directly to the appropriate hospital department rather than redirected to the minors queue. It is worth noting that patients with trivial conditions rarely present at the ED in UBTH since as discussed earlier, people with such issues usually carry out self-medication or go to the pharmacy for treatment.

From the data obtained, 13% of patients that present at the emergency department are brought-in-dead. Although, there is no 4-hour deadline incorporated in UBTH, trivial patients can be delayed for up to 6 hours. In 2006, a study showed that the average waiting time at UBTH is 2 hours 53 minutes (Ofili and Ofovwe, 2005); however this study showed a shorter waiting time as will be shown in chapter 5.

4.4.3 Processes and Exit

Figure 4.5 and 4.6 show the process map of the operations of MRI and UBTH respectively. Both hospitals carry out the same form of services such as; resuscitation, registration, triage, test, consultation, treatment, review, and diagnosis in all areas; after which the patient is either discharged or referred to other hospital departments.

In UBTH, 1 out of 20 patients that presents at the emergency department (ED) are unconscious based on the hospital data. If a relation or friend accompanies an unconscious patient to the ED, he/she is directed to get a case note from the medical record unit where he/she pays some money at the revenue and is issued a receipt as evidence of payment. This payment process is carried out simultaneously while the doctor commences treatment. The case note and the receipt are presented to record officer, who then issues a medical card to the individual. The case note and medical card are handed to the doctor in charge of the patient, while the relative or friend keeps the receipt. The case note contains information such as Name, Sex, Age, Address, Marital Status, Next of Kin, Next of Kin address and Next of Kin phone number. If a patient is brought to the ED by a Good Samaritan, Police, or FRSC, an emergency case note is used for the patient. Payment is eventually made after consciousness is regained or when a relation or friend arrives. 95.7% of Nigerians pay out-of-pocket for healthcare, compared to 56.8% in the UK (The World Bank, 2015); however, emergency treatment is free for UK residents under the NHS. Thus the payment procedure is more emphasized in the process map of UBTH (Figure 4.6).

Figure 4.5: Process map of MRI operation

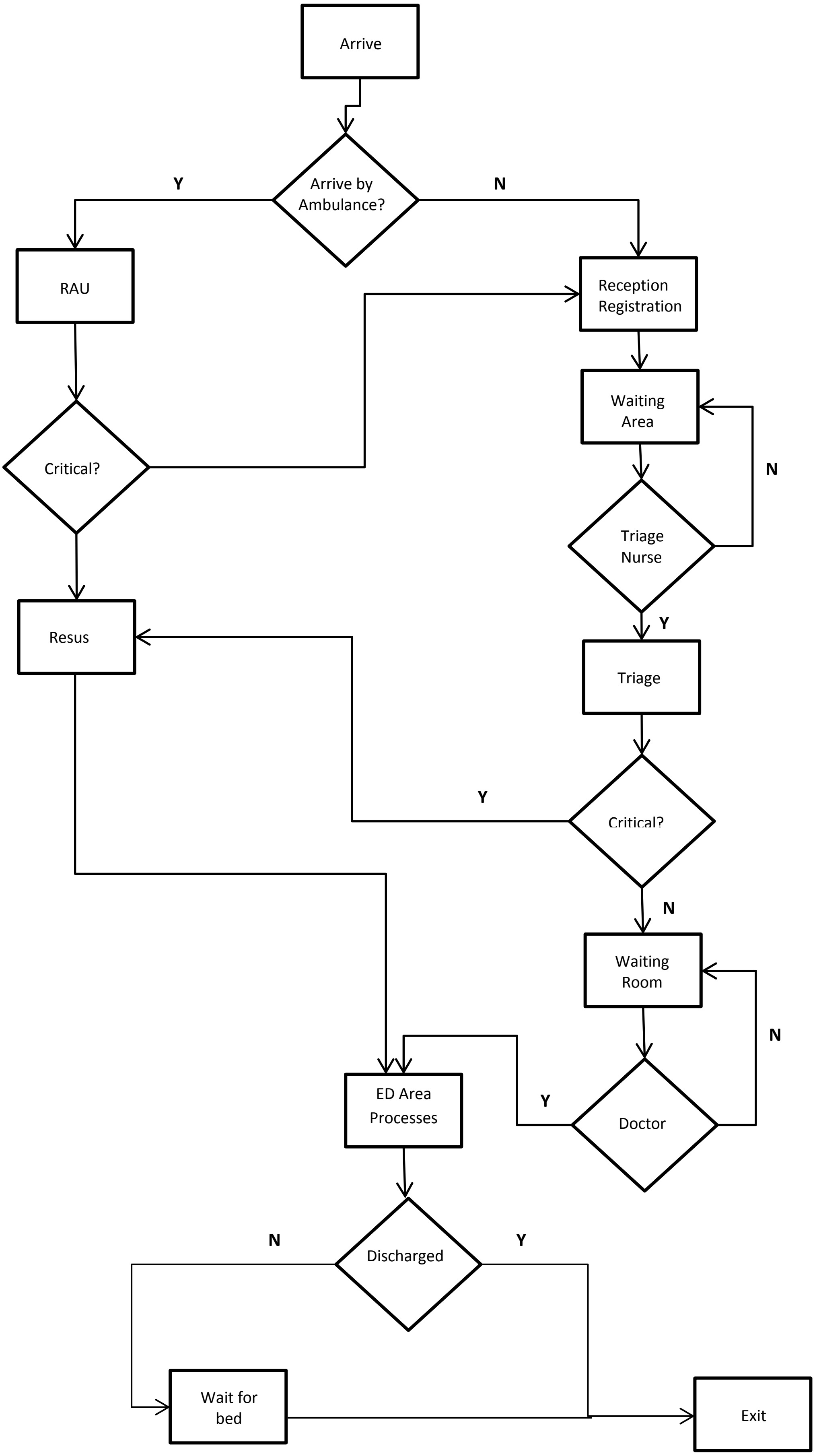
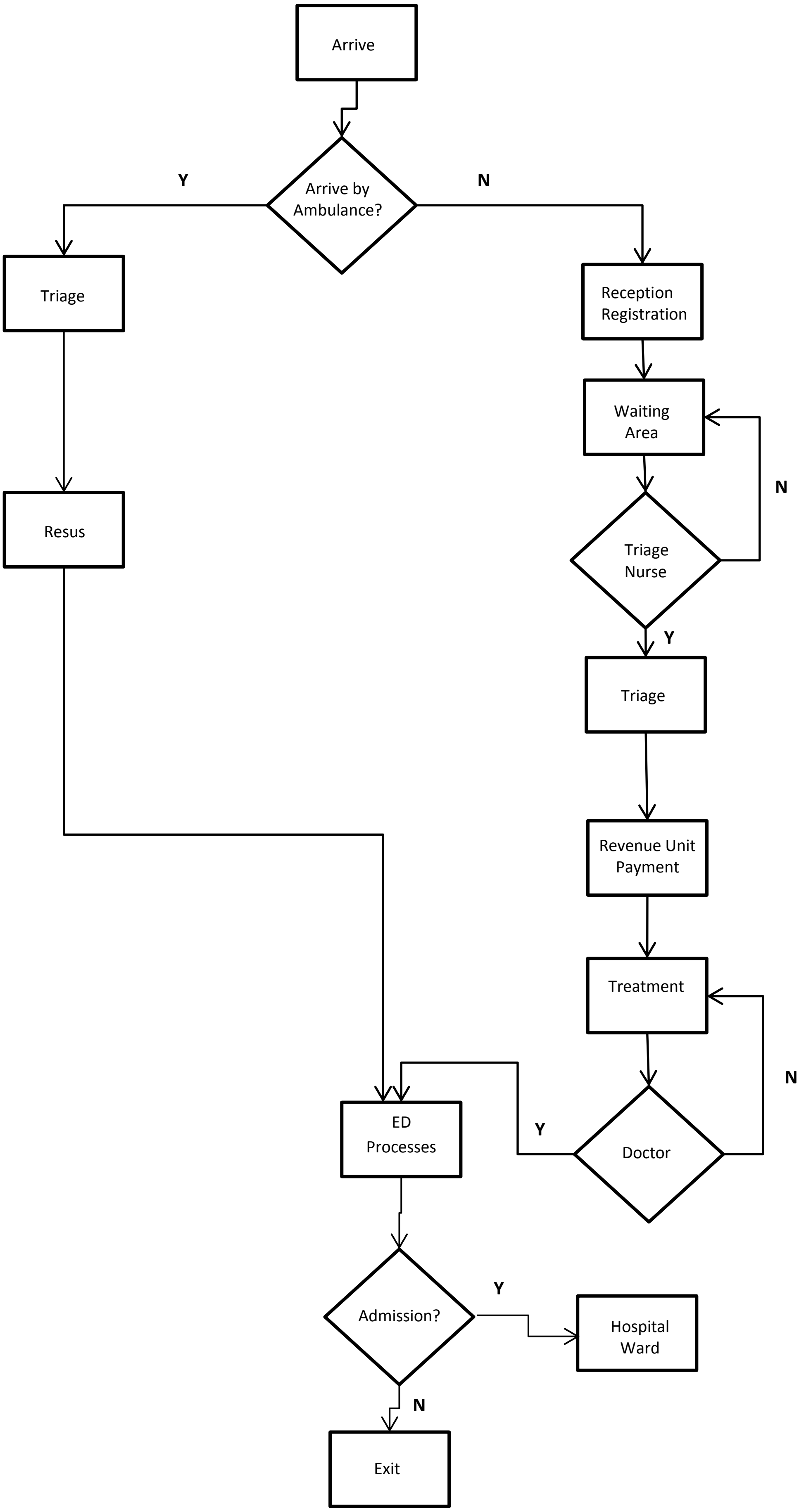


Figure 4.6: Process map of UBTH operation



4.5 Health workers

According to (Naicker et al., 2009), the key elements of any healthcare system are the doctors and nurses within it. In the UK, there are 21 doctors and 73 nurses/midwives (per 10,000 population) (Yar et al., 2006), whereas in Nigeria there are 4 doctors and 16.1 nurses/midwives (per 10,000 population); which is below the minimum density threshold of a total of 23 doctors, nurses and midwives per 10,000 population (World Health Organization, 2009, Liese and Dussault, 2004). This is poor because the healthcare service of a country is greatly dependent on the size, skills and commitment of its health workforce (Poz et al., 2007). The low staff to population ratio could be due to the high level of migration by Nigerian medical personnel to overseas country for better career opportunities and professional training. More on this topic is discussed in chapter 10. The above mentioned national statistic is highly reflective on the daily capacity for doctors and nurses as reported by ED staff at MRI and UBTH. For example, in MRI, 1 Doctor sees approximately 16 patients daily, while in UBTH 1 doctor treats 5 patients for the same amount of time. This could also suggest that patients in UBTH present with more serious ailment or there is lack of adequate equipment to treat patients quickly (Oluwadiya et al., 2010).

In MRI, there are four ranks of doctors based on their skills and experience. By ascending order of ranking, they are as follows; junior doctors, junior registrars, senior registrars and consultants. Based on the provided rota (see chapter 5), there is a maximum of 6 junior doctors, 4 junior registrars, 4 senior registrars and 3 consultants. The ED workforce also consists of at least 12 nurses in each shift, who are assigned to the four different areas in the ED as needed.

In UBTH, there are three teams of doctors namely; the casualty team, medical team and trauma team. There are 3 casualty doctors; while the medical team has 3 resident doctors and 1 consultant, and the trauma team is made up of 3 resident doctors and 2 consultants; totalling 6 resident doctors and 3 consultants. Hence it is safe to state that there are three ranks of doctors in UBTH; casualty doctors, resident doctors and consultants. Although likewise the doctors, the nurses work in shifts, however the ED has a capacity of 5 Nurses at all times. Nurses are distributed as required in the major and minor areas. The shift patterns for doctors and nurses in UBTH and MRI are described in more details in chapter 5.

According to the NHS circular for pay arrangements (Winnard, 2015), annual salaries in the UK range from £75,249 to £101,451 for consultants, £37,176 to £69,325 for doctors, and £15,100 to £98,453 for nurses; based on their roles, experience, and work schedule. From the world health report (David McCoy, 2008), nurses in Nigeria earn approximately £3,250. Salary information for doctors and consultants in Nigeria are scarce. However, from interviews with ED staff, resident doctors at UBTH earn about £6,000, while consultants earn about £20,000 annually.

It should be noted that in addition to clinical and medical hospital staff, the healthcare community includes an army of health workers. According to (Adams and P. and Goubarev, 2003), health workers are all people involved in the promotion, protection or improvement of the health of a population; which is consistent with the World Health Organization (WHO) definition of health systems as constituting all activities with the primary aim of improving health. Consequently, this means that family members taking care of the sick and other unpaid or paid care givers such as volunteers, receptionists and social workers who contribute to the improvement of health should be included as part of the health work force (Poz et al., 2007). This community is not considered here.

4.6 Data Collection

After the approval of the ethical protocol, there was an extensive amount of quantitative data made available from MRI in the form of spreadsheets of historical records for the period under study. By way of illustration, Table 4.3 shows the first ten records from one of the spreadsheets. This and the other data for all 98236 patients who attended MRI during the period of study are described in extensive detail in Chapter 6.

Table 4.3: Patient Journey Through ED at MRI

	A	B	C	D	E	F	G	H	I	J
1	Identifier	Age	ArrivalMode	AmbulanceTime	ArrivalTime	TriageTime	TriageComplain	TriageCategory	CareGroup	ClinicianTime
2	1	52	Own Transport		01/04/2012 00:04	01/04/2012 00:10	Shortness of breath	2	Amber	01/04/2012 00:32
3	2	26	Ambulance	01/04/2012 00:05	01/04/2012 00:05	01/04/2012 00:06	Assault	4	Green	01/04/2012 02:17
4	3	90	Ambulance	01/04/2012 00:10	01/04/2012 00:11	01/04/2012 00:11	Limb problems	4	Amber	01/04/2012 01:20
5	4	27	Ambulance	01/04/2012 00:10	01/04/2012 00:16	01/04/2012 00:16	Mental illness	3	Green	01/04/2012 04:01
6	5	19	Ambulance	01/04/2012 00:25	01/04/2012 00:25	01/04/2012 00:25	Shortness of breath	3	Amber	01/04/2012 01:25
7	6	51	Public Transport		01/04/2012 00:42	01/04/2012 01:33	Limb problems	4	Green/MIU	01/04/2012 00:47
8	7	24	Ambulance	01/04/2012 00:43	01/04/2012 00:45	01/04/2012 00:45	Abdominal Pain	3	Amber	01/04/2012 02:17
9	8	81	Ambulance	01/04/2012 00:55	01/04/2012 00:59	01/04/2012 01:00	Unwell adult	4	Amber	01/04/2012 02:06
10	9	19	Own Transport		01/04/2012 01:06	01/04/2012 01:21	Unwell adult	2	Amber	01/04/2012 03:23
11	10	25	Ambulance	01/04/2012 01:02	01/04/2012 01:04	01/04/2012 01:04	Wounds	4	Green/MIU	01/04/2012 02:45

Information for the five month period from April 1, 2011 to August 30, 2011 was obtained from UBTH and is shown in Table 4.4. The data cover 24 hours of operation of the ED during this period. This information was recorded manually in the “record book” by the ED receptionist. Even at first glance it is clear that the extent of this information is limited and incomplete compared with the data from MRI shown in Table 4.3.

Table 4.4: UBTH Historic Data for the period April 1 to August 30, 2011

Card No	Patient's Name	Patient's Arrival Date	Arrival Time	Time Attended To
0652	1	01-Apr-11	06:05	
0653	2	01-Apr-11	09:25	
0654	3	01-Apr-11	09:26	
0655	4	01-Apr-11	12:25	
0656	5	01-Apr-11	13:05	
0657	6	01-Apr-11	16:19	
0658	7	01-Apr-11	17:00	
0659	8	01-Apr-11	17:18	17:30
0660	9	01-Apr-11	18:08	
0661	10	01-Apr-11	18:09	
0662	11	01-Apr-11	19:14	
0663	12	01-Apr-11	20:00	
0664	13	01-Apr-11	20:10	

These data are scant, incomplete and inaccurate. For example, some IDs were repeated and some days were omitted. This may be attributed to human error on the part of the receptionist or as a result of poor communication by the patients or relative since the community has a high level of illiteracy. Information which is key not only for model building but also for the establishing of efficiencies, and which includes the time of triage, the treatment time, the time seen by a clinician and the exit time were not always recorded and hence was lost. In addition most of the patients' record cards could not be found during the time of data collection - which indicates poor housekeeping - and in any case it seemed that not all the patients who attended the ED recorded their information at reception.

For all of these reasons, the author spent a total of 336 hours between July 1, 2011 and August 29, 2011 tracking patients through the ED at UBTH. The data gathered during this period are shown in Table 4.5.

Table 4.5: Tracked Data at UBTH

S/N	SEX	AGE	DAY OF THE WEEK	TIME OF ARRIVAL	TIME RECEIVED BY TRIAGE TEAM	TIME ATTENDED BY DOCTORS	NATURE OF INJURY OR ILLNESS	RESCUE STATUS	MEANS OF TRANSPORTATION	REMARK
1	Female	43	Fri 01/07/2011	11:04	11:06	11:10	Bruises on leg	Family	Commercial Bus	Conscious and calm
2	Female	38	Fri 01/07/2011	12:42	12:53	13:02	Minor leg Fracture	Daughter	Private car	Unconscious
3	Male	29	Fri 01/07/2011	14:00	14:06	14:08	Arm and leg fracture	Good samaritan	Car	Conscious but bleeding
4	Male	62	Sat 02/07/2011	10:04	10:06	10:07	Kidney failure	Family	Private car	B.I.D
5	Male	50	Sat 02/07/2011	11:54	11:57	11:59	T.B	Son	Commercial car	Weak but conscious
6	Male	58	Sat 02/07/2011	13:22	13:25	13:26	T.B Referral	Family	Ambulance	Conscious but on oxygen
7	Male	35	Sat 02/07/2011	14:01	14:02	14:05	R.T.A	Family	Commercial car	Breathing but unconscious
8	Male	26	Sat 02/07/2011	14:25	14:25	14:37	Systemic	Family	Private car	Mentally ill
9	Female	24	Sat 02/07/2011	15:01	15:06	15:06	Systemic	Family	Church bus	Conscious but weak
10	Male	58	Sat 02/07/2011	16:20	16:21	16:26	Systemic	Son	Private car	Kidney failure

While tracking patients did generate information it proved to be a tedious and stressful process since there was only limited assistance from ED staff. It was made all the more difficult by the author being able to gather information at only one of the three entrances to the ED at any particular time. This made it impossible to keep track of all the patients who arrived at any one time and the hospital could not provide volunteers to help. Obtaining information such as time after treatment or exit time was also difficult since the author was not available for the entire 16 hours in a day. Furthermore, since multiple patients were being watched and tracked at the same time, the author inevitably missed the time some patients left the department. For all of these reasons, the data collection was focused on time of arrival, time of triage, time to see doctor and the number of attendances.

These data from UBTH were insufficient to generate anything but a superficial model of the ED at MRI. Nonetheless thee information is discussed in more detail in Chapter 5. The MRI data are described in detail in Chapter 6 and are used to develop models in Chapter 7 and Chapter 8.

For completeness, a summary comparison between the Departments is given in Table 4.6

Table 4.6 Key comparisons between MRI and UBTH

	Manchester Royal Infirmary	University of Benin Teaching Hospital
Date of Establishment	1752	1973
Operational Hours	24 hours	
Hospital Type	University Teaching Hospital	
Ethical Approval	Lengthy Application and time consuming	Quick, easy and straightforward. No particular framework
Time spent during study	208+ hours	525 hours
Annual Attendance	100,000	11,000
Population estimates of community	514,417	5 million
Doctor to Patient ratio	1:16	1:5
Population to ED Attendance ratio	5:1	455:1
Financial obligation	Treatment is free for UK residents	Payment is required before commencement of treatment
Method of data collection	Symphony software	Written manually on case notes
Total patients’ data obtained	98236	362
Quality of historic data provided	Rich but incomplete	Poor, scant, and incomplete

4.7 Lessons to be Learned on the Quality of Data from MRI and from UBTH

In Section 4.6 the contrast between the predominantly qualitative information from UBTH and the quantitative information from MRI present different challenges to the generation of DES models.

While the recorded data from UBTH are scant, there is openness and accessibility that, given time could be tapped in order to generate at least an anecdotal based model of the ED. The main issue here is the time it would take and the accuracy of the information. At best the resulting model would be applicable only to UBTH and only to the period under study and would lack the generality that a model should provide.

By contrast the comprehensive and quantitative data from MRI should provide all the information required to generate a robust model of the system. Given that the NHS by its nature imposes a common set of targets on all UK Emergency Departments any model which is derived from the ED at MRI is likely to have at least some features that are generally applicable. Yet this may not follow in that the recorded data while comprehensive are incomplete and, for example contain no data on the duration of any of the procedures which a patient undergoes on their journey through ED. In addition the implementation of the 4-hour deadline is impossible to interpret only from the documented data and requires along with other bits of information anecdotal information from clinical and from medical staff (Chapter 8).

Data collection in UBTH (and in Nigerian hospitals in general) could be improved to the level of that in MRI by the introduction of Electronic Health Records (EHRs).Walker et al (2006) describes EHRs as the whole of patient's health and health records - from birth to death which contains personal information about them and their contacts with healthcare organizations. They also stated that electronic health records (EHRs) creates the ability for patients and staff to work together in a quality way that is not possible without it. Therefore, the absence of EHRs is an obstacle to health professionals and hospital management in making the appropriate decisions towards effective healthcare delivery. This is not a recent issue in Nigeria and as long ago as 2003 the Nigerian health minister, Professor Onyebuchi Chukwu pointed out that demographic data is lacking in the healthcare sector (Nigerian Tribune, 2013). Data accessibility, knowledge management and information technology are the cause of many problems in healthcare systems (Kasiri et al., 2012).

The absence of EHRs is all the more alarming since Nigeria is ranked as the largest and fastest growing telecom market in Africa and has immense potential for future technologies (IT &

Telecom Digest, 2011). Despite this, patients' details are recorded manually and an ad hoc survey of staff at UBTH indicated that they have little or no computer skills, although there was great enthusiasm to learn. Ameh et al (2008) believe that introducing computer-based knowledge to medical students is the preferred way to do this. Indeed the introduction of computer skills to secondary schools is perhaps a more long term solution to this problem and there are measures in place to develop computer-based knowledge in younger students. For example E-learning has been introduced in Oyo State (a Western state in Nigeria) by the government (Adegbola, 2013) through the distribution of digital tablets with pre-loaded e-books, video/audio lectures and tutoring notes to secondary school students. It is anticipated that this will encourage the implementation of computer technology in various areas in Nigeria.

Indeed, Dr Pius Irigbhogbe stated that the management of UBTH is considering installing computers for data input. It is suggested that this decision is made and implemented as soon as possible, since it represents the first step towards generating robust data and, in due course the possibility of carrying out simulation modelling for optimizing the healthcare system.

While the shortcomings of the data recorded in the ED at UBTH can be identified with the absence of computers and the lack of computer skills amongst the staff, the main criticism of the quality of the data from MRI must focus on the absence of any quantitative information on the duration of the procedures that a patient undergoes during the journey through ED. By any standard this is a serious and unaccountable omission but one which appears to be common in departments throughout the UK. It is essential that the NHS consider the use of automatic tracking such as RFID tags, bar codes and other electronic devices sooner rather than later. This is elaborated on in Chapter 10.

4.8 Information required to create a robust ED model

Given the information in this and the following Chapters, it is useful at this stage to speculate on a template which describes the information from any ED that is necessary and sufficient to create a robust model of the system. This is shown in Table 4.7. The significance of these data is illustrated throughout Chapters 5-8. Note that this information should be recorded in real time, but in practice this is difficult to accomplish since the medical staff's priority is to ensure that the patient is provided with adequate and timely care. In ED at MRI the recording software (Symphony) insists on complete patient records and hence staff may have to use their initiative to estimate times after a particular event.

Table 4.7: Data required for DES Model

Patient's Age	Permits analysis by age
Arrival time	Based on the time of day and the day of the week. The clock starts at the arrival time
Arrival Mode	At least by "ambulance" or "other". Ambulance arrivals imply that the patient has a serious condition and should be treated in the ED with greater urgency
Exit Time	The time the patient is "off the clock". This can be as a result of discharge, transfer or referral. The exit details should be recorded so that these can be correlated with other information such as triage complaint and care group
Triage Score	Based on the Manchester Triage Score. Implies the path which the patient takes through ED
Care Group	More explicit description of the path taken by the patient
Triage Complaint	Allows for cohort comparisons
Assigned Unit	This can be provided explicitly or inferred from the triage score or Care Group
Journey	Effectively a process map of the patient's journey through the system including timestamps and durations for the various procedures and treatments. Should also include details of the resources used at each treatment station
Resources	The number of beds, treatment rooms, cubicles, etc, available in the ED and the number of all staff available in ED and their shift patterns

CHAPTER 5 ANALYSIS OF DATA FROM THE UNIVERSITY OF BENIN TEACHING HOSPITAL

5.0 Introduction

In Chapter 4, a comparative report was provided on the overview of the University of Benin Teaching hospital (UBTH) and Manchester Royal Infirmary (MRI). The paradox of the data availability was also discussed in both cases. In UBTH, data was obtained both quantitatively and qualitatively. Two groups of quantitative data were collected; one is historical, and the second was from tracked patients during field work.

Although the historical data was poor, the average number of daily and hourly attendances were deduced and compared to that of the tracked data. Note that most of the analyses were carried out on tracked patients. Note too that as stated in Chapter 4, not all patients who attended the ED during the collection period were tracked. Nonetheless, information including percentage attendances by hour of day, arrival mode, sex, age group, and journey times for specific milestones were derived for most of the patients and are described here.

Both the historical and manually collected (tracked patients') data were analysed using R[12] (Stowell, 2014, MacFarland, 2014) and Microsoft Excel in section 5.1. Qualitative data were obtained from interviews with the ED staff which includes staffing procedure and equipment availability and is described in section 5.2. The information is summarized in section 5.3.

5.1 Quantitative data collection

5.1.1 Historical data

As described in Chapter 4, historic data from UBTH for the period 1 April to 30 August, 2011 were obtained. These data were for 24 hours of operation during this period and contained limited information such as card number, patient's name, date and time of arrival and time seen by the doctor (Figure 5.1). There were no records of data which are required for model building such as time of triage, treatment time, time of exit, and end times of events.

Figure 5.1 shows the first 13 patients, with only one entry for "time attended to". This sparseness applies to the rest of the data and out of the 1230 patients' historical data recorded, only 6% had valid entries in the "time attended to" column. There were also 24 missing "arrival time" entries, and no information was entered for some days. For example, there were no entries on June 10, July 14 and 18, and August 6. Perhaps, genuinely, there were no attendances on those days.

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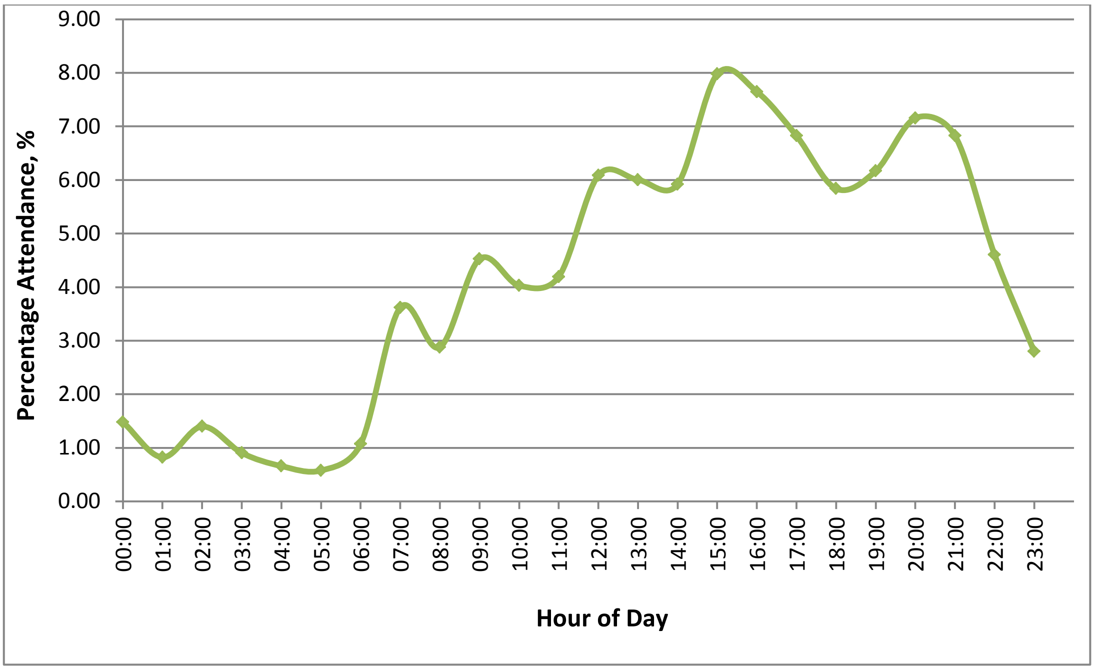
[12] *R is a scripting language software for carrying out statistical data analysis. For more details, see MATLOFF, N. 2011. The Art of R Programming: A Tour of Statistical Software Design, San Francisco, William Pollock.*

Figure 5.2 shows an interesting trend of attendances by hour of day. Note that patients are most likely to attend the ED of UBTH at 3pm, and less likely to attend at 5am.

Figure 5.1: UBTH historical data in spreadsheet format

Card No	Patient's Name	Patient's Arrival Date	Arrival Time	Time Attended To
0652	1	01-Apr-11	06:05	
0653	2	01-Apr-11	09:25	
0654	3	01-Apr-11	09:26	
0655	4	01-Apr-11	12:25	
0656	5	01-Apr-11	13:05	
0657	6	01-Apr-11	16:19	
0658	7	01-Apr-11	17:00	
0659	8	01-Apr-11	17:18	17:30
0660	9	01-Apr-11	18:08	
0661	10	01-Apr-11	18:09	
0662	11	01-Apr-11	19:14	
0663	12	01-Apr-11	20:00	
0664	13	01-Apr-11	20:10	

Figure 5.2: Percentage Attendances by Hour of Arrival for tracked patients in UBTH



The trend here is different from that of the tracked data as shown later in this Chapter. From the information provided by Dr Irigbhogbe, approximately 30 patients attend the ED daily. However from the data, the average daily attendance recorded is 8 patients, with April having the greatest number (11), and July the least (6).

5.1.2 Tracked patients' data

As described in Chapter 4, the author tracked patient arrivals at the ED in UBTH over a two month period from 1 July until 29 August, 2011. These data are shown in Figure 5.3.

Figure 5.3: UBTH data of first 10 tracked patients in spreadsheet format

S/N	SEX	AGE	DAY OF THE WEEK	TIME OF ARRIVAL	TIME RECEIVED BY TRIAGE TEAM	TIME ATTENED BY DOCTORS	NATURE OF INJURY OR ILLNESS	RESCUE STATUS	MEANS OF TRANSPORTATION	REMARK
1	Female	43	Fri 01/07/2011	11:04	11:06	11:10	Bruises on leg	Family	Commercial Bus	Conscious and calm
2	Female	38	Fri 01/07/2011	12:42	12:53	13:02	Minor leg Fracture	Daughter	Private car	Unconscious
3	Male	29	Fri 01/07/2011	14:00	14:06	14:08	Arm and leg fracture	Good samaritan	Car	Conscious but bleeding
4	Male	62	Sat 02/07/2011	10:04	10:06	10:07	Kidney failure	Family	Private car	B.I.D
5	Male	50	Sat 02/07/2011	11:54	11:57	11:59	T.B	Son	Commercial car	Weak but conscious
6	Male	58	Sat 02/07/2011	13:22	13:25	13:26	T.B Referral	Family	Ambulance	Conscious but on oxygen
7	Male	35	Sat 02/07/2011	14:01	14:02	14:05	R.T.A	Family	Commercial car	Breathing but unconscious
8	Male	26	Sat 02/07/2011	14:25	14:25	14:37	Systemic	Family	Private car	Mentally ill
9	Female	24	Sat 02/07/2011	15:01	15:06	15:06	Systemic	Family	Church bus	Conscious but weak
10	Male	58	Sat 02/07/2011	16:20	16:21	16:26	Systemic	Son	Private car	Kidney failure

From the data, patients arrive at the ED of UBTH via one of 9 methods namely; ambulance, private car, church vehicle, commercial vehicle, FRSC (Federal Road Safety Corps) van, motor bike, police car, school bus and trailer. The most common form of arrival in UBTH is by private car (35%). Note that only 16% of patients arrive by ambulance as described in chapter 4.4.1. Patients rarely arrive at the ED by trailers as shown in Figure 5.4. The average attendance was 9 patients per day which is close to the value of eight for the historical data and differs significantly from the 30 patients per day stated by Dr Irigbhogbe. Perhaps, he meant that 30 patients are seen daily, since most patients stay in the ED for more than 24 hours.

Figure 5.4: Attendances by Arrival Mode in UBTH

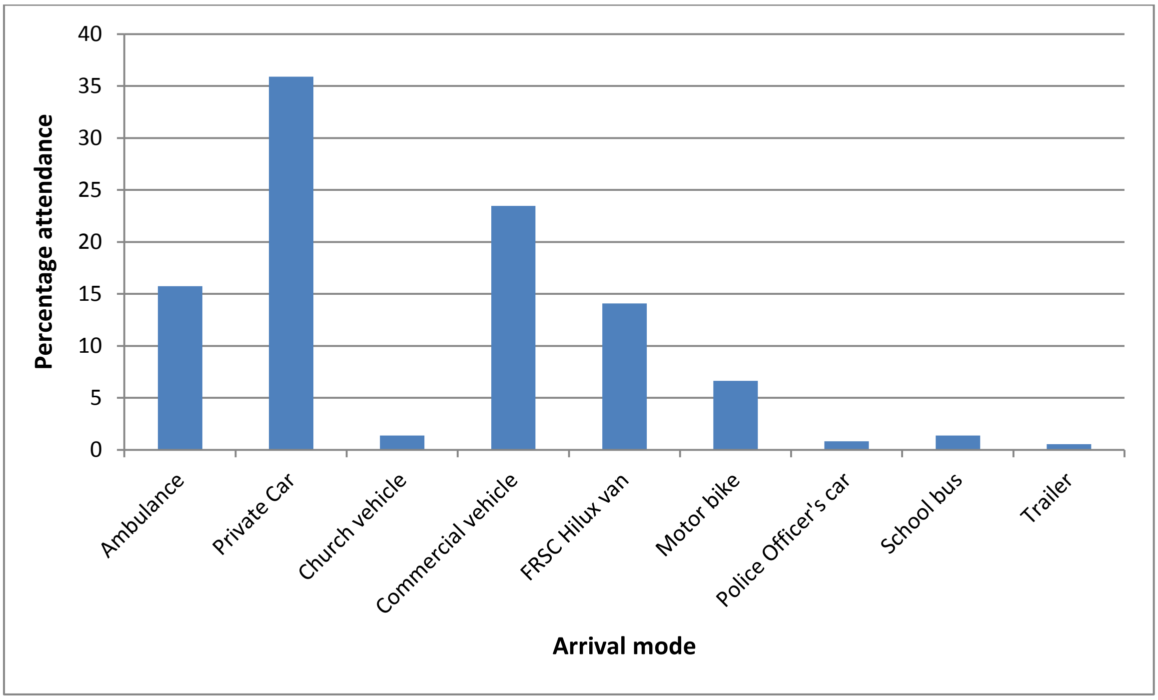
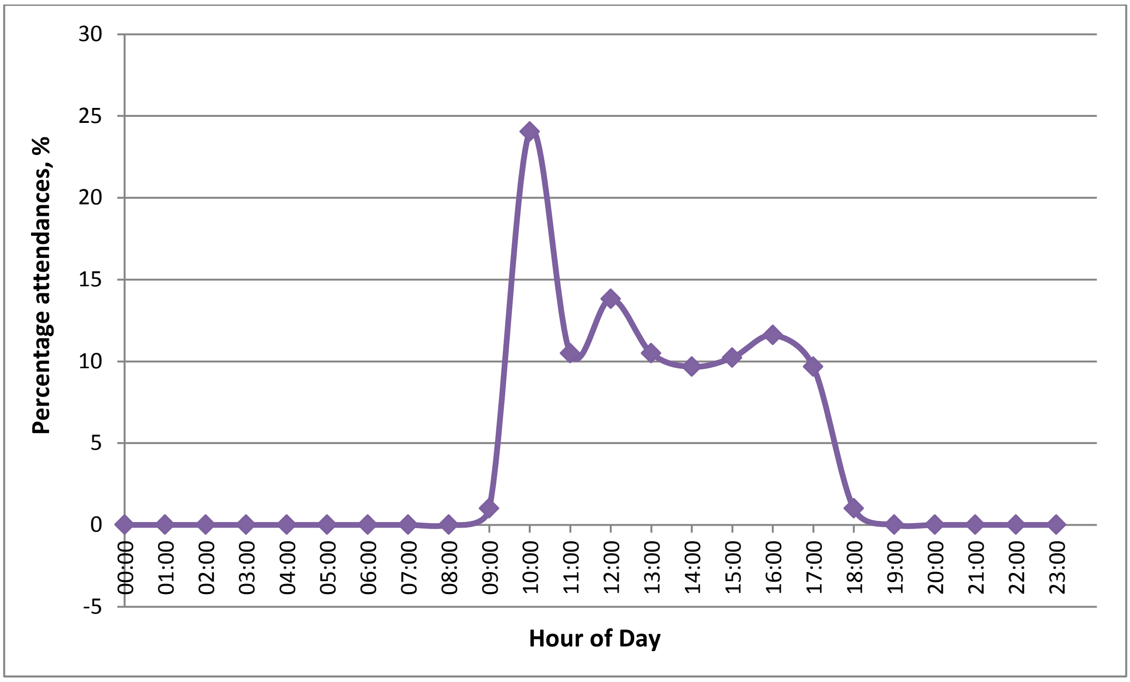


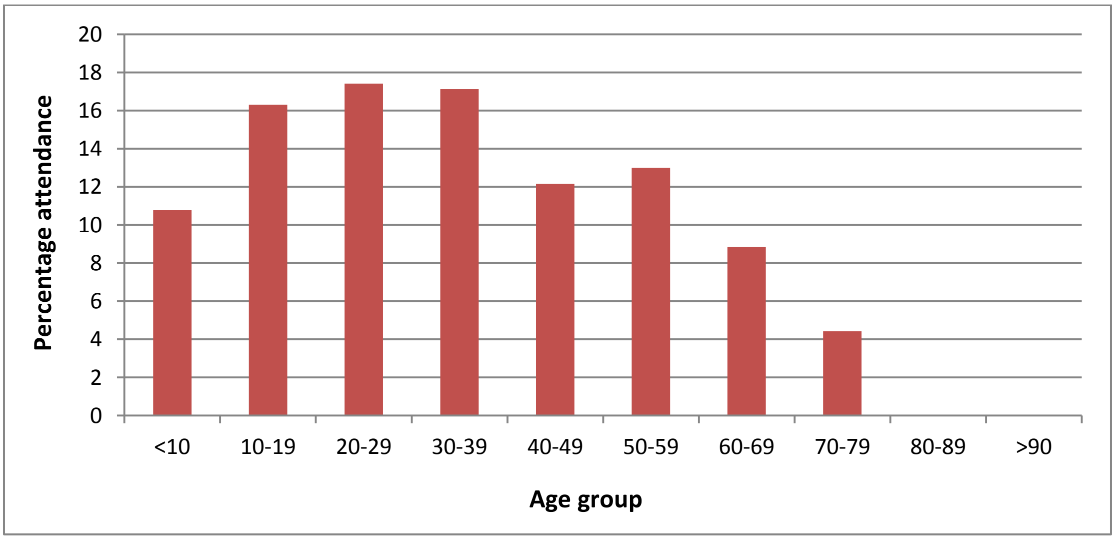
Figure 5.5 shows the percentage number of attendances by the hour of day. Here, most patients arrive at 10am, and the least attendance is seen between 1 and 3pm. Note that the trend here is in contrast with that of the historical data (Figure 5.2). Also note that patients were tracked only between 10am and 6pm and hence attendances for other times are defined here as zero.

Figure 5.5: Percentage Attendances by Hour of Arrival for tracked patients in UBTH



From Figure 5.6, patients between 20 to 29 years are most likely to attend UBTH, which is also the case in MRI (chapter 6). Note that there are no ED attendances for patients from 80 years and above. This could be due to the life expectancy, which is 53 years in Nigeria according to the World Health Organization data (WHO, 2012).

Figure 5.6: Percentage Attendances by Age group in UBTH



For completeness, Table 5.1 provides journey times for specific journey milestones for the tracked patients. Note here that the average time to see a doctor is 8 minutes although some patients can wait for up to 2 hours. The reason for the breadth of this time distribution is not known

Table 5.1: Specific Journey Times for patients in UBTH

	Mean (seconds)	**Percentiles (in seconds)**				
		0%	25%	50%	75%	100%
Arrival to Triage	213.6	0	120	180	240	7320
Triage to Doctor	292.5	0	120	240	360	4260
Arrival to Doctor	506.2	0	300	420	600	7500

5.2 Anecdotal data from UBTH

Interviews were conducted with the Emergency Department Co-ordinator who is also the Head of the Trauma team, Dr Irigbhogbe, the Head Nurse, Mrs Okafor, the founder of SAVAN (Save Accident Victims Association of Nigeria), Mr Jude and two experienced resident doctors (Dr Oduware and Dr Osa). The outcome of these interviews confirmed the daily operation of the department as described in the preceding data and provided information on staffing levels and equipment availability as described in Section 5.2.1 and 5.2.2.

5.2.1 Staffing

5.2.1.1 Doctors and nurses

Doctors and nurses operate on three shifts as shown in Table 5.2. There are three teams of doctors in the emergency department (ED), namely the casualty doctors (also known as triage doctors), the medical team and the trauma team.

Table 5.2: UBTH ED Staff shift pattern

Staff	**Shifts**		
	Morning	**Afternoon**	**Night**
Nurse	5	5	5
Casualty doctor	4	3	3
Resident doctor	3	2	2
Consultant	2	1	1
Receptionist	1	1	1

The trained casualty doctors are the first to see the patients on arrival at ED. They triage and stabilize patients and then decide if they need to see a trauma or medical resident doctor for further treatment. The casualty doctors run three shifts per day. The shifts (Table 5.2) run between 8am-4pm (morning), 4pm-8pm (afternoon) and 8pm-8am (night) every day, including weekends and bank holidays. There are usually 3 casualty doctors per shift except for the morning shifts when there are 4.

The medical and trauma teams (Resident doctors) are made up of experienced doctors who handle medical issues (such as stroke, acute coronial syndromes, renal failure, diabetes, chest pain, and electric shock) and traumatic cases respectively. These cases are referred to them by the casualty doctors. Five nurses work alongside the two teams and run same shift as the casualty doctors. The nurses report to the Head Nurse.

The trauma team also include interns (house officers) undergoing posting and are headed by one of its two consultants. The trauma team also comprises the airway doctor and nurse, the procedural doctor and nurse and the scribe nurse (who documents what goes on). The medical team has 1 consultant who is also the head of the team.

The medical and trauma team work between 8am and 4pm (morning) daily (during weekends and bank holidays), except on-call doctors who work 8am till 8am (morning till night shifts) the next day (this is termed “call hours” which amounts to 24 hours). Three doctors from each team are always on-call.

Casualty and resident doctors earn N1500/hr[13] (approximately £5/hr), the nurses earn N600/hr (approximately £2/hr) while consultants earn about N3000/hr (approximately £12/hr). However salaries are paid on a monthly basis as hourly rate for staff income is not the norm in Nigeria.

5.2.1.2 Social Workers, House keeper and Volunteers

There are also four social workers in the emergency department. Social workers collect patients’ jewelleries and personal belongings on arrival, if a relative is not available and help to contact the patient’s family members. They also carry out X-rays and laboratory enquiries. There are three housekeeping staff available to help keep the ED clean and tidy. They also render services such as laundry, linen changing and sterilization of equipment. There are also three volunteers who work for the Save Accident Victims Association of Nigeria (SAVAN) office. SAVAN works on trauma patients’ advocacy and run pre-hospital services when they have “functioning” ambulances.

[13] *N means Nigerian Naira*

Medical and Paramedic students often are on rotational postings in significant numbers and help in patient care under supervision of qualified medical staff.

5.2.2 Equipment availability

The ED has 7 cubicles which consist of 30 beds. There are also 1 Computed Tomography (CT) Scanner, 15 trolleys, 5 wheel chairs, an equipped theatre room for surgical cases, and 3 ambulances (which, as pointed out in Chapter 4.4.1 are rarely used as they are not well equipped for pre-hospital care).

5.3 Comments and Conclusion

The ED at UBTH is well staffed, well equipped and appears to cope well with the demand; its main problem lies with its administration. Both the recording of patients' journeys through ED and the maintenance of patient records from ED are very poor. Unless and until this housekeeping is brought up to the same standard as its other (medical) facilities it will be difficult to create a robust DES model of the facility. No doubt the proposed computer literacy drive (Chapter 4) will help but will take time to be implemented at this level and what is needed now is a better system of recording patient information or at least a better appreciation of the importance of this work amongst the current staff. Perhaps the roles of the scribe nurse and the receptionist are just undervalued.

This work gathered information by tracking patients through the ED. With some additional effort, perhaps using volunteers, patient tracking could be extended and generate a more complete picture of the ED which in due course would allow the generation of a DES model.

In the short term perhaps the introduction of a record card that is attached to the patient and on which is recorded time-stamps, locations and procedures might help. The card could be stored for transcription to a spreadsheet after the patient has been discharged. In due course the information such as that given in Table 4.7 could be recorded.

It is also interesting to note that the requirement for payment for treatment does impose a "non-medical" constraint on the development of a DES model in that non-payment has a knock-on effect on bed availability.

CHAPTER 6 ANALYSIS OF DATA FROM MANCHESTER ROYAL INFIRMARY

6.0 Introduction

The data from Manchester Royal Infirmary (MRI) was more comprehensive than that of University of Benin Teaching Hospital (UBTH), therefore was analysed more extensively. The information used in this study was supplied through an approved ethical protocol to the National Research Ethics Committee (NREC) (REC Reference 13/NW/0175, IRAS ID 124168, dated March 4, 2013). The submitted Protocol and NREC approval documents are available in the attached CD. The data cover records of patients' attendances at the department over a 12 month period between 1 April 2012 and 31 March 2013. The original data were hand-entered by the ED staff into the hospital record database using Symphony®. All data were anonymised by the hospital's Information Officer, Mr Ian Baskerville, to avoid compromising the confidentiality of individuals before collection. Data were provided electronically in form of Microsoft Excel spreadsheet files. Some of the analysed data are compared to the Hospital Episode Statistics (HES, 2014a) data for England in the same period, as there are no available HES data for solely MRI. Nonetheless, the HES data shows close similarity to that of MRI.

Researchers have specified data analysis as the most important aspect of carrying out successful robust simulation modelling (Goldsman, 2007b). However, data are usually either "too little" or "too much" (Sadowski, 2007). Some parts of the data provided were found to be complex and incomplete as will soon be shown. Therefore it needed to be manipulated in order to get useful information to build the model. This chapter describes the analysis of the data obtained and is presented in five sections. Preliminary data collected are described in Section 6.1. The raw data are modified and parsed using R (Stowell, 2014, MacFarland, 2014) in Section 6.2. Some information such as the availability of resources and staffing levels[14] were not included in the spreadsheet data, but were obtained through interviews with Dr Richard Body (ED Consultant), Jonathan Smith (the Head Nurse) and Mr Ian Baskerville (ED Analyst) and are presented in Section 6.3. Limitations to the data provided by the ED are discussed in Section 6.4. A conclusion to the Chapter is provided in Section 6.5. Some of the data presented in here are also described in the Festival of Evidence Conference (Cumberland Initiative) by Methven et al. (2014).

[14] *One-month's doctors rota was provided*

6.1 Preliminary Data

The raw data were supplied in four files[15] (DS1 to DS4) in form of Excel spreadsheets which are listed in Table 6.1.

Table 6.1: Original Data Sets

Our Reference	File Name (Excel)
DS1	Patient Journey Full Anonymous
DS2	ED Journey – Location Times Anonymous
DS3	ED Journey – Dept. Investigations Anonymous
DS4	ED Journey – Orders (from OCS) Anonymous
DS5	Merged DS3 and DS1

Details of Patient journeys from arrival to discharge for a year were provided in DS1, although some of the entries were incomplete as will be illustrated in Section 6.1.1. DS2, DS3 and DS4 were provided as “long, narrow” tables as rows of values and included information about patient location, investigation carried out on some patients and orders processed, at specific times through the emergency department.

There were a total of 98236 anonymous patient entries with the various fields and milestones (as time-stamps) which are displayed in Table 6.2.

Table 6.2: Fields (Recorded Milestones) from all spreadsheets

Identifier	Triage Time	Rapid Clinician Time	Left Department Time	Location
Age	Triage Complaint	Referral Time	Discharge Outcome	Location Time
Arrival mode	Triage Category	Bed Request	Discharge Destination	Orders
Ambulance time	Care Group	Bed Request Outcome	Dept. Investigation	Request Time
Arrival Time	Clinician Time	Specialty Referred To	Investigation Time	

6.2 Parsing the ED Data

The data were parsed using R and Microsoft Excel; the latter is slower and does not handle time and date calculations in a straight forward manner. Therefore most of the manipulations were done in R, some were done in Excel, while others were done in both to check for accuracy. The data were first manipulated in Excel to reduce the verbosity of particular entries, consolidate headings, correct minor spelling errors, and replace missing values with standard signal values.

[15] *The full datasets are available in the attached CD*

The resulting data were then imported as data frames into R for all subsequent manipulations. In addition, Excel is not useful when looking at repeated journeys, hence all such manipulations were carried out in R. Microsoft Access (SQL) and Perl could have also been used but at the cost of a steeper learning curve and hence a greater time investment.

It should be noted that some functions which were written in R were based on loops. This is deprecated amongst experienced R users since it does not exploit the essence of the language which allows functions to be applied to a list without iteration. Nonetheless the functions created in this work were sufficient for the purpose and the only penalty was the time taken for execution. The R codes used for this analysis and the outputs are provided in the Data Analysis folder in the Thesis CD.

6.2.1 Attendance Analysis

The following data are examined;

1. Attendances by hour of day
2. Hourly Attendances by care group
3. Hourly Attendances by discharge outcome
4. Attendances by weekday
5. Attendances by care group at particular time of day
6. Attendances by age group
7. Attendances by age group and discharge outcome
8. Attendances by Triage complaint
9. Attendances by mode of arrival
10. Attendances by mode of arrival and Triage category
11. Attendances by mode of arrival and Care group
12. Attendances by Care group and discharge outcome

Figures 6.1 shows the trend of hourly arrivals which is close to the Hospital Episode Statistics (HES) data for accident and emergency departments' attendances in England for the same time period (Figure 6.2) (HES, 2014a). In both cases, an incremental increase in attendances is seen from 7am to 11am; then it begins to decrease. In MRI, patients are less likely to attend the ED between five and six in the morning. It may be worth scheduling more ED staff between 7am and 12noon, which is evidently the busy period, and less between 11pm and 7am.

Figure 6.1: Percentage hourly attendance

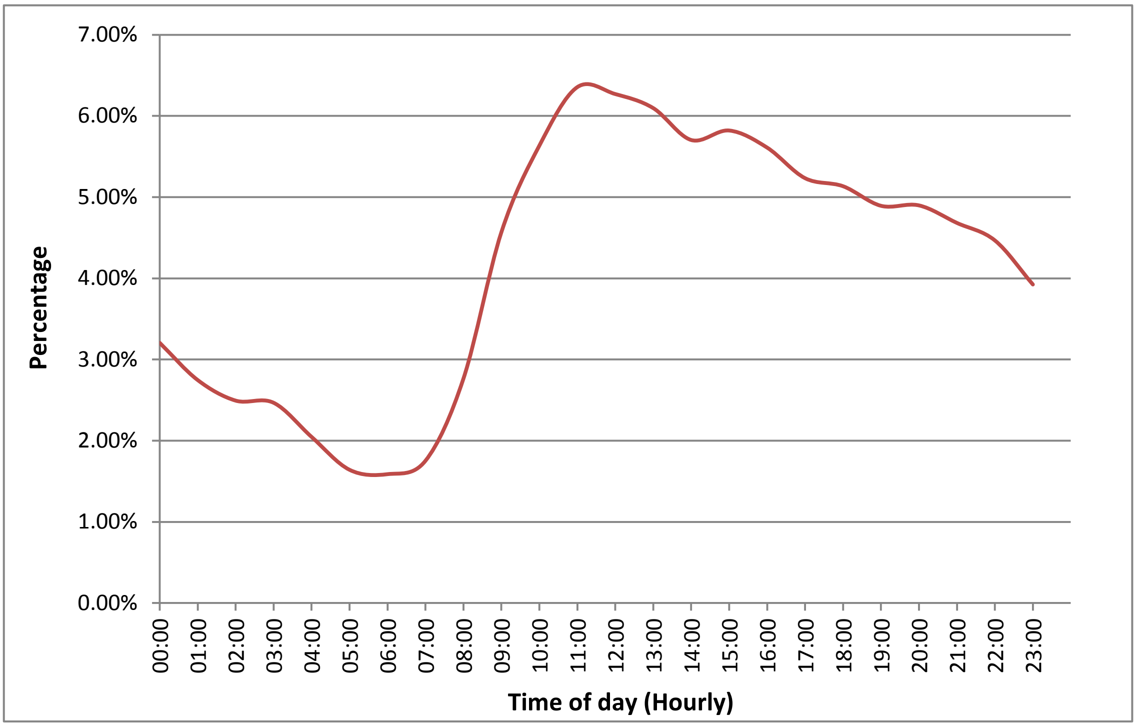
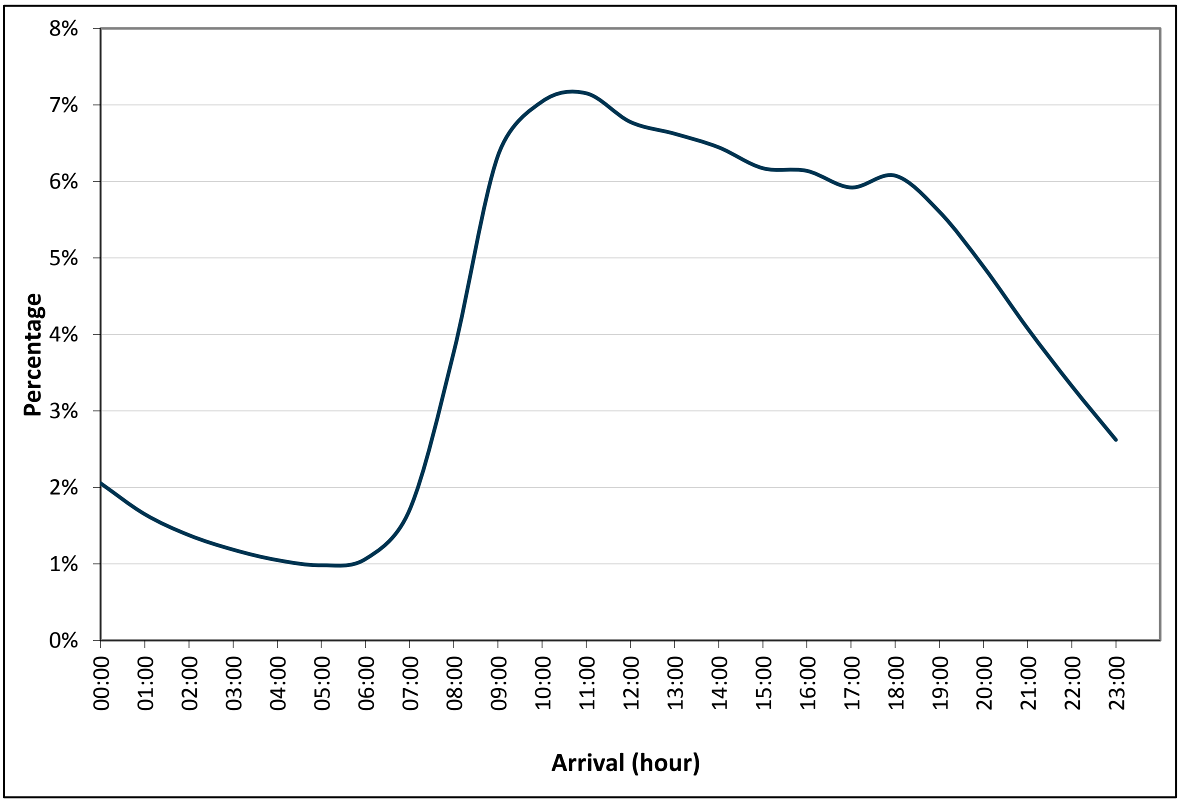


Figure 6.2: Trend of attendances by hour of arrival (percentage) for Accident and Emergency Departments in England from April 2012 to March 2013



More specifically, Figure 6.3 and 6.4 show the hourly attendances by care group and discharge outcome respectively; which is closely matched with the trend from the overall hourly attendances in Figure 6.1.

Figure 6.3: Hourly Attendances by Care Group

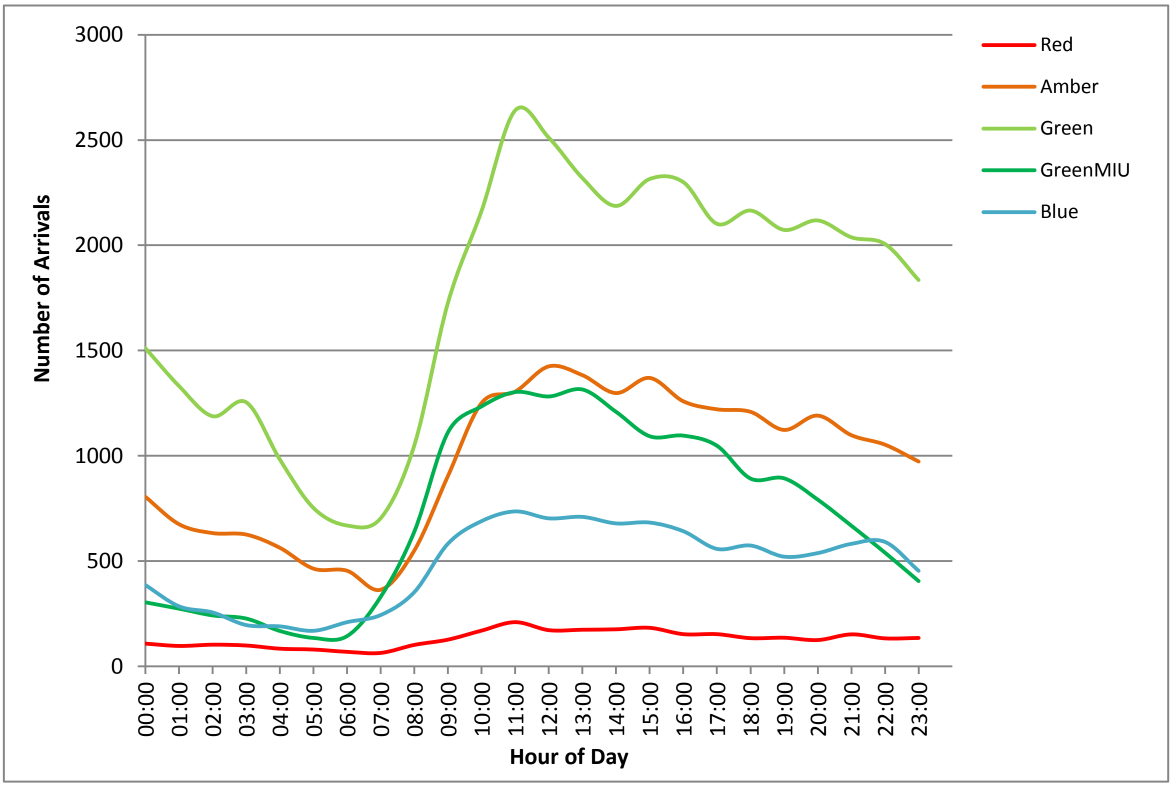
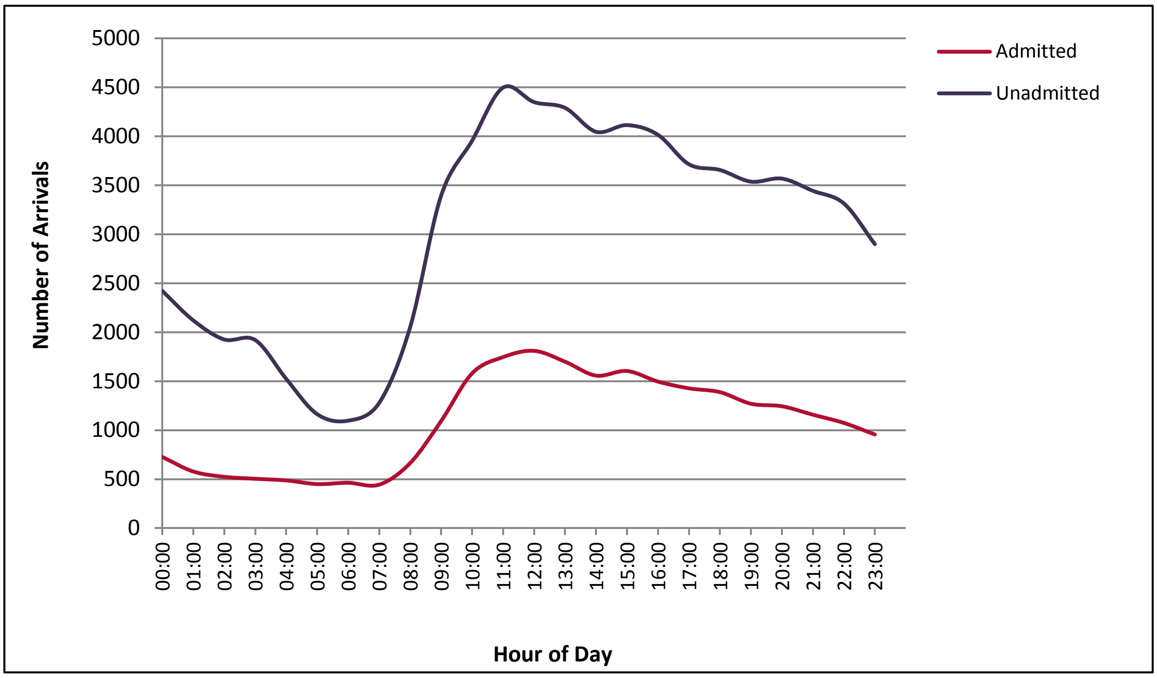


Figure 6.4: Hourly Attendances by Discharge Outcome (Admitted and Unadmitted)



From Figure 6.3, the peak time for all the care groups is 11am, except the amber patients whose busiest time is at 12noon. Consequently, more resources should be allocated to the Amber area between 7am and 1pm, rather than from 7am to 12noon.

Figure 6.5 shows the number of attendances by hour of the day and day of the week, which is used as arrival input for the model. From Figures 6.5, the maximum number of arrivals (15.3%) is seen on Monday at 11am, which confirms the peak time in Figure 6.1 and busiest day of the week as also shown in Figure 6.6. Although from Figure 6.6, Saturday is the quietest day of the week, Figure 6.5 shows that patients are less likely to attend the ED on Tuesday at 5pm. The HES data for ED attendances in England for the same time period is in agreement that Monday is the busiest day, but in contrast shows that Friday is the quietest (Figure 6.7) (HES, 2014a). Furthermore, in MRI, the number of patients who attend the ED on Fridays and Saturdays are closely matched; while in England, the attendances from Tuesday to Saturday are close.

For completeness, Figure 6.8 shows the percentage monthly attendances for this period. Note that

Figure 6.5: Hourly Attendances by day of week

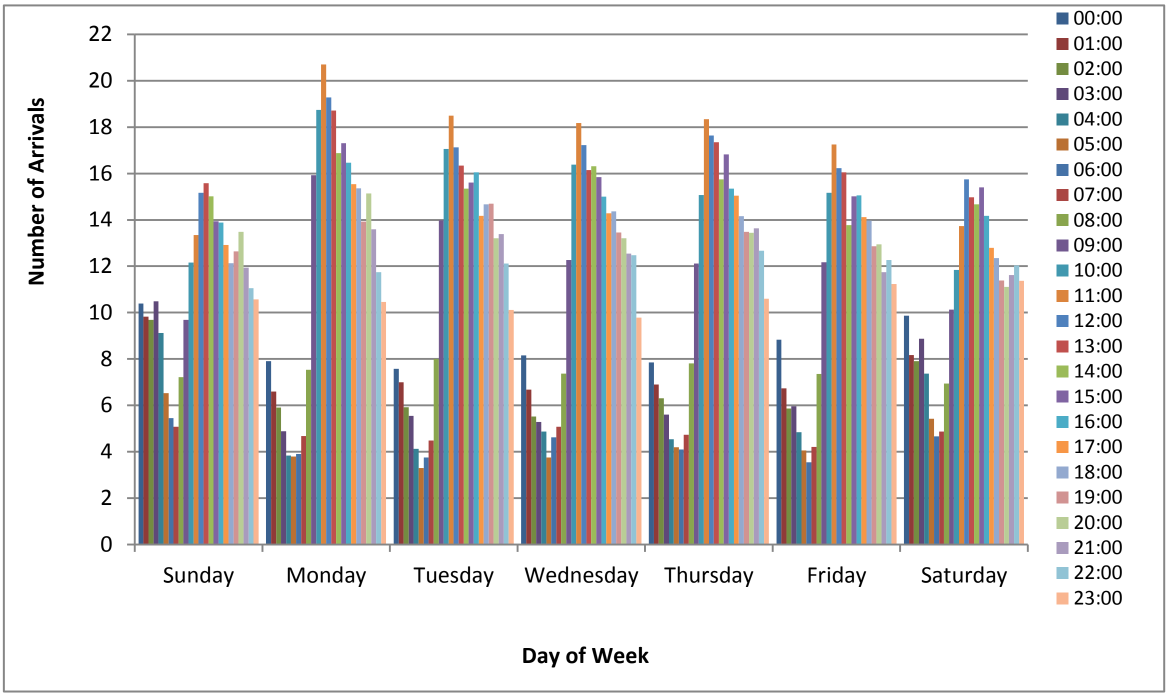


Figure 6.6: Percentage Attendances by day of week

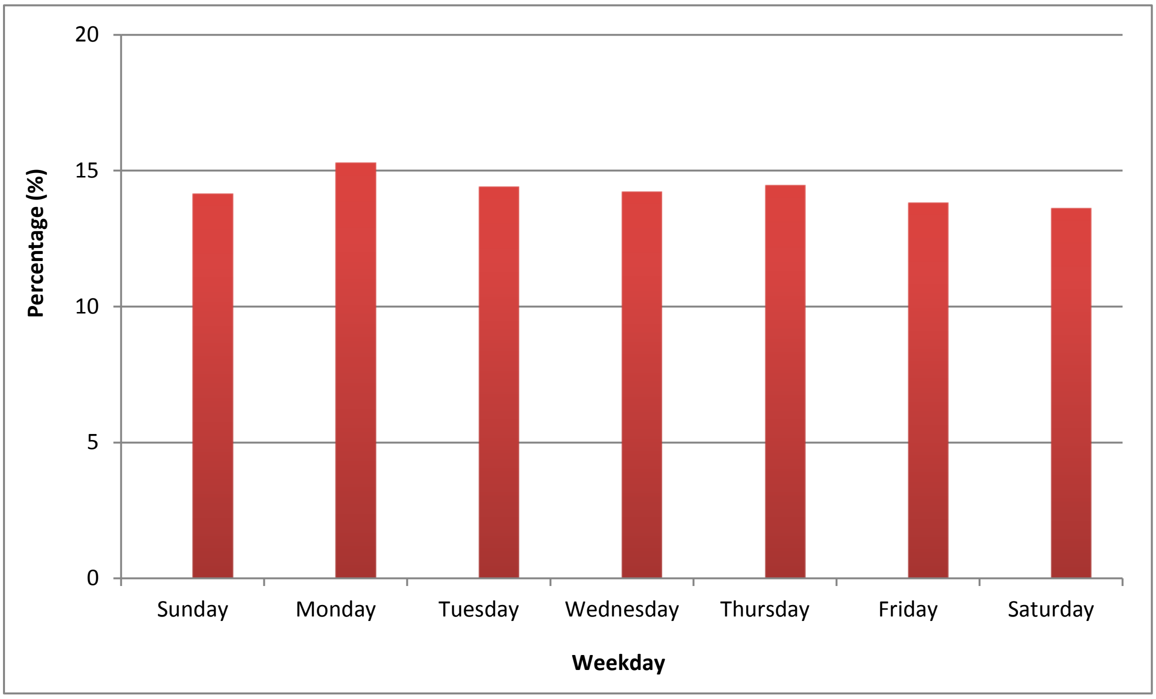


Figure 6.7: Accident and Emergency Departments attendances by day of arrival (percentage) in England from April 2012 to March 2013

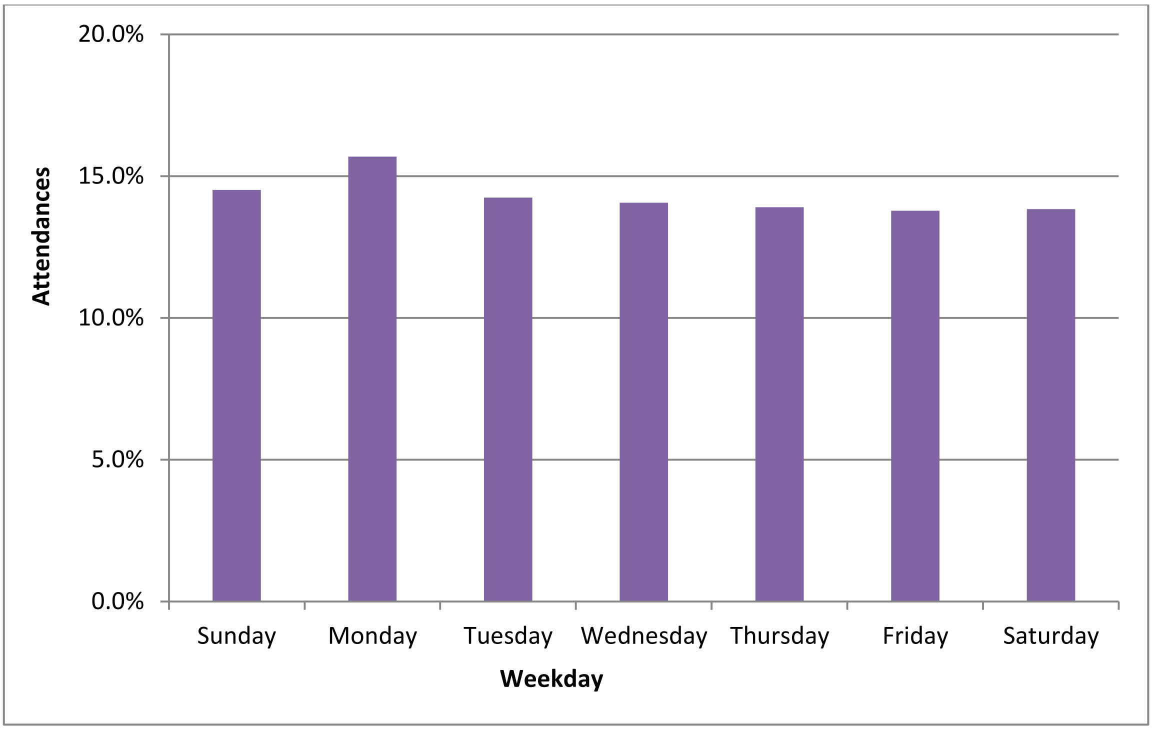
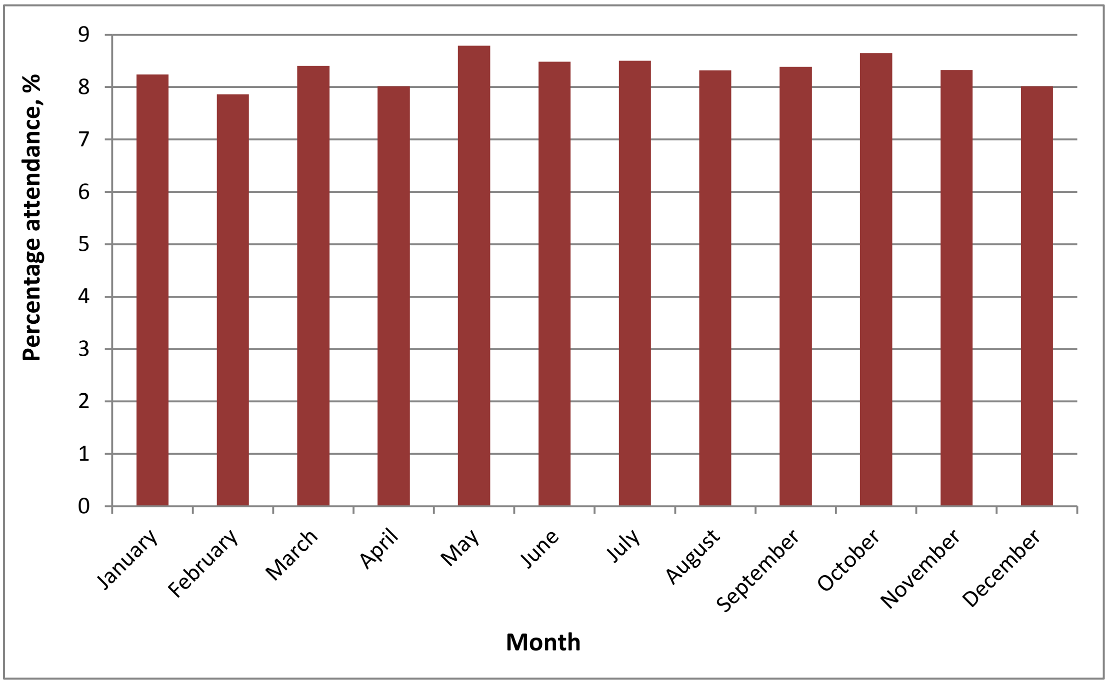


Figure 6.8: Percentage monthly attendances



From Figure 6.9 and 6.10, both data from MRI and the HES report shows that patients aged between 20 and 29 are most likely to visit the ED. In MRI, 29% of patients who visit the ED are aged 20 – 29 compared to 16.3% in the whole of England. Note that 16.5% of MRI attendances are aged 19 – 23. This is not surprising since MRI is a University Teaching hospital and one would anticipate that, students (who are usually within this age band) should frequent the ED patients. There were 140 missing age entries in the data, which were omitted from this analysis.

Figure 6.9: Attendances by Age group in MRI

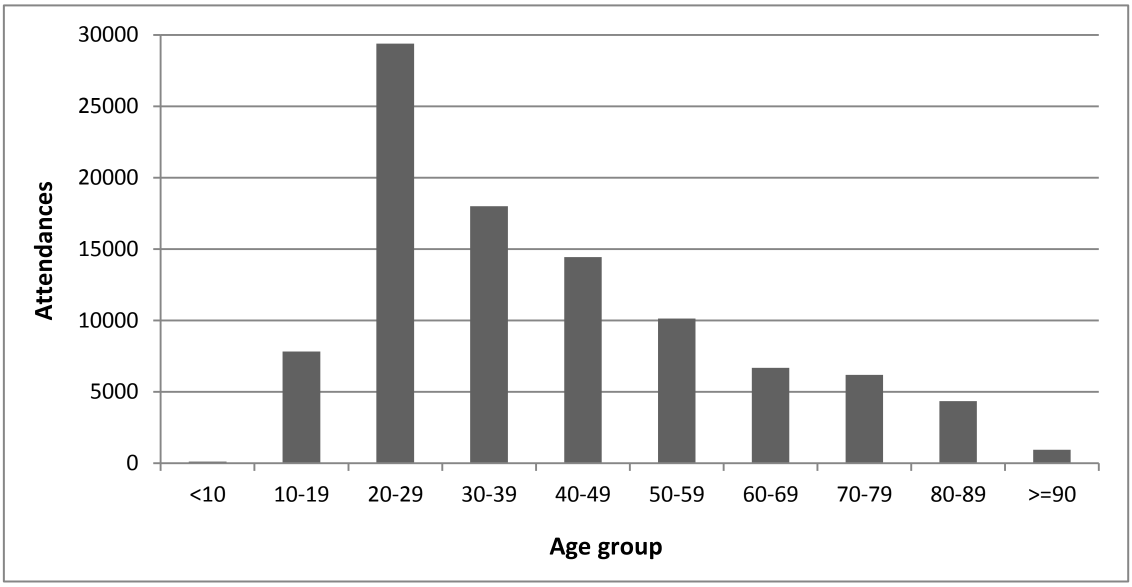
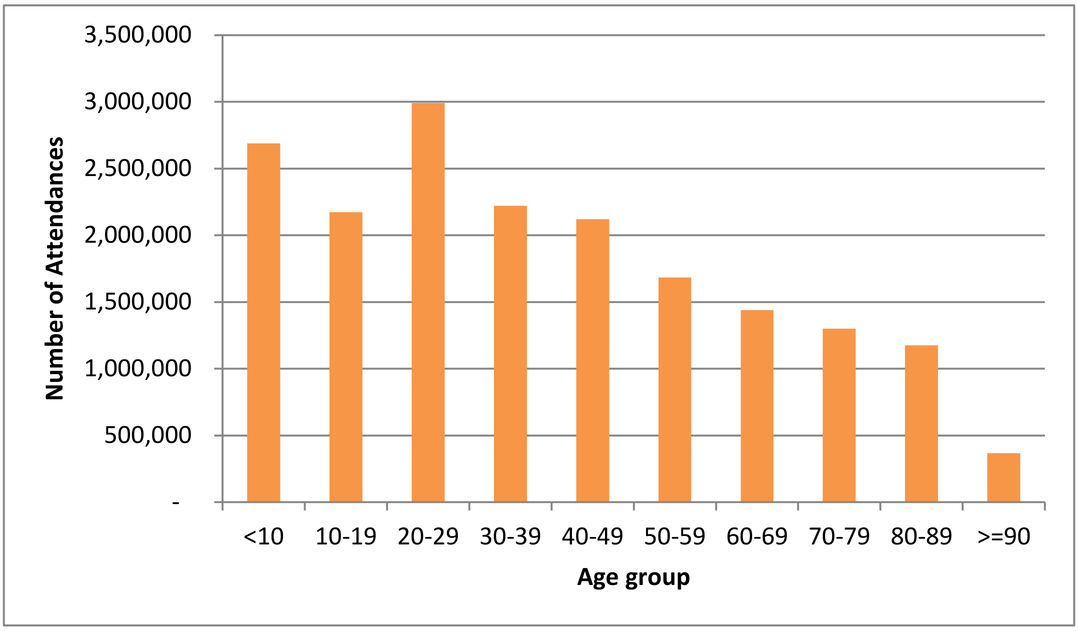


Figure 6.10: Attendances by Age group in England (Hospital Episode Statistics)



This study is focused on the adult ED at MRI, however, 0.1% of patients seen are under 10 years, and 2.7% are below 18. It is clear from Figure 6.9 and 6.10 that patients over 90 years rarely visit the ED.

Figure 6.11 shows an interesting trend of patients' discharge outcome by Age. The continual increase in admitted patients and decrease in discharged patients with increase and decrease in age (respectively) is captivating. This suggests that in MRI older patient are more likely to be admitted to the hospital.

Figure 6.11: Discharge Outcome by Patient's Age

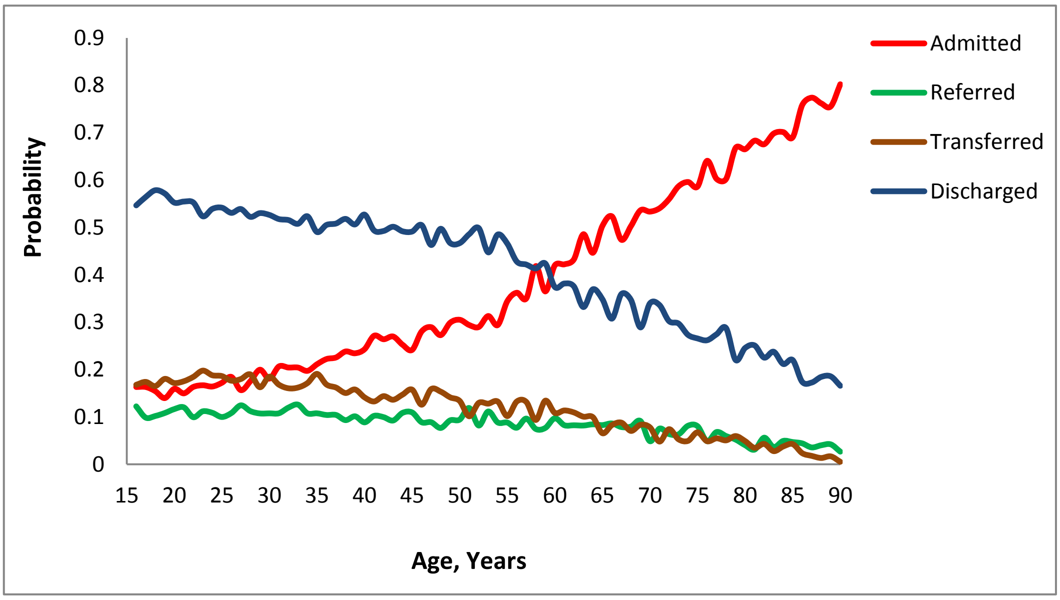


Figure 6.12 shows the percentage attendances by discharge outcome which can be compared to the HES output displayed in Figure 6.13. In MRI, 1 in 4 patients are admitted which is close to the HES output for admitted patients in England – 1 in 5 patients (Figure 6.13). In the HES data, 39% of patients are discharged with no follow up, which is higher than the 25.6% at MRI; although the "Discharge – GP follow up" and "Referred" categories are close in both cases.

Figure 6.12: Attendances by Discharge Outcome (percentage)

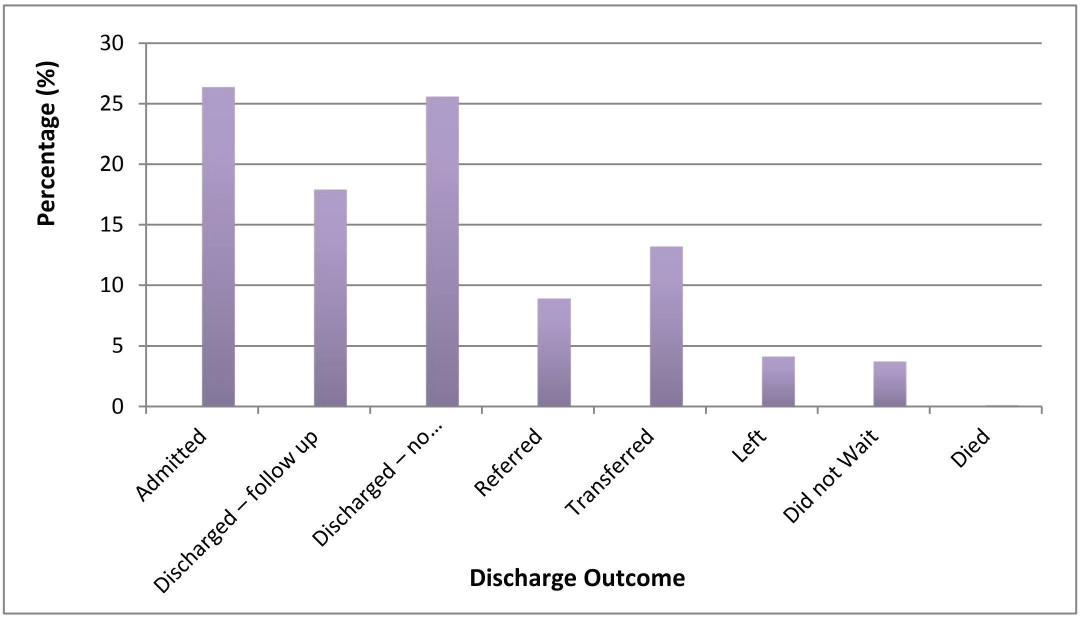


Figure 6.13: Accident and Emergency Departments attendances by discharge method (percentage) in England from April 2012 to March 2013

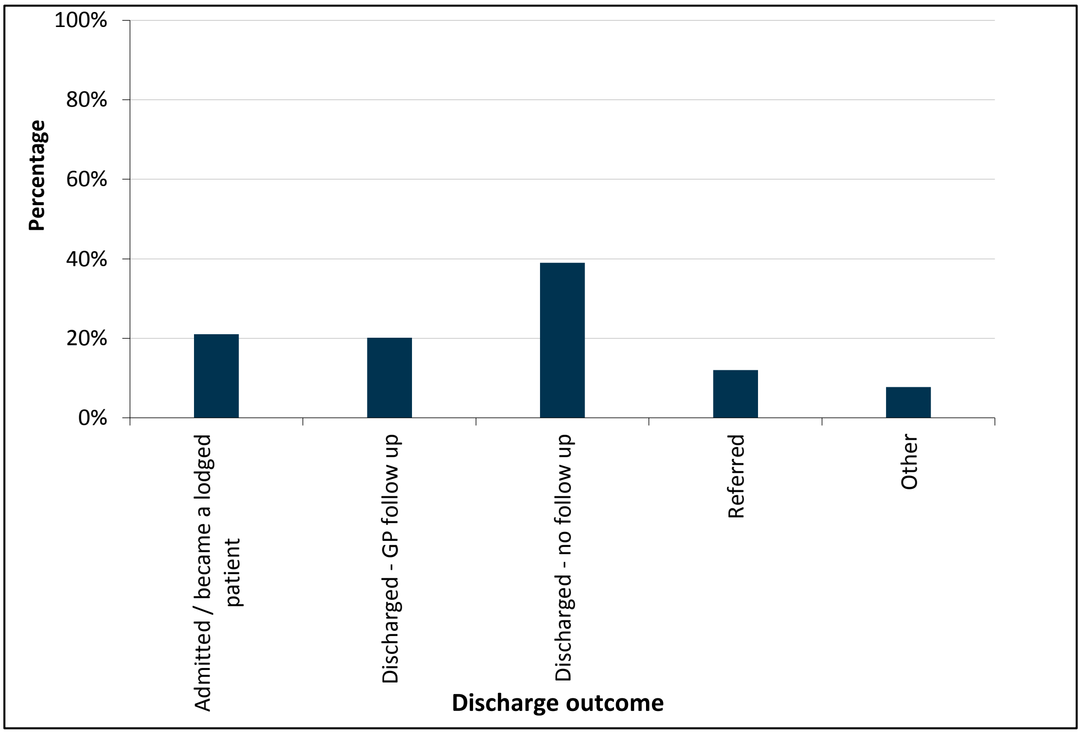
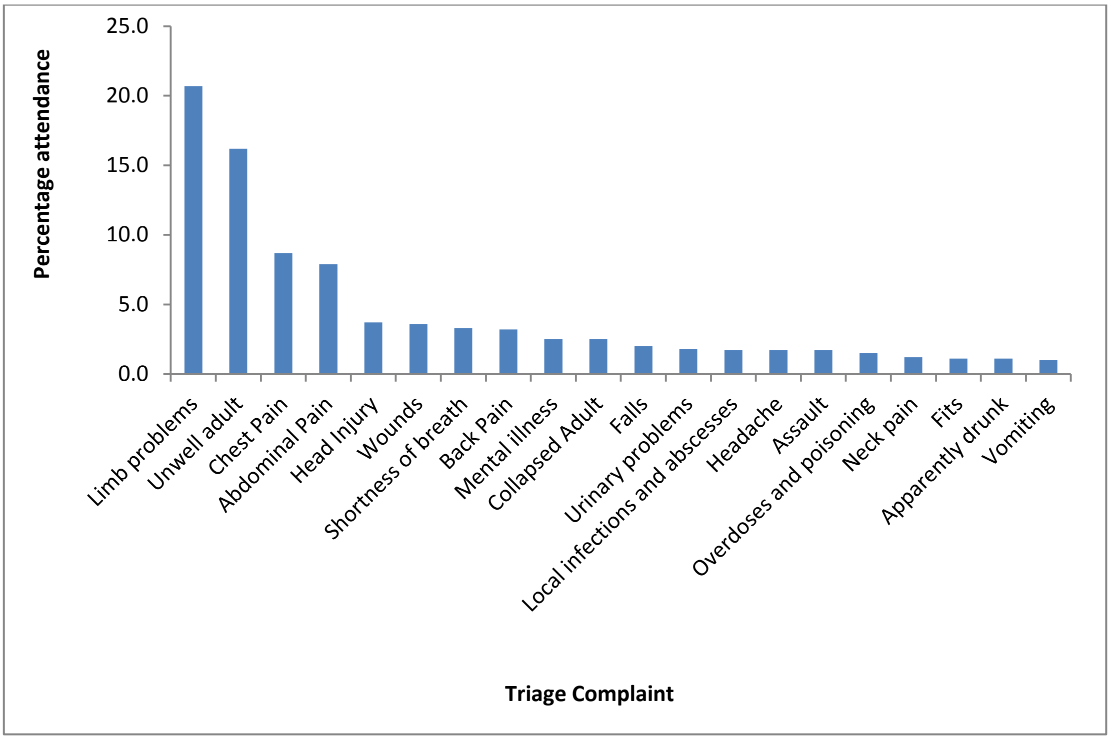


Figure 6.14 shows the top 20 triage complaint; there are 53 in total. Notice that patients with limb problems represent 20.7% of the cohort; it may be worth creating a Limb Unit in MRI to attend specially to such cases.

Figure 6.14: Attendances by Top 20 Triage complaint (percentage)



Attendances by Triage Category and Care Group are shown in Table 6.3. There are 1069 unrecorded care group entries and 927 unrecorded triage category entries which are shown in red fonts.

Table 6.3: Attendances by Triage Category and Care Group

Triage Category	**Total**	**Percentage Arrivals (%)**	**Care Group**	**Total**	**Percentage Arrivals (%)**
Triage Cat 1	654	0.7	Red	3139	3.2
Triage Cat 2	12667	12.9	Amber	23199	23.6
Triage Cat 3	35155	35.8	Green	41944	42.7
Triage Cat 4	48172	49.0	Green/MIU	17349	17.7
Triage Cat 5	661	0.7	Blue/PC	11533	11.7
Unknown	927	0.9	Pregnant	3	0.003
Total	**98236**	**100.0**	Unknown	1069	1.1
			Total	**98236**	**100.0**

From Table 6.4, there are eight Arrival methods namely; Ambulance, Other Arrival mode, Other ward/department, Own transport, Public transport, Police, Transfer from WIC (Walk-in Centre) and Standby/Courtesy Car. Attendances by mode of arrival are also displayed. According to Dr Richard Body, all arrival modes go through the same process in the emergency department except Ambulance arrivals. Consequently, when constructing the model, all other methods of arrival are assumed as "Walk-ins" which is 69.7% of the overall attendance.

Table 6.4: Attendances by Arrival Mode in MRI

ARRIVAL MODE	TOTAL	PERCENTAGE
Ambulance	**29766**	**30.3**
Public	6511	6.6
Other	22042	22.4
Own Transport	36340	37.0
Standby	1828	1.9
Transfer	1155	1.2
Police	594	0.6
Walk-in	**68470**	**69.7**
	98236	**100.0**

Tables 6.5 and 6.6 show attendances by mode of arrival based on Triage category and Care Group respectively. The probability of ambulance and walk-in arrivals in Table 6.6 are also used as input for the model. There are also "Unknown" (in red font) Triage Category and Care Group which represents missing figures during data entry. In the model, the unrecorded Care groups are considered at first since they are included in the total number of arrivals, but are then omitted when assigning streams based on care group since their unit in the ED could not be established. More on this will be discussed in Chapter 7. Furthermore, only 3 pregnant patients were seen in one year which is very minimal (Only 3 in total, 0% for ambulance and 0.003% for walk-in) when compared to the overall cohort, and hence are not considered in the model.

From Figure 6.12, there are 8 unique discharge outcomes in the facility. As with the arrival mode (ambulance or walk-in) described above, two generic discharge outcomes (Admitted and unadmitted) are assumed for the model. "Discharged", "Transferred", "Referred", "Died", "Did not Wait" and "Left" discharge outcomes are combined to form one outcome - "Unadmitted[16]". The percentage admitted and unadmitted patient for each care group are provided in Table 6.7.

[16] *This is also known as "Discharged" in the model*

Table 6.5: Arrivals by Triage Category and mode of Arrival

Triage Category	Ambulance	Percentage by Ambulance	Walk-in	Percentage by Walk-in	Average Arrivals per day
Triage Cat 1	318	1.07	336	0.49	2
Triage Cat 2	5777	19.41	6890	10.06	35
Triage Cat 3	14209	47.74	20946	30.59	97
Triage Cat 4	9316	31.30	38856	56.75	132
Triage Cat 5	116	0.39	545	0.80	2
Unknown	30	0.10	897	1.31	3
Total	**29766**		**68470**		**271**

Table 6.6: Arrivals by Care Group and mode of Arrival

Care Group	Ambulance	% of Ambulance Arrival	Walk-in	% of Walk-in Arrival	Average Arrivals per day
Red	1589	5.34	1550	2.26	9
Amber	14217	47.76	8982	13.12	64
Green	11194	37.61	30750	44.91	115
Green/MIU	1365	4.59	15984	23.34	48
Blue/PC	1297	4.36	10236	14.95	32
Pregnant	0	0.00	3	0.003	0
Unknown	104	0.35	965	1.41	3
Total	**29766**		**68470**		**271**

Table 6.7: Arrivals by Care Group and Discharge outcome

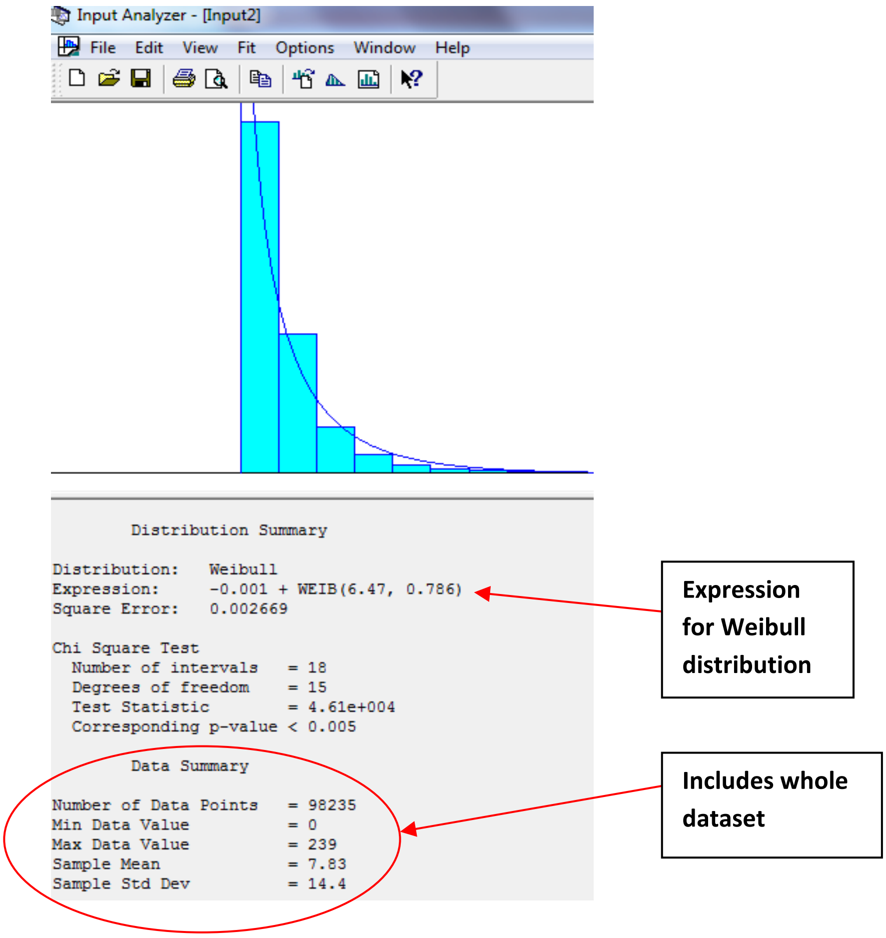
	Total Admitted	Total Unadmitted	% Admitted	% Unadmitted
Red	2433	706	77.51	22.49
Amber	13872	9327	59.80	40.20
Green	8387	33557	20.00	80.00
Green/MIU	669	16680	3.86	96.14
Blue/PC	469	11064	4.07	95.93
Pregnant	3	0	100.00	0.00
Unknown	110	959	10.29	89.71
	25943	**72293**	**26.41**	**73.59**

6.2.2 Inter-arrival Time Analysis

The Inter-arrival time is the time between two consecutive arrivals. From the original dataset (DS1), some of the arrival times were not in sequence. For example, the arrival of patient #10 occurred 2 minutes before the arrival of patient #9. There were 5929 zero and 11307 negative (out of 98235) inter-arrival time values. The absolute inter-arrival times distribution for the whole dataset was obtained and saved in a text file - InterArrivalTimes.txt. The text file was modified to remove commas and delimiters, and then imported into Arena Input analyser to estimate the inter-arrival time distribution function.

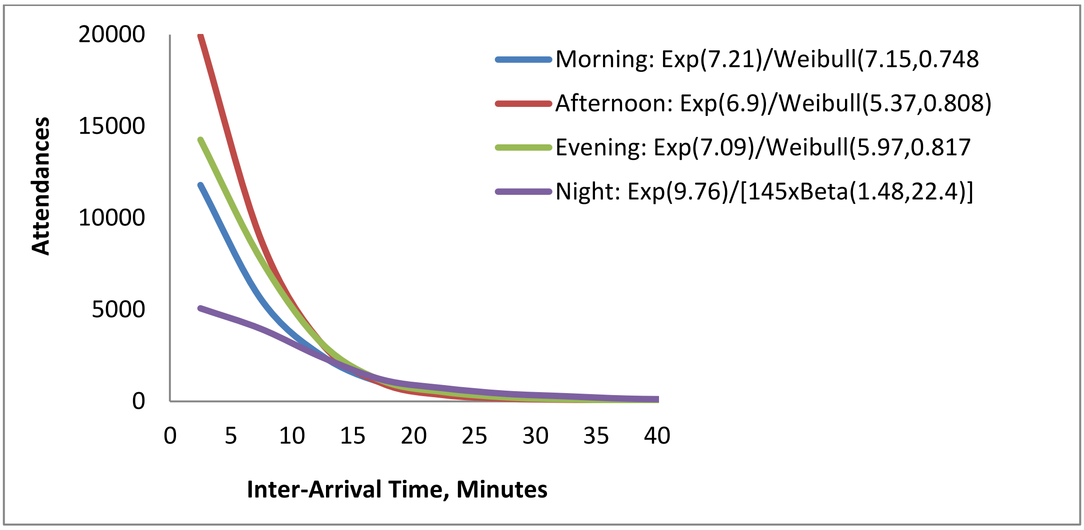
Figure 6.15 represents the resulting histogram and distribution function. The best fit was obtained as a Weibull distribution (-0.001 + WEIB (6.47, 0.786)) in minutes, using the "fit all" feature in Arena. This and other estimated distribution functions will be used to demonstrate the appropriate Arrival input for the model in the chapter 7. Note here that all the data are used including zero and absolute values since all arrivals are considered in the model. Also, it is assumed that patients could have arrived simultaneously, thus the negative and zero times between arrivals.

Figure 6.15: Inter-arrival Times Distribution Summary using Arena input Analyser



The Inter-arrival time distribution by the time of day was also derived as shown in Figure 6.16. The morning, afternoon, evening and night periods here is equivalent to the time interval shown in Figure 6.8.

Figure 6.16: Inter-arrival Times Distribution by Time of Day



6.2.3 Journey Time Analysis

Patients' overall journey time through the system was calculated using the time difference between when the patient left (ExitTime) and when they arrived (Arrival Time). Subsets of the overall journey (milestones) are shown in Table 6.2; these journeys were supposed to be in sequence. For example, Triage timestamp should be after arrival, clinician time before referral time and Exit time after bed request time. By contrast, some calculated journey times for these milestones produced negative and zero values. For example, some clinician times were recorded after patients had left the facility. This is surprising since they were meant to have seen the clinician before leaving the emergency department. This also applies to other journeys. Furthermore, there were also some "NA" values which showed evidence of missing data or invalid entries. Consequently, for the journey time analysis, only cohorts with finite times and valid entries are used in order to provide sensible results. In particular, the data was filtered to ensure they included finite times and were in the right sequence.

Table 6.8 shows the percentiles for journey times between successive milestones. Only patients with valid entries in the "From" and "To" fields are included. For more detailed explanation of patients' journeys, see section 6.2.4.

Table 6.8: Journey Times by Milestone

Journey		Percentiles in Minutes						Number and Sense of Data Values			
From	**To**	**0**	**0.25**	**0.5**	**0.75**	**1**	***0.95***	**Total**	**Positive**	**Zero**	**Negative**
Arrival	Exit	1	114	185	234	1398	*440*	98235	98229	6	0
Arrival	Triage	1	5	12	22	253	*43*	97308	76520	20650	138
Triage	Clinician	1	46	88	142	1059	*230*	85817	81760	425	3632
Clinician	Referral	1	32	57	93	452	*156*	32761	25279	346	7136
Referral	Bed Request	1	1	1	1	931	*43*	29198	7421	21323	454
Bed Request	Bed Outcome	1	24	72	158	815	*422*	18490	18460	17	13
Bed Outcome	Investigation	1	16	34	65	678	*205*	18484	17494	266	724
Investigation	Exit	1	1	2	15	671	*54*	82692	54150	25913	2629
Bed Request	Exit	1	22	40	70	966	*198*	18491	17651	440	400

From the above table, all journey milestones have zero and negative journey times, except for Arrival to Exit which has no negative value. From Table 6.7, 25943 patients were admitted, yet there were only 18490 entries with values for “BedRequestTime” and “BedOutcome” , that is to say 7453 entries are missing.

The Percentiles of Journey Times (in hours) from arrival to exit for the overall data, and by care group and discharge outcomes is shown in Table 6.9. This shows that 11.1% of patients spends more than 4 hours in the emergency department. Interestingly, patients in all the care groups exceeded the 4 hour target and not, as might be anticipated, for only the red and amber group; although Amber patients are most likely to exceed 4 hours than any other group. This is possibly because of their population compared to Red patients. Furthermore, admitted patients are most likely to exceed 4 hours compared to other discharge outcomes. This may demonstrate the lengthy time taken to find a bed. Note that approximately 71 beds are needed daily in this ED for successful admission into hospital.

For completeness, Figures 6.17 shows journey times for the overall cohort and by care group, while Figure 6.18 shows journey times by discharge outcome. According to Dr Body, a patient may likely stay longer in the ED if more treatments are required or the patient needs further observation. The “wall” displayed in both figures indicates that as the four-hour deadline approaches, clinicians try to ensure that most patients are discharged before the deadline. In contrast, the Green/MIU and Blue patients have different journey trend compared to the others in the sense that there is no evidence of pressure just before the 4-hour mark. The Green/MIU shows steady incremental journey times across board.

It is interesting to notice the two peaks in the blue patients journey time above; one within the first 20 minutes of their journey, and the other on the 4-hour mark. This reflects the early exit of blue patients from the ED after triage (which will be described in more details in chapter 7), and the rapid action taken to meet the target.

Figure 6.18 shows that almost all patients, regardless of their discharge outcome, are discharged before the deadline. Therefore, it is safe to say that MRI is not involved in the “gaming” measure described by Gunal and Pidd (2009) to admit patients into hospital in order to meet the four-hour target.

Table 6.9: Journey Times in Hours

			Percentiles: Hours					**Journey Exceeding 4 Hours**	
by Care Group	0	25	50	75	100	*0.95*	Patients	Number	%
All	0	1.9	3.08	3.9	23.3	*7.33*	98235	10905	11.1
Red	0.03	3.35	3.95	6.29	22.62	***11.44***	3139	1118	**35.6**
Amber	0.05	3.33	3.91	4	22.07	*10.33*	**23198**	5695	24.5
Green	0	2.12	3.1	3.85	23.3	*6.18*	41944	3586	8.5
Green/MIU	0.03	1.7	2.48	3.28	21.03	*3.97*	17349	341	2.0
Blue/PC	0	0.32	1.12	2.11	15.42	*3.82*	11533	144	1.2
by Outcome									
Admitted	0.03	3.68	3.95	5.43	22.62	***10.77***	25942	7344	**28.3**
Discharged	0	2.1	2.97	3.67	23.3	*4.83*	42717	2497	5.8
Transferred	0	0.3	0.95	1.83	22.07	*3.51*	13005	331	2.5
Referred	0	2.03	2.88	3.63	18.67	*4*	8770	416	4.7

Figure 6.19 displays the probability of attendances by length of stay in the emergency department which can be compared with the HES data (HES, 2014a) in Figure 6.20. Note the peak and abrupt drop in attendances at the 4-hour mark, which is equivalent to the histogram shown in Figure 6.17 for the overall journey time. From Figure 6.19 and 6.20, it is evident that the trend in MRI is different from that of the HES data. It is worth noting that the Hospital Episode Statistics data

includes information of 18.3 million attendances from 189 A&E departments in England; which has more substantial data than MRI which only contains 98236 patients' information.

Figure 6.17: Histograms of Overall Journey Time and by Care Group

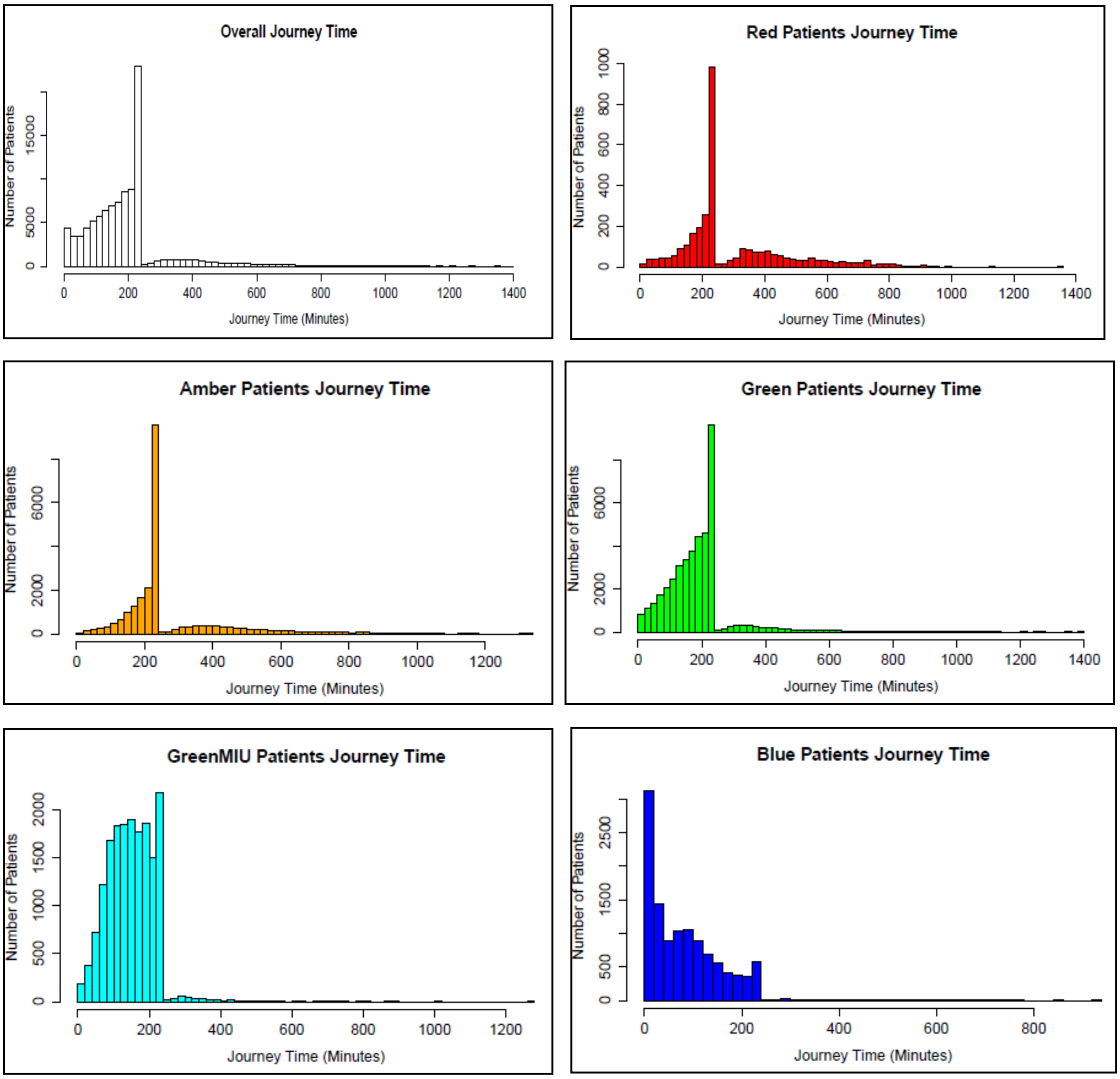


Figure 6.18: Histograms for Journey Times by Discharge Outcome

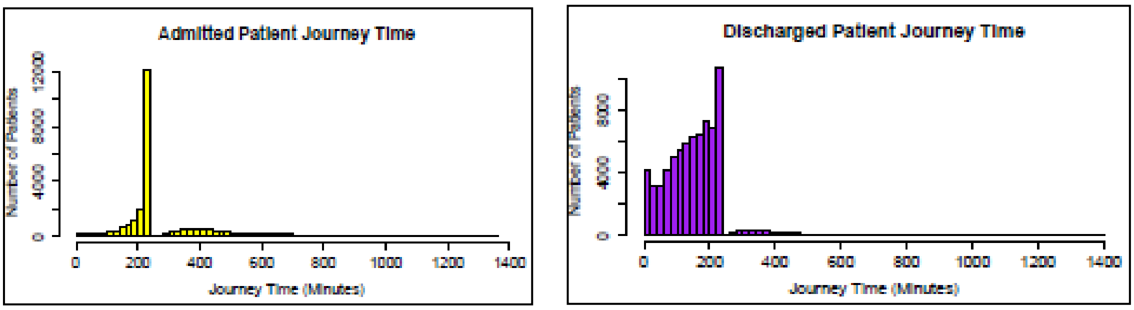


Figure 6.19: Attendances (probability) by Length of stay

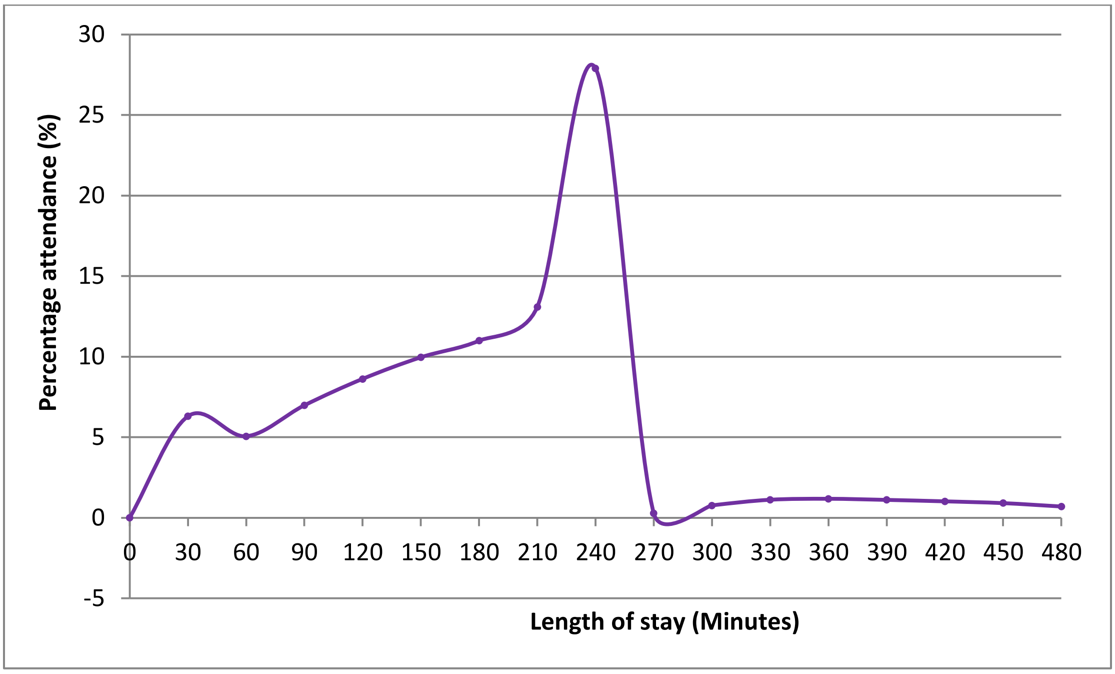
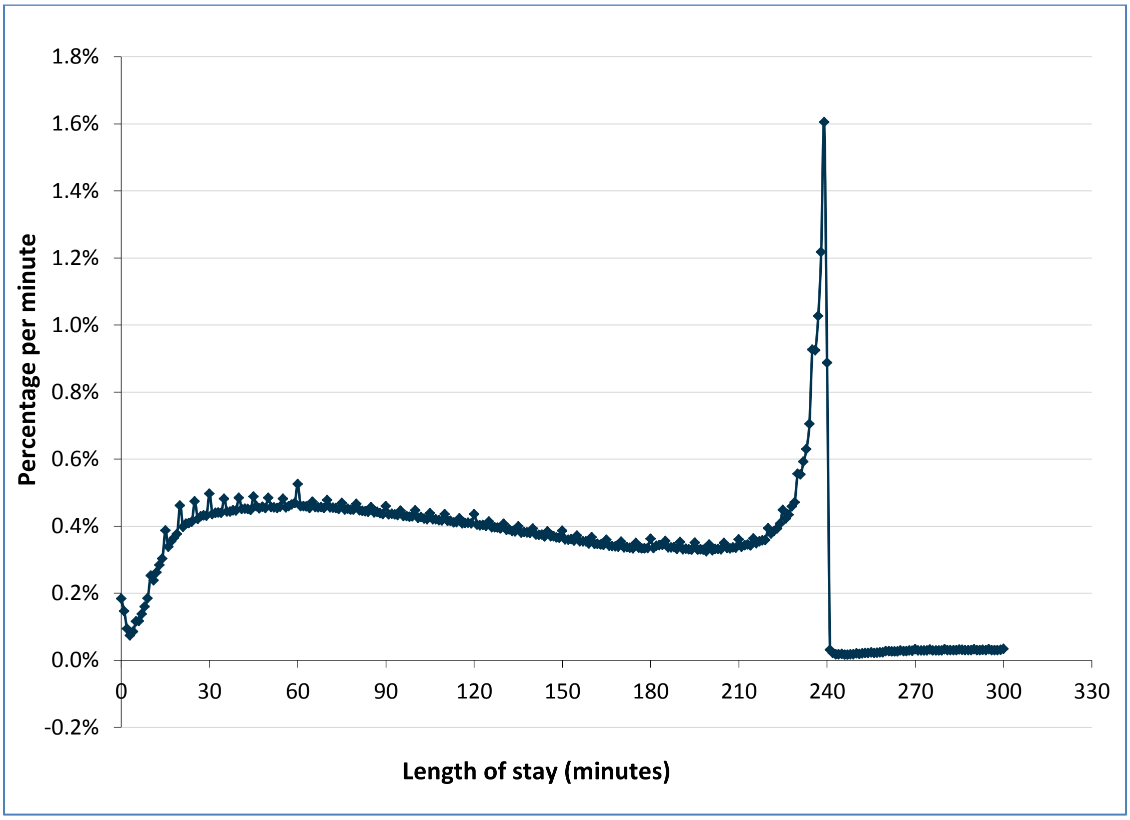


Figure 6.20: Accident and emergency attendances in England: Distribution of A&E attendances by total time spent (by minute)



6.2.4 Location and Journey-Path Analysis

The spreadsheet "DS2" provides key information on times and locations of patients' journey through the system. The Journey time analysis in Section 6.2.3 only provides few details of patients' journeys (milestones) through the emergency department. Here, these journeys are expressed as sets of journey-strings, and these were used as the basis for the journey-path model.

Journey strings for the full set of locations visited (including all the assessment rooms, cubicles, etc., rather than a generic location) were used to generate a large (168 by 168) transition matrix which provides the probability of a patient going from one location to **any** another Part of this matrix is shown in Figure 6.21.

Figure 6.21: Part of the Transition Matrix for Journeys in ED

	To																
From	AMB	AR1	AR1.1	AR1.2	AR10	AR10.1	AR10.2	AR11	AR11.1	AR11.2	AR12	AR12.1	AR12.2	AR12.3	AR14	AR14.1	AR14.2
AMB	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
AR1	0	0	0.008235	0	0.000588	0.000588	0	0.004706	0	0	0.001765	0	0	0	0.001176	0	0
AR1.1	0	0	0	0.016129	0	0	0	0	0	0	0	0	0	0	0	0	0
AR1.2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
AR10	0	0.000553	0	0	0	0.00332	0	0.005534	0.002214	0	0.00332	0.000553	0	0	0.002214	0	0
AR10.1	0	0	0	0	0	0	0	0	0	0.020408	0	0	0	0	0	0	0
AR10.2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
AR11	0	0.002766	0.001383	0	0.006916	0	0	0	0.006224	0	0.00899	0	0	0	0.005533	0	0
AR11.1	0	0	0	0	0	0.041667	0	0	0	0	0	0	0	0	0	0.020833	0
AR11.2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
AR12	0	0.004488	0.000748	0	0.005236	0	0	0.00374	0.000748	0	0	0.00374	0	0	0.023934	0.000748	0
AR12.1	0	0	0	0	0.029412	0	0	0	0	0	0	0	0.029412	0	0	0	0
AR12.2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
AR12.3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
AR14	0	0	0	0	0.001575	0	0	0.00315	0.000787	0	0.011811	0.001575	0	0	0	0.003937	0
AR14.1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
AR14.2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
AR15	0	0.001695	0	0	0.004237	0.001695	0	0.001695	0	0	0.002542	0	0	0	0.008475	0.001695	0
AR15.1	0	0	0	0	0.035714	0	0	0	0	0	0	0	0	0	0.035714	0	0
AR15.2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
AR16	0			0	0	0	0	0.001074	0	0	0.010741	0	0	0	0.006445	0	0
AR16.1								1		0	0	0	0	0	0	0.030303	0

To create the transition matrix, the journey strings were first delimited by separating each entry with a comma. The strings were delimited by adding "STA" to the beginning of each string and "FIN" to the end of each string. The modified strings were then combined (concatenated) to produce a single string which was then split into paired "from-to" sequences. The transition matrix was generated by counting each pair. Note that as a check the number of occurrences of the pair "FIN,STA" was 98235 which is one less than the total number of strings as it should be. The transition matrix quantifies the probabilities of a patient at a particular location proceeding to any other location in the system. In effect the transition matrix reflects all the decisions which were made (A to B, B to X etc.) at each step of the patient's journey through the system. The spread (number) of destinations from a particular source reflects the options available at a particular instant in time (or a measure of the difficulty in making a decision) while the size of each probability reflects the preferred destination. Taken over a patient's journey, the coefficients of the transition matrix, together with the duration and resource requirement of each pair's destination, is in effect, a process map for that patient through the ED.

For many patients in the data, more than one location was visited during their journey. For example patient #6, the same location is visited more than once at different times. It was therefore necessary to distinguish these by appending a visit number. For example, WR.1 is the second visit to the waiting room (WR) and R2.2 is the third visit to Red Area 2 (R2) (Figure 6.22). The first visit is just WR or R2. Table 6.10 shows the location abbreviations and their meaning.

Figure 6.22: Abbreviated and unique Locations

	A	B	C	D
1	Identifier	ArrivalTime	Location	LocationTime
2	1	01/04/2012 00:04	WR	01/04/2012 00:04
3	1	01/04/2012 00:04	A2	01/04/2012 00:18
4	2	01/04/2012 00:05	WR	01/04/2012 00:08
5	3	01/04/2012 00:11	RAB	01/04/2012 00:15
6	3	01/04/2012 00:11	A8	01/04/2012 00:58
7	4	01/04/2012 00:16	MH	01/04/2012 00:20
8	4	01/04/2012 00:16	TR5	01/04/2012 00:21
9	5	01/04/2012 00:25	RAC	01/04/2012 00:28
10	5	01/04/2012 00:25	A6	01/04/2012 00:58
11	6	01/04/2012 00:42	WR	01/04/2012 00:42
12	6	01/04/2012 00:42	C2	01/04/2012 00:47
13	6	01/04/2012 00:42	WR.1	01/04/2012 01:34
14	7	01/04/2012 00:45	RAA	01/04/2012 00:47
15	7	01/04/2012 00:45	A9	01/04/2012 01:30
16	8	01/04/2012 00:59	RAB	01/04/2012 01:03
17	8	01/04/2012 00:59	A7	01/04/2012 01:50
18	8	01/04/2012 00:59	A2	01/04/2012 03:15
19	8	01/04/2012 00:59	R1	01/04/2012 07:40
20	8	01/04/2012 00:59	R3	01/04/2012 07:44
21	9	01/04/2012 01:06	WR	01/04/2012 01:07
22	9	01/04/2012 01:06	A1	01/04/2012 01:30
23	10	01/04/2012 01:04	WR	01/04/2012 01:08
24	10	01/04/2012 01:04	C2	01/04/2012 03:25

Table 6.10: Abbreviations for the Journey Milestones and their meaning

Assess[x]	Assessment Room x = 1-17	WICWR	Walk-in-Centre Waiting Room
B[x]	Bed x = 1,3, 4	MH	Mental Health
Cub[x]	Cubicle x=1-10	Arrive	Arrival Time
T[x]	Treatment Room x=1-5	Triage	Triage Time
RAU[A-E]	Rapid Assessment Unit A-E	Clin	Clinician Time
Red[x]	Red Area x=1-6	Inv	Investigation Time
GMIU	Green/MIU Area	Exit	Exit Time
WR	Waiting Room	BRT	Bed Request Time
WA	Waiting Amber	BRO	Bed Request Outcome

The “uniquedata” function took over an hour to run on the 160k+ rows in the original data sets, while the cast function actually failed on the entire data frame and had to be applied to (roughly) subsets of about 30,000 rows. These were then merged together and generated the spreadsheet shown in Figure 6.22. This data was pivoted in R and consolidated with other factors in Table 6.2 to generate the “All Milestone” (AM) data frame shown as a spreadsheet in Figure 6.23. The data frame consists of 211 factors and is evidently scanty. The journey through the system for each patient was generated by collecting and sorting timestamps for each factor and expressing the journeys as ordered text strings.

Figure 6.23: All Milestone (AM) data frame

	A	B	C	D	E	F	G	H	I	J	K	L	M
1	Identifier	A1	A1-1	A10	A10-1	A11	A11-1	A12	A12-1	A14	A14-1	A15	A15-1
2	1	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
3	2	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
4	3	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
5	4	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
6	5	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
7	6	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
8	7	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
9	8	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
10	9	01/04/2012 01:30	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
11	10	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
12	11	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
13	12	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
14	13	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
15	14	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
16	15	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
17	16	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
18	17	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
19	18	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
20	19	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
21	20	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
22	21	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
23	22	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA

The unique journeys were counted for the whole cohort and by care groups. There were 16722 unique journeys. Table 6.11 shows the top 5 unique journeys. It is surprising that there are so many paths for patients, especially, in the same care group. On the face of it, one would expect that if a patient is assigned a care group, they will follow a specific path for that care group through the system. This is considerably simpler than counting all the time stamps for each treatment room for all patients from the AM data-frame and then finding the intersection of the totals. For many entries, the recorded times at *successive locations* are identical and, in other cases, different times are recorded for the *same location*. The prevailing medical interpretation is that in the first case the earliest time is taken as valid and others ignored. In the second case, such as R1, T1 followed by R3, T2 should be taken as the single entry R3, T1. An example of this manipulation is shown in Table 6.12. This was not fully implemented by creating a separate data frame but was taken into account in the interpretation of the data which were derived from the AM data-frame.

Table 6.11: Top 5 Unique Journeys by Triage Category

ALL PATIENTS	**Count**	**RED PATIENTS**	**Count**
Arrival WR Triage Clin Inv Exit	29015	*Arrival Triage R3 Clin BRT BRO Inv Exit*	76
Arrival WR Triage WICWR Exit	10098	*Arrival Triage R4 Clin BRT BRO Inv Exit*	75
Arrival Triage WR Clin Inv Exit	3818	*Arrival Triage R2 Clin BRT BRO Inv Exit*	65
Arrival WR Triage Clin BRT Inv Exit	1371	*Arrival Triage R1 Clin BRT BRO Inv Exit*	51
Arrival WR Clin Triage Inv Exit	1271	*Arrival Triage R3 Clin BRT Inv Exit*	34
AMBER PATIENTS		**GREEN PATIENTS**	
Arrival WR Triage Clin Inv Exit	784	*Arrival WR Triage Clin Inv Exit*	15347
Arrival Triage RAE WR Clin Inv Exit	135	*Arrival Triage WR Clin Inv Exit*	3072
Arrival WR Triage A1 Clin BRT BRO Inv Exit	93	*Arrival WR Triage WICWR Exit*	1664
Arrival WR Triage Clin BRT Inv Exit	92	*Arrival WR Triage Clin BRT Inv Exit*	1129
Arrival WR Triage BRT BRO Clin Inv Exit	85	*Arrival WR Clin Triage Inv Exit*	779
GREEN/MIU PATIENTS		**BLUE/PC PATIENTS**	
Arrival WR Triage Clin Inv Exit	12296	*Arrival WR Triage WICWR Exit*	7912
Arrival Triage WR Clin Inv Exit	593	*Arrival WR Triage Clin Inv Exit*	578
Arrival WR Triage WICWR Exit	485	*Arrival Triage WICWR Exit*	565
Arrival WR Clin Triage Inv Exit	425	*Arrival WR Triage WICWR WR.1 Clin Inv Exit*	386
Arrival WR Triage Clin Exit	309	*Arrival WR Clin Triage WICWR Exit*	227

***WR** = Waiting Room; **Rx** = Red Area x; **Ax**= Assessment Room x; **RAx** = Rapid Assessment Room x; **WICWR** = Walk in Centre Waiting Room; **Clin** = Clinician Time; **Inv** = Investigation Time; **BRT(O)** = Bed Request Time(Outcome)*

Patients' physical location were also generated in the same way as that used for the data frame shown in Figure 6.23 but without including the milestones from DS2. This focuses on only the physical locations visited and has benefit of reducing the number of specific locations from 16772 to 6434, distributed amongst 204 factors (rather than 211).

The number of visits to only Waiting Area Locations (WR, WICWR, etc) for all patients is shown in Table 6.13. One interesting observation from here is that over 58,000 patients appear to remain in the waiting areas throughout their journey. This means that about 59% of all patients do not visit other locations listed in Table 6.10. According to Mr Baskerville, the "Waiting Room" only locations actually represent cubicles. This suggests that while these patients are treated, their journeys were not logged when in fact they were in cubicles. This implies that the resources used (clinicians and nurses) also were not logged; thus the absence of staffing information in all four provided data.

In Table 6.14, the number of patients recorded in the "waiting area only" is significant in the Green (67%), Green/MIU (88%), and especially the Blue/PC patients (96%), of which the majority are in the Walk-in Centre Waiting Room (WICWR). This is no surprise for the Blue/PC group since majority of them are directed to the WICWR (which is in the Blue area and outside the scope of the ED) after triage as explained. For completeness, Table 6.15 shows percentiles for journey times by care group for this cohort.

Table 6.12: Patient #45716 Amber, Triage Category 2

Actual Recorded Journey				***Probable Journey***	
Location	Time	Location	Time	Location	Time
Arrival	09.13	A8	09.30	Arrival	09.13
Triage	09.13	A8.1	09.30	Triage	09.13
RAA	09.15	RAD.4	09.48	RAD	09.15
RAA.1	09.15	RAD.5	09.48	A8	09.26
RAD	09.18	A12	10.07	RAD	09.48
RAD.1	09.18	A12.1	10.07	A12	10.07
RAD.2	09.20	Clin	10.24	Clin	10.24
RAD.3	09.20	Inv	12.20	Inv	12.20
A14	09.26	Exit	12.24	Exit	12.24
A14.1	09.26				

Table 6.13: Physical Location by Count

Paths	**Count**
WR	42878
WICWR WR	11013
WICWR WR WR.1	1071
WR RAE	790
WRC3	715
WRC6	658
WICWR	635
WRC10	566
Total	***58326***

Table 6.14: Breakdown of Waiting-Only Patients by Care Group

Care Group	Total	Waiting Only	Probability
Red	3139	7	0.2
Amber	23198	1543	0.067
Green	41944	28259	0.67
Green/MIU	17349	15291	0.88
Blue/PC	11533	11088	0.96

Table 6.15: Total Journey Times for Waiting Room cohort

Percentiles in Minutes						Count	% Within 4 hours
0	25	50	75	95	100		
0	81	142	199	239	801	56188	98

Some mutually exclusive paths through the system by care group are computed by logically manipulating the journey strings obtained from the “All Milestone” in Figure 6.23. For generic locations, no repeats, and assuming there is no bias, there are 936 unique journey paths. In this context, the lack of bias means that amongst specific locations that the same purpose, consecutive visits are consolidated to the same location. For example, Cubicle 1 is as likely to be visited as Cubicle 8 and hence all Cubicles may be considered as “a Cubicle”. This is done for selected journey locations by care group and mode of Arrival (Ambulance and non- Ambulance[17]).

The top 25 paths are selected for all the Care Groups except for Green, of which the top 40 are used. This is because Green Care Group has the highest diversity of paths and it is important to include as many as possible for higher precision. Furthermore, at least 90% of the cohort was included in the combined selected paths. For instance, Table 6.16 shows the top 10 paths for Red Patients by Ambulance. The table represents 94.7% of the patients but only 16.7% of the unique journeys for the red cohort (See Full details in the Location Analysis Folder of the Thesis CD). This shows the huge variety in the number of paths, which also applies to other cohorts. For this cohort, 6 selected path combinations were generated as shown in Table 6.17. This process is repeated for other care groups by arrival mode and the results are displayed in Appendix B. Table 6.18 shows a summary of the number of patients in both generated and combined (selected) paths by care group.

[17] *Non-ambulance represents all arrival mode except by ambulance, which is assumed as Walk-in as explained in Section 5.3 (C)*

Table 6.16: Top 10 Generic Paths for Red Care Group by Ambulance Arrival

Reference	RED Patients by Ambulance: Journey Strings	Count
1	Red	846
2	Red, Assess	330
3	RAU, Red	140
4	RAU, Assess	85
5	RAU, Red, Assess	50
6	Red, Assess, Red	18
7	Assess	10
8	Red, Assess, Red, Assess	10
9	RAU, Assess, Red	8
10	WA, Red	8

Table 6.17: Selected Journeys for Red Care Group

Red Ambulance	Count	Probability (%)	Red Non-Ambulance	Count	Probability (%)
Red	872	56.15	Red	958	64.12
Red, Assess	368	23.70	Red, Assess	392	26.24
RAU, Red	151	9.72	RAU, Red	61	4.08
RAU, Assess	85	5.47	RAU, Assess	28	1.87
RAU, Red, Assess	66	4.25	Assess	40	2.68
Assess	11	0.71	RAU, Red, Assess	15	1.00

Table 6.18: Summarized Journeys Path Analysis by Care Group

Care Group	Number of Generated Paths	Number of patients in generated paths	Number of selected Paths	Number of patients in selected paths	Percentage included (%) in selected paths
Red Ambulance	60	1589	6	1553	97.73
Red Non-ambulance	72	1550	6	1494	96.39
Amber Ambulance	310	14216	9	13297	92.06
Amber Non-ambulance	252	8982	12	8269	93.54
Green Ambulance	416	11194	20	10235	91.43
Green Non-ambulance	249	30750	19	30312	98.58
Green/MIU Ambulance	122	1365	18	1232	90.26
Green/MIU Non-	86	15984	13	15904	99.50
Blue Ambulance	61	1297	14	1256	96.84
Blue Non-ambulance	66	10236	13	10184	99.49

Basically, this original approach will be applied to create an evidence-based (what actually happens) model, which will be compared to the anecdotal-based (what people think happens) model of the emergency department. These Paths information will be used as a basis for an evidence-based (Journey-Path) model in Chapter 7.

6.3 Resources and Staffing Pattern

Resource availability and staffing level information were obtained from Dr Richard Body, Ian Baskerville and Jonathan Smith as follows;

6.3.1 Resources

Table 6.19 shows the resource information which will be used as input for the model

Table 6.19: Resource Availability provided by Dr Richard Body

Resource	Quantity	Emergency Department Area
Trolleys	3	RAU
Assessment Cubicles	2	RAU
Bays	4	Red
Assessment Room	16	Amber
Triage Room	2	Green
Cubicles	8	Green
Treatment Rooms	5	Green
Consulting Rooms	2	Green
Mental Health room	1	Amber
Clinical Decision Unit (CLDU)	1	Green
Radiology Room	2	Green

6.3.2 Shift Pattern for Nurses

Nurses provide care to patients and work based on shifts. Information on Nurses shifts were provided by Jonathan Smith who is the Head of Nurses at Manchester Royal Infirmary (MRI) during an interview on 7 November 2013. There are a total of 53 Registered Nurses in the emergency department (ED). There are three available Nurses shifts as follows;

i. Morning shift from 7:30am to 3:30pm
ii. Afternoon shift from 12:30pm to 8:30am
iii. Evening shift from 8:30pm to 7:45am

Nurses take 30 minutes break during their shifts; however there are always available nurses in the ED. The Nurse capacity for each Area in the ED and their shift pattern are as shown in Table 6.20 and 6.21 respectively.

Table 6.20: Nurse Capacity provided by Jonathan Smith

ED Area	Nurse Capacity and Work area
Red (Resus)	2 (nurse takes care of 4 bays)
RAU	1 (takes care of 2 Assessment cubicle and 3 curtained Trolleys, thus taking care of 5 patients at a time)
Amber (Majors)	3 (takes care of the 16 Assessment Rooms)
Green (Minors) and Minor Injury Unit (MIU)	2 Triage Nurses 4 Nurse Practitioner
Lead Charge Nurse	1 (All Areas)

Table 6.21: Nurse Shifts provided by Dr Richard Body

	07:30 – 15:30	12:30 – 20:30	20:30 – 07:45
Registered Nurse (RN)	10	11	10
Emergency Nurse Practitioner (ENP)	1	1	1
Leader	1	1	1

6.3.3 Shift Pattern for Doctors

A-month doctors' rotas – from 27 August to 30 September was provided by Dr Body. The unanimous rota was in form of an Excel spreadsheet file called Staff Shift Pattern in the Thesis CD. There are four ranks of doctors – Junior doctor, Junior Registrar, Senior Registrar and Consultant. Figure 6.24 displays the spreadsheet of the Junior doctors' rota. The blue team and red team spreadsheets hold rotas for the Senior and Junior Registrars respectively. The rotas were analysed and modified in terms of daily availability based on the shift pattern, which vary with the different ranks as shown in Table 6.22. Table 6.23 represents the resulting hourly doctors' schedule which was verified by Dr Body before usage in the model.

Figure 6.24: One-Month MRI Doctors' Rota

Week	Sat 27 Aug	Sun 28	Mon 29 Aug	Tue 30 Aug	Wed 31 Aug	Thur 01 Sept	Fri 02 Sept	VLE time "
			BH					
1	----	----	21.00-08.00	21.00-08.00	2100 - 0800	2100 - 0800	2100 - 0800	
2	2100 - 0800	2100 - 0800	----	----	----	----	1200 - 2200"	1400 - 1600
3	1200 - 2200	11.00-21.00	1700 - 0100	1700 - 0100"	1700 - 0100"	1700 - 0100	----	1800 - 1900 x2
4	----	----	8.00-17.00	1000 - 1900"	1000 - 1900	1000 - 1900	1000 - 1900	1400 - 1600
5	~~8.00-18.00~~	~~8.00-18.00~~	----	----	----	----	1700 - 0100"	1800 - 1900
6	1700 - 0100	1700 - 0100	1200 - 2200	1200 - 2200"	1200 - 2200	S/L	----	1500 - 1700
7	A/L	A/L	A/L	A/L	A/L	A/L	A/L	
8	----	----	1700 - 0100"	1700 - 0100"	-------------	----	2100 - 0800	1800 - 1900 x2
9	2100 - 0800	2100 - 0800	2100 - 0800	2100 - 0800	2100 - 0800	2100 - 0800	----	
10	----	----	----	0800 - 1800"	0800 - 1800	0800 - 1800"	0800 - 1800	1300 - 1500
11	0800 - 1800	0800 - 1800	0800 - 1800	----	----	1200 - 2200"	1200 - 2200	1500 - 1700
12	1200 - 2200	1200 - 2200	1200 - 2200	1200 - 2200	1200 - 2200"	----	----	1500 - 1700
13	----	----	1100 - 2100"	1100 - 2100	1700 - 0100	1700 - 0100	1200 - 2200	1500 - 1700
14	1200 - 2200	1100 - 2100	---------	------------	8.00-18.00	0800 - 1800	0800 - 1800	1300 - 1500
15	0800 - 1800	0800 - 1800	0800 - 1800"	0800 - 1800	----	----	1700 - 0100	1300 - 1500
16	1700 - 0100	1700 - 0100	----	----	1100 - 2100	1100 - 2100"	1100 - 2100	1500 - 1700
17	A/L	A/L	A/L	A/L	A/L	A/L	A/L	
	16.00-02.00	16.00-02.00	16.00-02.00	F2 Teaching				

Week	Sat 03 Sept	Sun 04	Mon 05	Tue 06 Sept	Wed 07	Thur 08 Sept	Fri 09 Sept	VLE time "
1	----	----	21.00-08.00	21.00-08.00	2100 - 0800	2100 - 0800	2100 - 0800	
2	2100 - 0800	2100 - 0800	----	----	----	----	1200 - 2200"	1400 - 1600
3	1200 - 2200	1200 - 2200	1700 - 0100	~~1700 - 0100"~~	~~1700 - 0100"~~	1700 - 0100	----	1800 - 1900 x2
4	----	----		~~1000 - 1900"~~	1000 - 1900	1000 - 1900	1000 - 1900	1400 - 1600
5	8.00-18.00	8.00-18.00	----	----	----	----	1700 - 0100"	1800 - 1900
6	1700 - 0100	1700 - 0100	1200 - 2200	1200 - 2200"	1200 - 2200	1200 - 2200	----	1500 - 1700
7	A/L	A/L	A/L	A/L	A/L	A/L	A/L	
8	----	----	1700 - 0100"	1700 - 0100"	-------------	21.00-08.00	2100 - 0800	1800 - 1900 x2
9	2100 - 0800	2100 - 0800	2100 - 0800	2100 - 0800	2100 - 0800		----	
10	----	----	10.00-19.00	0800 - 1800"	0800 - 1800	0800 - 1800"	0800 - 1800	1300 - 1500
11	0800 - 1800	0800 - 1800	0800 - 1800	----	----	1200 - 2200"	1200 - 2200	1500 - 1700
12	1200 - 2200	1200 - 2200	1200 - 2200	1200 - 2200	1200 - 2200"	----	----	1500 - 1700
13	----	----	1100 - 2100"	1100 - 2100	1700 - 0100	1700 - 0100	1200 - 2200	1500 - 1700
14	1200 - 2200	1100 - 2100	---------	------------	~~8.00-18.00~~	0800 - 1800	0800 - 1800	1300 - 1500
15	0800 - 1800	0800 - 1800	0800 - 1800"	0800 - 1800	----	----	1700 - 0100	1300 - 1500
16	1700 - 0100	1700 - 0100	----	----	1100 - 2100	1100 - 2100"	1100 - 2100	1500 - 1700
17	A/L	A/L	A/L	A/L	A/L	A/L	A/L	

Table 6.22: Doctors' Shift Patterns based on Rank

Rank	Shift Pattern	Quantity
Junior doctor	8am to 6pm	2
	11am to 9pm	1
	12noon to 10pm	2
	5pm to 1am	1
	9pm to 8am	2
Junior Registrar	8am to 6pm	1
	10am to 8pm	1
	12noon to 10pm	1
	5pm to 2am	1
	6pm to 8pm	1
	10pm to 8am	1
Senior Registrar	8am to 6pm	2
	12noon to 10pm	1
	5pm to 2am	1
	10pm to 8am	1
Consultant	8am to 5pm	2
	4pm to 12 midnight	1

Table 6.23: Doctors Hourly Schedule from Rotas

HOUR OF THE DAY	JUNIOR DOCTOR	JUNIOR REGISTRAR	SENIOR REGISTRAR	CONSULTANTS	TOTAL
08:00	2	1	2	1	6
09:00	2	1	2	2	7
10:00	2	2	2	2	8
11:00	3	2	2	2	9
12:00	5	3	3	2	13
13:00	5	3	3	2	13
14:00	5	3	3	2	13
15:00	5	3	3	2	13
16:00	5	3	3	3	14
17:00	6	4	4	1	15
18:00	4	4	2	1	11
19:00	4	4	2	1	11
20:00	4	2	2	1	9
21:00	5	2	2	1	10
22:00	3	2	2	1	8
23:00	3	2	2	1	8
00:00	3	2	2	0	7
01:00	2	2	2	0	6
02:00	2	1	1	0	4
03:00	2	1	1	0	4
04:00	2	1	1	0	4
05:00	2	1	1	0	4
06:00	2	1	1	0	4
07:00	2	1	1	0	4

6.3.4 Shift Pattern for Support Workers

The availability and shift pattern of support workers are as shown in Table 6.24 and 6.25 respectively. During the night shift, two support workers are situated in the neediest part of the ED. In the model, it is assumed that the two neediest areas are the Green/MIU and RAU.

Table 6.24: Support workers availability

Emergency Department Area	Quantity
Rapid Assessment Unit (RAU)	2
Resus or Red	0
Amber	0
Green and MIU	2

Table 6.25: Shift pattern for Support workers

07:30 – 15:30	12:30 – 20:30	20:30 – 07:45
4	4	2

6.4 Data Limitation

The data provided was of poor quality; this is not new and has been reported in literature (Sharp, 2013). Some of the issues encountered are as follows;

- ***Incomplete data entries***

There were some unrecorded data; For example there were 927 unrecorded triage category and 1069 unrecorded care group details (out of 98236). At first it was anticipated that this could be due to patient who left before triage, however this is not the case. Also, 110 admitted patients had no valid care group entries. One ought to expect that bed request is made for all patients who require hospital admission. However of the 25943 admitted patients, 7453 had no valid "bed request or outcome" entries.

Most journey locations through the system were not recorded. From the data, 59% of patients remained in the waiting room throughout their journey. In essence, 74% of patients in the waiting room cohort which represents the "Waiting Room only" are actually located in cubicles. This implies that not all patient location was recorded.

- ***Zero and negative Inter-arrival and Journey Time***

It was not surprising to get zero inter-arrival time values, since there are 2 receptionists and patients may have arrived simultaneously. Also, patients who arrive by ambulance (and into the Rapid Assessment Unit (RAU)) could also have same time arrival stamps as walk-in patients. For example, Patient A arrives at the emergency department by walk-in at 1pm and gets to the receptionist who puts down an arrival time – 1:01pm. Simultaneously, Patient B arrives at the RAU and an arrival time – 1:01pm was recorded. This would lead to an inter-arrival time of 0 minutes. However the zero journey times is quite perplexing and is impossible.

Now, assuming the zero inter-arrival values represent patients who arrive in parallel; which usually happens in practice. On arrival, they must undergo registration during which their arrival time is recorded in the database. According to ED staff, the minimum duration for registration process is 5 minutes. Therefore, even though a patient reneges or balks immediately after registration, the minimum time should be 5 minutes. From the Arrival to Exit journeys, 6 patients had zero journey time which implies that they did not undergo registration but they had "Arrival Time" entries. It seems like if a patient leaves the emergency department before seen by a clinician (or balks), the "Exit time" is recorded as the "Arrival time"; since the time of exit is unknown. This is confirmed by Dr Body who stated that, "*The time data probably aren't valid, they are usually entered as patients are discharged*".

This implies that the software used for collecting data usually require *something* to be entered in response and that medical staff will, under pressure, occasionally enter *anything* which the software will accept*,* even if it is not (nor even close to) the intended *something*[18]. To be fair, the information has been generated for a purpose which has more to do with accountability than with analysis (HSCIC, 2014).

- ***No specified time duration for the processes***

The general form of the data provided showed records of times by which a process "starts". Other than the time when a patient leaves the department, there was no data that states explicitly when a process "ends". This made it difficult to estimate the duration of any activity which is very important for the model. For example the triage start times were shown, but the time this ended was not specified, instead the next time recorded was "clinician time". This is the same for all process times in the dataset. It was therefore difficult to compute the duration for each process which is required for building computer models.

- ***Verbose data***

The data provided were not in their third normal form. In particular, DS2 and DS4 had multiple row entries for same the patients. This was a challenge to analyse. Also, from DS4 there were investigation entries with "None required" and corresponding times, there were also empty cells; the former could not be reconciled with the later. Furthermore, the time format in the provided spreadsheet could not be used directly for time-based calculations and had to be converted in R before subsequent manipulations.

6.5 Comments and Conclusion

The data obtained from the emergency department of Manchester Royal Infirmary (MRI) was analysed in detail in order to provide basis for the proposed model. It seems also that some of the information derived in the analysis was new to the ED staff. The information was found to be comprehensive but incomplete in some areas. It also showed an underlying complexity.

On one level the data provides information on attendances, inter-arrival times, care group and triage category populations, triage complaints, etc., all of which can be used as a starting point for

[18] *This is likely to account for records that show patients being in two places at the same time and some being investigated **after** they have been discharged*

the model. It is also straightforward to combine elements of the data such as care group and triage complaint, which allow more specific cohorts to be identified.

It is worth noting that the only factual (recorded) information which is available from ED is recorded via Symphony®. This does **not** include process times for any activity and such information must be found from consultation with ED clinicians. This is discussed further in chapter 10.

An original method for deriving journey paths was created. In the course of this workout, this too shows the complexity of the system with for example, the total number of unique journeys by Care Group and by Triage Complaint numbering in the hundreds.

In summary;

- 98236 patients attended the emergency department from 1 April 2012 to 31 March 2013 (which is an average of approximately 269 patients daily).
- 11% of patients spent over four hours in the emergency department which exceeds the target set by Government. Patients in all care groups exceeded the 4-hour target.
- 71 beds are required daily for successful admission of ED patients into hospital. It appears that this is excessive and enough reason for the deceleration in patient flow. Russell Emeny (2013), a NHS advisor on emergency care, highlighted tactical solutions to minimize the issue of bed unavailability. They include dealing with avoidable admissions, focusing on "*home-based"* rather than "bed-based" solution and improving patient flow. He also highlighted that the possibility of experienced clinician managing admission could minimize unnecessary hospitalization.
- Some patients who did not require hospital admission stayed up to 23 hours in the emergency department. This is an interesting finding because it was anticipated that such long hours could have been due to the lengthy wait for hospital bed.

CHAPTER 7 THE MANCHESTER ROYAL INFIRMARY EMERGENCY DEPARTMENT MODEL

7.0 Introduction

In Chapter 6[19], the data obtained from Manchester Royal Infirmary (MRI) was analysed and interpreted. Despite its shortcoming, it was used to build a model which will be presented in this Chapter. In fact, two models are described; the "*Base"* and "*Journey-Path*" model. The Base model uses data from the analysis and anecdotal information obtained from ED staff as inputs while the Journey-path model is evidence-based by using the journey strings described in Chapter 6 (Table 6.16 and Appendix B). To the knowledge of the author, this type of model is original.

The emergency department (ED) is modelled as a queuing system which is made up of patients, queues and resources. In Arena, patients are entities which have attributes attached to them such as care groups which in turn define process delay times. They compete for resources such as doctors, nurses, cubicles, assessment rooms, trolleys and treatment rooms, in order to travel through the system. A patient seizes a resource for a procedure when available and releases it when finished. More than one resource may be required for one or more procedures. For instance a patient may require a cubicle and nurse for consultation (and probably treatment). Detailed description of the emergency department procedures are illustrated in Section 7.1. Input parameters such as the arrival, process durations, and patient flow through the system, resource availability, staffing levels and schedules are also described. There is currently no information on process time duration in literature, so the model is dependent on information from ED staff. Ball park statistical distributions for each process by Care Groups were provided by the ED consultant, Dr Richard Body. Section 7.2 provides detailed illustration of the Base model while Section 7.3 describes the Journey-Path model. The chapter is summarized in Section 7.4.

7.1 Modelling the Emergency Department

Before describing the model, it is imperative to illustrate the basic elements that make up the system (emergency department). A system is made up of a start activity, a process and an end activity, and can be described in more detail by a process map. In the case of the emergency department (ED), the start activity is the *arrival* of patient into the ED, *processes* are the operations patients undergo which include the use of *resources*, while the end activity is their exit from the ED; as described in the process map in Chapter 4.

In Chapter 4, a brief description on the arrival and triage operations of MRI were provided. It is necessary to illustrate procedures of the emergency department in more details as well as

[19] Chapter 6 will be referred to frequently since the data used for the model is described there.

subsequent implications in the model. For better understanding of the model description, some resource information are mentioned, however more details are presented in Section 7.1.3.

7.1.1 Emergency Department Procedures and Model implications

There are 4 primary areas at the emergency department of Manchester Royal Infirmary (MRI) namely - Rapid Assessment Unit (RAU), Majors, Minors and Primary Care Emergency Centre (PCEC). Patients are directed to these areas are based on the severity of their ailment; with RAU as the most critical and PCEC, least critical. Majors consist of Red and Amber areas, Minors include Green area and Green/MIU (Minor Injury Unit), and PCEC is the Blue area (or Walk-in Centre).

The RAU was introduced relatively recently. In effect it replaced what was called the RESUS unit and the RESUS unit became what is now called the Red Area. The activity in the RAU is still referred to as “resuscitation” but does not necessarily imply that a patient has stopped breathing.

Approximately 269 patients attend the emergency department of MRI daily, although this varies by time of day and day of week (Chapter 6). Roughly 30 out of 100 patients arrive by ambulance while the rest are referred to as “walk-in” patients irrespective of their actual mode of transportation. In general, patients who arrive by ambulance are directed to the RAU while the rest (except Red patients) go to the reception for registration. All Red “walk-in” patients are transferred from the reception to RAU. This can be during registration or triage – depending on when the criticality of the patient condition is acknowledged. In the model, it is assumed that this occurs after registration, since this is when the patient first presents at the ED.

The Rapid Assessment Unit (RAU) is effectively a triage area for critical patients. Critical patients are those in the Red and Amber care groups, while Green, Green/MIU and Blue care groups are non-critical. For ambulance arrivals, the clock starts when patients present at the RAU. For critical patients, if a trolley or assessment cubicle is available, resuscitation is done by a doctor and nurse. If there are no available resources, the patient will wait in the RAU corridor while being looked after by paramedics. This means one less ambulance on the road. Resuscitation includes triage, test, evaluation and preliminary treatments – all done simultaneously. Tests are carried out by Support Workers. Since a patient’s journey time is not directly affected by the time to carry out tests (as this is done in parallel with treatment), only the time to collect test sample is modelled. The patient proceeds to appropriate care group area for other services such as consultation, treatment and review. If a non-critical patient arrives by ambulance, they are directed to the reception.

At the reception, the patient's arrival time and personal details are recorded by the receptionist. For walk-in and non-critical ambulance Arrivals, this is the time the clock starts[20]. During busy periods, the patient may wait for an available receptionist.

After registration, the patient enters triage for initial assessment, if there is available resource. The assessment is made using the medical skills of the triage personnel and results in each patient being assigned a priority (red through blue based on the Manchester Triage Score (see Chapter 3)) according to their condition. The assessment takes time and this is reflected in a delay to the progress of the patient through the system. The assessment consumes resources in the form of triage nurse. Give or take the prevailing demand, the assessment can also result in a greater or lesser queue at the triage station. If there is no ambulance arriving at the ED, and waiting time for triage is exceeding 15 minutes, the RAU nurse assists in carrying out triage, in an available cubicle. If a blood test is required, the blood sample is taken from the patient by a support worker. The patient is then routed to the appropriate care group area for further investigations. In the model, it is assumed that all tests are requested during triage (in a triage room) except for Red patients who are triaged in the RAU, thus their initial test request is carried out there. Often treatments are provided before the test results arrive, so tests are done in parallel with treatment. Therefore only the time to collect tests samples and information is modelled, except for those Green/MIU patients who require X-ray since they have to wait for test results before treatment commences.

In all Areas except the PCEC, a patient undergoes consultation, treatment, review and decision procedures. In the Red area, all procedures are carried out by both doctors and nurses except treatment, which is carried out by only nurses. In the Amber area, consultation, review and decision processes are carried out by only doctors, while nurses carry out treatments. In the Green area, either doctors or nurses (whichever one is available) can do all four procedures. All patients in the RAU require tests. As described by Dr Body, 1 out of 5 patients in the Red area may require further tests after the initial treatment, and subsequently further treatment; 1 out of 5 Green/MIU patients may need X-ray which is carried out by a technician in the radiology room. Most patients in the blue care group are directed to the Primary Care Emergency Centre (PCEC). The PCEC is considered as a separate unit from the emergency department and therefore outside the scope of this research. Although, some patients who were initially directed to the blue area may be moved back to the green area if emergency treatment is required. It is important to demonstrate this in the model; however the exact number of blue patients who return to the ED is not available. Therefore, it is assumed that all blue patients who require admission into hospital

[20] Arrival Time in DS1 shown in Figure 5.1 of Chapter 5

are directed from the blue to the green area. Note that the time spent in the PCEC before re-admission into the ED is included in blue patients' journey time.

Depending on the outcome of the review and decision process, a patient may need hospital admission or be discharged[21]. If admission is required the patient goes to the waiting area until a bed becomes available in hospital. Patients waiting for too long or exceeding 4 hours are moved to the CLDU (Clinical decision Unit)[22]. The CLDU is considered as an external ward and not part of the ED. From the provided data, there are only 16 of such patients; therefore it is not included in the model. The clock stops when the patient leaves the ED. For patients who require admission, this happens when a bed request is approved and the patient is admitted into the hospital. In practice, some patients tend to revisit the emergency department. In the model, revisits are not considered since it was impossible to deduct from the data if a patient returns to the ED or not; so every patients is treated as a new attendee.

7.1.2 Process Times

The model must establish quantitative time taken for those skill-based procedures that are encountered within the ED. It is a key feature of this work that duration for these procedures are represented by distribution functions and it is essential to establish such distributions for a range of procedures, rather than simply lump these together in the form of a generic "delay" to the progress of the patient. It has been established that the duration of a skill-based process can be represented by a uniform distribution, a triangular distribution or a beta distribution (Altiok and Melamed, 2007, Kelton et al., 2006). All three distributions require a range which is bounded by a minimum time and a maximum time. In the uniform distribution the density function is constant and hence there is an equal probability of selecting any time within the range. The density functions for the two other distributions are calculated from the minimum (optimistic) bound, the maximum (pessimistic) bound and a most likely value which lies between the two. In this study uniform and triangular distributions are used.

The bounds of such putative distributions were established by talking with the ED consultant, Dr Richard Body. Ball park figures of processing times which vary by care groups were provided as shown in Table 7.1.

[21] Discharged here could also mean "referred" or "transferred"
[22] This is now known as the Observation Medical Unit (OMU)

Table 7.1: Input parameters for patients' operations based on Emergency Department Area

ED Areas/Operations	Duration	Operations	Duration
RAU		**GREEN**	
Resuscitation	TRIA(30,60,120)	Consultation	TRIA(10,15,20)
Test Order request	UNIF(10,15)	Treatment	TRIA(25,40,60)
ED ENTRANCE		Review and Decision	UNIF(15,20)
Registration	TRIA(2,3,5)	Wait for Bed	TRIA(90,180,240)
Triage and Test Request	TRIA(10,12,15)		
RESUS/RED		**GREEN/MIU**	
Consultation/Preliminary Treatment	TRIA(30,40,45)	Consultation	TRIA(10,15,20)
Treatment	TRIA(50,120,180)	Test Preparation	UNIF(5,10)
More Test	UNIF(5,10)	Test	UNIF(15,25)
More Treatment	TRIA(60,90,120)	Treatment and Review	TRIA(25,40,60)
Review and Decision	UNIF(20,30)	Wait for Bed	TRIA(90,180,240)
Wait for Bed	TRIA(60,150,240)		
AMBER		**BLUE**	
Consultation	TRIA(15,20,25)	Consultation	TRIA(5,10,15)
Treatment	TRIA(40,60,80)	Treatment	TRIA(30,60,90)
Review and Decision	UNIF(10,15)	Review and Decision	UNIF(10,20)
Wait for Bed	TRIA(80,150,240)	Wait for Bed	TRIA(90,180,240)

These above processes are modelled as sequential procedures which entities follow through their lifetime in the facility as shown in the process map in chapter 4 (Figure 4.6). Although in real life, there is no rigid sequence for patient flow as evident in the numerous patients' journey-path locations described in chapter 6.

7.1.3 Resource Input Description

Resource and staff information were obtained from the ED consultant, Dr Richard Body. Doctors' rota was provided in a spreadsheet, which was used to derive doctors' schedule as displayed in Table 7.2. Information on receptionists and technicians were also provided. Nurses and Support workers' data were provided by the head of Nurses, Mr Jonathan Smith.

In Arena, both equipment and staff are known as "*Resources*" and are allocated in the model by assigning resource sets membership (see section 7.2 for further details). Resource (equipment) capacity and schedule inputs are as described in Chapter 6 (Section 6.3). More details are as follows;

<u>Doctors</u>

Doctors (also known as clinicians) are usually assisted by nurses and support workers. They mostly carry out consultation and review/ decision processes. There are a total of 14 doctors; 6 Junior doctors, 4 Junior Registrars, 4 Senior Registrars and 3 Consultants. From the shift pattern derived in Chapter 6 (Table 6.22), doctors' schedule and distribution by areas of operation are outlined in Table 7.2.

Table 7.2: Doctors'/Consultants' Schedule and work area

Staff	Schedule	ED Work Area
Junior Doctor		
Doc_1	00:00 – 00:00	RAU, Red
Doc_3	00:00 – 00:00	RAU, Amber
Doc_5	11:00 – 01:00	Red
Doc_9	12:00 – 22:00	Green, MIU
Doc_11	12:00 – 18:00	Green, MIU
Doc_13	17:00 – 18:00	Green, MIU
Junior Registrar		
Doc_6	00:00 – 00:00	Amber
Doc_7	10:00 – 02:00	Green, MIU
Doc_10	12:00 – 20:00	Amber
Doc_12	17:00 – 20:00	Green, MIU
Senior Registrar		
Doc_2	00:00 – 00:00	RAU, Red
Doc_4	08:00 – 02:00	Red
Doc_8	12:00 – 18:00	Amber
Doc_14	17:00 – 18:00	Amber
Consultant		
Consultant_1	08:00 – 00:00	RAU
Consultant_2	09:00 – 17:00	Red, Amber
Consultant_3	16:00 – 17:00	RAU, Amber

In practice, consultants and senior registrars are more experienced than junior doctors; therefore work faster for particular processes. For example, for consultation, if junior doctor has a capacity of 0.9, senior doctor and consultants should be attributed capacities of 1.0 and 1.1 respectively. However, this is not considered in the model because in Arena capacity has to be an integer; hence we assume all doctors have the same level of expertise.

Some doctors work in multiple areas, although priority is given to the RAU and Red areas. In Arena, there are 3 levels of queue priority; low, medium and high. To ensure that RAU and Red areas are prioritized, doctors' scheduled capacity and queue priority are "high" in these areas. Also, breaks were already incorporated in the rota, therefore when creating the schedule in the model, they were exempted. More detailed explanation is provided in Section 7.2.

Nurses

The general role of nurses is to "care for" and treat patients. Nurses administer antibiotics and oral medications such as pain relief, assessment as well as treat Minor Injuries. The period of care is the entire time the patient is in the area over which the nurse has responsibility and the number of patients nurses look after differ. The capacity by area of operation is as shown in chapter 6 (Table 6.20).

In the model, a patient "seizes" resources such as a room or cubicle and a doctor and/or nurse for a duration that represents a procedure (such as triage, consultation, treatment, review and decision) and then "releases" these resources so that they can be used for the next patient. This seize, do "something" and release sequence is linear in time and contributes directly to the journey time of the patient. In the "care for" role of a nurse the implication is that the nurse is doing something throughout this sequence (effectively in the background) and not necessarily only with this particular patient (multi-tasking). Moreso whatever the nurse does is not the rate determining step in the sequence; this is a challenge to model. In these circumstances the best way to do this is to seize a nurse when a patient actually requires treatment by a nurse and release the nurse afterwards. This will account for the utilisation of nurses. Also, one nurse may be assigned to take care of a number of patients. For example in the Amber area, there are 3 nurses distributed among 16 assessment rooms. This implies that 2 nurses take care of 5 rooms and 1 looks after 6 rooms. In discrete event simulation, resources cannot be modelled as fractions. Consequently, in the model, nurses are given capacities based on the number of patients they are assigned to. For instance, in the Amber area the three nurses have capacities of 5, 5, and 6. Note that in reality, they are actually 3 nurses. For this reason, nurses' shifts and breaks are not considered in the model.

Receptionist

A receptionist registers patients as they arrive at the emergency department. Patients who arrive by ambulance are taken to the Rapid Assessment Unit (RAU) and are not registered by the receptionist. Instead, they are registered and triaged in the RAU during resuscitation by the team of doctors and nurses. In MRI, there are always 2 receptionists.

<u>Support worker</u>

Support workers assist the doctors and nurses to take care of patient. They also help to take samples from patient for blood tests and X-rays. There are 2 support workers in the Rapid Assessment Unit (RAU), Green, and Green/MIU areas. Using the provided shift pattern described in chapter 6, a schedule is derived for the model as shown in Table 7.3.

Table 7.3: Support workers' Schedule

Staff (Resource)	Schedule	ED Area
Support Worker_1	00:00 – 00:00	RAU
Support Worker_2	07:30 – 20:30	
Support Worker_3	00:00 – 00:00	Green/MIU
Support Worker_4	07:30 – 20:30	

<u>Technician</u>

Technicians do X-rays. There are always 2 technicians in the facility. They work in shifts but since there are always two available, their capacities are not based on schedule in the model. Also, they are only modelled in the MIU stream since it is assumed that only Green/MIU patients require X-ray.

7.1.4 Input and Output parameters

Model parameters can be classified as inputs and outputs. Inputs are fed into the model, while outputs are used to verify the model. As patients go through the system, their journeys are recorded in an output file, which will be used to compare with the original data.

The input parameters are as follows;

1. Arrival pattern by hour of day and day of week
2. Percentage arrivals by care group and triage category
3. Percentage arrivals by care group and arrival mode
4. Sequence of operations/processes and durations in the emergency department (as described in 7.1.2)

5. Available resources and schedule taking account of areas of operation in the emergency department (as described in 7.1.3)

The output parameters are as follows;

6. Number of arrivals by care group, triage category and overall cohort
7. The overall patient journey time and by care group
8. Resource and Staff Utilization

7.1.5 Assumptions

Some assumptions have previously been described for staff/resources, the following are some general ones made in the model;

a) At initialization, the emergency department is empty (No patient is present), and staff and resources are idle. Although this is compensated for during the 7 days warm-up period, since it is assumed that the system will settle after a week.
b) Bear in mind that the model has no medical knowledge. The journeys are determined by taking the data from MRI and using the probabilities for the various care groups. These probabilities are assigned to patients when they arrive at the ED. The triage in the model is merely a delay, while in practice it is the process of assessing the acuity of the patients.
c) Emergency department staff never go on break during scheduled hours and resources never breakdown.
d) Transfer time from one area to another is zero since most of the illustrated movement in the model implies that patients are actually in one position in practise. Although some transfers actually occur in practice, this is not considered in the model since the time duration for this is not available.

7.1.6 Triggers

For any ED process to occur, the corresponding resource must be available. However, there are two major waiting room triggers, the first is: available Triage Nurse for triage after registration (i.e. TRIAGE NURSE > 1) and second is: available Doctor or Nurse Practitioner for each procedure. It is assumed that once a patient has been seen by a doctor or nurse practitioner, they have priority over the remaining patient in that area. Patients who arrive by ambulance do not partake in the first trigger since they are triaged in either the ambulance or Rapid Assessment Unit (RAU).

In a nutshell, the release or availability of one resource and/or staff triggers the release of a patient from a queue.

7.1.7 Particular Elements in Arena used for the model

Arena uses flowchart and data modules to create models (Altiok and Melamed, 2007). The modules are selected from panels in the Project bar. Three panels were mainly used in the model namely; Basic Process, Advanced Process and Advanced Transfer. In the Basic Process panel, the flowchart modules used include; Create, Process, Assign, Decide, Record, and Dispose, while the data modules used are; Entity, Attribute, Queue, Resource, Variable, Schedule and Set. In the Advanced Process panel, the flowchart modules used include; Delay, Seize, and Release, while the data modules used are; Expression and File. In the Advanced Transfer panel, Station and Route modules are used. See Kelton et al (2006) and Altiok and Melamed (2007) for more details on the function of each module. In general the following should be noted;

- The “thing” which is followed in Arena is called an *entity*
- Any number of (different) entities may be used in a model and each can be created singly or in batches of any size
- The time interval between the *creation* of successive entities is usually taken from a particular *density distribution* and can also follow a user-defined *schedule*
- An entity can be assigned any number of user-defined *attributes*
- The value of an attribute can be used in conditional statements
- A *process* is something which happens to an entity
- An entity *seizes* one or more *resources* for a process then *releases* the resources when the process is complete
- A seized resource is unavailable until it is released
- A process has a finite *duration*, typically taken from a *density distribution*
- The duration of a process can be made a function of a *specific* entity

7.2 Building the Base Model

The emergency department is modelled as a network of streams. Each stream is an epitome of an ED area (or care group). For simplicity, the base model is divided into eight parts namely;

1. Arrival Process
2. Red Area Process
3. Amber Area Process
4. Green and Green/MIU Area Process
5. Emergency Department Test
6. Blue/Primary Care Area Process

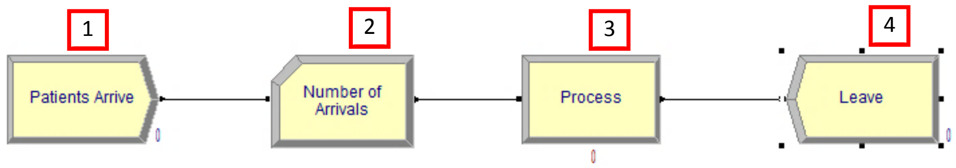
7. Admission and Discharge Logic
8. Exit and Statistics Collection Logic

7.2.1 Arrival Process

Arena allows the ability to model arrivals using four methods; Random distribution, by schedule, constantly and by using an expression. It is imperative to determine the most appropriate arrival input as this is a key to building a robust model.

Kelton et. al. (2006 Pg 515) stated that many arrival processes in simulations are modelled as being randomly distributed. Emergency department arrivals are non-stationary events over time, therefore making events occur as an "average" rate will be inappropriate. Thus, to yield accurate results, the emergency department arrivals should be modelled as Non-stationary Poisson process. For confirmation, a test is carried out to ascertain the accurate input measure for patient arrival. A simple model (Figure 7.1) is constructed to illustrate this. The goal is to establish the arrival method that will produce the expected number of arrivals (98236) in a year, based on the recorded data from the hospital.

Figure 7.1: Simple model for Arrival Input Test



In the model, patients arrive [1], they are counted [2] and a simple process [3] is carried out for 1 second, then they exit the emergency department [4]. Note that for this experiment, the "process" is irrelevant, rather the recorded "number of arrivals" is.

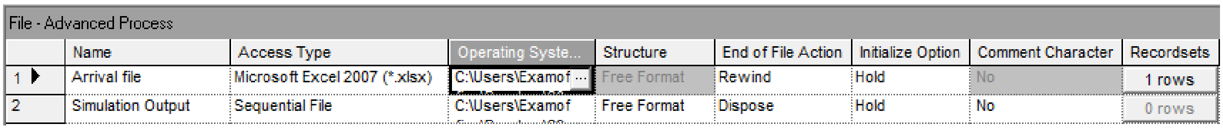
The two types of arrival input considered are;

1. By schedule
2. By distribution

<u>By Schedule</u>

The arrival pattern is obtained from the Excel file - Arrival Pattern Result (from the R analysis) described in chapter 6. This is the hourly arrival rate of patients by day of the week – from Sunday to Saturday. The excel file is saved in the File module (Figure 7.2) and read into the model at the start of the simulation run. In the create module, schedule is selected as the type of "Time between Arrivals" with the name - "Arrival Schedule" (Figure 7.3).

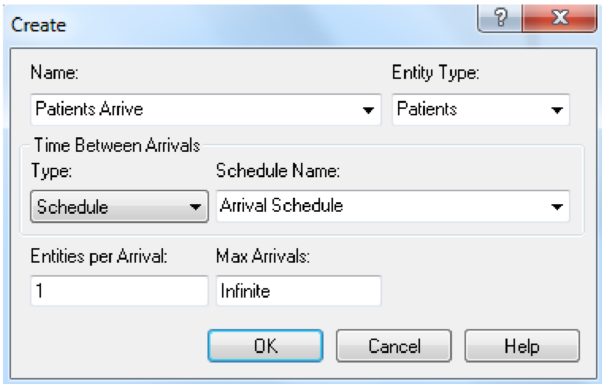
Figure 7.2: File module for arrival file input



File - Advanced Process

	Name	Access Type	Operating Syste...	Structure	End of File Action	Initialize Option	Comment Character	Recordsets
1	Arrival file	Microsoft Excel 2007 (*.xlsx)	C:\Users\Examof ...	Free Format	Rewind	Hold	No	1 rows
2	Simulation Output	Sequential File	C:\Users\Examof	Free Format	Dispose	Hold	No	0 rows

Figure 7.3: Create module dialog box for scheduled arrivals



The model is run for 1000 replications in 372 days with a warm-up period of 7 days, since statistics are not collected during the warm-up period and 365 days' worth of output is required.

1. <u>By distribution</u>

The inter-arrival time for the data was also derived from the R analysis described in Chapter 6. Five arrival input distributions were obtained using Arena's fit all feature as outlined below;

- Expo (8) minutes
- Expo (7) minutes
- -0.001 + WEIB (6.47, 0.786)) minutes
- -0.001 + 239 * BETA(0.253, 7.47) minutes
- -0.001 + EXPO(7.83) minutes

These expressions were inputted individually into the "Time between Arrivals Type" field of the create module. The model is run for subsequent distributions. The results are as displayed in Table 7.4.

Table 7.4: Arena output results for Arrival Input Test

Input mode	Number of patients (365 days)
By schedule	98253 ± 16
By distribution expressions	
Expo(8) minutes	65706 ± 16
Expo(7) minutes	75093 ± 17
Expo(6) minutes	87604 ± 18
-0.001 + WEIB (6.47, 0.786)) minutes	68066 ± 23
-0.001 + 239 * BETA(0.253, 7.47) minutes	83395 ± 23
-0.001 + EXPO(7.83) minutes	67104 ± 16

Evidently, the scheduled arrival method produced a total of 98253 arrivals, with a half-width of 95% confidence interval of 16, which is clearly most accurate compared with the number of arrivals from the original data (98236). Although, this method slows down the simulation run, the result shows that using probability distribution could be misleading and also validates the fact that "input data will have significant impact on the robustness of a simulation study" (Goldsman, 2007a). It is also seen that using the mean inter-arrival time or distributions will significantly change the model output. Therefore, it is assumed that the cohort as a whole exhibits a non-stationary arrival process since patients' arrival rates vary over time. Individual care groups may also have non-stationary arrival rate, but this is not considered, since the whole cohort is included in the general arrivals.

The arrival times could also be read directly from a text or excel file into the model using the ReadWrite module of Arena, however the format of the arrival time is in calendar dates and cannot be reconciled to suit this option. Furthermore, this method slows the model even further. Nonetheless, the ReadWrite module is used to read the specified outputs from the simulation as will soon be shown.

Having established the arrival input method, the Arrival process is split into four parts;

i. the actual appearance at the ED (creation of the patient entities)
ii. Ambulance arrival operation (in the Rapid Assessment Unit)
iii. Walk-in arrival operation via the emergency department (ED) entrance
iv. Routing of patient to appropriate care group areas.

Part 1: Creation of the Entities

For clarity, the initial arrival process is divided into three parts. The 3 parts are displayed in Figures 7.4 – 7.6. The Create module dialog box is the same as that in the arrival by schedule illustration (Figure 7.3).

From Figure 7.4, patients arrive by schedule based on hourly rate by day of the week (Figure 6.5). The File, Schedule and Variable modules were used to feed the arrival pattern into the model. The schedule entries are based on the pre-defined variable – v_Arrivals for 24 X 7 entries (Figure 7.4a). As patients arrive, they are assigned attributes and variables [1]. The Arrival Time attribute (Figure 7.4b) keeps track of patients' journey through the system and enable the calculation of journey times between various parts of the model. TNOW, which is a variable in Arena for the current simulation time, is used to achieve the journey time computation. The time a patient enters and leaves a queue or starts and ends an activity can also be derived by assigning time-stamps (TNOW) at specific points throughout the model. The variable attributes assign numbers to patient entities as they arrive, while the priority queue attributes were used to manipulate patient positions in various queues as will be shown during the care area description. "IDENT" is a variable that assigns numbers to patients as they arrive in order to keep track of their journeys. After the initial assignments, the time between patient arrivals is recorded [2].

The model has no medical knowledge and hence patients must be assigned a particular stream to follow through the system. In practice, this stream represents the care group and is only decided during triage process or for critically ill patients, at the RAU. This assignment is made based on probability (chance) of the arrival rates of patients with each score so that the overall rate of patient arrival matches that found in reality. The "Determine Care Group" block [3] tests for this probability. As noted in the ED description, there were some missing care group entries (unknown) in the recorded data. These entries are removed from the model at this point since their stream cannot be established [4]. It is assumed that this will have no significant impact on the model since the number of "unknown" is minimal compared to the overall cohort (1%). In fact, they can be accounted for by patients who balked or reneged. For verification purpose, they are counted using the record module and routed to the exit.

Figure 7.4: First Part of the Initial Arrival Process

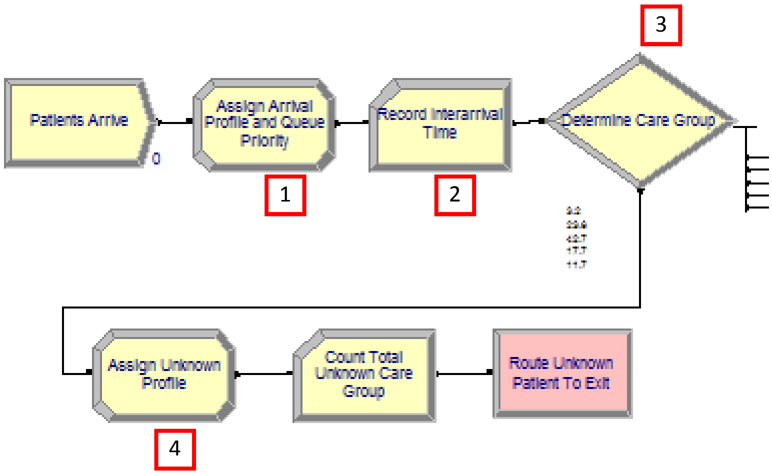


Figure 7.4(a): Variables for Arrival Schedule

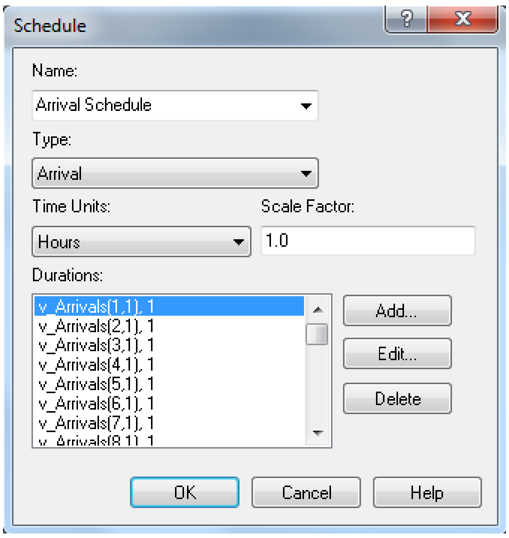
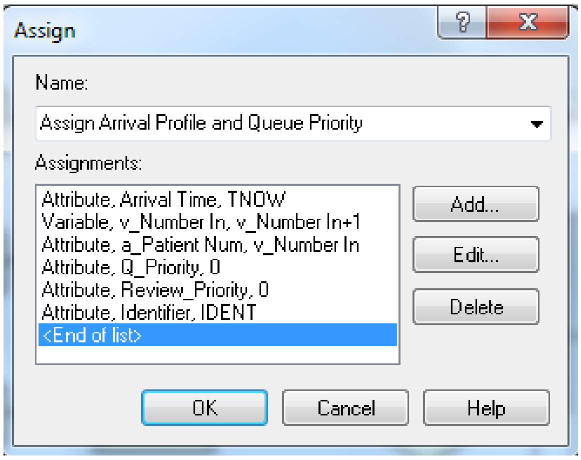


Figure 7.4(b): Patients Arrival attribute



The second part of the arrival process is depicted in Figure 7.5. Here care group attributes are assigned [5], counted [6] and their arrival mode is determined [7]. The care group and acuity attribute, processing times delay variables and entity pictures are allocated to each care group (Figure 7.5a). Processes are modelled as delays and the time durations are defined as expression variables for Treatment, Consultation, Review/Decision and Bed wait times (Figure 7.5b). For instance Red patients are assigned “e_Red Treatment Delay” for treatment time. The statistical distributions are then entered in the “Expression Values” column of the Expression spreadsheet module (Figure 7.5b). Figure 7.5(c) shows all defined attributes in the model. Note that care group, arrival mode and discharge outcome are defined as “string” data type, since they are not “real” numbers. The probability of patients arriving by ambulance or walk-in is also derived. This leads to the third part of the arrival process displayed in Figure 7.6.

Figure 7.5: Second Part of the Initial Arrival Process

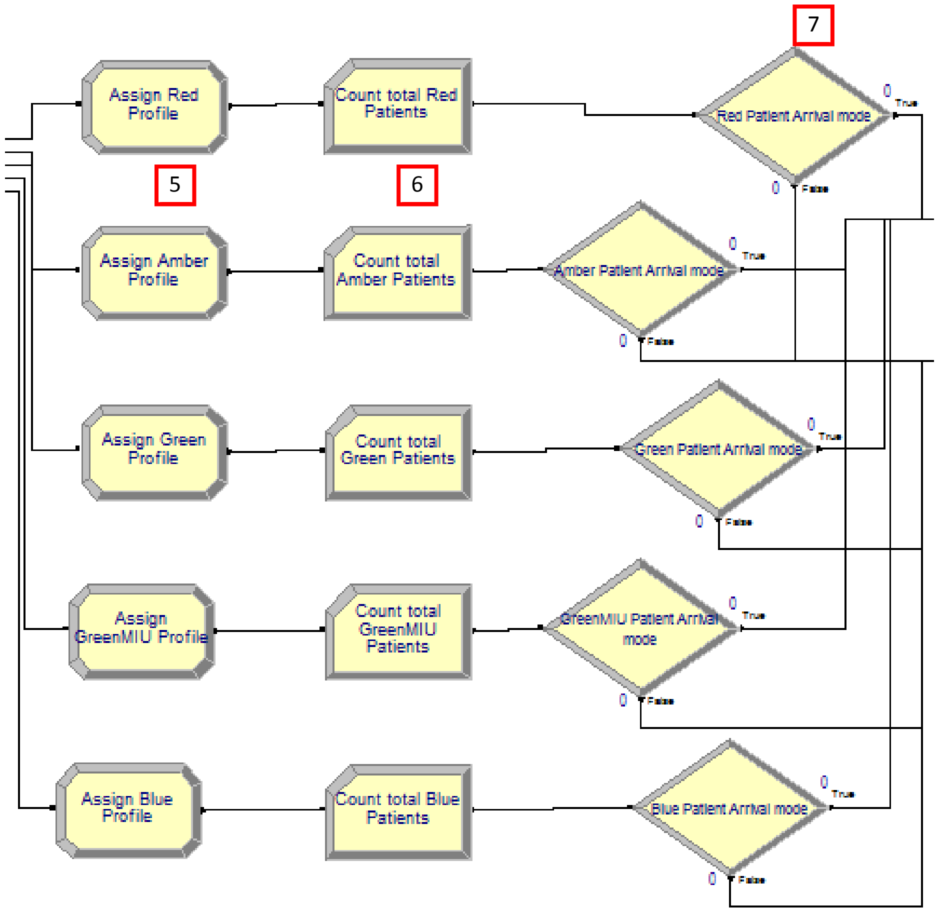


Figure 7.5(a): Defining Red Patients Care Group, Acuity Level and Processing Times

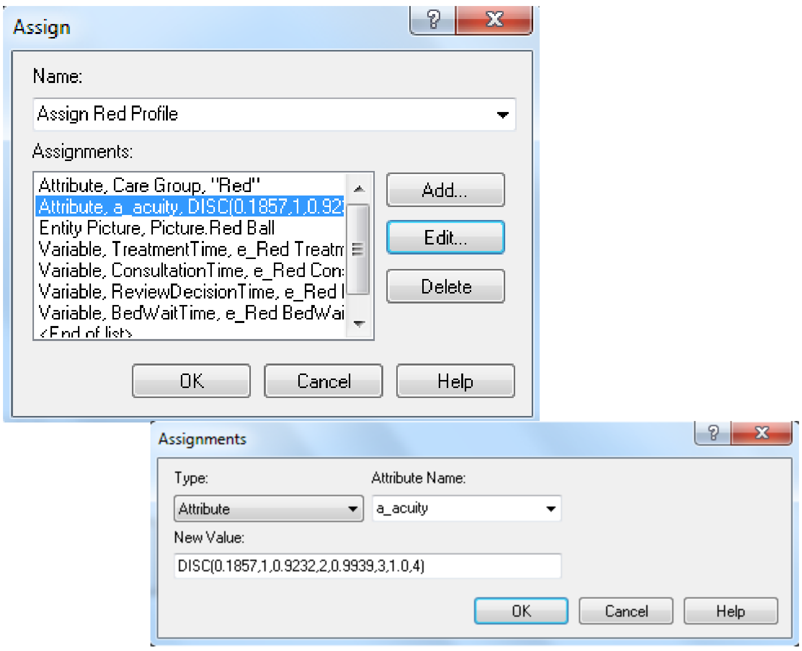


__Figure 7.5(b): Expression spreadsheet module showing all expressions in the model and some process time distributions__

Expression - Advanced Process

	Name	Rows	Columns	Data Type	File Name	Expression Values
2	e_RAU Test Delay			Native		1 rows
3	e_Registration Delay			Native		1 rows
4	e_Triage Delay			Native		1 rows
5	e_Red Consultation Delay			Native		1 rows
6	e_Red Treatment Delay			Native		1 rows
7	e_Red More Test Delay			Native		1 rows
8	e_Red More Treatment Delay			Native		1 rows
9	e_Red Review Delay			Native		1 rows
10	e_Red BedWait Delay			Native		1 rows
11	e_Amber Consultation Delay			Native		1 rows
12	e_Amber Treatment Delay			Native		1 rows
13	e_Amber Review Delay			Native		1 rows
14	e_Amber BedWait Delay			Native		1 rows
15	e_Green Consultation Delay			Native		1 rows
16	e_Green Treatment Delay			Native		1 rows
17	e_Green Review Delay			Native		1 rows
18	e_Green BedWait Delay			Native		1 rows
19	e_GreenMIU Consultation Delay			Native		1 rows
20	e_GreenMIU Treatment and Review Delay			Native		1 rows
21	e_GreenMIU BedWait Delay			Native		1 rows
22	e_GreenMIU Test Delay			Native		1 rows
23	e_GreenMIU Test Prep Delay			Native		1 rows
24	e_Blue Consultation Delay			Native		1 rows
25	e_Blue Treatment Delay			Native		1 rows
26	e_Blue Review Delay			Native		1 rows
27 ▸	e_Blue BedWait Delay			Native		1 rows

Expression Values

TRIA(30,40,45)

Expression Values

UNIF(10,15)

Expression Values

TRIA(25,40, 60)

Expression Values

UNIF(15,25)

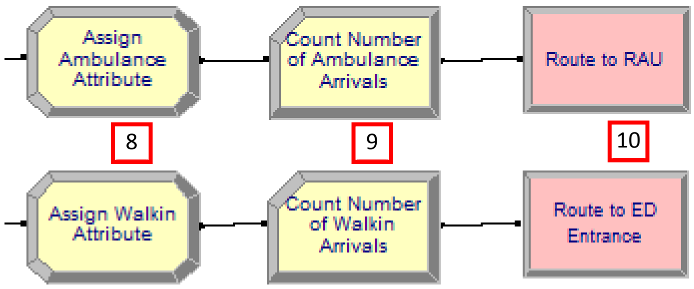
__Figure 7.5(c): Attribute spreadsheet module showing all assignments in the model__

Attribute - Basic Process

	Name	Rows	Columns	Data Type	Initial Values
1 ▸	Arrival Time			Real	0 rows
2	Receptionist_Index			Real	0 rows
3	Red Nurse_Index			Real	0 rows
4	Red Doctor_Index			Real	0 rows
5	Amber Nurse_Index			Real	0 rows
6	Amber Doctor_Index			Real	0 rows
7	TR_Index			Real	0 rows
8	Red Bay_Index			Real	0 rows
9	AssessmentRm_Index			Real	0 rows
10	Green Staff_Index			Real	0 rows
11	MIU Staff_Index			Real	0 rows
12	MIUTR_Index			Real	0 rows
13	Exit Time			Real	0 rows
14	a_Patient Num			Real	0 rows
15	TrolleyCub_Index			Real	0 rows
16	RAUDoctor_Index			Real	0 rows
17	Q_Priority			Real	0 rows
18	Review_Priority			Real	0 rows
19	BedReq_Time			Real	0 rows
20	Timefor_Resuscitation			Real	0 rows
21	Timeafter_Resuscitatio			Real	0 rows
22	Timeafter_Consultation			Real	0 rows
23	Timefor_Consultation			Real	0 rows
24	Timefor_Treatment			Real	0 rows
25	Timeafter_Treatment			Real	0 rows
26	Timefor_Review			Real	0 rows
27	Timeafter_Review			Real	0 rows
28	Identifier			Real	0 rows
29	Journey_Time			Real	0 rows
30	TriageNurse_Index			Real	0 rows
31	TriageRoom_Index			Real	0 rows
32	a_acuity			Real	0 rows
33	TEnterTriage_Q			Real	0 rows
34	Time_after_Triage			Real	0 rows
35	RAUSW_Index			Real	0 rows
36	MIUSW_Index			Real	0 rows
37	Triage Process Time			Real	0 rows
38	Area Process Time			Real	0 rows
39	Care Group			String	0 rows
40	a_Arrival mode			String	0 rows
41	a_Discharge Outcome			String	0 rows

Patients are assigned [8] either Ambulance or Walk-in arrival attributes (Figure 7.6) based on the outcome of [7] (Figure 7.5). The number of arrivals by both methods are then calculated [9]. Ambulance arrivals are then routed to the RAU station while walk-in arrivals are directed to the ED entrance [10]. It is assumed that there is no time associated with transfers from one area to another, thus the Route times are zero.

Figure 7.6: Third Part of the Initial Arrival Process



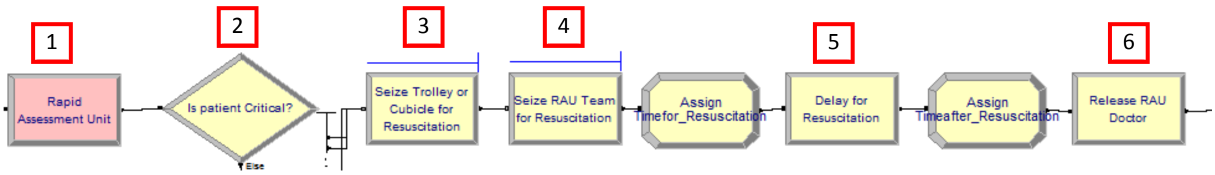
Part 2 and 3: Rapid Assessment Unit and ED Entrance

The Rapid Assessment Unit and ED Entrance model logic of the arrival process are linked together. For clarity, each process is divided into subsets of two and described in detail.

<u>Rapid Assessment Unit (RAU) Process</u>

The RAU logic is divided into two parts as displayed in Figures 7.7 and 7.8. Figure 7.7, illustrates the initial arrival into the RAU, seizing available resources and staff for resuscitation process and releasing them afterwards.

Figure 7.7: Rapid Assessment Unit (RAU) - Resuscitation Process



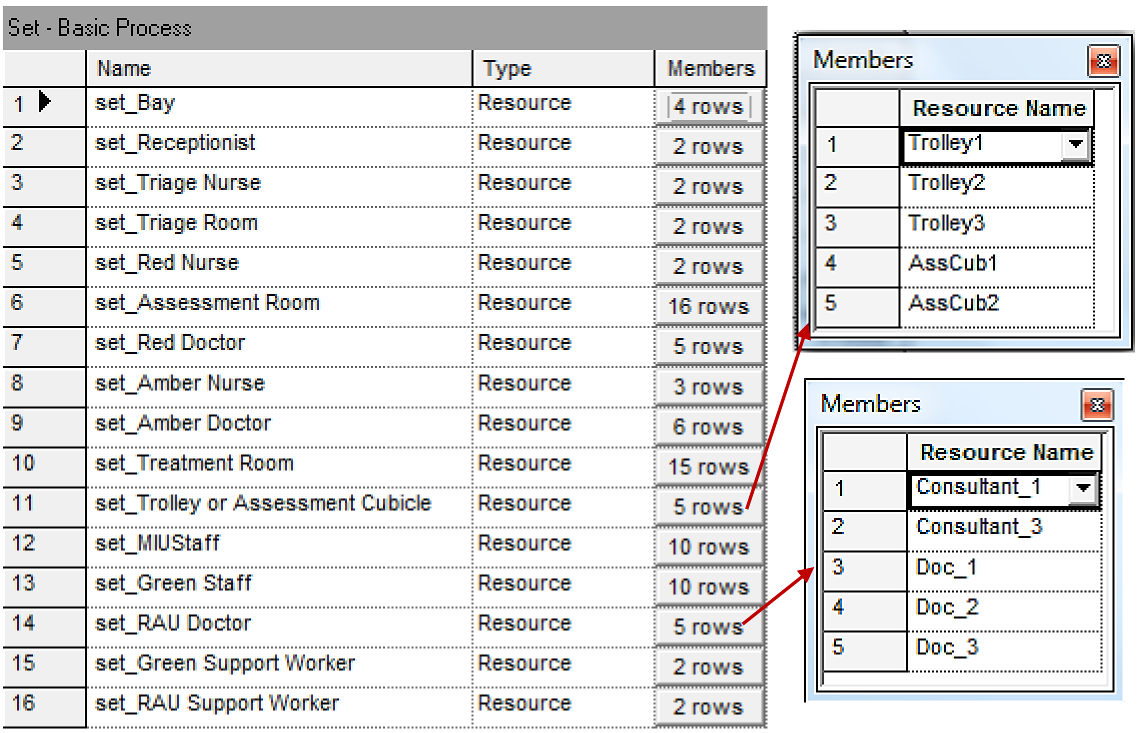
All ambulance arrivals first presents at the Rapid Assessment Unit (RAU) station [1]. Since only the Red and Amber patients are seen in the RAU, a decide module is used to check a patient’s care group [2]. The patient then seizes a trolley or cubicle [4], a doctor and a nurse if available [5], and then undergoes resuscitation else the patient is directed to the emergency department reception [13].

Before going further, it is important to illustrate how the resources are modelled.

Modelling RAU Resources

From the consultant and doctor schedule (Table 7.2) and resource description in section 7.1.3, doctors may work in multiple areas. Also, resources such as Cubicle and Treatment Rooms can be used by multiple care groups. In the model, resources are classified as members of resource sets as shown in Figure 7.7a. For instance, there are 3 Trolleys and 2 Assessment Cubicles which are members of "set_Trolley or Assessment Cubicle". There are also five members of RAU Doctor Set namely; Consultant_1, Consultant_3, Doc_1, Doc_2 and Doc_3. During the seize operation, a resource is assigned a Set Index, to allow the entity release a particular resource that was initially seized. For instance in the dialog boxes shown in Figure 7.7(b), when a RAU doctor is seized, an attribute called RAUDoctor_Index is assigned. In the release operation (Figures 7.7c), the specific member in the Set Index is freed. More explicitly, if a patient seizes Doc_1 for a procedure, the RAUDoctor_Index is 3 (since it is third in the set members list), Doc_1 is released afterwards.

Figure 7.7(a): Spreadsheet view of Set module showing allocated Members



Set - Basic Process

	Name	Type	Members
1	set_Bay	Resource	4 rows
2	set_Receptionist	Resource	2 rows
3	set_Triage Nurse	Resource	2 rows
4	set_Triage Room	Resource	2 rows
5	set_Red Nurse	Resource	2 rows
6	set_Assessment Room	Resource	16 rows
7	set_Red Doctor	Resource	5 rows
8	set_Amber Nurse	Resource	3 rows
9	set_Amber Doctor	Resource	6 rows
10	set_Treatment Room	Resource	15 rows
11	set_Trolley or Assessment Cubicle	Resource	5 rows
12	set_MIUStaff	Resource	10 rows
13	set_Green Staff	Resource	10 rows
14	set_RAU Doctor	Resource	5 rows
15	set_Green Support Worker	Resource	2 rows
16	set_RAU Support Worker	Resource	2 rows

Members

	Resource Name
1	Trolley1
2	Trolley2
3	Trolley3
4	AssCub1
5	AssCub2

Members

	Resource Name
1	Consultant_1
2	Consultant_3
3	Doc_1
4	Doc_2
5	Doc_3

Figure 7.7(b): Resource set allocation for RAU doctors

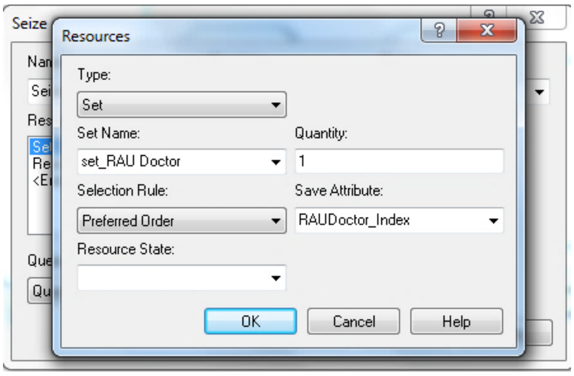
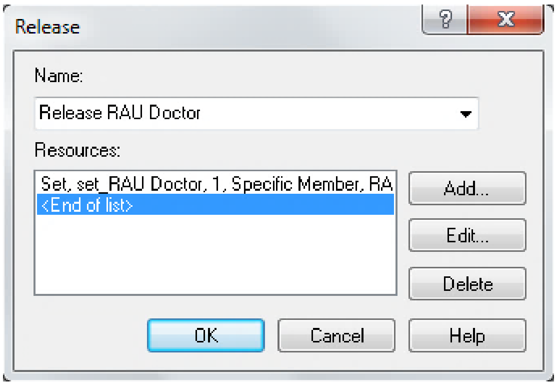


Figure 7.7(c): Releasing particular RAU doctor after resuscitation



The availability of staff who work in shifts are modelled based on schedule using the Schedule spreadsheet module and graphical editor. Figure 7.7(d) and 7.7(e) display some resources defined in the model. For resources "based on schedule" a schedule name is specified in the resource spreadsheet, while for fixed capacity, the resource availability is entered. Note that RAU nurse has a fixed capacity of 5 (Figure 7.7e) based on the "care for" role of nurses described in section 7.1.2. Since consultants and doctors work in shifts, their availabilities are based on schedules, which are inputted in the model by entering their hourly capacities in the Graphical Schedule Editor. For example, Figure 7.7(f) displays the schedule for Consultant_1 which is from 8am to 12 midnight as shown in Table 7.2.

Figure 7.7(d): Resource Spreadsheet Module showing some resource capacity

Resource - Basic Process

	Name	Type	Capacity	Schedule Name
1	Doc_1	Based on Schedule	Doc_1 Schedule	Doc_1 Schedule
2	Doc_2	Based on Schedule	Doc_2 Schedule	Doc_2 Schedule
3	Doc_3	Based on Schedule	Doc_3 Schedule	Doc_3 Schedule
4	Doc_4	Based on Schedule	Doc_4 Schedule	Doc_4 Schedule
5	Doc_5	Based on Schedule	Doc_5 Schedule	Doc_5 Schedule
6	Doc_6	Based on Schedule	Doc_6 Schedule	Doc_6 Schedule
7	Doc_7	Based on Schedule	Doc_7 Schedule	Doc_7 Schedule
8	Doc_8	Based on Schedule	Doc_8 Schedule	Doc_8 Schedule
9	Bay_1	Fixed Capacity	1	1
10	Bay_2	Fixed Capacity	1	1
11	Bay_3	Fixed Capacity	1	1
12	Bay_4	Fixed Capacity	1	1
13	Receptionist_1	Fixed Capacity	1	1
14	Receptionist_2	Fixed Capacity	1	1
15	Triage Nurse_1	Fixed Capacity	1	1
16	Triage Nurse_2	Fixed Capacity	1	1
17	Triage Room_1	Fixed Capacity	1	1
18	Triage Room_2	Fixed Capacity	1	1
19	Red Nurse_1	Fixed Capacity	2	2
20	Red Nurse_2	Fixed Capacity	2	2
21	AssRoom_1	Fixed Capacity	1	1
22	AssRoom_2	Fixed Capacity	1	1

Figure 7.7(e): Resource Spreadsheet Module highlighting RAU Nurse

Resource - Basic Process

	Name	Type	Capacity	Schedule Name
56	Cubicle_5	Fixed Capacity	1	1
57	Cubicle_6	Fixed Capacity	1	1
58	Cubicle_7	Fixed Capacity	1	1
59	Cubicle_8	Fixed Capacity	1	1
60	ConsultingRm_1	Fixed Capacity	1	1
61	ConsultingRm_2	Fixed Capacity	1	1
62	Consultant_1	Based on Schedule	Consultant_1	Consultant_1
63	Consultant_2	Based on Schedule	Consultant_2	Consultant_2
64	Consultant_3	Based on Schedule	Consultant_3	Consultant_3
65	Green Nurse_4	Fixed Capacity	4	4
66	Green Nurse_3	Fixed Capacity	4	4
67	Support Worker 1	Based on Schedule	SW_1 Schedule	SW_1 Schedule
68	Support Worker 2	Based on Schedule	SW_2 Schedule	SW_2 Schedule
69	Support Worker 3	Based on Schedule	SW_3 Schedule	SW_3 Schedule
70	Radiology Room	Fixed Capacity	2	2
71	Support Worker 4	Based on Schedule	SW_4 Schedule	SW_4 Schedule
72	Charge Nurse	Fixed Capacity	1	1
73	RAU Nurse	Fixed Capacity	5	5
74	Technician	Fixed Capacity	2	2
75	Doc_14	Based on Schedule	Doc_14	Doc_14
76	Doc_9	Based on Schedule	Doc_9 Schedule	Doc_9 Schedule
77	Doc_10	Based on Schedule	Doc_10	Doc_10
78	Doc_13	Based on Schedule	Doc_13	Doc_13
79	Doc_11	Based on Schedule	Doc_11	Doc_11
80	Doc_12	Based on Schedule	Doc_12	Doc_12

Figure 7.7(f): Graphical Schedule Editor for Consultant_1 Schedule

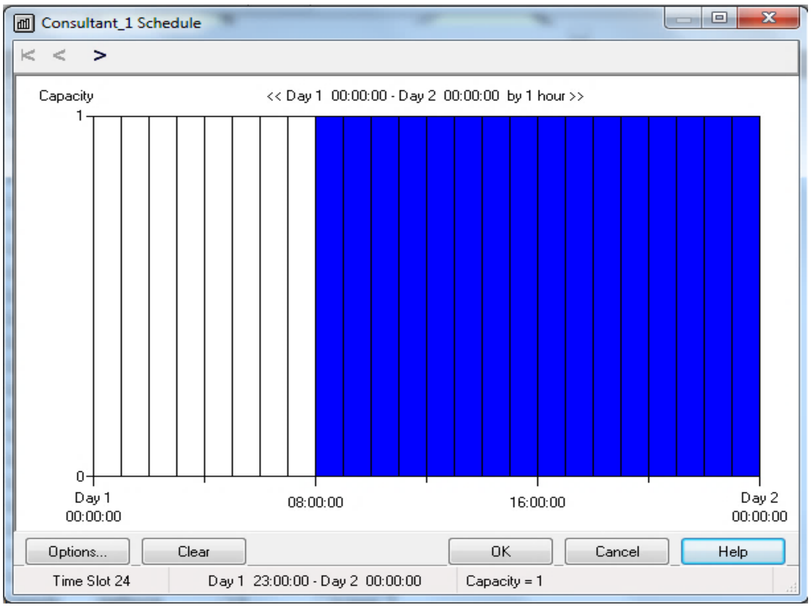
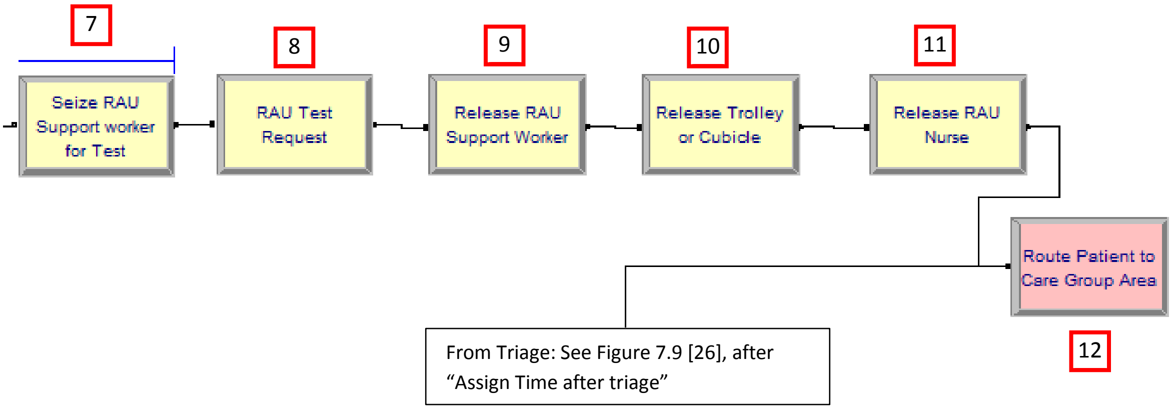


Figure 7.8 shows the second part of the RAU model logic. This section illustrates the allocation of a support worker [7] for Test Request process [8] and release of the same support worker [9], trolleys/cubicles [10] and RAU Nurse before proceeding to the care group area [11]. Since the actual test is done in parallel with treatment, only the time duration for test preparation/request is included in the model.

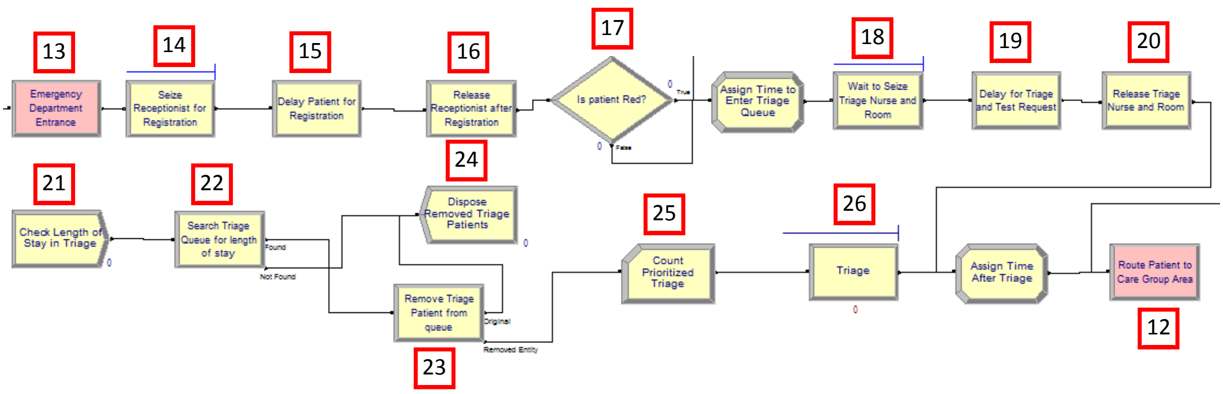
Figure 7.8: Rapid Assessment Unit (RAU) – Test Request Process and Release of Resources



<u>Emergency Department Entrance</u>

Walk-in patients access the emergency department via this entrance and present at the reception. Non-critical ambulance arrivals also present here. Figure 7.9 shows the allocation and release of resources for Registration and Triage processes.

Figure 7.9: Emergency Department Entrance – Registration and Triage Process and Release of Resources



Basically, a patient arrives at the reception [13], seizes a receptionist [14], is delayed for registration [15] and releases the particularly seized receptionist [15] to make availability for other patients.

In practice, Red patients who present at reception are directed to the RAU irrespective of their arrival mode. This is illustrated in the model by using the "Is patient Red?" decide module [17]. If a patient is not in the Red care group, he/she proceeds to seize a triage nurse and room [18] for triage process [19].

The care group assignment in the arrival logic (Figure 7.5) is a representation of triage in the model. The delay [19] takes account of the (distribution of) times for the real assessment and a commitment of the appropriate number of resources (triage nurse and room).

<u>Allocating extra Resource (RAU Nurse) for Triage</u>

As mentioned earlier, if a patient is exceeding 15 minutes for triage, the RAU nurse assists in the triage process if available. This is demonstrated in the model by creating a demon called “check” [21] to search the triage queue [22], identify patients waiting for more than 15 minutes, removes them from the queue [23]. They are counted [25] and triaged by the RAU nurse [26], the demon is then disposed [24].

A demon is launched every 25 minutes and stops at the end of the simulation run (Figure 7.9a). The search is made based on the condition shown below;

TNOW-TEnterTriage_Q >= 15 && NQ(Triage.Queue) <= 5

The left end of the condition calculates the difference between the current simulation time and time an entity entered the triage queue. This is essentially the length of time spent in the queue. The right end of the condition is to avoid backlog in the new queue. For every demon that is launched, one patient is removed from the “Wait to SeizeTriage Nurse and Room” queue if the above condition is true (Figure 7.9b). The patient then enters a new queue to undergo triage by RAU nurse. If the condition is false, patient will remain in the queue. After registration and triage, the patient is routed to the care group station to determine appropriate care area.

Figure 7.9(a): Create module – dialog box for dummy entity to check length of stay in Triage

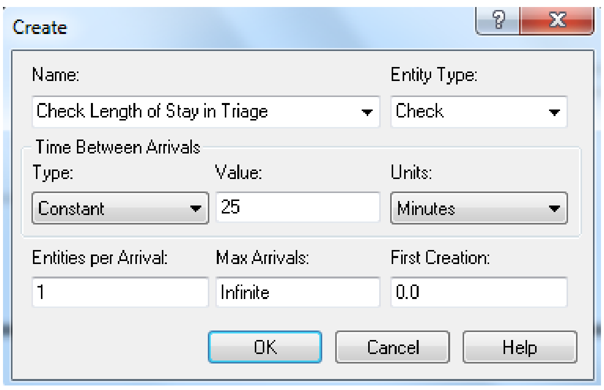
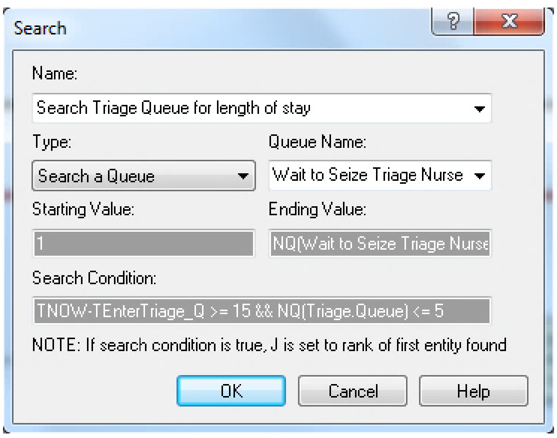


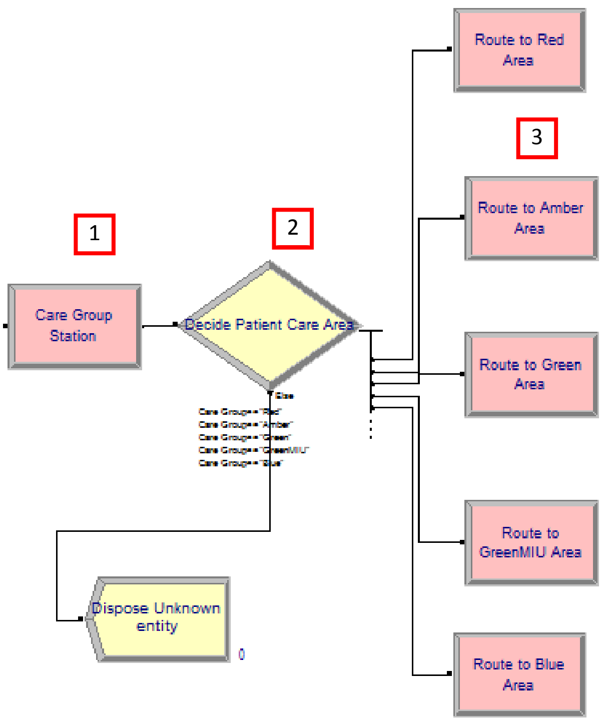
Figure 7.9(b): Search module – dialog box to identify patient entity in Triage Nurse Queue



Part 4: Routing of patient entities to appropriate care group areas

Figure 7.10 represents the final part of the arrival process logic. Here, all patient entities from the RAU and Triage arrive at the Care Group station [1]. Care group areas are determined based on the assigned attributes using the decide module [2]; patients are then routed accordingly to particular areas [3].

Figure 7.10: Determination of Care Group and Routing to Emergency Department Area



7.2.2 Red Area Process

The model of operations in the Red area has been divided into four subsets which are displayed in Figure 7.11 – 7.14.

In Figure 7.11, the “seize and time-stamp” assignment modules are similar to those in the RAU and ED entrance process logic. A patient arrives at the Red Area Station, seizes a bay, nurse and doctor, undergoes consultation and preliminary treatment processes, and then releases the doctor for further treatment by the nurse. Queues here are also of high priority, except the “Seize Red Doctor” queue which is of medium priority. This will be explained in more details when describing the allocation of doctors for Review process (Figure 7.13).

Figure 7.11: Red Area logic - Allocation of resources, Consultation and Treatment processes

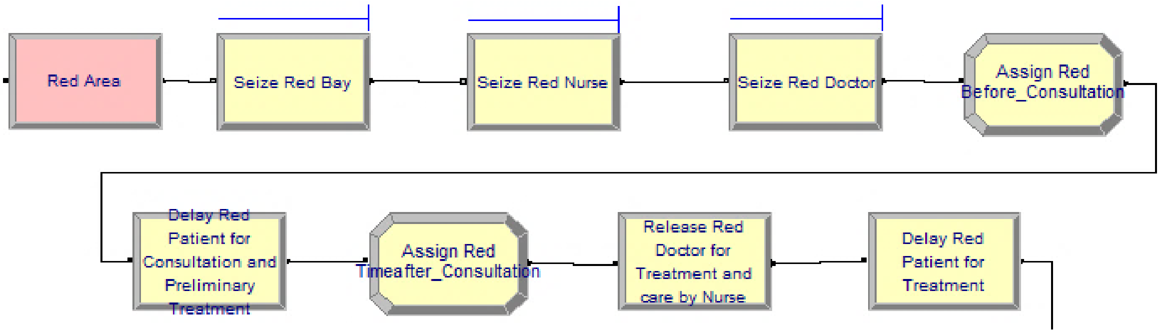


Figure 7.12 shows the second part of the Red area process logic. Here, if further test is required after treatment; the nurse does the test and further treatment; 20% of red patients require further test (Figure 7.12a). If this is true, the patient entity is delayed for further test and treatment. Here, the actually test process is included since the result determines what further treatment is required. Recall that on arrival patients were assigned Review priority value - 0. Since patients who have to undergo more test and treatment are assumed to have been in the system longer than those who go straight to the review process, they should be seen first. Consequently, to ensure that they have priority over other entities in the "seize doctor for review" queue, they are reassigned a review priority value – 1 (Figure 7.12b).

Figure 7.12: Red Area logic - More tests, treatment and Queue priority assignment

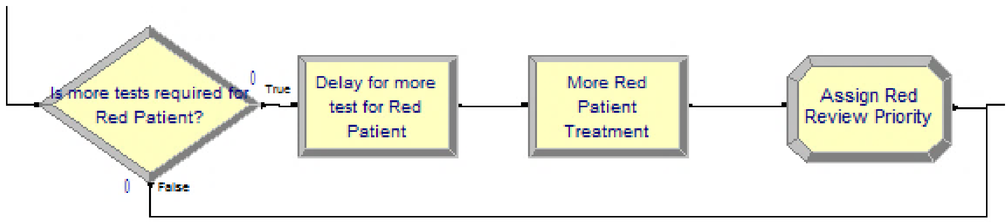


Figure 7.12(a): Determine if more tests required for Red Patient?

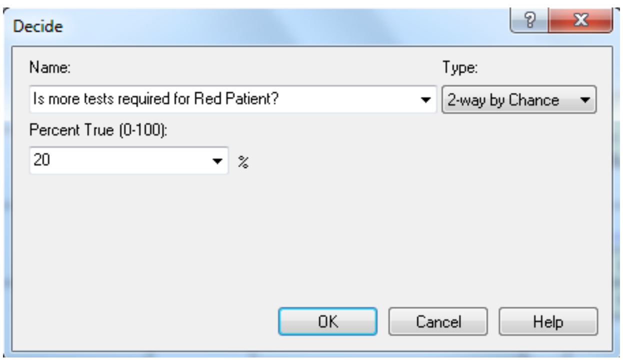
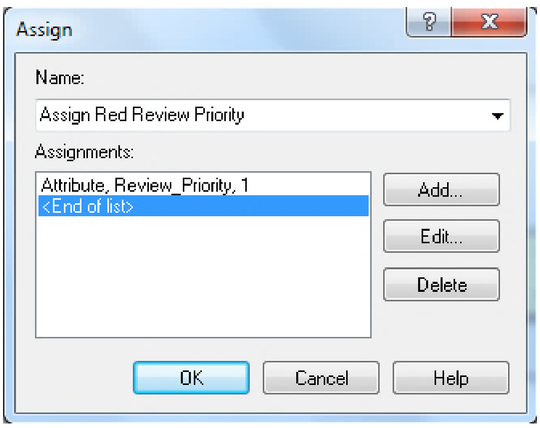


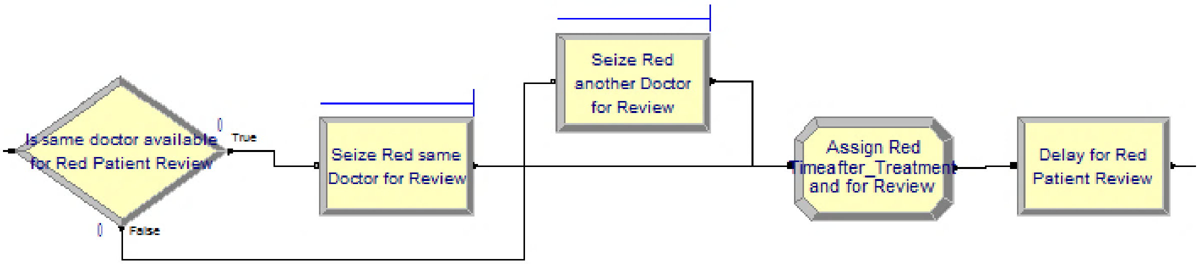
Figure 7.12(b): Assigning Review Priority



In practice, the same doctor who initially saw the patient does the Review/Decision process. However due to schedule, a doctor may not be available at this time. For example, Doc_12 is only available for three hours in a day (from 17:00 to 20:00). If Doc_12 treats Patient A at 19:00 and leaves at 20:00 before Patient A reaches Review and Decision process, he/she will have to wait till 17:00 the next day to be seen by Doc_12. To avoid this, a check is made to determine if Doc_12 is still available. From the set member Doc_12 and Consultant_2 are not available throughout the day. Consequently, if the initial doctor was Doc_12 or Consultant_2, another doctor is seized for Review/Decision process; else the same doctor is allocated.

Figure 7.13 shows the process of allocating either the same doctor or another doctor to carry out the review/decision process.

Figure 7.13: Red Area logic - Allocation of doctor for/and Review process



The dialog box shown in Figure 7.13(a) decides if a doctor is available or not using the expression;

Red Doctor_Index <= 2

If this is true, it implies that the same doctor is still available and entity will seize this resource, as shown in the “specific member” selection rule depicted in Figure 7.13(b). If this is untrue, entity will seize a different available doctor depicted by the “cyclical” rule.

Figure 7.13(a): Checking same Red Doctor Availability

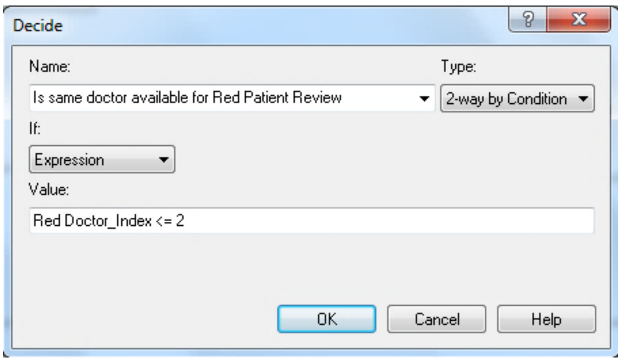
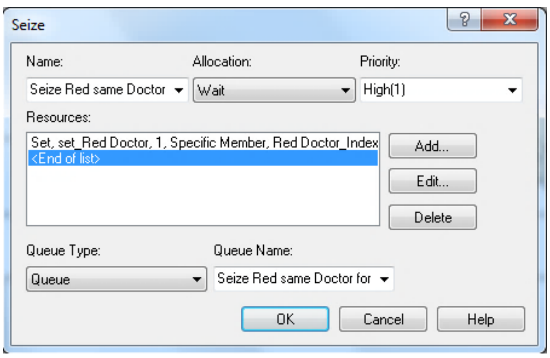


Figure 7.13(b): Allocate same previous Red doctor



Recall that in the description of the first section of the Red area logic, the seize doctor queue was assigned a “medium priority”. In the “seize same and another red doctor” queues, the priority is changed to “high” as shown in Figure 7.13(b). This ensures that patients in this queue are seen quicker since they have been in the system longer.

Figure 7.13(c) shows the queue spreadsheet module for seizing same and another Red doctor which are outlined in Queue #5 and #18 respectively. Note the Queue type and Attribute name columns. This ensures that those having higher attribute value (in this case, Review_Priority: 1) have higher priority in the queue.

Figure 7.13(c): Queue Spreadsheet module for particular queues showing Review_Priority Attribute

Queue - Basic Process

	Name	Type	Attribute Name
3	Seize Red Doctor.Queue	First In First Out	Attribute 1
4	Seize Technician for	First In First Out	Attribute 1
5	Seize same Red Doctor for	Highest Attribute Value	Review_Priority
6	Seize Amber Doctor.Queue	First In First Out	Attribute 1
7	Seize same Amber Doctor for	Highest Attribute Value	Review_Priority
8	Seize Red Doctor for	First In First Out	Attribute 1
9	Seize Trolley or Cubicle for	First In First Out	Attribute 1
10	Seize Red Bay.Queue	First In First Out	Attribute 1
11	Seize Amber Assessment	First In First Out	Attribute 1
12	Seize Green Doctor or	First In First Out	Attribute 1
13	Seize RAU Support worker for	First In First Out	Attribute 1
14	Seize Radiology Room.Queue	First In First Out	Attribute 1
15	Seize Green Cubicle or	First In First Out	Attribute 1
16	Seize RAU Team for	First In First Out	Attribute 1
17	Wait for Triage.Queue	First In First Out	Attribute 1
18	Seize another Red Doctor for	Highest Attribute Value	Review_Priority
19	Seize another Amber Doctor	Highest Attribute Value	Review_Priority
20	Seize Red Nurse.Queue	First In First Out	Attribute 1
21	Seize Green Treatment Room	First In First Out	Attribute 1
22	Seize NP or Doctor.Queue	First In First Out	Attribute 1
23	Seize another NP or Doc for	Highest Attribute Value	Review_Priority
24	Seize same NP or Doc for	Highest Attribute Value	Review_Priority
25	Seize Support Worker.Queue	First In First Out	Attribute 1

The final part of the Red Area model is depicted in Figure 7.14. Here, the time after the Review/ Decision Process is recorded and all previously seized resources are released. Patient entity is the routed for discharge outcome procedure.

Figure 7.14 Red Area logic showing allocation of doctor for/and Review process

7.2.3 Amber Area Process

Similar to the Red area logic, the Amber area process model is also divided into four sections represented by Figure 7.15 to 7.18. On arrival to the Amber Area, if available, the patient seizes an assessment room and a doctor, and undergoes consultation. Time-stamp is collected and the doctor is released for treatment by nurse.

Figure 7.15: First section of the Amber Area process model

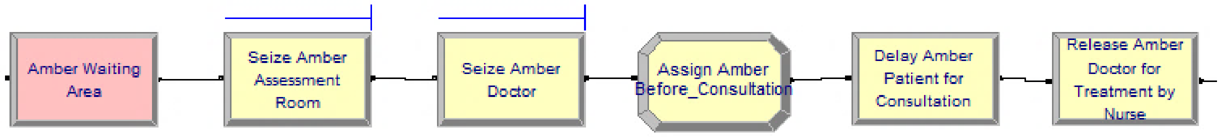


Figure 7.16: Second section of the Amber Area process model

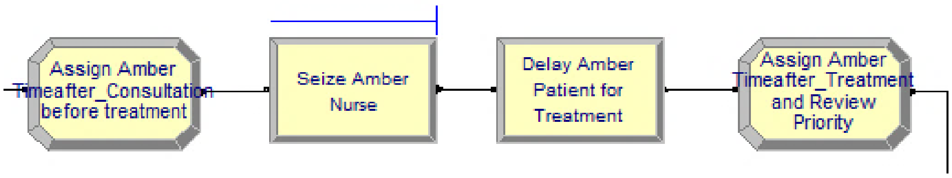


Figure 7.17: Third section of the Amber Area process model

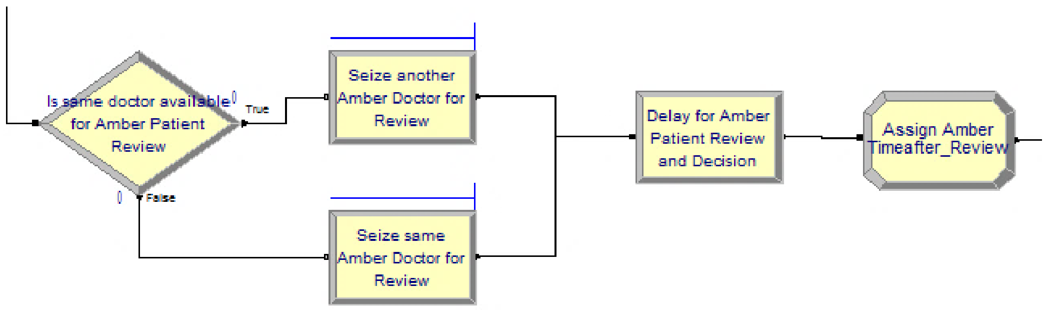
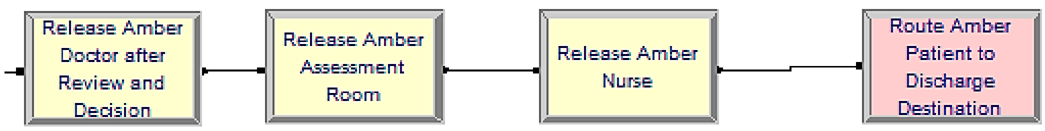


Figure 7.18: Fourth section of the Amber Area process model



The Amber Area process is very similar to the Red but differs in the Treatment operation. In the Red area, doctors carry out all the operations and are assisted by nurses except if further treatment is required then the nurses do this, whereas in the Amber area, it is assumed that nurses treat the patients and there are no further test and treatments required.

Figure 7.16 shows the time-stamp assignment after consultation, before and after treatment. The treatment process is also depicted. Here, the review priority assignment is also increased to 1, as done in the Red area.

Figure 7.17 shows the seize doctor operation for review/decision process. Similar to the Red doctor, a check is made to ensure that the previously seized doctor is still in the system. If the doctor is not scheduled at the time, another doctor is seized to carry out the Review/ Decision process. Here, the condition to check for doctor availability is;

Amber Doctor_Index >= 2

If this condition is true, another doctor is allocated, else same previous doctor is assigned. In Figure 7.18, all previously allocated resources are release as explained for the Red group.

7.2.4 Green Area and Green/ Minor Injury Unit Processes

In practise, patients in the Green/Minor Injury Unit are treated in the green area; as well as, Blue Patients who require emergency treatment. In the model, they still operate in the same area, but MIU patients use a different stream; therefore, the green area and green/minor injury unit will be described separately.

<u>Green Area Process</u>

Figure 7.19 depicts the overview for the Green area process. Unlike the Red and Amber areas, all processes can be done by either a nurse practitioner or a doctor. Here, the patient seizes a treatment room, cubicle or consulting room and a green staff, if available. Note that the seize priority here is “low” (Figure 7.19a). More explanation will be provided when describing the Green/MIU process.

Figure 7.19: Overview of Green Area process model

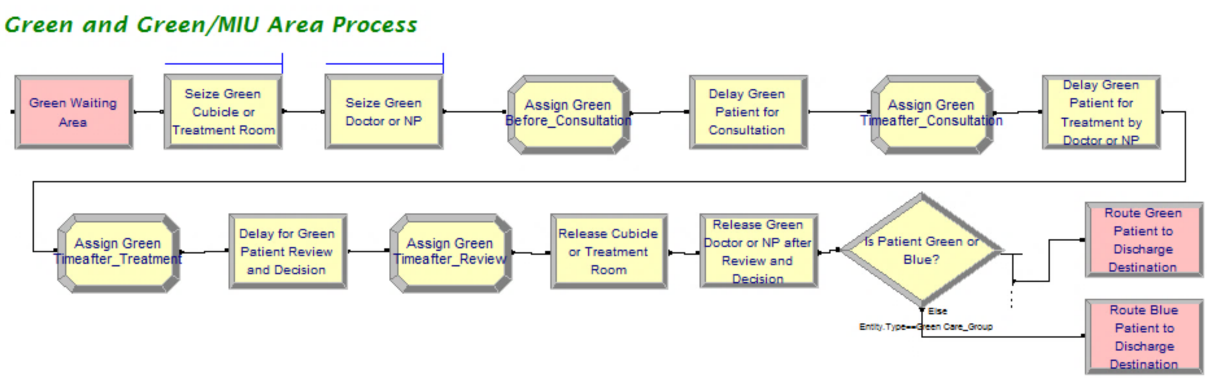
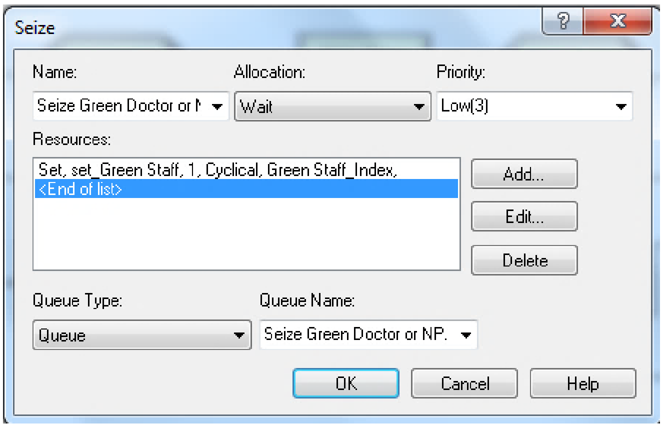


Figure 7.19(a): Seize module dialog box to seize Green Staff (Nurse Practitioner or Doctor) resource set



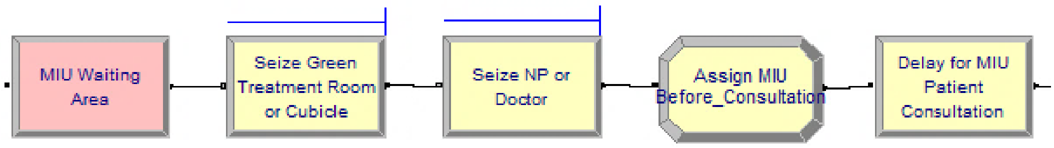
As with the previously described areas, process durations are inputted as Variables using Expression Values. For instance, for Green patient treatment time duration, the Expression name is "*e_Green Treatment Delay*" and consultation time is named "*e_Green Consultation Delay*".

Since some Blue patient also use the Green stream, it is necessary to identify the appropriate Care Group of an entity is at this point, in order to determine the discharge outcome. The entity type attribute is used to ascertain this using the "Is Patient Green or Blue" decision module.

7.2.5 Green/MIU Area Process

For clarity, the Green/MIU process model is divided into three parts displayed in Figure 7.20 – 7.22. The first part of the Green/MIU process logic displayed in Figure 7.20 is similar to that of the Green area. Here entity seizes resources and MIU staff, and then delayed for consultation process. Note here that MIU staff also have low queue priority so ensure that Red Amber area are first seen by shared doctors in those areas.

Figure 7.20: First part of Green/MIU Area process model



Any MIU staff can carry out all MIU processes except X-ray which is done by a technician. Also, test samples are collected by a Support worker. The second part of the Green/MIU process model displayed in Figure 7.21 determines X-ray requirement and routes patients for either Treatment or X-ray. There is a 20% chance that MIU patient will require X-ray. If this is true, entity will release previously seized staff and a support worker is allocated for test preparation. Patient entity is then routed to the radiology room for X-ray, after which they will; return for treatment and review. If test is not required MIU staff is not released, instead they proceed with treatments and review processes, before they are finally freed.

Figure 7.21: Second part of Green/MIU Area process model

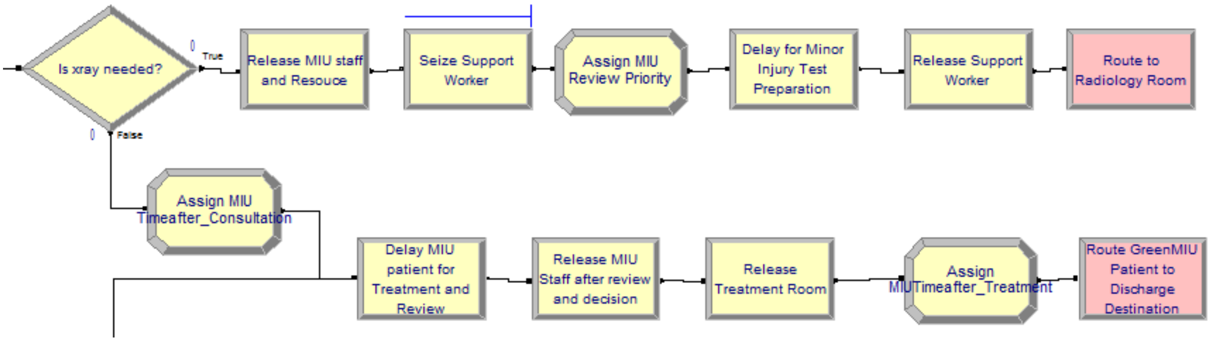


Figure 7.22: Third part of Green/MIU Area process model

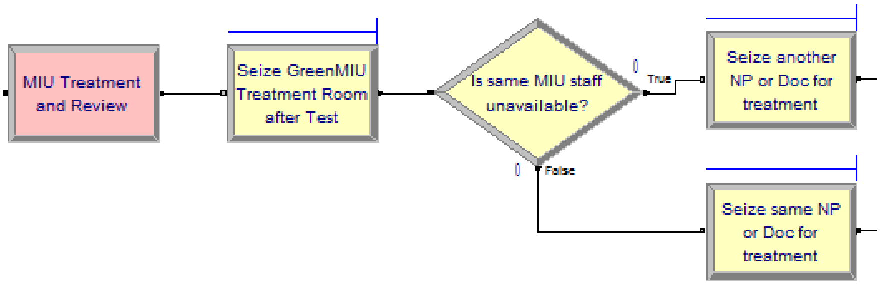
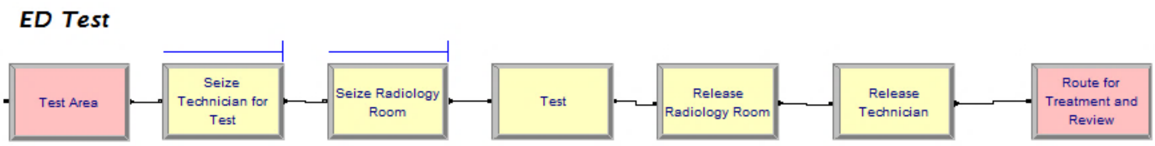


Figure 7.22 shows the third part of the Green/MIU process model. As done in the Red Area, a check is made to determine if a specific previously seized MIU Staff is available. If he/she is unavailable, another Staff is seized, else the same staff is carries out Treatment and Review/Decision processes. Note the priority here is "medium" which is higher than the previous MIU staff queue, but still lower than the Red and Amber "seize doctor" queues.

7.2.6 Emergency Department Test

Figure 7.23 represents the overview of the Emergency Department (ED) Test process (or Radiology Room) model.

Figure 7.23: Emergency Department Test process (or Radiology Room) model



This part of the model is only used by MIU patients, since only MIU patients require X-ray. The MIU patient seizes a Technician and Radiology room for X-ray, releases them after the process and is routed back to the MIU Treatment and Review station.

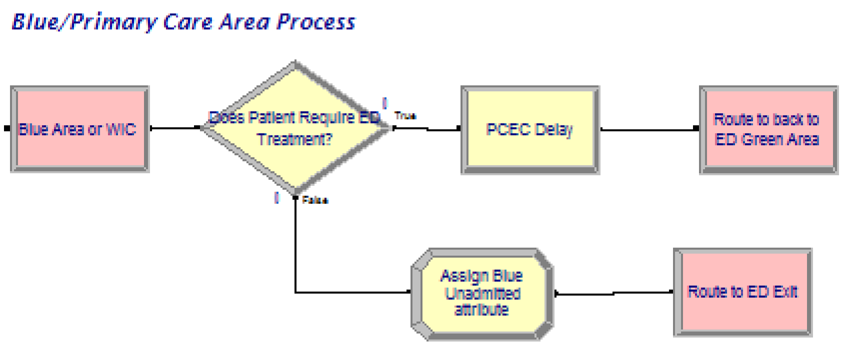
There are 2 Technicians and Radiology rooms. As with the other ED processes, X-ray (Test) processing time is also defined in the Expression module spreadsheet and named e_GreenMIU Test Delay. The patient is then directed back to the MIU for treatment and review processes.

7.2.7 Blue/Primary Care Area Process

The Blue area is also known as the Primary Care Emergency Centre (PCEC) or Walk-in Centre. In practise, this the processes undergone in this area is not part of the Emergency Department. However some patients in the blue area require emergency treatment and are directed back to the green area after observation. In order to demonstrate this return to the green area, it is necessary to consider the segment of the blue area involved. Note that although, resources are not considered, the time spent in the PCEC is modelled since it is included in ED time (Figure 7.24).

From the provided data the exact number of blue patient who returned to the ED could not be ascertained. Consequently in the model, it is assumed that only admitted blue patients were directed back to the ED for treatment and are eventually admitted into hospital. The remaining (95.93%) blue patients are routed to the ED exit, which also implies the Blue area or PCEC in practice.

Figure 7.24: Blue/Primary Care Area Process model

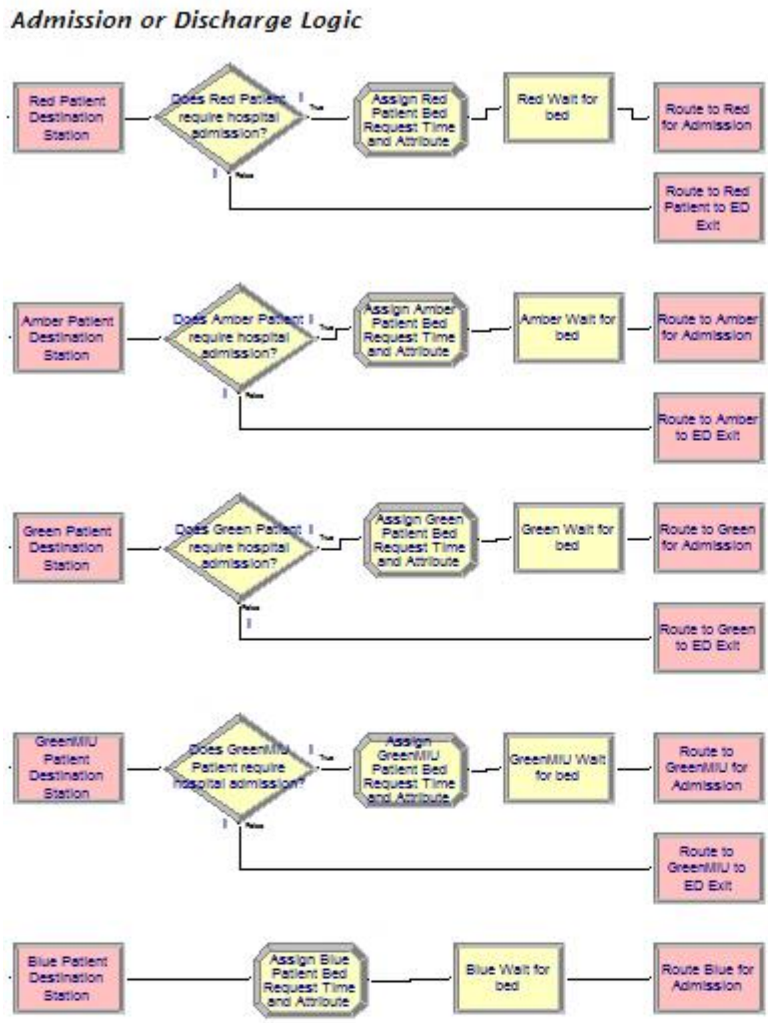


7.2.8 Admission and Discharge Logic

After review and decision process in all areas, patients requiring admission into the hospital wait for available bed in the waiting area. In practise support workers and nurses take care of them during this wait. However resource utilization during wait for bed is not considered in the model since they are not dependent on this time delay; but rather the availability of hospital bed. Also patients waiting too long for bed or requiring further observation while waiting for hospital admission are moved to the Clinical Decision Unit (CLDU). Since the CLDU is not part the ED and patients there are off the clock, this area is not modelled. From the data, there are only 16 of such patients, which is minimal compared to the overall admitted patients (25943).

Figure 7.25 shows the overview of the admission logic of the model for all care groups. For clarity, the admission logic for Red care group will be described further (Figure 7.26); this applies to other groups.

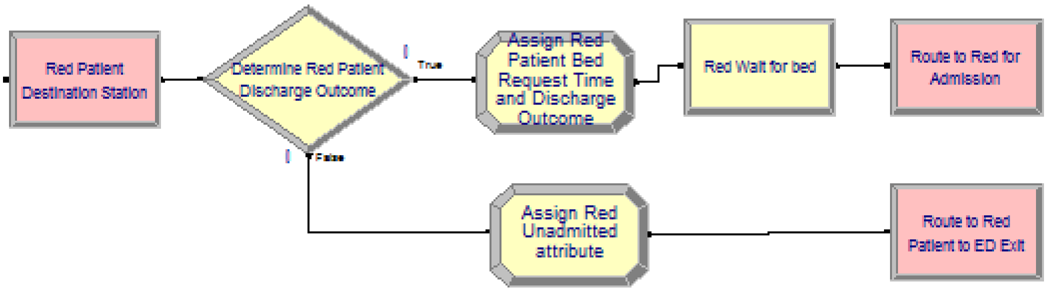
Figure 7.25: Bed Wait for Hospital Admission Process Logic



On arrival at admission station, the discharge outcome of a patient is determined. From the data in chapter 6, 77.51% of Red patients are admitted into hospital. This percentage value is inputted into the decide module. If admission is required, the patient is assigned Bed Request Time and Admitted attributes, else they are assigned Discharged attribute. The Bed Request Time keeps record of the start time to wait for bed, while the Admitted and Discharged attributes tag the patient's discharge outcome. Patients are delayed for the attributed BedWaitTime delay which was pre-assigned in the Arrival process logic. The distribution for the BedWaitTime is also entered in the Expression Spreadsheet. The patient is then routed to the relevant care group admission station.

If admission is not required the patient is routed to the care group discharge

Figure 7.26: Red Patient Bed Wait for Hospital Admission Process Logic



7.2.9 Exit and Statistics Collection Logic

Figure 7.27 provides an overview of the exit logic for the model. This is a continuation of the admission logic in Figure 7.25 and basically involves recording of statistics. This exit logic is divided into three parts; arrival (to appropriate station) and collection of statistics by care group and discharge outcome; overall journey time and counts statistics collection; and finally, record of particular attributes for each patient and exit from the ED.

For the first part, the Red exit process is displayed in Figure 7.28, while Figures 7.29 and 7.30 show the second and third parts of the logic respectively. From Figure 7.28, journey time and count statistics by discharge outcome are collected using the record module. The journey time is computed as the time interval between arrival and position of the record module – which represents the exit time.

In order to collect entity statistic by discharge outcomes, it is necessary to differentiate them at this point. Firstly, the decide module is used to check if patient's discharge outcome is "Admitted", which was assigned in the admission logic. Patient counts and journey time statistics are then recorded; else, the patient goes through the "Unadmitted" statistics collection stream.

Figure 7.27: Model of Emergency Department Exit Process

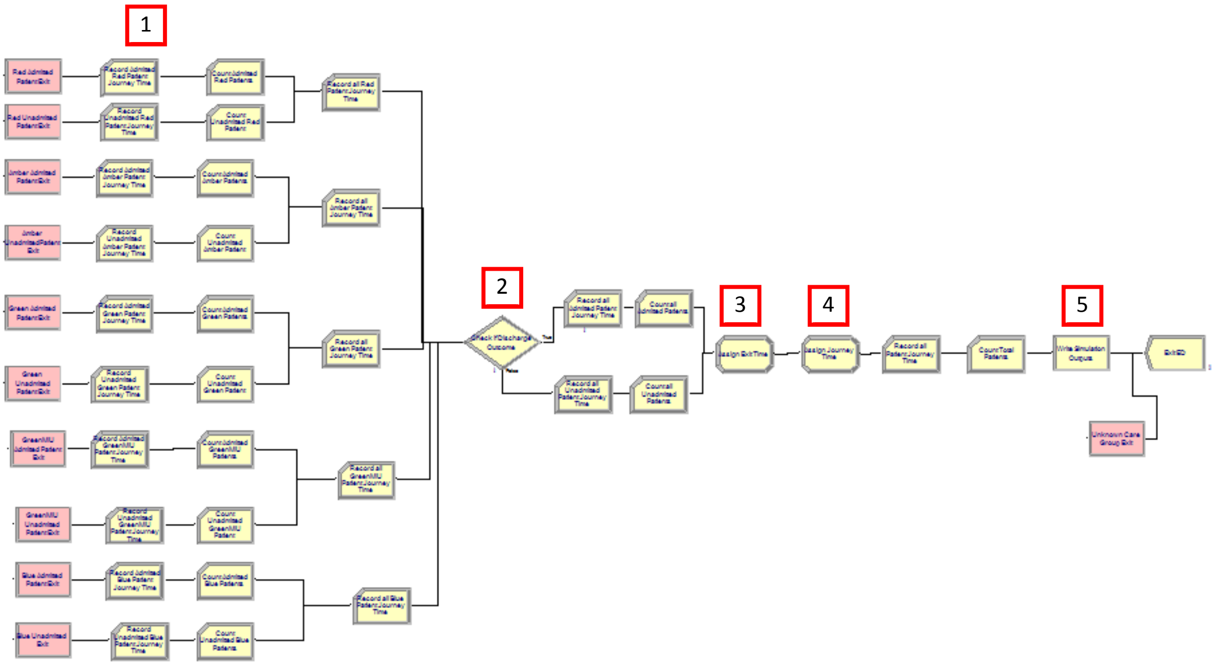


Figure 7.28: Red Patients admission and discharge statistics collection Logic

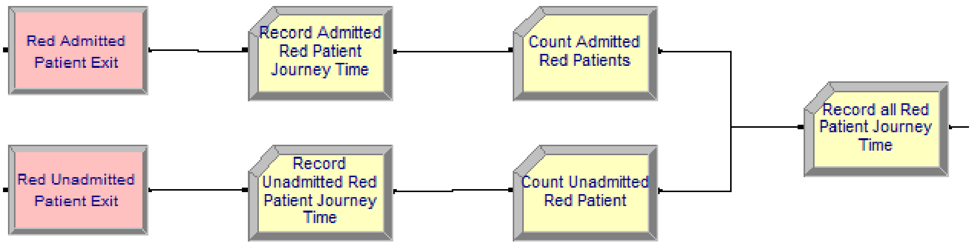
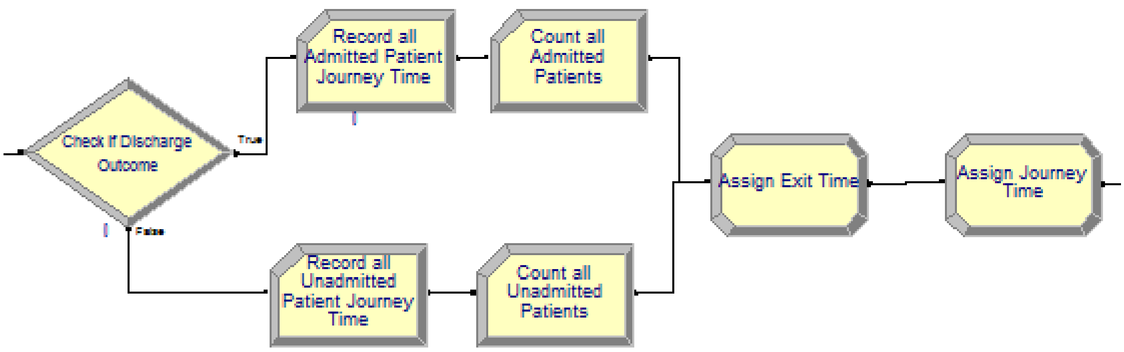


Figure 7.29: Admission and Discharge statistics collection Logic



To enable the collection of output statistics such as processing and journey times, patients are assigned time attributes throughout their journey. Before exiting the system, the "Assign Exit Time" module assigns an Exit Time attribute for each patient. Furthermore, triage time, processing times in all areas and overall journey times are computed and assigned to each patient. For example, Triage time is calculated using the expression;

Time_after_Triage - TEnterTriage_Q

These are the same time assignments in Figure 7.9 done before and after Triage. Note that RAU patients are not included in this computation since they did not go through the triage stream.

Figure 7.30 shows a clearer view of the right end of the Exit model logic. All patients' journey time and count statistics are recorded. The ReadWrite module is used to write simulation outputs of particular attributes (Figure 7.30a). During each replication, these statistics are collected and written continually to an Output text file named *BaseModelOutput.txt* using the File spreadsheet module. A demon logic is created to write the headings for the output file (Figure 7.31). These headings (Figure 7.31a) correspond to the defined attribues in Figure 7.30(a). Note that this is only done once and in the first replication. Note that unknown (care group) patients are not included in the statistics collection, since they did not undergo any process. The daily attendance of patients in the emergency department for a one year period is also derived.

Figure 7.30: All statistics collection Logic

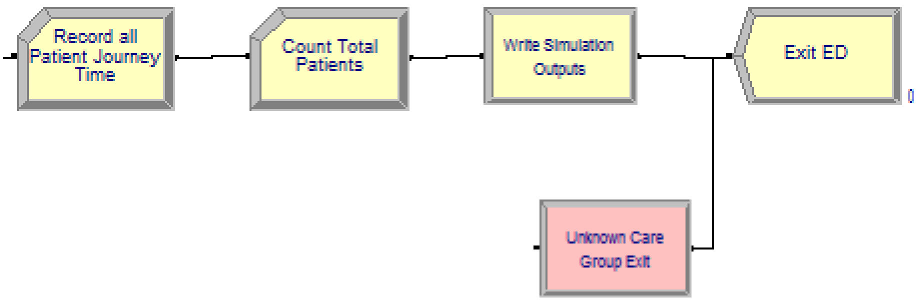


Figure 7.30(a): ReadWrite module dialog box to record specific statistics

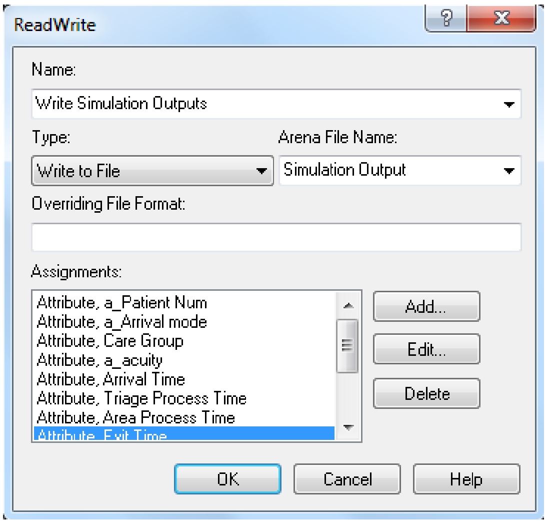


Figure 7.31: Model to write Output Headings

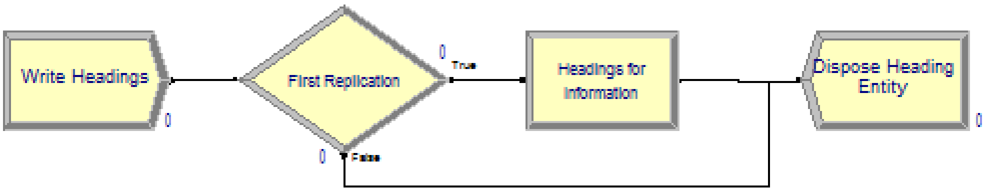
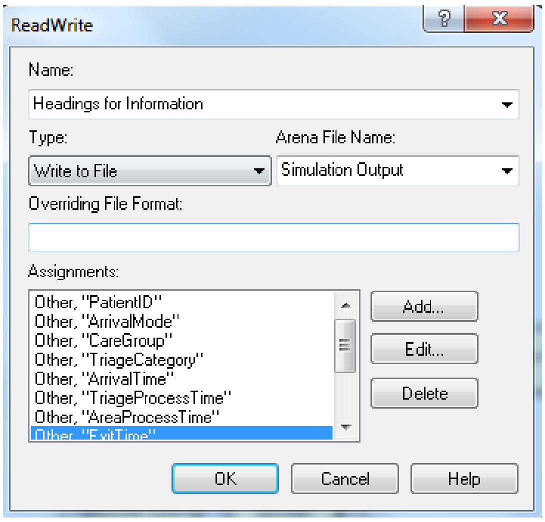


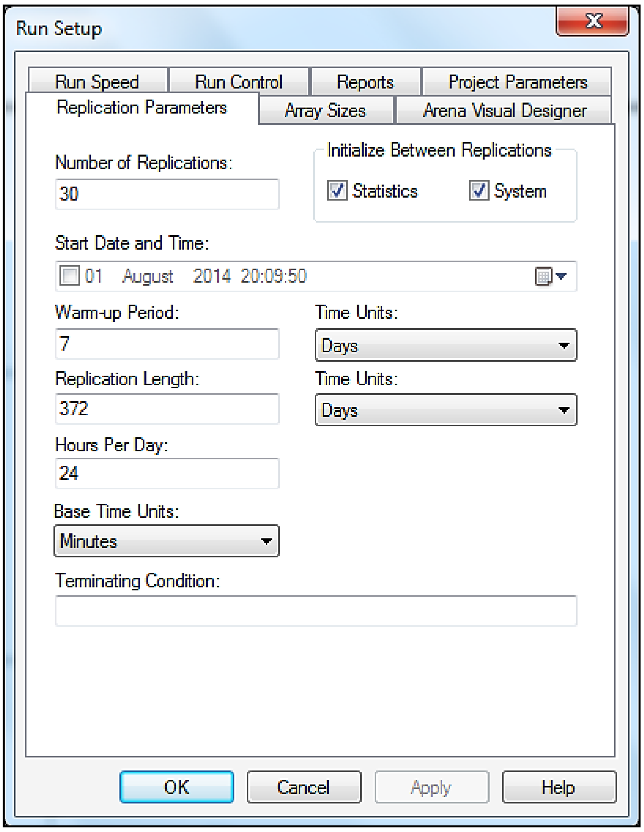
Figure 7.31(a): Write Headings



<u>Simulation Run Parameters</u>

The actual required simulation length is 365 days; however during the warm-up period, there is no statistics collection. Thus, in order to achieve complete output results, the model is simulated for 372 days with a warm up period of 7 days (since the arrivals vary by the days of the week). The run parameters are entered in the Run Setup dialog box shown in Figure 7.32, from the Run Setup menu. It takes about 20 minutes to run the model 30 independent replications on a 2.10GHz machine. The output from the run is discussed in Chapter 9.

Figure 7.32: Run settings for Base model



7.3 The Journey-Path Model

In Chapter 6, journey strings of patients based on probabilities of their recorded location was established. In this section, a model is created using the notion of these strings. In order to do this, patients are assigned sequence of paths to follow through the system based on the derived probabilities. This is done by using the "By Sequence" feature of the Route module. Resources are taken from the pools assigned to each path. Before going into details of the model, it is important to describe its input parameters.

7.3.1 Establishing Care Group Paths and their probabilities

From Chapter 6, there were many derived paths, and it will be tedious and time consuming to include all of them. However to ensure viability of the model, the following are considered;

- At least 90% of the cohort is used
- All Waiting Room locations are used as Cubicles (as explained in Chapter 6)

- In the Red path, all RAU strings including other locations such as Red and Assess are combined to form *RAU, Red, Assess* path. This is also done for the Blue string; RAU is combined with *RAU, WIC*.
- In the Amber string, all Cubicle and Treatment room strings are combined. For example, *RAU, Cub* and *RAU, T* are combined to form *RAU, Cub/T* path. In order to compute the *RAU, Cub/T* path, the probabilities of *RAU, Cub* and *RAU, T* are summed up. Also, *Cub, Assess* and *T, Assess* are combined to produce *Cub/T, Assess* path
- In the Green path, all MH, Cub, T, Red, GMIU are combined to form *Cub/T , GMIU* string, while *RAU* and *RAU, Cub* are combined to form *RAU, Cub*.
- In the Green/MIU string, all Cub, T, GMIU and Assess locations were combined to form *Cub/T* path.

The derived strings (or paths) and their probability derived by Care Group are displayed below (Table 7.5).

Table 7.5: Probability of Journey Paths by Care Group

Care Group	Paths	Probability (%)
Red	Red, Assess	24.97
	Red	60.14
	RAU, Red, Assess	13.20
	Assess	2.05
Amber	RAU, Assess	43.64
	Assess	33.81
	Cub, T	12.79
	RAU, Red, Assess	9.78
Green	Cub/T, GMIU	79.84
	RAU, Cub	11.62
	RAU, Assess	4.28
	WIC	4.27
Green/MIU	Cub/T	89.78
	RAU, Cub	7.77
	WIC, Cub	2.13
Blue	WIC	83.92
	Cub/T	9.43
	RAU, WIC	3.56
	WIC, Cub	3.11

7.3.2 Assumptions

The assumptions are same as those in the Base model, including the following;

1. Registration process is not considered since it was not evident in the data.
2. If a patient goes through the RAU, they undergo all the processes, that is resuscitation and test. If their paths include more than one other area, they only undergo Consultation process in the first for the predefined time duration and the remaining processes (Treatment and Review) in the second area. For example in the *RAU, Red, Assess* path, patient undergoes all processes in the RAU then proceed to the Red Area for only Consultation, and finally goes to the Amber Area for Treatment and Review before waiting for bed for admission or exiting the ED.
3. All tests and further treatments described in the Base model apply.
4. Delay in the Blue area before re-admission into ED is not considered

Building the Journey-Path Model

All input parameters such as Arrival, processes, resources and Process Time delays are the same as that of the Base model, although, some changes were made in the model logic as will soon be shown. Since most parts of the model are similar to the Base model, only these changes are described. The model is divided into 9 sections as follows;

1. Arrival logic
2. Triage Process logic
3. RAU Process logic
4. Red Area
5. Amber Area
6. Green and Green/MIU Area
7. Blue Area (or PCEC)
8. Admission Logic
9. Exit Logic

The logic in the Amber and Green areas similar the base model, except patients are routed by sequence rather than stations (as done in the base model). Therefore they are not described as that will be repeating the obvious. Furthermore, there are similarities in other logic, thus only the differences are explained.

7.3.3 Arrival logic for Journey-Path Model

The arrival process is basically the same as the Base model, except the addition of the Sequence assignments by care group as shown in Figure 7.33.

Figure 7.33: Arrival process for Journey-Path model

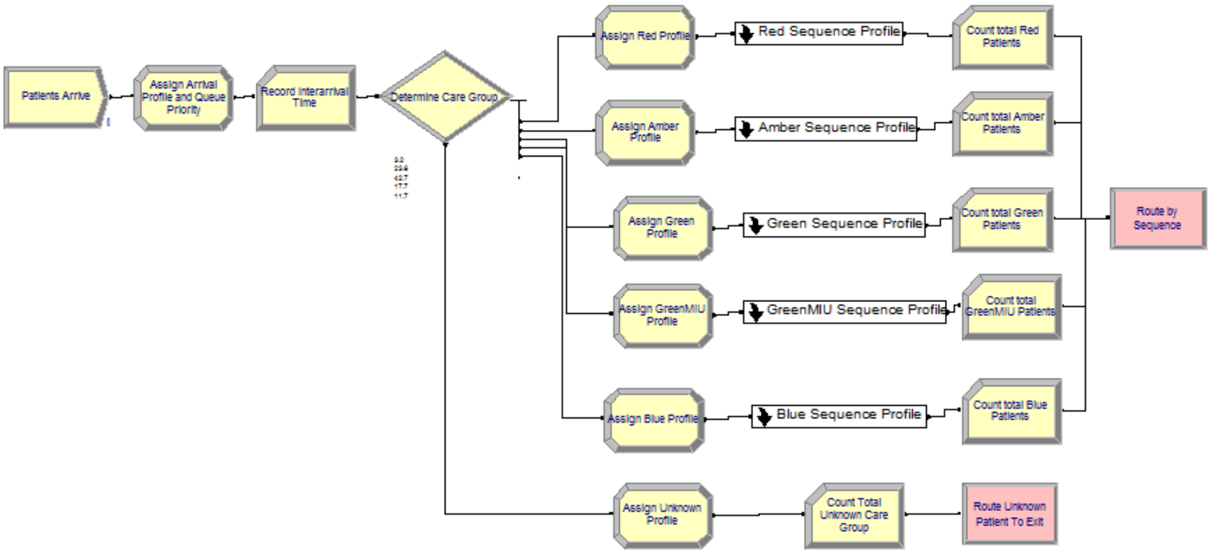
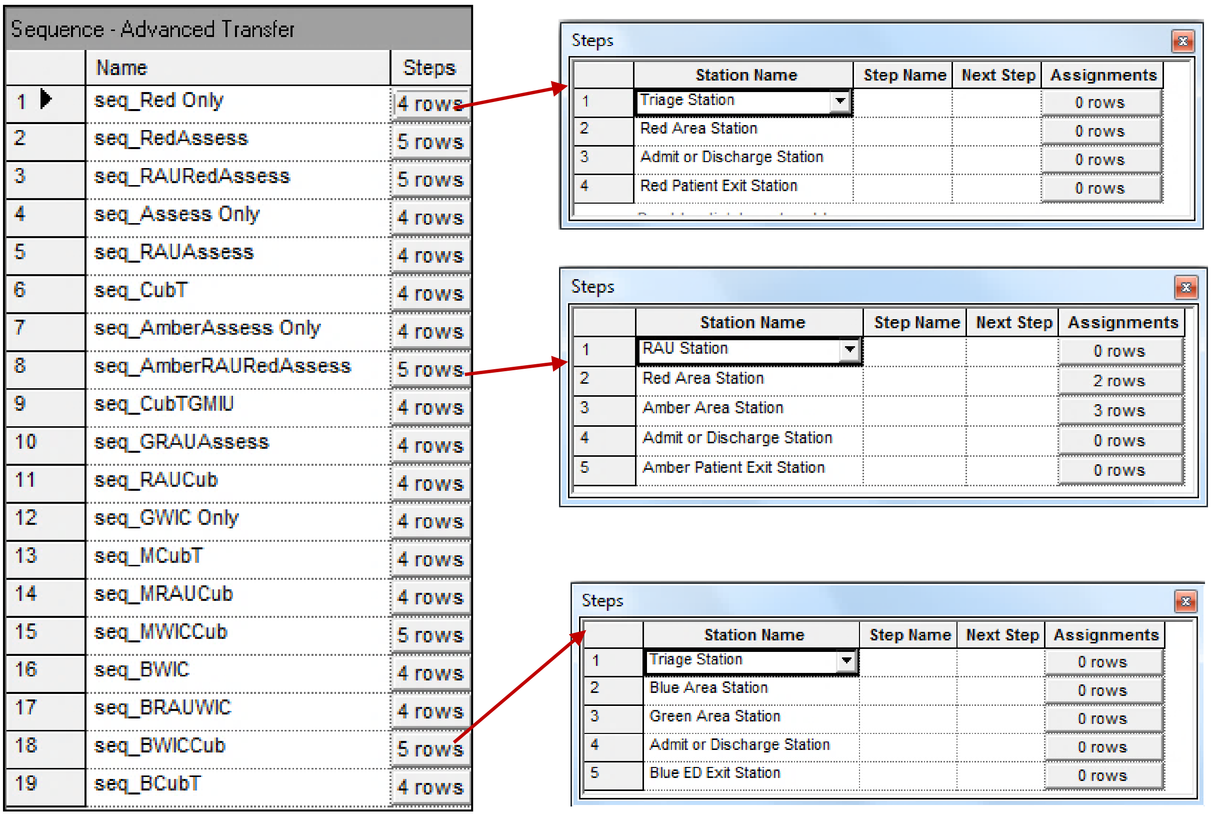


Figure 7.34: Assignment of Sequences in the Sequence Spreadsheet module



Sequence - Advanced Transfer

	Name	Steps
1	seq_Red Only	4 rows
2	seq_RedAssess	5 rows
3	seq_RAURedAssess	5 rows
4	seq_Assess Only	4 rows
5	seq_RAUAssess	4 rows
6	seq_CubT	4 rows
7	seq_AmberAssess Only	4 rows
8	seq_AmberRAURedAssess	5 rows
9	seq_CubTGMIU	4 rows
10	seq_GRAUAssess	4 rows
11	seq_RAUCub	4 rows
12	seq_GWIC Only	4 rows
13	seq_MCubT	4 rows
14	seq_MRAUCub	4 rows
15	seq_MWICCub	5 rows
16	seq_BWIC	4 rows
17	seq_BRAUWIC	4 rows
18	seq_BWICCub	5 rows
19	seq_BCubT	4 rows

Steps

	Station Name	Step Name	Next Step	Assignments
1	Triage Station			0 rows
2	Red Area Station			0 rows
3	Admit or Discharge Station			0 rows
4	Red Patient Exit Station			0 rows

Steps

	Station Name	Step Name	Next Step	Assignments
1	RAU Station			0 rows
2	Red Area Station			2 rows
3	Amber Area Station			3 rows
4	Admit or Discharge Station			0 rows
5	Amber Patient Exit Station			0 rows

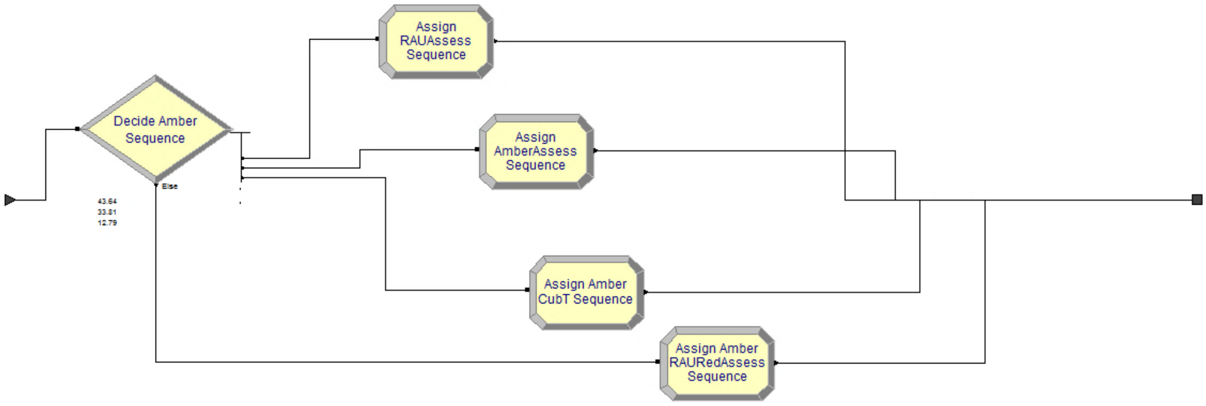
Steps

	Station Name	Step Name	Next Step	Assignments
1	Triage Station			0 rows
2	Blue Area Station			0 rows
3	Green Area Station			0 rows
4	Admit or Discharge Station			0 rows
5	Blue ED Exit Station			0 rows

Figure 7.34 presents the patients' paths through the system using the Sequence Spreadsheet module. Sequences for Red care group are indicated in 1 to 4, for Amber in 5 to 8, for Green in 9 to 12, for Green/MIU in 13 to 15 and for Blue in 16 to 19 of the spreadsheet.

For clarity, the probability of sequences for each care group is entered in a sub-model. For instance, for Amber patients, the sub-model – "*Amber Sequence Profile*" is displayed in Figure 7.35. Based on these probabilities, Amber patients are assigned paths and then routed accordingly. Patients are then routed to according to their next step in their established paths.

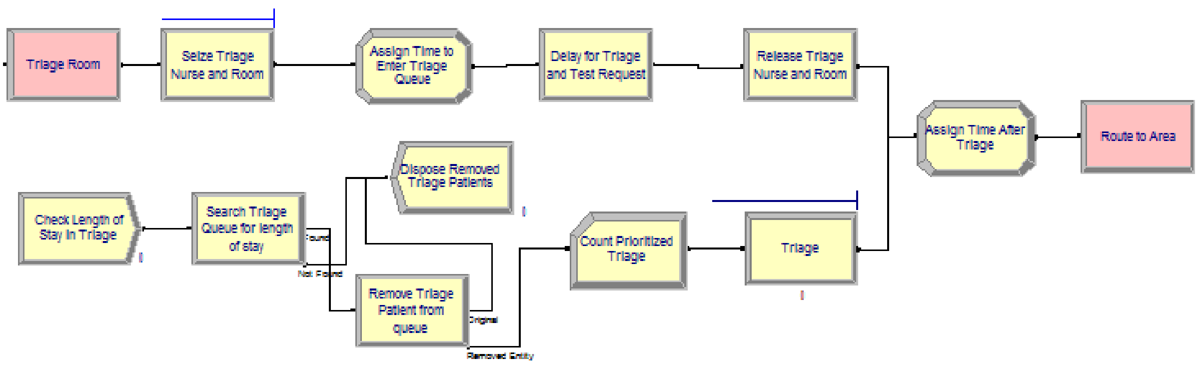
Figure 7.35: Assignment of Sequences for Amber Care Group



7.3.4 Triage Process logic for Journey-Path Model

Figure 7.36 displays the Triage process logic. Similar to the Base model, a patient seizes a Triage room and nurse, undergoes triage and test request processes, releases previously seized resources, and then goes to the next step in its sequence. The addition of an RAU nurse for triage described in the base model also applies here.

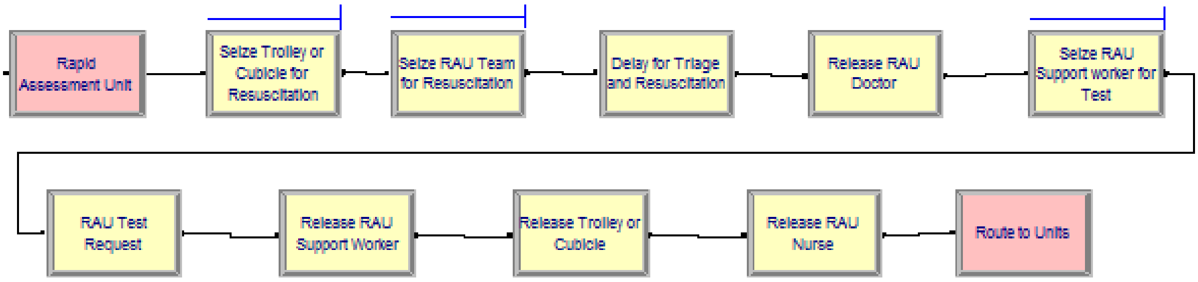
Figure 7.36: Triage process logic for Journey-path model



7.3.5 Rapid Assessment Unit Process logic for Journey-Path Model

The RAU logic shown in Figure 7.37 is very similar to the Base model, except that critical patients have not been distinguished.

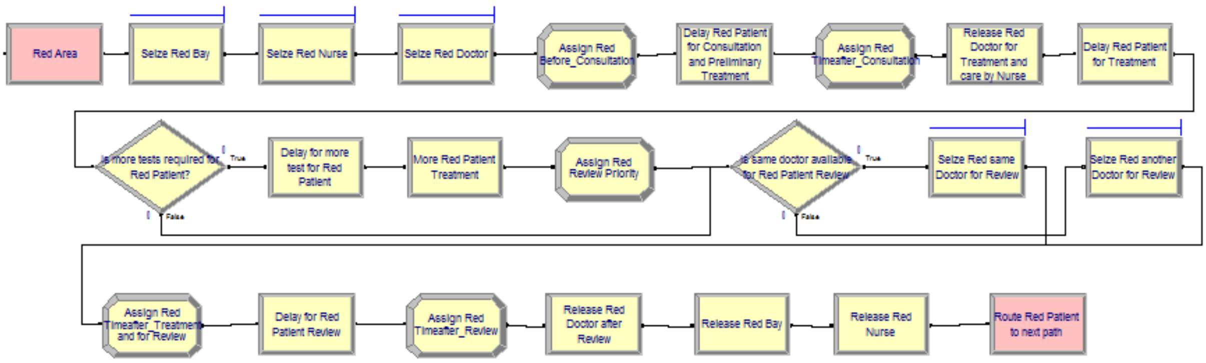
Figure 7.37: RAU process logic for Journey-path model



7.3.6 Red Area Process logic for Journey-Path Model

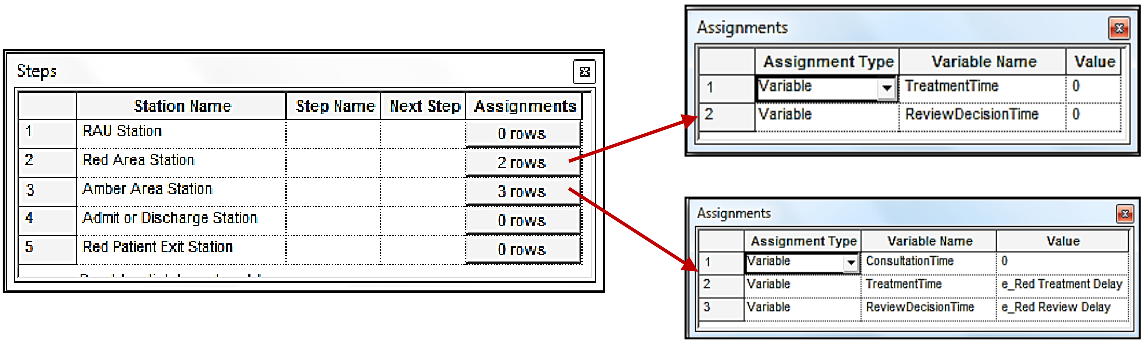
Figure 7.38 show the Red area logic which is same as the Base model, except the last route module which directs patients to the next sequence step.

Figure 7.38: Red Area process logic for Journey-path model



From Figure 7.35, in the "seq_AmberRAURedAssess" sequence, there are two assignments in the Red Station and three in the Amber Station. From the Base model description, delays for process times are assigned to care groups in the arrival logic. Since it is assumed that if a patient's path includes two areas with same processes, they do not go through all the processes in the first Station. In particular, they undergo only the first process in first Station and the rest in the second station. This is modelled by assigning a process time of 0 minutes in the first Station for processes which will be done in the second Station and vice versa. Also, the previously assigned zero time are changed to the originally assigned time in the second station. For example, Figure 7.39 shows the sequence steps for the Red path – RAURedAssess. This sequence entails that patient goes to RAU, then Red Area and Assessment room (in the Amber area). They then undergo resuscitation and test request processes in the RAU and proceed to the Red Area. In the Red area, the processes are Consultation, treatment and review/Decision. These processes are similar to the ones done in the next step of this Red patient's path which is in the Amber Area. Therefore, it will not be realistic for a patient to undergo the same process in both areas. To avoid this repetition of processes, in the Red area station, patients are assigned a zero time delay for Treatment and Review/Decision times as shown in Figure 7.39. This implies that only the Consultation process is done in this area. The Red patient goes to the Amber area for other processes. Since the patient has already undergone Consultation process in the Red area, the time duration for Consultation process is zero. Also, the original delay for Treatment and Review processes is reassigned to the original value in the Expression spreadsheet module. This is repeated for other similar paths.

Figure 7.39: Sequence Spreadsheet module showing new Processing Time Delay Assignments



7.3.7 Green/MIU Area Process logic for Journey-Path Model

Figures 7.40 and 7.41 display the process logics for the Green/MIU path. This is similar to the Green/MIU logic in the base model, except that the Test logic is combined with the MIU logic. Patient seizes ED staff and resource, undergoes Consultation process. If X-ray is required patient releases ED staff and treatment room or cubicle, undergoes test and check if previously seized ED staff is still in the system. If ED staff is not found, patient seizes another staff, else patient will proceed with the same staff for Treatment and Review processes, after seizing an available treatment room or cubicle.

Figure 7.40: Green/MIU Area process logic for Journey-path model (1)

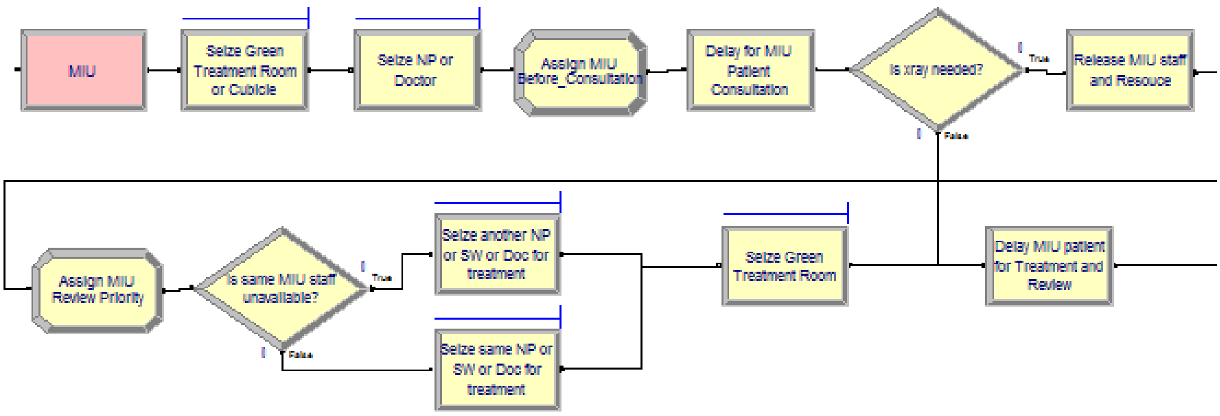
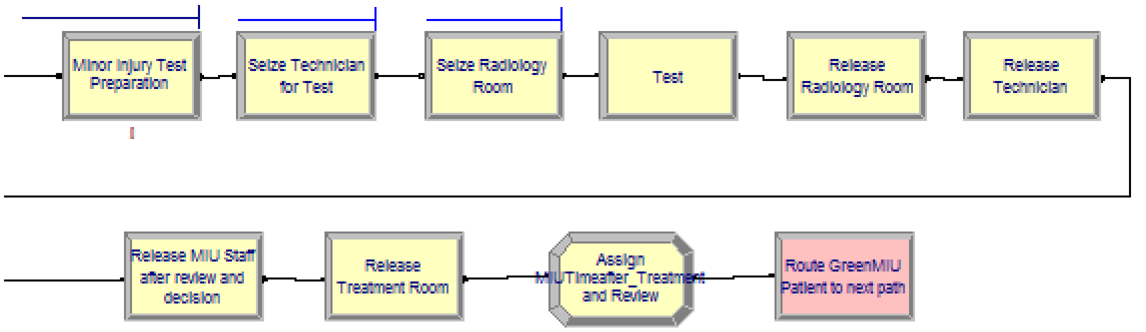


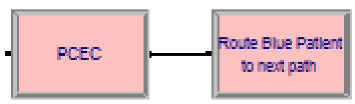
Figure 7.41: Green/MIU Area process logic for Journey-path model (2)



7.3.8 Blue Area Process logic

As mentioned earlier, the Blue area is outside the scope of this work; therefore it is not modelled in details. From the journey information, 3.11% of Blue patients go to the Green area from the PCEC. Likewise the other paths, Blue patients are routed accordingly as shown in Figure 7.42. Time spent in the PCEC is not considered since this was not evident in the data.

Figure 7.42: Blue Area process logic for Journey-path model



7.3.9 Admission Process logic

Figure 7.43 displays the admission logic for all journey paths. All entities are routed to the "Admit or Discharge Station" after undergoing ED procedures. For all care groups, sub-models are used to determine the probability of discharge outcome. Figure 7.44 shows the sub-model of Red Care Group. If admission is required, patient waits for a bed as described in the Base model. Journey time and entity count statistics are then collected by discharge outcome (admitted and unadmitted).

Figure 7.43: Admission process logic for Journey-path model

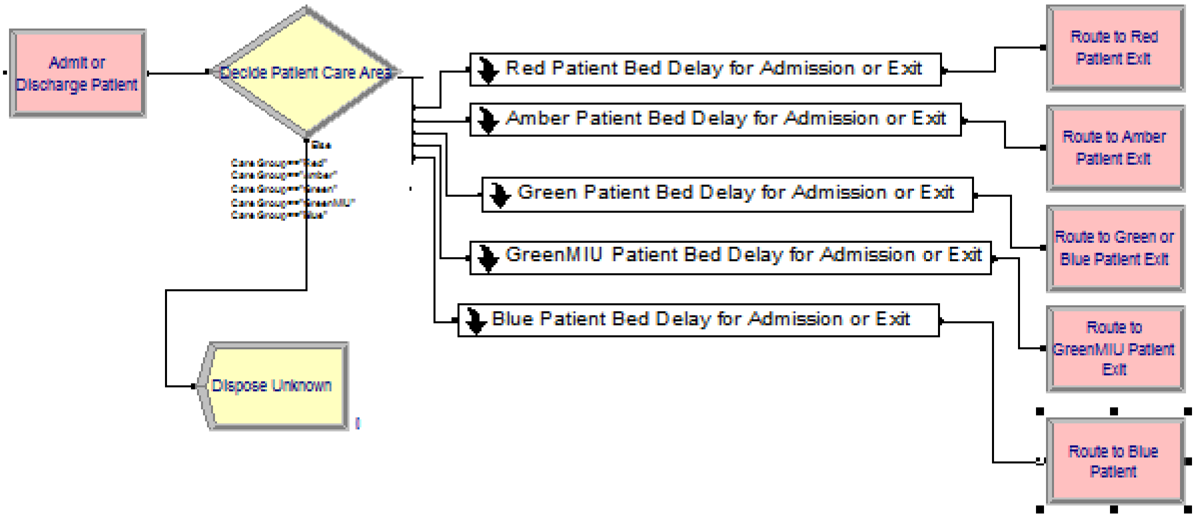
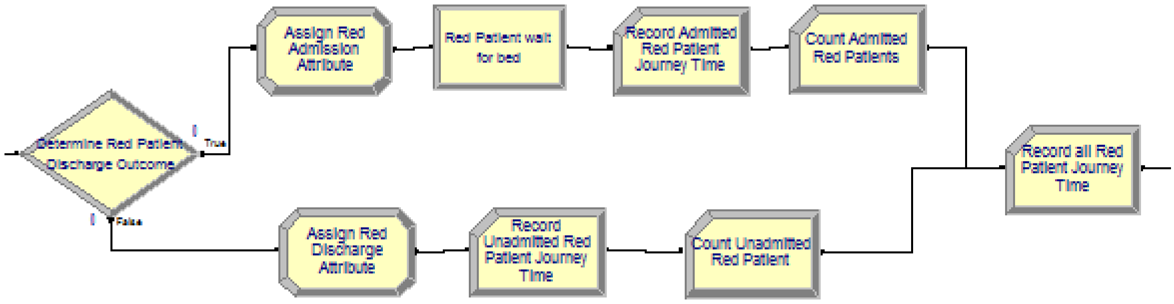


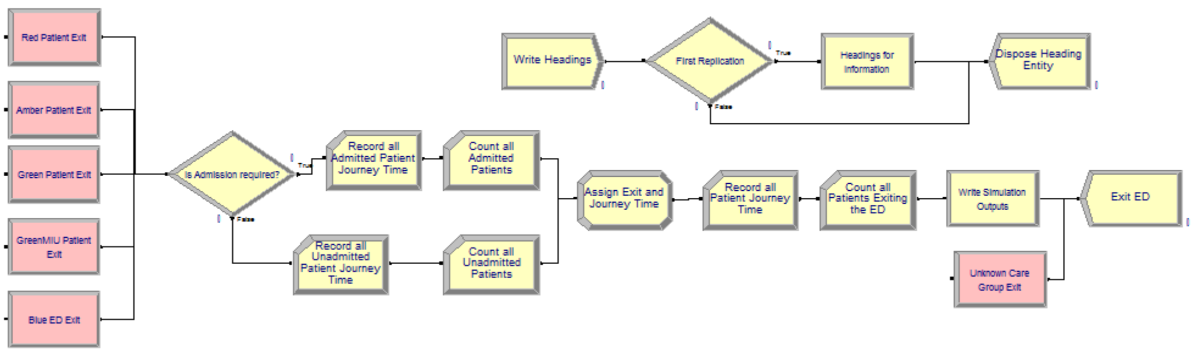
Figure 7.44: Sub-model to determine admitted Red Care Group and collect tally and count statistics



7.3.10 Exit logic

Figure 7.45 shows the exit process logic which mainly includes the second and third part of the Exit logic in the Base model. The first part is already included in the admission logic described above.

Figure 7.45: Exit logic for Journey-path model



Similar to the base model, the journey-path model also takes about 20 minutes for 30 replications.

7.4 Comments and Conclusion

The purpose of any model is to define the sequence of operations which results in the transformation of an input entity (ill patient) into a (changed) output entity (treated patient). Typically, the sequence involves one or more processes that are performed on the entity as it passes through a system. Each process requires a unique set of resources (people and equipment) and has a particular duration. According to the prevailing number of resources and the rate of arrival of the input entities, queues may form before one or more of the various processes resulting in delays.

Two models were described namely; the Base model and Journey-Path model. The Base model is based on the ED data and anecdotal interpretation by staff. The Journey-Path model uses probabilities from mutually exclusive location data. Both models represent the operations of the emergency department of MRI, which includes resource multi-tasking, scheduling and ED procedures. However, it does not capture special circumstances like the 4-hour deadline or major trauma, which will be discussed further in chapter 8. Hence, it represents the normal activities of the ED which could be beneficial in the improvement of the facility. The outputs from both models are compared to the ED data in the Chapter 9.

CHAPTER 8: MODELLING THE FOUR-HOUR DEADLINE

8.1 Introduction

In very general terms, the output profile (distribution of journey times) for a sufficiently large number of replications of any DES model should follow a normal distribution according to the central limit theorem. This is the basis for Arena's calculation of the significance of the various outputs of a model and is the basis of any derived sensitivity analysis. In practice, the measured output profiles (Chapter 6) rise to a sharp peak at four hours and then follow a broad distribution for longer times. Earlier studies (Eatock et al., 2011) show what appears to be a normal distribution which peaks earlier than 4 hours but which is truncated at this time and which thereafter resembles the data found here. The discontinuity in both studies reflects the fact that a key performance target for ED is that for 95% of patients the total journey time should be no more than four hours. It is the imposition of this target that is responsible for the characteristic shape of the journey time distributions found in this work and shown in Chapter 6.

In effect the observed four hour "wall" means that any ED model has to incorporate an algorithm that imposes a time constraint on a patient's journey through the system. The simplest metric that can be used to take account of the imposed target limit is the difference between the imposed target time (deadline) and the length of stay in the system at any particular time in the journey. We can refer to this as the *trigger-time*. In effect the difference between the trigger time and the deadline is the time remaining for the patient to complete their journey within the deadline.

In very general terms this algorithm can include any or all of the procedure outlines in Table 8.1.

Table 8.1: Algorithms for the four-hour deadline

Algorithm	**Acronym**	**Description**
(a)	priority	According to the trigger-time, patients are assigned a higher priority so that they effectively queue-jump later processes.
(b)	fast-track	According to the trigger-time, patients can be fast-tracked through the system by being transferred to a parallel (faster) process.
(c)	resource	According to the prevailing length of queues in the system, resources can be re-allocated dynamically among different processes

By far the majority of reports in the literature use the priority approach (Table 8.1.a). In practice, staff in the ED at MRI monitor the waiting times (possibly the lengths – it is not clear) of the various queues in the treatment areas (Red, Amber, Green, Green/MIU) and adjust the resources which are allocated to the processes associated with the queues in real time. This follows procedure (b) in Table 8.1.

Unfortunately, the monitoring procedure appears to be carried out at unspecified (and unrecorded) intervals and it has to be assumed that resources are moved from the "fastest" queue to the "slowest" queue. The main issue here is that these adjustments are made to the prevailing resources and that no additional resources are made available. The procedure is described as "resource re-allocation".

The information from the ED is that the re-allocation is made only once or twice per shift and not until the waiting time in the longest queue approaches three hours. It is not clear exactly how this waiting time is assessed. Of course the penalty with this approach is that the queue associated with the process from which resources are taken will get longer. In addition there has to be a second trigger that "removes" resources from a queue that is short (or shorter than another). That is to say the process is dynamic and involves the periodic addition and removal of resources from different queues. Providing this balancing act achieves the four hour target for all the queues, it has been successful.

Clinicians at MRI are at pains to stress that the target journey time is NOT achieved by diverting patients to a parallel, *fast-track* operation (Table 8.1(b)), which has a shorter process duration or has resources with increased capacity[23]: it is achieved only by moving existing (scheduled) resources from one process to another, and all <u>process durations remain unchanged</u>.

In reality the ED does a good job given the data from Chapter 6. However, given the vagueness of the procedures involved, the four hour deadline was not incorporated into the final model in Chapter 7. However possible means of modelling this are considered in this Chapter. The issue will be re-visited as part of the future work described in Chapter 10.

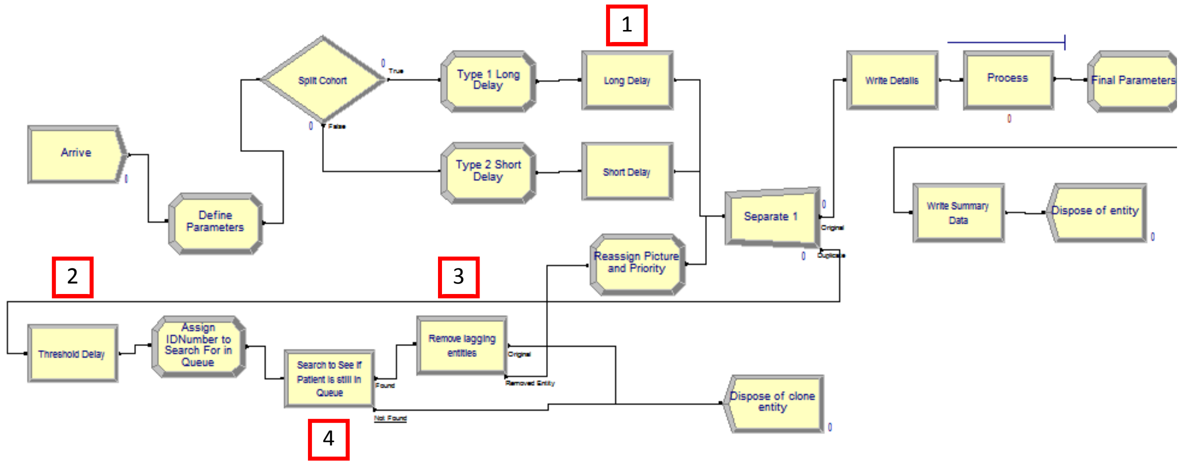
8.2 Simple Models based on Patient Priority

In many queuing systems, a situation can arise when individuals in a queue leave before being served because they perceive the queue to be too long (reneging) or because they are impatient (balking). Space constraints may also impose a limit on the maximum length of a queue and in the

[23] Note that the capacity for all clinicians is 1, irrespective of their actual status and experience.

case of supermarkets, banks, etc, multiple servers are used to limit the prospect of reneging and the consequent loss of revenue. Reneging and baulking can be handled in Arena. A simple version of this is shown in Figure 8.1.

Figure 8.1: Patient Priority Model



Here, patients arrive at a particular rate and are split into two groups. These groups are delayed for different times to simulate patients in the real system travelling on different journeys (box 1). In effect this ensures that the two groups have significantly different journey times up to the point of entering the process queue. Before entering the queue each patient is cloned and the clone is delayed for a target time (box 2). If the patient that corresponds to the clone is still in the queue after this target time has elapsed they are removed and assigned a higher priority (box 3) before being returned to the queue. Since the queue is ordered by priority the patient will jump ahead of patients with lower priority. In this example, the maximum patient priority is not fixed.

Note that this model is akin to that published by Eatock et al (2011). The manipulation of the queue follows the reneging model in Arena, the key feature of which is to ensure that it is the patient index which is returned on a successful search rather than the clone index (box 4).

For the histograms that follow unless otherwise stated, the ordinate is the number patients within each bin on the abscissa and the units of the abscissa are minutes. Note also that figures 8.2, 8.16 and 8.19 are derived from the same parameters. They are reproduced for ease of comparison.

The outputs from this model are shown in Figures 8.2(a) and 8.2(b) for, respectively, no queue jumping and queue jumping after a trigger time of 120 minutes.

It is clear that the priority here makes very little difference to the journey profile. In fact over a range of different delay times (Figure 8.1, box 1), a range of different trigger times and a range of different process times, the effect of changing the patient priority is insignificant. It is also the case, here at least, that patient priority can reach values in excess of 20. This may be acceptable for a model of the system but in reality it does not reflect the practice in MRI, which implies that updating the patient priority takes place only a few times.

Figure 8.2a: Output from Patient Priority with No Queue Jumping

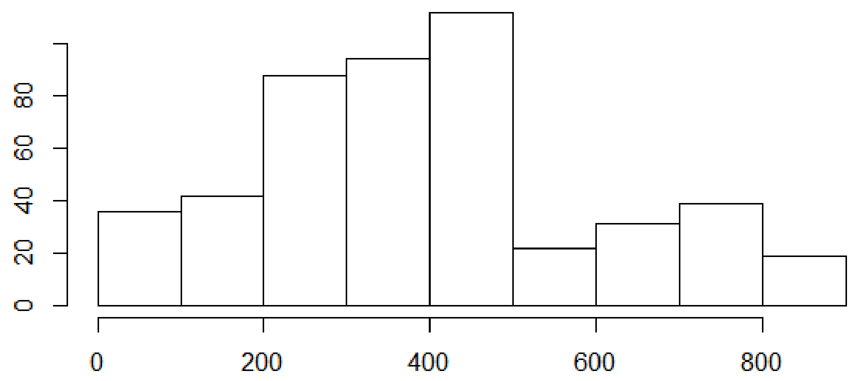
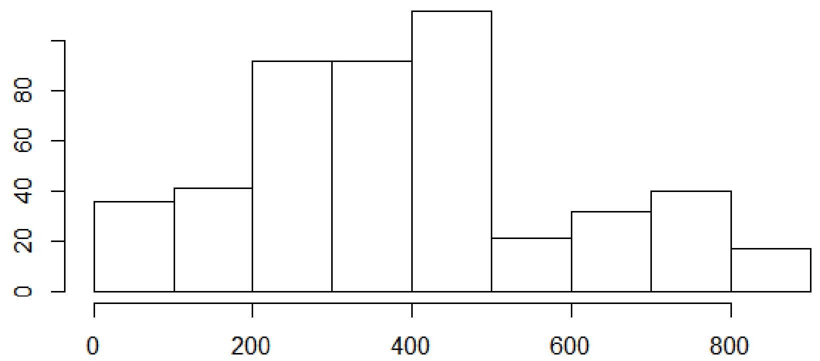


Figure 8.2b: Output from Patient Priority with Jump Trigger at 120 minutes



8.3 Simple Models based on Resource Re-Allocation

For any process in the ED journey, the average time taken for a patient to reach the front of the queue which is associated with the process is

$$t = \frac{N t_p}{R} \qquad \text{Eq 8.1}$$

Here, N is the number of patients already in the queue, tp is the average processing time of the queue and R is the number of resources assigned to the queue each with a capacity of 1.

The time spent *in the system* AFTER processing in the queue is

$$t_{system} = t_{eq} + \frac{(N+1)\,t_p}{R} \qquad \text{Eq 8.2}$$

Where t_{eq} is the time elapsed since arrival to the time the patient entered the queue. For a series of k processes each with a queue, t_{eq} for the first queue is zero and t_{eq} for the N^{th} queue is t_{system} for the $(N-1)^{th}$ queue so that the total journey time is

$$t_{journey} = \sum_{1}^{k}\left[\frac{(N+1)\,t_p}{R}\right]_i \qquad \text{Eq 8.3}$$

And the governing condition for the deadline, t_d is

$$t_{journey} = \sum_{1}^{k}\left[\frac{(N+1)\,t_p}{R}\right]_i \le t_d \qquad \text{Eq 8.4}$$

In reality the averages are the expected values of the distribution of the process times for each of the processes.

If we take the LAST process in the sequence equation 8.4 can be re-cast in terms of the number of resources <u>required</u> to meet the deadline as follows.

$$R \ge \frac{(N+1)\,t_p}{t_d - t_{eq}} \qquad \text{Eq 8.5}$$

The number of required resources can be updated as a persistent global variable as each new entity arrives in the queue and then compared with the actual number so that resources may be added (or subtracted) when necessary. Conceivably the model should include a “smoothing” element that considers, for example, any difference between target and actual resources to have to persist for a set time (or a number of arrivals), otherwise the actual re-allocation of the resources would be unrealistically rapid.

Alternatively, the role of the clinician in charge of ED can be modelled as a demon that fires at regular intervals. The role of the demon is to perform this same calculation on the queue and to make the necessary changes to the level of resources. In this case the firing interval is key, since if it is too short the model will slow considerably and result in spikes and if it is too long it could be too late for the added resources to be effective.

There are a few, if any, ED models in the literature that use a re-allocation of resources algorithm. Its main advantage and inherent complexity is that unlike a priority based algorithm it must both increase and reduce resources according to the prevailing demand. This contrasts with a priority-based model which in effect tends only to increases the priority of a patient and in so doing acts like a one-way-switch which is difficult to turn off when a queue becomes quiet.

Modelling resource re-allocation in Arena is not as straightforward as it might be since membership of resource sets such as AmberDoctors or GreenDoctors cannot be changed easily during execution of the model. The preferred way to model resource re-allocation in Arena is to create resources as separate entities and to pick resources from the created "pool" in a hold block and then return them after they have been used (Jajo and Matawie, 2014). This approach would have meant a considerable re-write of the various models that had been created during the project and was not pursued further at this stage.

The underlying model is shown in Figure 8.3 and a simple approach to re-allocating resources is to allocate different sets of clinicians to each of the default queues but with each set containing a common clinician. This is shown in Figure 8.4 for sets of Amber (Figure 8.4a) and Green (Figure 8.4b) doctors. The SwapDoctorinAmber and the SwapDoctorinGreen are in reality the same doctor.

In the "quiet" state of the model the capacity of the SwapDoctorinAmber is zero and the capacity of the SwapDoctorinGreen is 1 (Figure 8.3). That is to say, at this instant, the "SwapDoctor" is working exclusively in the set of Green Doctors and there are 3 active doctors in the Amber set and 3 active doctors in the Green Set. The initial capacities of the doctors in each set is shown in Figure 8.4

Figure 8.3: Re-allocation Model SS1

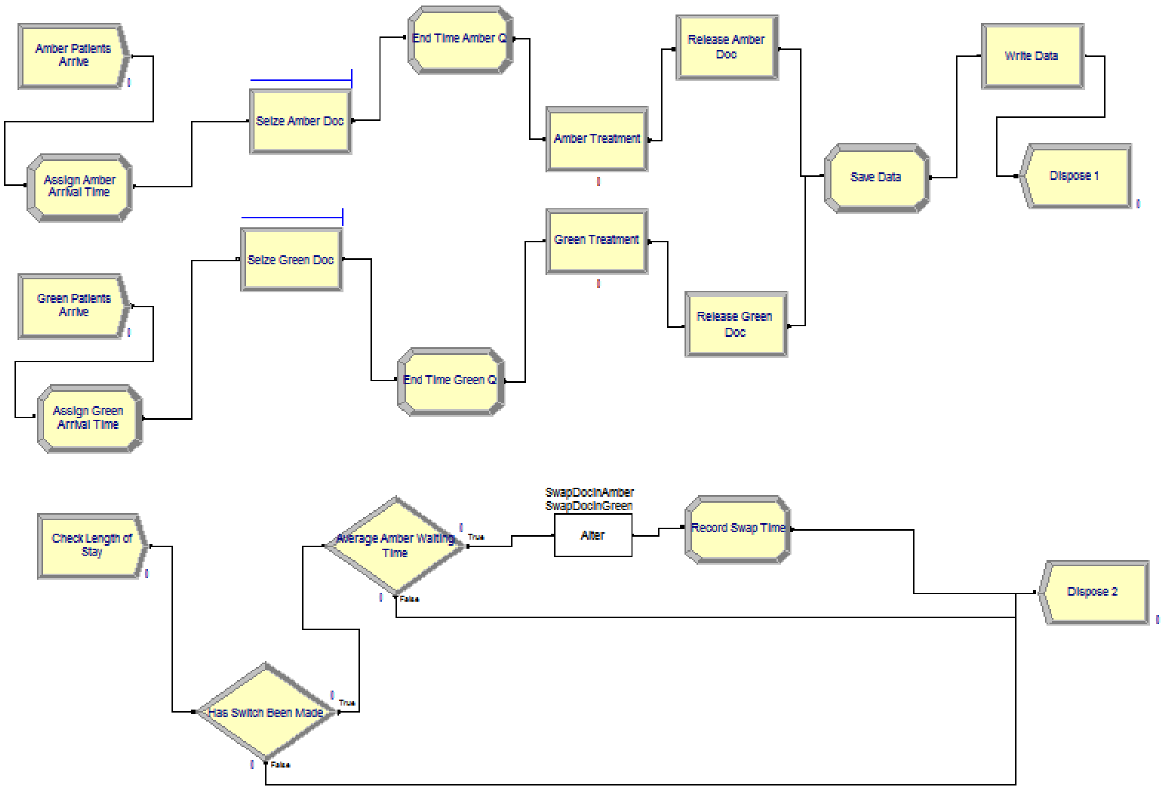


Figure 8.4(a): Amber Docs Set

	Resource Name
1	AmberDoc1
2	AmberDoc2
3	AmberDoc3
4	SwapDocinAmber

Figure 8.4(b) Green Docs Set

	Resource Name
1	GreenDoc1
2	GreenDoc2
3	SwapDocinGreen

Figure 8.5: "Quiet" Capacities of Resources

Resource - Basic Process

	Name	Type	Capacity
1	SwapDocinAmber	Fixed Capacity	0
2	GreenDoc2	Fixed Capacity	1
3	GreenDoc1	Fixed Capacity	1
4	SwapDocinGreen	Fixed Capacity	1
5	AmberDoc1	Fixed Capacity	1
6	AmberDoc2	Fixed Capacity	1
7	AmberDoc3	Fixed Capacity	1

Double-click here to add a new row.

In the model, a demon entity is launched at regular intervals (Figure 8.6) and checks the average waiting time in the Amber queue. When this exceeds 3 hours (Figure 8.7), the capacities of the SwapDoctors are changed by an *Alter Block* (Figure 8.8). In effect this means there are now 4 active doctors in the Amber set and 2 active doctors in the Green Set.

Figure 8.6: Demon to Check the Amber Queue Waiting Time

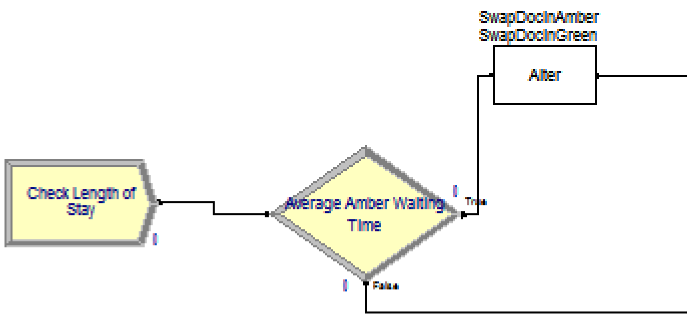


Figure 8.7: Test Waiting Time in Amber Queue

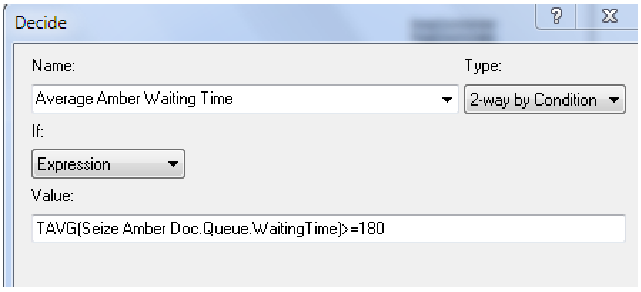
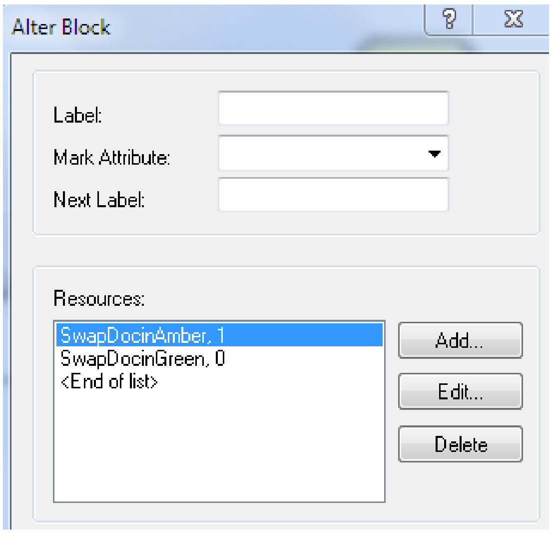


Figure 8.8: Change the Capacities of SwapDoc



When the swap is made a *flag* is set and this is tested in the same loop as shown in Figure 8.6 so that the capacity of the SwapDoc does not exceed 1. The decision module for this is included in the model diagram in Figure 8.1.

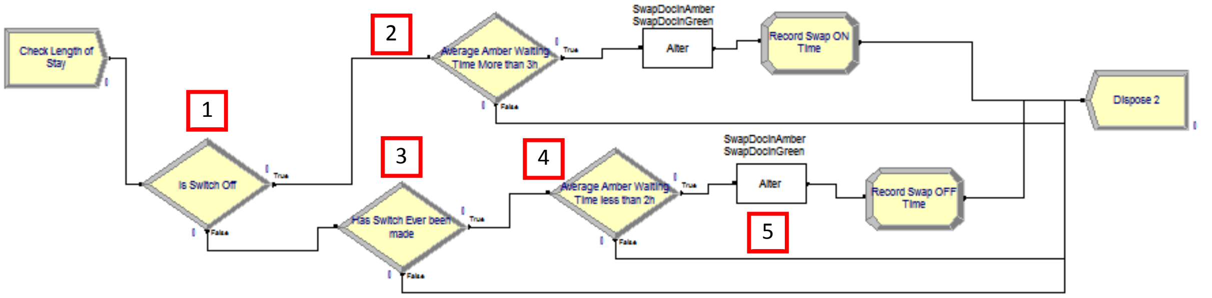
In effect the model runs for the time taken for the switch to engage with 3 amber doctors and for the rest of the time with 4 amber doctors. Thus the average waiting time in the amber queue is highly dependent on these times as shown in Table 8.2.

Table 8.2: Effect of Swapping Resources on Waiting Time and Queue Length

Inter-Arrival Time, min	Doctors at time zero	Doctors after swap time	Swap Time	Average Waiting Time	Average Queue Length
Run Length =30 days					
4	3	4	1250	4559.87	1108.81
4	3	3		8605.83	2107.37
5	3	4	1850	395.04	77.85
5	3	3		5559.43	1100.85
6	3	4	4120	47.35	7.91
6	3	3		2315.9	385.31
Run Length = 2 days					
4	3	4	1250	436.92	107.15
4	3	3		509.17	129.17
5	3	4	1850	280.6	52.61
5	3	3		314.75	62.45
6	3	3	Does not switch	110.29	18.77
6	3	3		110.29	18.77

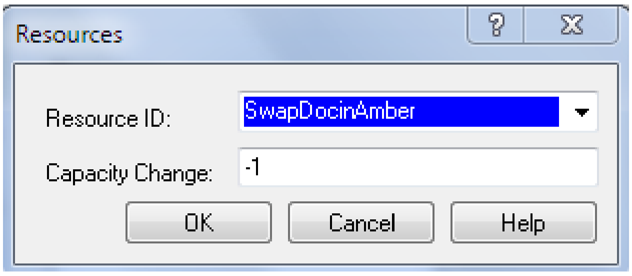
The limitation of model SS1 is that it controls only the upper waiting time limit. By altering the control loop (Figure 8.9) a revised model (SS2) allows switching of SwapDoc between the amber and green member sets according to set upper and lower limits for the waiting time in the Amber queue.

Figure 8.9: Control Code for Model SS2



Here, the decision block [1] tests a flag (Switch) that is clear if the capacity of the SwapDocinAmber is zero. If it is zero the next dialog block [2] tests if the upper waiting time limit is exceeded. If it has, the swap is made and the variable *Switch* is set. A second variable *Switched* is also set to indicate that the switching cycle has started. This variable does not change. If *Switch* is set [1] the next dialog ensures that the cycle has started by checking that *Switched* is also set [3]. The next decision [4] checks that the lower waiting time limit has been reached and, if so makes the reverse swap [5]. Note that the reduction in capacity has to be entered as a negative number (Figure 8.10).

Figure 8.10: Reducing the SwapDocinAmber Capacity



For SS2, the inter-arrival time is EXPO(6) minutes, the process time is TRIA(15,20,25) minutes. The upper and lower queue times are 180 minutes and 90 minutes. The run length is 90 days, and the demon interval is either 15 minutes or 5 minutes.

Figure 8.11 shows the average waiting time from SS2, and Figure 8.12 shows histograms of the total journey times and waiting times of the patients. While the lower limit is well controlled, the upper limit is exceeded, and this may reflect the faster rate of increase of the waiting time in the queue when the resource is removed; compared with the slower rate of reduction in waiting time when the resource is added. In effect, the conditions mean that even with 4 doctors the system is struggling to cope. Both histograms show a peak at relatively short times and a long tail extending to very high times. This is not what is shown by, for example, the total journey time from the recorded data in Chapter 6.

Figure 8.11: Average Waiting Time from Model SS2

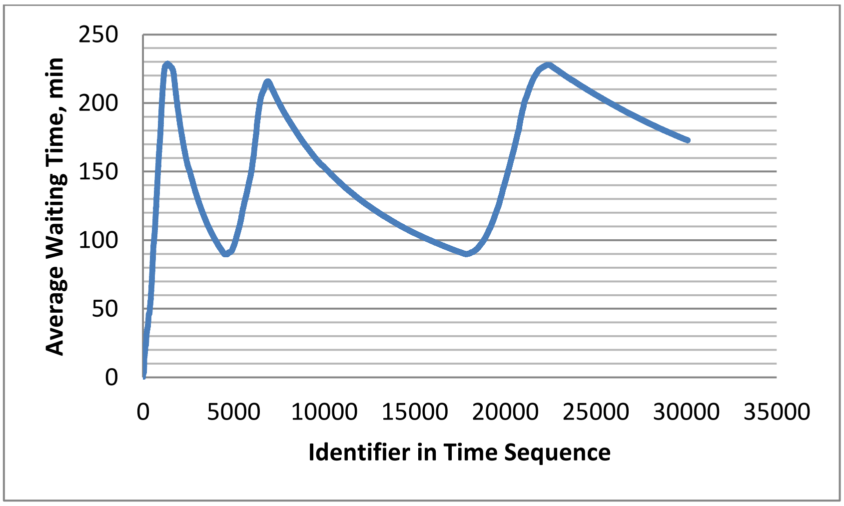
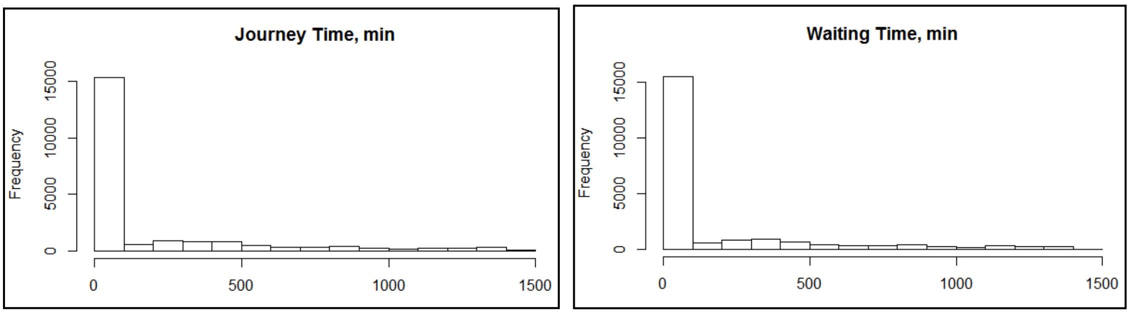


Figure 8.12: Journey Times and Waiting Times from Model SS2



8.3.1 Re-Directing Entities

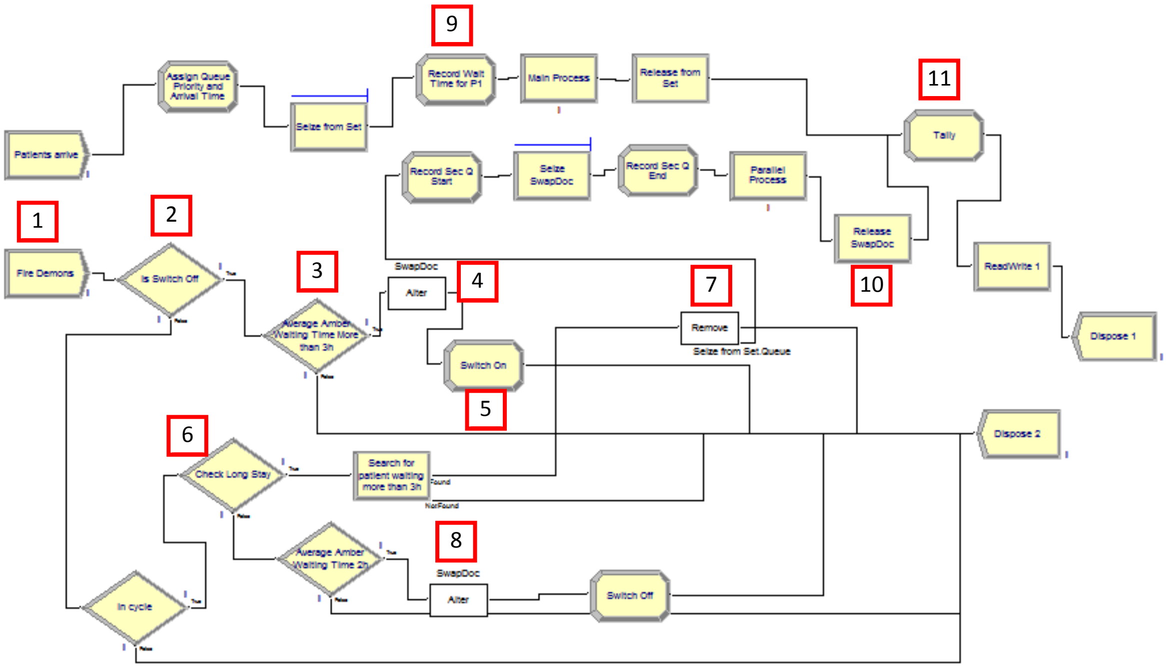
An alternative is to the set-based control used in SS1 and SS2 to search the amber queue for patients with waiting times which exceed the upper limit and to remove them from this queue (the *main* queue) and place them in another queue (the *parallel* queue) which is resourced by an extra doctor (*SwapDoc*). The total waiting time of a patient is the sum of the waiting times in each queue. In this model (ER1), the capacity of *SwapDoc* changes according to the length of the main queue and in this case (unlike SS1 and SS2), *SwapDoc* is treated as a single entity. The model is shown in Figure 8.13.

Here, the control demon [1] checks for the current status of the control by checking a flag [2]. If this is not set, it means that the control loop has not been established and it continues to check the average waiting time in the main queue [3]. If this exceeds the target (3 hours) the capacity of *SwapDoc* is increased to 1 [4].

At the same time various flags are set [5] so that the NEXT demon that passes through the system can either divert patients to *SwapDoc* by removing patients from the queue [7] or the lower limit of the queue can be checked and, if appropriate the capacity of SwapDoc can be set to zero [8]. One flag which is set by the first demon is persistent so that the lower part of the control cycle is used thereafter. Note that in this model only one patient is removed for every demon that is launched which in reality means as often as the queue is inspected. It is of course possible to launch many demons simultaneously although this was not pursued here.

The waiting time of an entity in the main queue is recorded in the attribute *MainQTime* [9] and the waiting time in the parallel queue is recorded in the attribute *SecQTime* [10]. For those patients who do not enter the parallel queue the attribute *SecQTime* is set to zero [10]. The total waiting time, *TotalWaitTime*, is the sum of these times [10].

Figure 8.13: Model for Removing Entities (ER1)



The journey times and total waiting times as histograms from this model are shown in Figures 8.14 and 8.15. The run length was 90 days and other parameters are the same as those for model SS2.

Figure 8.14: Outputs of ER1 for Demon Interval of 15 minutes

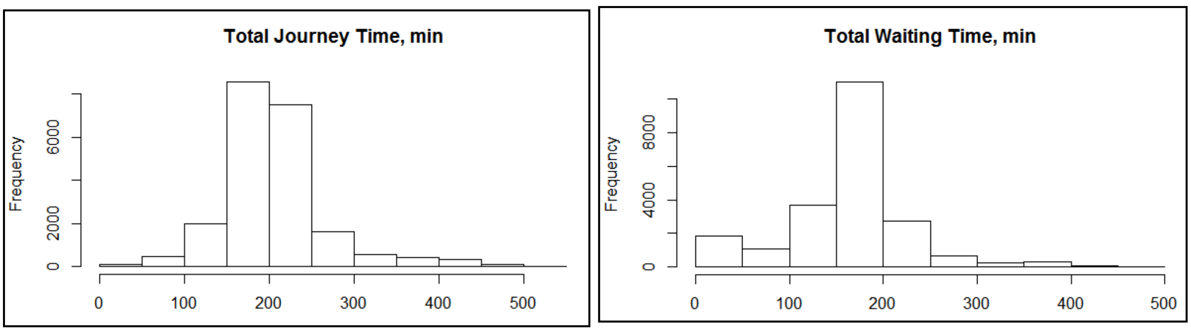
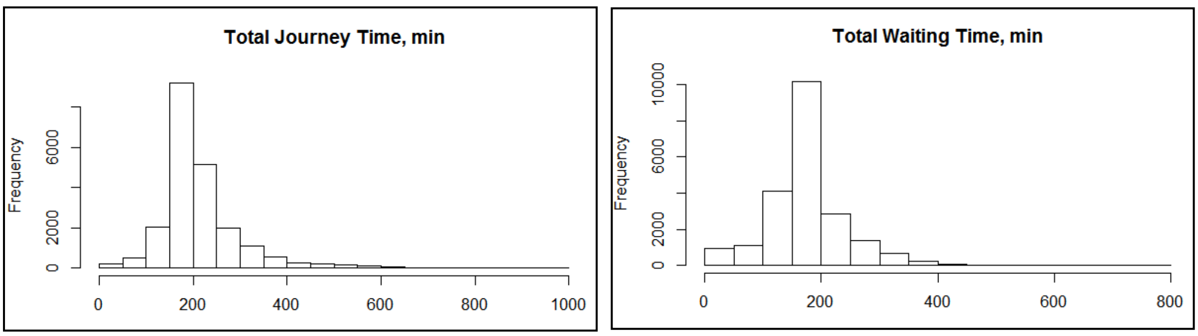


Figure 8.15: Outputs of ER1 for Demon Interval of 5 minutes



Based on the histograms in Figures 8.14 and 8.15, this model more closely mimics the recorded data from the ED shown in Chapter 6. Both the journey time and the waiting time distributions show the characteristic "wall" close to the set upper waiting time limit, although this is less distinct in the model. The model also gives more of a long-time tail than is found in the recorded data, suggesting an overshot of the upper control limit.

8.4 Fast-Tracking Patients

While the feedback from MRI was that no fast-tracking of patients was carried out, it is straightforward to make changes to the model in Figure 8.1 to accommodate this. The modified model is shown in Figure 8.16. Here, the patients are assigned two attributes (Min_Time and Max_Time) on arrival. These values determine the minimum and maximum limits of a uniform distribution which defines the duration of the process shown in box 1 in Figure 8.16. The default duration is UNIF(10,15). For those patients who wait beyond the critical time, the process duration is changed in box 2 in the figure to UNIF(5,10). The default journey profile with no fast tracking is shown in Figure 8.17. With fast tracking set to a waiting time of 120 minutes, the resulting profile is shown in Figure 8.18.

Figure 8.16: Fast Track model

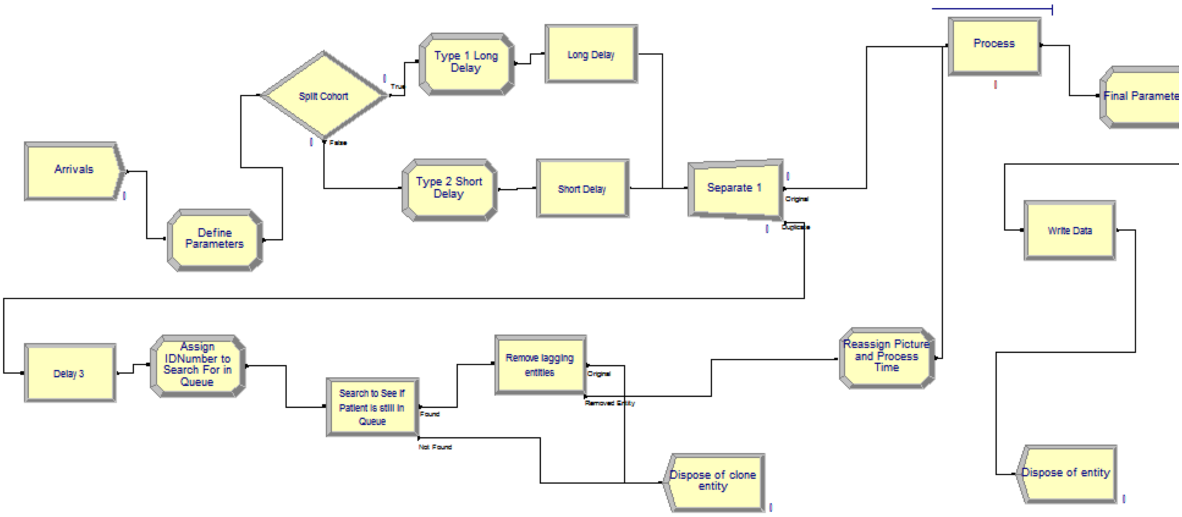


Figure 8.17: No Fast Tracking

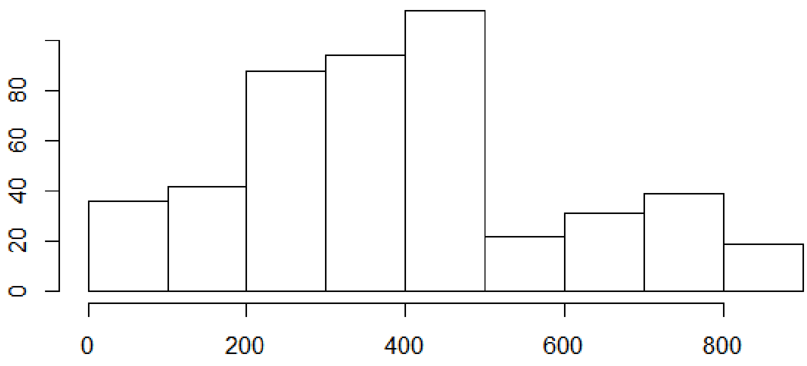
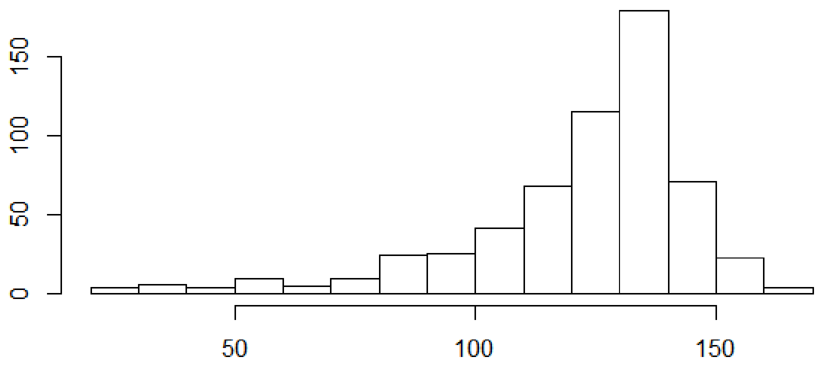


Figure 8.18: Fast-Tracking Triggered at 120 minutes



Note that not only does the shape of the distribution in Figure 8.18 resemble closely that found in the original data, but as expected, fast-tracking reduces considerably the average length of stay of the patients.

Note that fast-tracking can also be implemented by the introduction of a parallel process as shown in Figure 8.19. This requires an extra resource and should really be considered in Section 8.2. Nonetheless since the model is less complex that those considered in that section, and like that of the previous model has a common root in the model shown in Figure 8.1, it is considered here.

Figure 8.19: Parallel Process

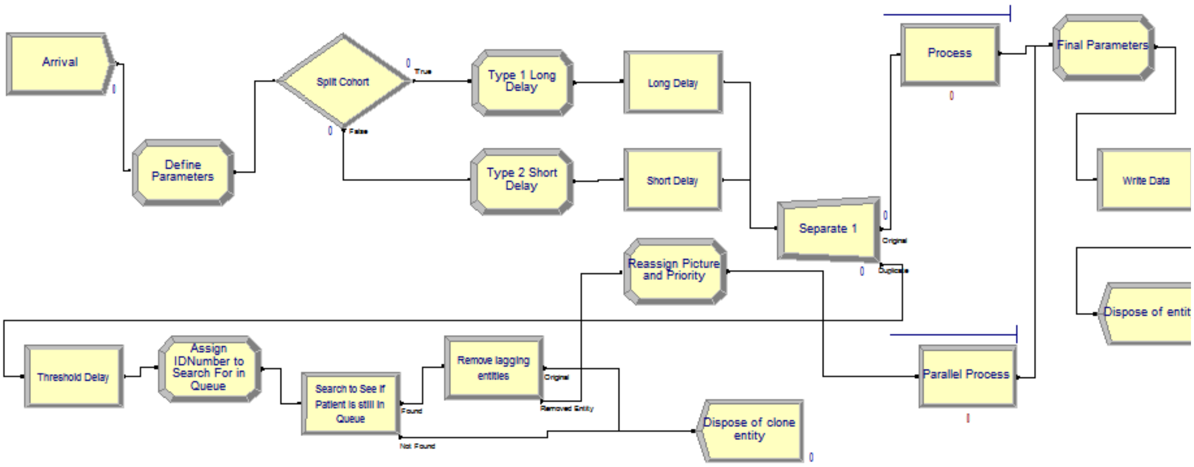


Figure 8.20: No Parallel Process

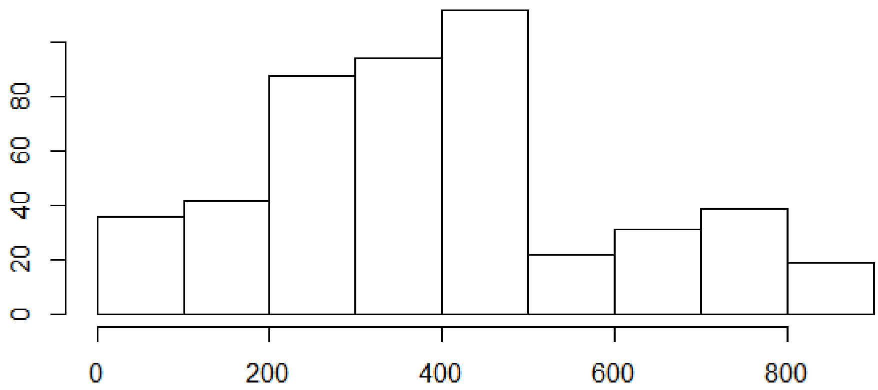
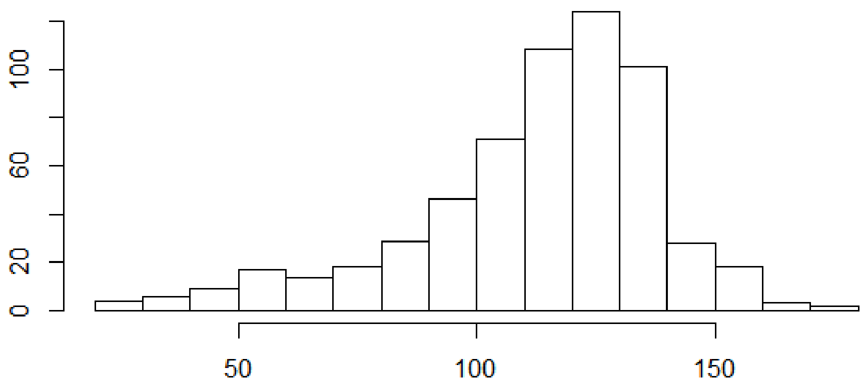


Figure 8.21: Parallel Process Triggered after 120 minutes



Data are shown in Figures 8.20 and 8.21 for the same parameters as Figures 8.17 and 8.18. The parallel model again shows a similar shape to that of the measured profile and as expected results in a shorter length of stay.

8.5 Comments and Conclusion

As reported in the literature (Eatock et al., 2011), the 4-hour deadline is difficult to model since in general and in the case of ED at MRI the implementation of the control is rather poorly defined.

With the simplified models described here, changing the patient priority makes very little difference to the journey profile and does not mimic the 4h “wall” encountered in practice. This is the case even over a range of delay times, trigger times and process times. In addition the patient priority is updated a great deal faster than that which is said to take place in MRI, which implies that updating the patient priority takes place only a few times.

The resource re-allocation models more closely mimic the recorded data from the ED, and the entity-removal model shows a closer relationship to the recorded data than the swap-sets model. Both the journey time and the waiting time distributions show the characteristic “wall” close to the set upper waiting time limit, although this is less pronounced in these simple models than it is in the ED data. The model also gives more of a long-time tail than is found in the recorded data, suggesting an overshoot of the upper control limit.

The parallel process model shows even closer agreement with the measured profile and should be seen as an extreme (one-way) version of the more general resource re-allocation model.

A fast-track model which of course is not practised in MRI, shows the closest resemblance to the ED data.

In a recent report (The Scottish Parliament, 2014), it was implied that the journey profiles through the ED may be changing over time. The Hillingdon data reported by Eatock (2011) were generated for 2011, while the data generated for this study at MRI applies to 2012. In fact, later data from Hillingdon (Eatock, 2015) does show a closer resemblance to the MRI data and exhibits no peak prior to the 4 hour wall. Thus far it has not been possible to obtain earlier data from MRI. However, should such data resemble the original data from Hillingdon then, taken together, the findings may well support the idea (The Scottish Parliament, 2014) that journey profiles are changing over time and is in effect suggesting that EDs are struggling to cope with the imposed 4-hour deadline.

CHAPTER 9 PRESENTATION AND ANALYSIS OF RESULTS

9.0 Introduction

Simulation allows the overall transformation to be quantified by calculating the transit time of the entity through the system, and the usage of the various resources. Also, the various outputs must be compared with reality. In chapter 7, two models; Base and Journey-path were described and simulated. In this chapter, the outputs from the models are presented and compared with the actual ED data.

In a typical model, the arrival rate, the various delays and the various process times are probabilistic. In order to establish statistically robust values for the various outputs the model has to be run many times (replications) (Kelton et al., 2006 Pg 79). Limits of estimates can be calculated from the replications using the central limit theorem (Altiok and Melamed, 2007 Pg 41, 172 - 176). This is built-in to Arena's reports for time-persistent variables and can be calculated for other parameters by saving data to one or more files. In the Base and Journey-Path models, the output data are saved in text files which are then imported into R for subsequent analysis.

During a simulation run, Arena takes all the summary results for specified output from each replication, average them over the replications, calculate the standard deviation, and finally calculate the *half width* of a 95% confidence interval on the expected value of this performance measure (Kelton et al., 2006 Pg 79). This is demonstrated in section 9.2 using R. If the replication length is not long enough, no half width is produced; instead messages such as "insufficient" and "correlated" will be displayed in the output. Data collected during the warm up period is not included in the half width computation and output report. After a simulation run, Arena provides statistic reports such as Category Overview (which is a summary of all replications), Category by replication, Entities, Queues, Processes, Resources and User specified. A SIMAN Summary Report (.out file) is also generated which includes relevant information for all replications. In this chapter, only specific parts of the Category Overview report are referred to. The complete reports are provided in the thesis CD.

The outputs from the simulation run for the Base model are presented in Section 9.1. In Section 9.2, the Arena summary report described above is compared with similar calculation in R. Journey times output from the base and journey-path models are compared with actual data from the ED in Section 9.3. The comparison is based on journey time distributions, percentiles and the Kolmogorov-Smirnov test. The Kolmogorov-Smirnov test determines if two datasets differ significantly (Stowell, 2014) and has the advantage of not making assumption about the distribution of data, therefore it is non-parametric and distribution free (Kirkman, 1996). In addition to the previous experiment in chapter 7, Section 9.4 verifies the arrival input parameter by care group and triage category. Resource utilization from the base model is compared to that of the actual data in Section 9.5. It is believed that this also applies to the journey-path model since the same resource input was used in both models. The chapter is summarized in Section 9.6.

9.1 Importing Datasets in R

From the models, time stamps of journeys and other attributes were recorded and saved in a text files. Figures 9.1 and 9.2 show the outputs for the Base and Journey-path model respectively. There are 12 recorded milestones in the Base model data which are outlined in Table 9.1. From Figure 9.2, the fields for the Journey-path model are similar to that of the Base model, except the omission of the Arrival mode, as this was not required for the model. The datasets were imported into R.

Figure 9.1: Base Model Dataset

PatientID	ArrivalMode	CareGroup	TriageCategory	ArrivalTime	TriageProcessTime	AreaProcessTime	ExitTime	JourneyTime	DischargeOutcome	Replication
3	Walk-in	Blue	4	5.387616	20.09363	0.00000	29.32019	23.93257	Discharged	1
17	Walk-in	Blue	4	53.275216	37.75915	0.00000	94.58780	41.31258	Discharged	1
2	Walk-in	GreenMIU	4	4.572379	14.16830	75.50906	97.00154	92.42916	Discharged	1
4	Walk-in	Amber	3	6.541035	22.08305	74.67575	108.21998	101.67894	Discharged	1
23	Walk-in	Blue	4	111.652849	11.94171	0.00000	127.62267	15.96982	Discharged	1
24	Walk-in	Blue	4	112.996981	12.77559	0.00000	129.25839	16.26141	Discharged	1
28	Walk-in	Blue	3	127.247543	21.51322	0.00000	150.82595	23.57841	Discharged	1
7	Walk-in	Green	4	17.007244	25.79904	115.54868	160.56201	143.55477	Discharged	1
6	Walk-in	Green	4	14.905971	24.98022	120.43480	163.68365	148.77768	Discharged	1
8	Ambulance	Green	4	21.177871	33.71209	116.74573	173.73796	152.56009	Discharged	1
1	Walk-in	Amber	2	1.999991	11.56796	101.93814	177.40651	175.40651	Admitted	1
11	Walk-in	Green	4	43.655005	23.15375	114.32221	183.30498	139.64997	Discharged	1
18	Walk-in	GreenMIU	3	54.184022	42.34404	84.68157	183.99340	129.80938	Discharged	1
13	Walk-in	Green	3	46.051232	21.93077	114.32221	185.44085	139.38962	Discharged	1
21	Walk-in	Green	3	68.807540	38.68224	83.15467	193.77644	124.96890	Discharged	1

Figure 9.2: Journey-Path Model Dataset

PatientID	CareGroup	TriageCategory	ArrivalTime	TriageProcessTime	AreaProcessTime	ExitTime	JourneyTime	DischargeOutcome	Replication
3	Blue	4	5.387616	11.79399	0.00000	27.25261	21.86499	Discharged	1
8	Blue	4	26.006514	12.52623	0.00000	52.32351	26.31699	Discharged	1
11	Blue	4	42.432417	13.06520	0.00000	65.38871	22.95629	Discharged	1
9	Amber	2	39.284908	14.20257	38.17587	92.91354	53.62864	Discharged	1
5	GreenMIU	4	8.171322	37.66461	63.87412	101.53873	93.36741	Discharged	1
2	GreenMIU	4	4.572379	11.37258	96.92028	112.86524	108.29286	Discharged	1
4	Green	2	6.541035	12.69967	106.23175	134.87638	128.33534	Discharged	1
6	Green	3	9.196653	12.54468	115.09823	154.89552	145.69886	Discharged	1
7	Green	3	12.644240	11.89047	115.09823	155.63333	142.98909	Discharged	1
14	Green	3	70.259444	13.41713	103.86360	187.54018	117.28073	Discharged	1
10	Green	3	41.421189	62.11964	132.11568	194.23532	152.81413	Discharged	1
16	GreenMIU	4	99.687031	13.40750	86.21665	199.31117	99.62414	Discharged	1
15	Blue	4	98.212700	14.04173	101.83460	214.08903	115.87633	Discharged	1
18	Amber	4	100.642070	12.21247	90.31815	214.78505	114.14298	Discharged	1
23	GreenMIU	4	131.638292	12.67320	78.74774	223.05923	91.42094	Discharged	1
19	Green	4	102.227970	13.48594	0.00000	227.03787	124.80990	Admitted	1

Table 9.1: Fields (Recorded Milestones) from Base Model Output

Patient ID	Triage Category	Area Process Time	Discharge Outcome
Arrival mode	Arrival Time	Exit Time	Replication
Care Group	Triage Process Time	Journey Time	

The fields in Figures 9.1 and 9.2 can be compared to the original data milestone in Table 6.1. Note that the "Patient ID" here represents the "Identifier" field in the original datasets. The Area process time is the time between the first process (consultation) and last (review/decision) in all care group areas. From Figure 9.1 note that the first two patients (#3 and #7), for example, have zero Area process durations. This is expected since they are blue patients (from the care group field), and most of them do not undergo ED processes (except patients who required admission). However in the journey-path model, this assumption was not made, so even discharged patients underwent ED processes, for example patient #15 in Figure 9.2.

9.2 Comparing Arena Summary Output with Calculation in R

It is important to verify the output from Arena to ensure that it is accurate. For example, the statistics from the particularly recorded journey times can be calculated in R and compared with the Arena outputs.

From the Arena summary result, journey time outputs for the base and journey-path models are provided in Appendix D. For instance, from the base model the average overall journey time is 191.9 minutes with a half width of 0.57, while for the journey-path model the average journey time is 176.03 ± 0.61 minutes. Clearly, the average journey time of the base model corresponds to that of the actual ED data (191.6 minutes) derived in chapter 6. These journey time statistics can also be derived in R. From the Table 9.2 which shows the summary from outputs of both calculations, it is evident that the outputs recorded by Arena are accurate. Note that the half-widths are based on the central limit theorem described in chapter 1.

However, comparing the means does not imply that the models represent the actual system. Consequently, it is necessary to compare the journeys for the models to that of the actual system. Histograms and percentiles of journey times and comparison using Kolmogorov-Smirnov test are employed.

Table 9.2: Journey Times Comparison between Arena Output and Analysis in R

(In Minutes)

Parameter	Arena Output for Base Model	Base Model Analysis	Arena Output for Journey-path Model	Journey-Path Analysis
Average	191.94	191.938	176.03	176.026
Half-width	0.57	0.574	0.61	0.613
Max Average	189.39	189.391	173.10	173.095
Min Average	196.84	196.840	179.26	179.261
Max Value	12.19	12.186	10.02	10.019
Min Value	1486.55	1486.547	1310.93	1310.932

9.3 Comparing Journeys

Figures 9.3[24], 9.4 and 9.5 display journey times for the actual data, base model and journey-path model for the whole cohort and by care group; which were plotted in R. These show that the journeys in the model are different from that of the actual system. The “wall” in the actual data is not represented in the outputs from models as a result of the exclusion of the four-hour procedure as described in chapter 8.

As described in chapter 7, most blue patients do not undergo treatments in the ED and are directed to the Primary Care Emergency Centre (PCEC) after triage. However, some patients who need emergency care are directed back to the ED. From the blue patients’ journeys in Figures 9.3, 9.4 and 9.5, the peak (first 20 minutes) in the actual data is more represented in the journey-path model output. This is probably because of the assumption made in the base model that only admitted patients return to the ED from the PCEC. It is can therefore be said that the journey-path model is a better representation of the actual system.

For completeness, Figure 9.6 shows the distribution by probability of arrivals for the actual system, base model and journey-path model which corresponds to their overall journey times (Figures 9.3, 9.4 and 9.5). Note the “peak” at the four-hour mark of the actual data and as expected, none for the model outputs.

[24] *This is the same histogram shown in chapter 6. This is replicated here for convenience purpose (ease of reach)*

Figure 9.3: Histograms of Journey Times (Overall and by Care Group) from Actual ED Data

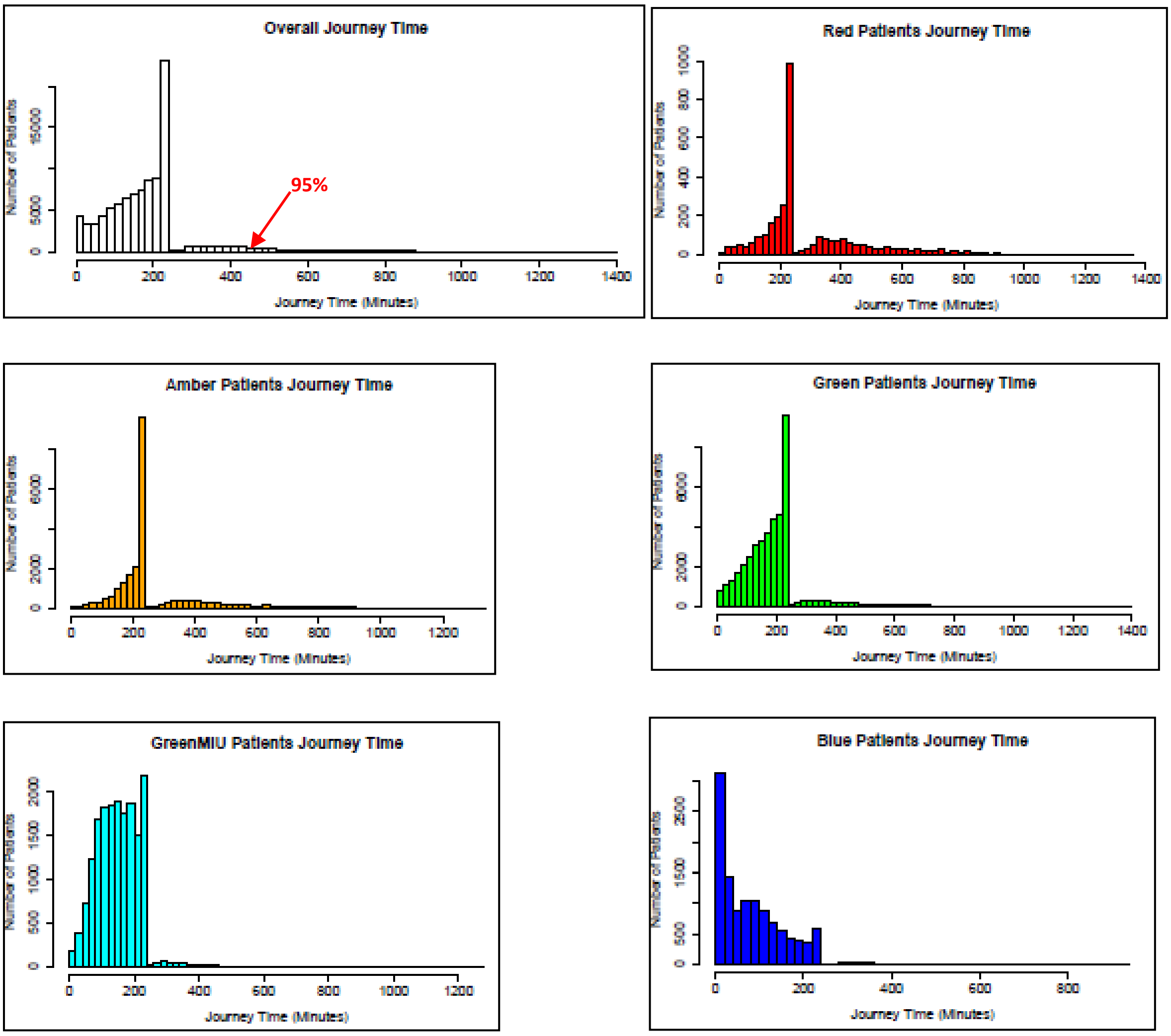


Figure 9.4: Histograms of Journey Times (Overall and by Care Group) from Base Model Simulation Output

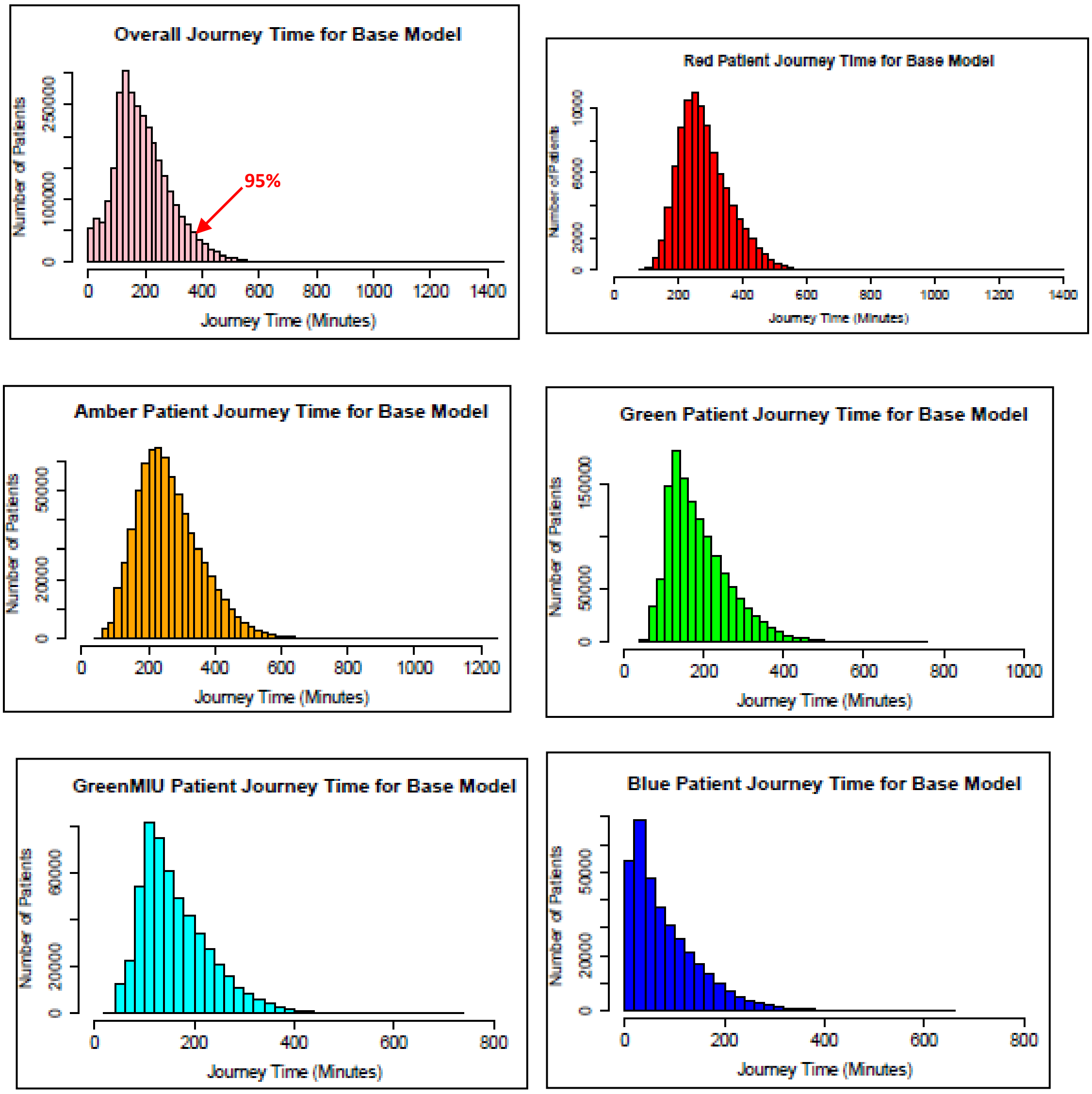


Figure 9.5: Histograms of Journey Time (Overall and Care Group) from Journey-path Model Output

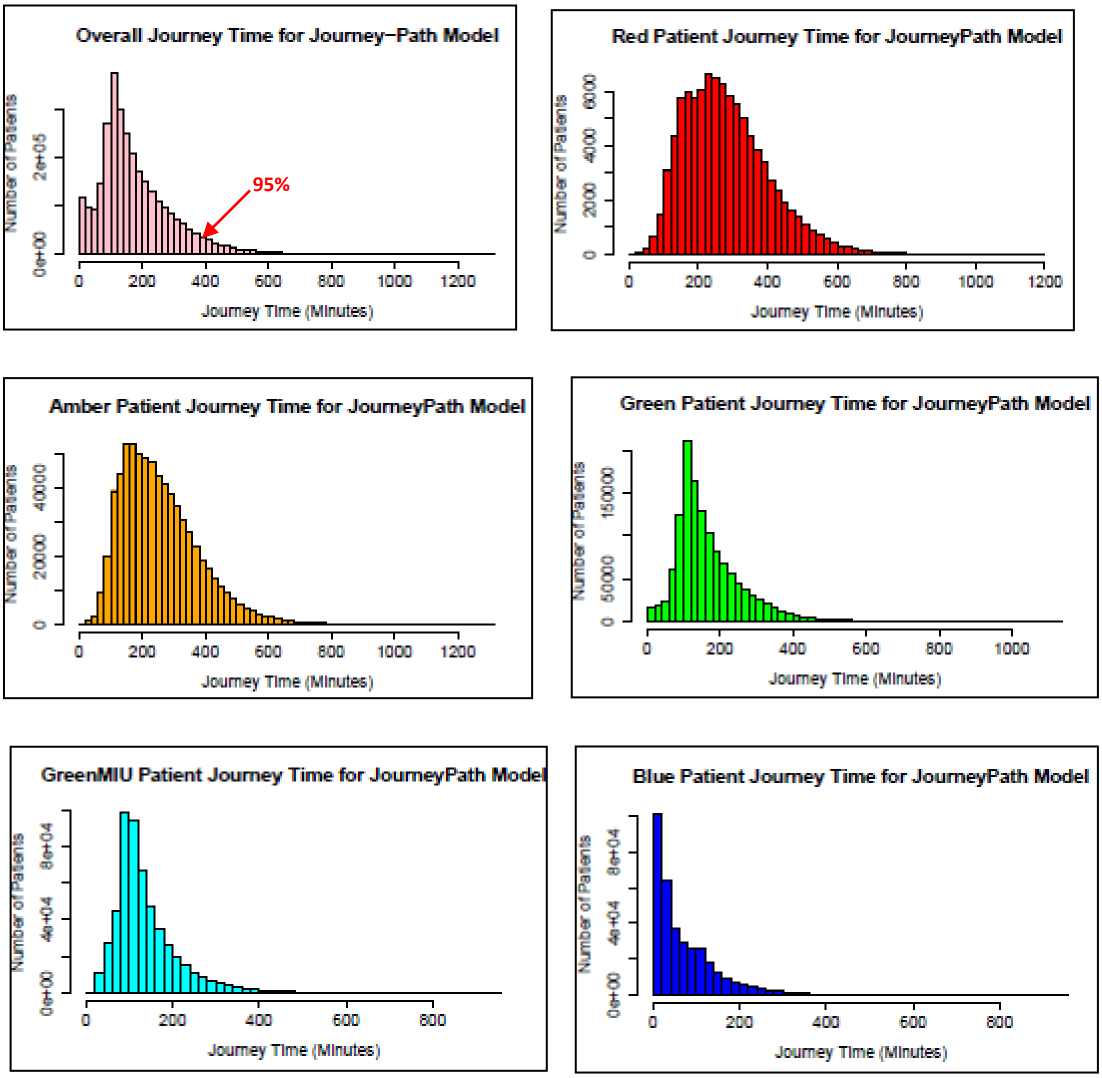
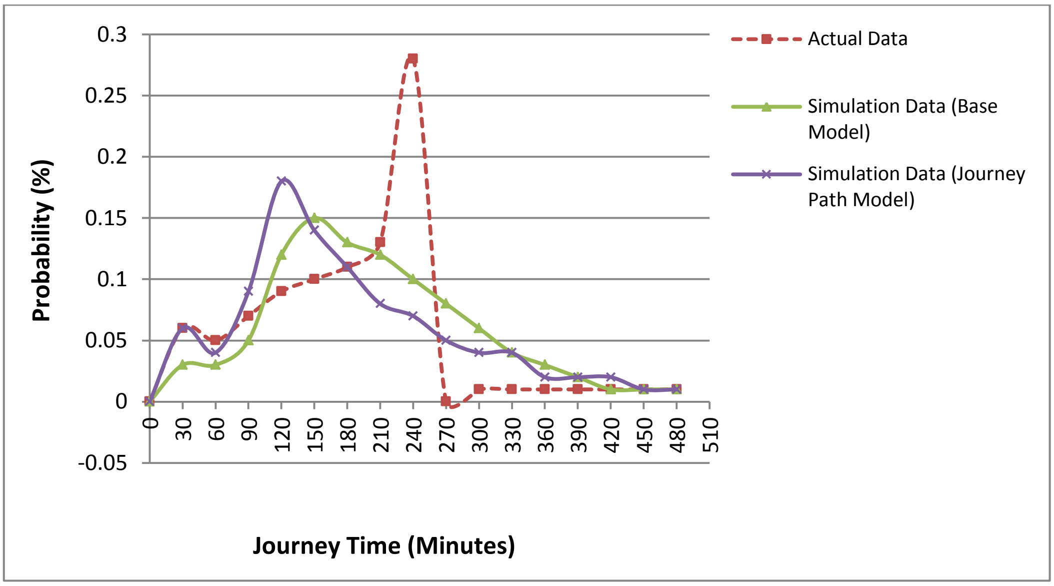


Figure 9.6: Comparing Journey Times by probability of attendance



In addition, a two-sample Kolmogorov-Smirnov test can be carried out for the various journey time outputs in order to determine if they are from the same distribution. The tests carried out are; Actual versus Base model, Actual versus Journey-path model and Journey-path model versus Base model. The test is carried out using the R function *ks.test()*. For instance, for the Actual and Base model journey times, the following is used;

```
# Actual versus Base model
>ks.test(PosActualEDJTime,BMOverallJourneyTime,alternative=c("two.sided","less","greater"),e
xact=NULL)
            Two-sample Kolmogorov-Smirnov test
data:  PosActualEDJTime and BMOverallJourneyTime
D = 0.1632, p-value < 2.2e-16
alternative hypothesis: two-sided

Warning message:
In ks.test(PosActualEDJTime, BMOverallJourneyTime, alternative = c("two.sided",  :
  p-value will be approximate in the presence of ties
```

All three tests showed similar output except the D values were different as shown in Table 9.3.

Table 9.3: Kolmogorov – Smirnov Test Results

K-S Test	D	p-value	Hypothesis
Actual versus Base	0.1632	< 2.2e-16	Two-sided
Actual versus Journey-path	0.1485		
Journey-path versus Base	0.1310		

In the K-S test, the null hypothesis H_0 is that the specified datasets do not differ significantly, while the alternative hypothesis H_1 is that they are different (Stowell, 2014 Pg 68). In R, the alternative hypothesis: *"two-sided"* means that the null hypothesis is true (Kerns, 2011, Stowell, 2014). The D value is the maximum distance between the distributions of both datasets. Note that the smaller the value of D, the better the correlation of the two distributions (Kirkman, 1996). This is not the important number, the p-value is.

In order to accept the alternative hypothesis, the p-value must be > 0.05 (MacFarland, 2014 Pg 66). However, large values do not confirm H_0, they merely fail to demonstrate evidence against it (Kirkman, 1996). From Table 9.3, the p-value is significantly low (< 2.2e-16) for all three tests which could imply that the journey time distributions do not match. This is probably due to the variability or the shape of the distribution of the journey times (Figure 9.6).

Note that the warning message shown in the R output implies that the two datasets have similar values, thus the p-value may not be exact (Stowell, 2014 Pg 68).

9.4 Comparing Attendances (for verification of input parameters)

Following the arrival input experiment carried out in Chapter 7, patients' attendances can also be compared. Since the inputs are the same for the base and journey-path model, only one of them (base) is used for this analysis. The attendance by Triage category and Care group for the actual and base model data are as shown in Tables 9.4 and 9.5 respectively. Note the similarities, which imply that the model inputs are accurate.

Table 9.4: Percentage attendance by Care Group and Triage Category from ED Data

	Percentage (%)				
	1	**2**	**3**	**4**	**5**
Red	18.57	73.75	7.07	0.61	0.00
Amber	0.19	33.70	56.17	9.91	0.02
Green	0.02	5.46	43.78	50.22	0.53
Green/MIU	0.01	0.90	16.15	82.71	0.23
Blue	0.00	0.25	6.05	90.30	3.40

Table 9.5: Percentage attendance by Care Group and Triage Category from Simulated Data of Base Model

	Percentage (%)				
	1	**2**	**3**	**4**	**5**
Red	18.47	73.81	7.14	0.59	0.00
Amber	0.18	33.76	56.14	9.89	0.03
Green	0.02	5.48	43.74	50.25	0.52
Green/MIU	0.01	0.92	16.11	82.73	0.23
Blue	0.00	0.26	6.08	90.28	3.38

Figure 9.7 shows an average of 267 patients' attendance per day from the Arena summary report of the base model which is close when compared with the ED data (269 patients). This is the same for the journey-path model (see Thesis CD for all the Arena output reports).

Figure 9.7: Daily Throughput Base Model Simulation Output

Output	Average	Half Width	Minimum Average	Maximum Average
Daily Throughput	266.79	0.34	265.04	269.27

9.5 Comparing Resources

Figure 9.8 and 9.9 can also be used for verification of the model. Figure 9.8 shows Arena summary for the number of scheduled doctors for the base model, which corresponds to the shift patterns described in Chapters 6-7. Note that Doc_1, Doc_2 and Doc_3 work 24 hours a day based on the data, hence they have a capacity of 1. Also, Doc_14 is scheduled for 1 hour per day, which corresponds to a capacity of 0.041.

The scheduled utilization can be compared to the actual data to verify the model, using the formula $\rho = \lambda/\mu$ (Altiok and Melamed, 2007 Pg 74). Where ρ is the utilization, λ is the arrival rate, and μ is the processing rate. From chapter 7, Doc_6 is scheduled to treat Amber patients only and they are scheduled for 24 hours a day. Therefore for simplicity, Doc_6 will be used for the verification. From Figure 9.8, the utilization of Doc_6 is 0.62. There are 64 Amber arrivals per day, thus the arrival rate is 0.0156. The maximum time duration for consultation and review/decision process is 40 (25+15) minutes, so the processing rate 0.025. Indeed, the ratio is 0.624 which is close to the simulation output indicated in Figure 9.9. This could also be applied to other resources.

Figure 9.8: Simulation result for Number of Scheduled doctors for Base Model

Number Scheduled	Average	Half Width	Minimum Average	Maximum Average
Doc_12	0.1221	0.00	0.1219	0.1225
Doc_13	0.04054044	0.00	0.04041096	0.04063927
Doc_14	0.04155251	0.00	0.04155251	0.04155251
Doc_2	1.0000	0.00	1.0000	1.0000
Doc_3	1.0000	0.00	1.0000	1.0000
Doc_4	0.7497	0.00	0.7496	0.7499
Doc_5	0.5830	0.00	0.5828	0.5831
Doc_6	1.0000	0.00	1.0000	1.0000
Doc_7	0.6522	0.00	0.6508	0.6544
Doc_8	0.2493	0.00	0.2493	0.2493
Doc_9	0.4074	0.00	0.4064	0.4085

Figure 9.9: Simulation result for Utilization of Scheduled doctors for Base Model

Scheduled Utilization	Average	Half Width	Minimum Average	Maximum Average
Doc_12	0.8165	0.01	0.7816	0.8504
Doc_13	1.1181	0.01	1.0450	1.2375
Doc_14	0.3524	0.01	0.3096	0.4184
Doc_2	0.5491	0.00	0.5340	0.5626
Doc_3	0.7419	0.00	0.7311	0.7586
Doc_4	0.02780920	0.00	0.02475829	0.03061950
Doc_5	0.06664565	0.00	0.06038202	0.07254914
Doc_6	0.6205	0.00	0.6014	0.6353
Doc_7	0.7466	0.00	0.7372	0.7572
Doc_8	0.4582	0.01	0.4028	0.5234
Doc_9	0.7543	0.00	0.7411	0.7750

9.6 Comments and Conclusion

Simulation outputs from the Base and Journey-Path models have been presented and analysed. They have also been compared to the original data from the emergency department. This chapter provided quantifiable evidence that the data inputted were accurate. Due to the absence of the 4-hour procedure, the models do not exactly represent the actual system, however evidence in this chapter show that the activities, throughputs and resource utilization in the models and the real facility are in agreement. It could therefore be said that the models are a crude representation of the actual system.

The absence of the 4-hour "wall" in the blue cohort from the actual data shows that there is less implementation of the four-hour procedure for this cohort. The Journey-Path model showed a better fit for the blue patients than the base model when compared with the actual data. This suggests that, perhaps, the use of evidence-based data is better than anecdotal-based ones.

CHAPTER 10 DISCUSSION, CONCLUSION, AND FUTURE WORK

10.0 Introduction

In this study, literature review on Simulation and Modelling in healthcare systems including description of Discrete Event Simulation (DES), System Dynamic (SD) and Agent-based simulation (ABS) were provided in Chapter 2. Literature review were also carried out on the healthcare systems in the UK, Nigeria and overseas as presented in Chapter 3. A comparative report on experiences for visits made to University of Benin Teaching Hospital and Manchester Royal Infirmary were described in Chapter 4. A major part of this work was the data collection and analysis in R for both hospitals which were presented in Chapters 5 and 6. Specific parts of the analysed MRI data were compared to the Hospital Episode Statistics reports (2014a, 2013). Two models were described and created in chapter 7, which did not incorporate the four hour deadline. Detailed description of this disparity is provided in Chapter 8. In chapter 9, the simulation outputs from the Base and Journey-path models were presented and analysed.

In this chapter, various findings from this study are discussed in Section 10.1 and conclusions are made in Section 10.2. Future works are outlined in Section 10.3. Some points highlighted in this chapter are also described in the Festival of Evidence Conference (Cumberland Initiative) by Methven et al. (2014)

10.1 Discussion

Data analysis was a key part of this research. The technique used to analyse the data required special coding skills and good understanding of R. The process was time consuming and more tedious than anticipated.

Raw data for patient journeys, locations, investigations and test orders for the 98,236 patients who attended ED at MRI during the 12-month period between April 2012 and March 2013 were provided as spreadsheets. From this data, statistics including inter-arrival times by time of day and weekday, care group assignment and triage category population, breakdown of triage complaints and test orders, total journey times and mutually exclusive paths through the system, were calculated; all of which is key to building a computer model. Patient cohorts, journeys and location visits were determined for a range of classifications by manipulating the raw data in R.

A major focus of the work was to identify journeys through the system, that is to say, the sequence of visits for each patient to any or all of red areas, rapid assessment rooms, assessment rooms, treatment rooms, cubicles, etc. Journeys were generated by collecting and sorting the timestamps for each visit and finally expressed as ordered text strings which were then further analysed by regular expression searches. As well as enabling the patient count for each unique journey to be related to, for example, the relevant care group, the probabilities of mutually exclusive journeys through the system were calculated. However, duration for ED procedures which are undergone in the various locations were not recorded.

In a typical manufacturing or assembly enterprise, the transformation of raw material into a finished product is accomplished by performing a sequence operations, each of which is allocated resources such as time, machines and operators (Altiok and Melamed, 2007, Jahangirian et al., 2010a). On this level an ED is exactly the same albeit that the raw material is an ill individual which arrives at a varying rate and is itself not constant. Here, the sequence of operations, (the journeys), are determined by care groups which are assigned at triage. Journeys differ only in the number, order and frequency of the visits to various locations and it ends only when stability (discharge outcome) is achieved. In the industrial context every operation has a duration, which is either fixed or is described by a particular "skill-based" time distribution.

By contrast in the ED only time-stamps for arrival at each location are recorded, but there is no record of the duration of tasks such as consultation, treatment and review which take place at these locations. No business could plan for the future, consider expansion or even survive using this approach, yet Government assumes there is sufficient knowledge in and control of ED systems for them to be able to meet standards which include cost minimisation, a minimum re-attendance rate within a prescribed period (within 28 days) after discharge, a satisfaction score that reflects the degree of stress experienced by patients on their journey through the system, and most importantly 95% of patients not exceeding 4-hours in the ED (Department of Health, 2013, NHS England, 2013).

From the MRI data analysis (Chapter 6), the ED sees approximately 269 patients per day. Mondays are the busiest day of the week, while Saturdays are the less busy days. Most patients are seen between 10am and 12noon. 11 out of 100 patients spend more than 4 hours in the ED, irrespective of the severity of their ailment. However, Amber patients are more likely to spend more than 4 hours. Also, 28% of patients who are admitted into the hospital are most likely to exceed 4 hours. This may indicate the long waiting time for a bed. This could also be due to patients requiring more treatment or uncertainty about diagnosis or treatment (Gunal and Pidd, 2009). In MRI, a patient could wait up to 13.5 hours for a bed. The analysis also shows that bed waiting time dramatically increases the journey time of patients. For MRI, 71 beds are required in the ED daily for hospital admission. Discharge outcomes are based on doctors' medical expertise.

The use of more experienced doctors for Review/ Decision process at MRI may prioritize discharge activities more effectively, and thus improve patient flow (Emeny, 2013).

Evidence shows that, about 21% of patients who attend the ED of MRI present with Limb problem (Chapter 6). It may probably be worth creating a Unit specifically for this purpose. In MRI, 1 out of 5 patients who attend the ED require tests and there are 355 unique tests carried out in a year. It was interesting to find that 90% of patients who require test use only 15 of these tests. This is one instance of the complexity of the ED.

It has been shown that data recorded routinely in the ED can be manipulated to form a key element of a general DES model. However the absence of any recorded durations of visits to the various locations on a patient's journey means that input is required from clinicians and other medical staff before the model is complete. This input, no matter how accurate, is anecdotal, and makes any derived DES model bespoke rather than general. Furthermore, it is surprising that with the increasing rate of healthcare simulation modelling in literature (Ingalls, 2002, McHaney et al., 2002, Wilson, 1981), there is no information on durations for procedures, which is a huge part of a successful simulation study. For instance, in this study, processing times were obtained from the ED consultant, Dr Richard Body. These durations were ball-park figures of triangular and uniform distributions which may not be reliable. There is no detail on duration for medical procedures in literature to confirm them, and therefore there is no choice but to utilize the available source of information. It is necessary in future for medical personnel to publish quantified duration of skill-based procedures, thereby minimizing the dependency on such information from ED staff.

In MRI, patients' data are recorded by ED staff via Symphony®. This work shows that the data exhibit incompleteness and complexity. The most revealing part is the number of journeys patients go through the system. For example, there were a total of 936 unique journeys as described in chapter 6. Also, there was high disparity in the journeys. For example, of the 103 unique journeys for the Red cohort, 94% of the patients represent only 14 of these journeys. This is also the case for the Triage Complaints cohort. These disparities show the complexity of the ED and journeys are probably inter-dependent. Furthermore, journeys include what appear to be waiting-only paths which do not include any locations such as Assessment Room, a Treatment Room or a Cubicle. This applies particularly to Blue/PC patients (96%) but also to 67% of the Green Patients and to 88% of the Green/MIU patients (Chapter 6). In fact, these journeys are not logged and in practice patients are treated in Cubicles. However, this is not apparent from the data provided.

Two models of MRI were created and described in Chapter 7 called the Base and Journey-Path models. As previously stated, the Base model takes account of anecdotal information from ED staff, while the Journey-Path model is less reliance on ED staff and focuses on actual patients' journeys. Throughout the development of the models, the techniques for verification and validation were employed as described by Kelton et al. (2006 Pg 547). All input parameters were verified by ED staffs before utilizing them for the models. At the initial stage of this work, the ED staff indicated that the key resources in the department were doctors, nurses and "available space" which could be cubicles, rooms, ED beds or trolleys. These resources including others such as radiology room were incorporated in the models as shown in Chapter 7. Doctors' schedule which was obtained from a-month ED rota was also taken account of. The scheduled utilization from the simulation run was compared to that expected in the ED in Chapter 9 and both showed close similarity. It is assumed that the other resources are also accurate.

Other important features of the system captured by the models include non-stationary arrivals, queue priority among patients, multi-tasking of doctors and nurses, and variable processing times depending on the seriousness of a patient's condition. For instance, the multi-tasking behaviour of doctors is represented in their release for treatment by nurse (or for X-ray in the Green/MIU area) after consultation. They then go to see another patient in a "different" location and returns to review the previous one. This previous patient is given priority over other patients in the area since they have been there longer. This is demonstrated by assigning a queue priority to them. Also, repeated checks were made to ensure a previously seized doctor was still available in the ED to carry out the Review process, since they may not be scheduled at the time the patient is required to undergo the procedure. Another multi-tasking example is the addition of RAU nurse to carry out triage at busy times. Also, the "care for" role of nurses described in Chapter 7 allowed for one nurse to treat multiple patients at a time. Patients' arrival was modelled based on their rate of attendance by day of week and hour of day. Processing times were obtained from Dr Richard Body. Most of the time procedures used were triangular distributions, while others were uniform. In particular, the registration, triage, consultation, treatment and Bed delay times were the former, while the review and tests durations were the later.

From the histograms in Chapter 6, the "wall" on the 4-hour mark shows that there are strategic measures used by ED staff to ensure that patients' length of stay do not exceed this timeline. This has also been proven by Gunal and Pidd (2009) who compared two emergency departments and found one to be involve in a "gaming" measure to ensure they meet the NHS standards. This work shows that most patients (irrespective of their discharge outcome) are discharged before the deadline. Therefore, it is believed that MRI is not involved in such “gaming” measure described by Gunal and Pidd (2009) to admit patients into hospital as inpatients in order to meet the target.

According to Dr Body, the 4-hour target is not achieved by diverting patients to a parallel or *fast-track* operation which has a shorter process duration or has resources with increased capacity (due to experience), however more information on the procedure was not provided. There is no doubt that the technique used in practise is difficult to model, and studies (Eatock et al., 2011, Wolstenholme et al., 2007) are in agreement. Given this, a proposed procedure on how to model the 4-hour deadline has been described in Chapter 8 which involves swapping, re-allocation of doctors and redirecting patient entities. Alternative ways have been described by Eatock et al. (2011) and Jajo and Matawie (2014). Eatock et al. used a fast-track system where patient who have the possibility of exceeding the four-hours are diverted to an alternative path. Jajo and Matawie (2014) illustrated the use of dynamic modelling of resources. This method models resources as entities, holding them in a queue and releasing them for a procedure, after which they return to the queue until required. However, due to vagueness of evidence provided by ED staff at MRI, this aspect of the ED is not incorporated in the model which is evident in the simulation outputs for patient journeys shown in Chapter 9. Further investigation will be carried out in future study.

Emergency Department processing times vary because there are many variables to be accounted for and many different scenarios and conditions to be considered. For instance, from this work, there are 53 different complaints presented by patients who attend the ED, and of course each complaint has a distinct process time duration. This variability in processing times increases the complexity of the system. Another reason for the limitation of the model could be the processing time input. Even studies (Eatock et al., 2011) that took account of the 4-hour strategy did not include any duration for procedures described. Consequently, there was no evidence to back up the viability of the information provided by Dr Body.

10.2 Conclusion

This work has compared the procedures used in the Emergency Departments in the University of Benin Teaching Hospital in Nigeria (UBTH) and in the Manchester Royal Infirmary (MRI) in the UK. It has also created a discrete event model of the latter in Rockwell Arena®.

The work has highlighted the contrast between the predominantly qualitative and scant information from UBTH and the quantitative and comprehensive information from MRI and has attempted to create a template that describes the information from any ED that is necessary and sufficient to create a robust model of the system.

The ED at UBTH is well staffed, well equipped and appears to cope well with the current demand. However, the recording of patient journeys through the ED and the maintenance of patient records from ED are very poor. It is argued this could be improved to the level of that in MRI by the introduction of Electronic Health Records (ERHs). Given that Nigeria is ranked as the largest and fastest growing telecoms market in Africa, it is surprising that this need has not yet been met. The introduction of E-learning programmes in certain regions of Nigeria may well encourage the more widespread implementation of computer-based technology but this will take time to develop. In the meantime it is proposed that the existing paper based approach to the recoding and maintenance of patient data in the ED is modified so that patient's records remain with the patient throughout their journey. It is also proposed that record-keeping is recognised as an important function within ED rather than as it appears to be, something of no real value.

Compared with the formalism and protocols required for access to patient data in MRI, there was far greater accessibility granted to the author in UBTH to the extent that she was able to track patients directly in the ED to gather data. By contrast the comprehensive and quantitative data from MRI should provide all the information required to generate a robust model of the system. In addition since the NHS imposes a common set of targets on all UK Emergency Departments, any model which is derived from the ED at MRI is likely to have at least some features that are generally applicable.

It was intended that the MRI model be based exclusively on documented information from historic patient journeys and from staffing and resource data, rather than be based on anecdotal evidence from clinicians and other hospital staff. In order to accomplish this, much of this work focuses on the analysis and the interpretation of the available data and identifies patterns and connections amongst cohorts of patients with common attributes such as triage complaint, care group, etc.

This approach led to the creation of the “journey-path” model of the system which generated time-ordered sequences of the locations and the events which each patient was subjected to on their journey through ED. From these a set of unique journeys were generated. The journey strings were combined (concatenated) to produce a single string which was then split into paired “from-to” sequences. From a count of each pair it was possible to generate a transition matrix for the ED which quantified the probabilities of a patient at a particular location proceeding to any other location in the system. In effect the transition matrix reflects all the decisions which were made (A to B, B to X etc.) at each step of the patient's journey through the system. The spread (number) of destinations from a particular source reflects the options available at a particular instant in time (or a measure of the difficulty in making a decision), while the size of each probability reflects the preferred destination. Taken over a patient's journey, the coefficients of the transition matrix, together with the duration and resource requirement of each pair's destination, is in effect, a process map for that patient through the ED. It is believed that this is an original contribution.

This approach is flawed only because durations of all tasks on a patient's journey are currently not recorded in the ED. This key information is available only anecdotally by consultation with clinicians. By any standard this is a serious and unaccountable omission but one which appears to be common in emergency departments throughout the UK. It is essential that the NHS consider the use of automatic tracking such as RFID tags, bar codes and other electronic devices sooner rather than later.

In the final model of the ED at MRI, the constraint imposed by the 4 hour deadline was not implemented. The decision to omit this in the full model was taken because its implementation in MRI was rather vague and difficult to interpret. Nonetheless some simpler models were developed and analysed in order to explore different approaches to the general idea of speeding patients who were liable to miss the deadline through the system. The approaches included increasing the queue priority of a patient who had been in the system beyond a particular length of stay (called a trigger time), increasing and reducing the resources which process queues in the system according to the prevailing queue length and the trigger time of patients in the queue, and finally fast-tracking patients within the system beyond a trigger time though a parallel (faster) process. According to the clinicians in the ED at MRI this latter procedure does not take place. For the simple models the closest agreement with the measured 4-hour "wall" was the fast –track system. The next best was the resource re-allocation model and the poorest model was that which involved only the alteration of queue priority. It is proposed that this aspect of the work is further explored in a continuing study.

There was some evidence to support the notion that journey profiles are changing over time by comparing data for different calendar years, and are in effect suggesting that EDs are struggling to cope with the imposed deadline. This too, will be pursued as part of the continuing study.

10.3 Future work

The following are proposed future studies;

- Pursue the handling of the 4-hour deadline both as a generic constraint in terms of queue priorities, resource allocation etc., and in particular to apply this to the ED at MRI
- Pursue the proposal of changing journey time profiles by seeking earlier data from MRI
- Pursue the transition matrix procedure developed in this work as a general approach to the manipulation of data which can be used to generate a DES model
- Purse the ideas proposed here for a revision of the data gathering and record maintenance procedures in ED at UBTH
- Explore the potential for the introduction of RFID tagging in ED departments in the UK so that future models can be exclusively evidence-based rather than have to rely on anecdotal input from medical staff
- Carry out sensitivity analyses such as adding one or more resource such as triage nurse, RAU trolleys, cubicles and examining how doubling the arrival rate will affect the system. In effect to see how the system responds to extreme loading
- Investigate the effect of changing the model so that Green and Green/MIU patients go directly to the Primary Care Emergency Centre (PCEC) on the basis that Green and Green/MIU have the highest attendance rate in the emergency department.
- Create an animation of the ED model as a means of making the analysis more accessible to NHS managers, stakeholders and the public.
- Incorporate major trauma incidents in the model

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APPENDICES

Appendix A: Clarification of the Central Limit Theorem

The mean of replication i is $\bar{x}_i$

The number of replications is N

The average of the averages is $\tilde{x} = \frac{1}{N}\sum_{i=i}^{N}\bar{x}_i$

The variance of ALL the replications is

$$S_{Total}^2 = \frac{1}{N-1}\sum_{i=i}^{N}\left[\bar{x}_i - \tilde{x}\right]^2$$

The Standard Error is $SE = \frac{S_{Total}}{N}$

Appendix B: Specific Journeys for Amber, Green, Green MIU and Blue Patients by mode of arrival

Table B1: Selected Journeys for Amber Care Group

Amber Ambulance	Count	Probability (%)	Amber Non-Ambulance	Count	Probability (%)
RAU, Assess	10129	76.18	Assess	4670	56.48
Assess	708	5.32	RAU, Assess	639	7.73
RAU	898	6.75	WR	1303	15.76
RAU, Red	437	3.29	Cub	504	6.10
RAU, Assess, Red	521	3.92	T	233	2.82
RAU, Cub	293	2.20	Red	244	2.95
RAU, T	153	1.15	Cub, Assess	144	1.74
Red	87	0.65	T, Assess	98	1.19
Red, Assess	71	0.53	Red, Assess	239	2.89
			RAU, Red	86	1.04
			WIC	47	0.57
			RAU, Red,	35	0.42
			T, Cub	27	0.33

Table B2: Selected Journeys for Green Care Group

Green Ambulance	Count	Probability (%)	Green Non-Ambulance	Count	Probability (%)
WR	4289	41.91	WR	21399	70.60
RAU	1694	16.55	Cub	2957	9.76
RAU, Assess	717	7.01	T	1595	5.26
Cub	865	8.45	Assess	1125	3.71
T	610	5.96	WIC	2068	6.82
MH	338	3.30	MH	206	0.68
MH, T	222	2.17	Cub, Assess	215	0.71
RAU, Cub	346	3.38	GMIU	151	0.50
RAU, T	221	2.16	Cub, T	192	0.63
GMIU, T	100	0.98	T, Assess	75	0.25
Assess	153	1.49	Red	72	0.24
GMIU, Cub	96	0.94	MH, T	84	0.28
WIC	165	1.61	Red, Assess	55	0.18
GMIU	130	1.27	WIC, Cub	29	0.10
T, Cub	149	1.46	RAU	22	0.07
RAU, GMIU, Cub	37	0.36	RAU, Assess	18	0.06
RAU, MH	31	0.30	Cub, Red	18	0.06
Cub, Assess	29	0.28	GMIU, Cub	21	0.07
RAU, GMIU	22	0.21	T, GMIU	10	0.03
RAU, Red	21	0.21			

Table B3: Selected Journeys for Green/MIU Care Group

Green/MIU Ambulance	Count	Probability (%)	Green/MIU Non-Ambulance	Count	Probability (%)
WR	725	58.85	WR	13857	87.13
Cub	157	12.74	Cub	1136	7.14
RAU	52	4.22	WIC	618	3.89
RAU, Cub	50	4.06	T	122	0.77
T	50	4.06	GMIU	49	0.31
GMIU, Cub	27	2.19	Red	43	0.27
RAU, Assess	24	1.95	Assess	26	0.16
RAU, GMIU, Cub	23	1.87	Cub, Assess	13	0.08
GMIU	46	3.73	T, Cub	11	0.07
RAU, T	18	1.46	Cub, Red	12	0.08
GMIU, T	10	0.81	Red, Assess	6	0.04
Cub, T	10	0.81	WIC, Cub	6	0.04
RAU, Red	9	0.73	RAU, Assess	5	0.03
RAU, GMIU	8	0.65			
T, Cub	8	0.65			
RAU, Cub, T	7	0.57			
Assess	4	0.32			
WIC	4	0.32			

Table B4: Selected Journeys for Blue Care Group

Blue Ambulance	Count	Probability (%)	Blue Non-Ambulance	Count	Probability (%)
WIC	980	78.03	WIC	9146	89.81
WR	114	9.08	WR	816	8.01
RAU, WIC	76	6.05	WIC, Cub	81	0.80
WIC, Cub	38	3.03	Cub	41	0.40
Cub	12	0.96	WIC, Assess	34	0.33
RAU	8	0.64	WIC,T	25	0.25
WIC, Assess	8	0.64	T	13	0.13
WIC, T	6	0.48	WIC, Cub, Assess	5	0.05
T	3	0.24	WIC, GMIU	9	0.09
RAU, WR, Cub	3	0.24	Assess	4	0.04
WR, Assess	2	0.16	WIC, T, Cub	4	0.04
RAU, Assess	2	0.16	RAU, Assess	3	0.03
WR, Red	2	0.16	Cub, Assess	3	0.03
WIC, Cub, Assess	2	0.16			

Appendix C: Comparison of 5 level Triage Scales (Kantonen et al., 2012)

Table C1: ABCDE, the Emergency Severity Index (ESI), the Canadian Triage and Acuity Scale (CTAS), the Manchester Triage System (MTS) and the Australasian Triage Scale (ATS)

	Primary Health care ED	Hospital ED	Validity and Reliability Research	Vital signs	Acuity-based	Resource-based
ABCDE	X	-	-	-	X	-
ESI	-	X	X	X	X	X
MTS	-	X	X	X	X	-
CTAS	-	X	X	X	X	-
ATS	-	X	X	X	X	-

Appendix D: Particular Arena Summary Outputs

Figure D.1: Arena Summary Output for particular Journey Time Statistics from Base Model Simulation Output

User Specified

Tally

Between	Average	Half Width	Minimum Average	Maximum Average	Minimum Value	Maximum Value
Record Interarrival Time	5.3380	0.01	5.2872	5.3726	0.00000036	188.41

Interval	Average	Half Width	Minimum Average	Maximum Average	Minimum Value	Maximum Value
Record Admitted Amber Patient Journey Time	296.61	1.24	290.38	303.51	79.1370	1486.55
Record Admitted Blue Patient Journey Time	257.37	1.64	247.03	263.61	91.1772	653.20
Record Admitted Green Patient Journey Time	250.28	0.65	246.46	253.96	80.7178	759.96
Record Admitted GreenMIU Patient Journey Time	239.45	1.37	230.77	246.02	71.1364	730.86
Record Admitted Red Patient Journey Time	298.88	0.57	296.28	302.40	110.93	1386.53
Record all Admitted Patient Journey Time	279.58	0.85	274.90	285.12	71.1364	1486.55
Record all Amber Patient Journey Time	264.54	1.15	258.74	271.45	46.7133	1486.55
Record all Blue Patient Journey Time	84.8351	0.51	82.6934	87.8817	12.1859	653.20
Record all Green Patient Journey Time	186.69	0.55	184.40	190.68	44.7991	759.96
Record all GreenMIU Patient Journey Time	162.28	0.50	160.22	166.50	33.5099	730.86
Record all Patient Journey Time	191.94	0.57	189.39	196.84	12.1859	1486.55
Record all Red Patient Journey Time	281.15	0.51	278.59	284.79	92.4165	1386.53
Record all Unadmitted Patient Journey Time	160.15	0.53	158.33	164.94	12.1859	1371.84
Record Unadmitted Amber Patient Journey Time	216.87	1.08	210.65	223.36	46.7133	1371.84
Record Unadmitted Blue Patient Journey Time	77.4541	0.49	75.9199	80.8448	12.1859	564.29
Record Unadmitted Green Patient Journey Time	170.76	0.55	168.52	175.18	44.7991	692.97
Record Unadmitted GreenMIU Patient Journey Time	159.19	0.51	156.93	163.67	33.5099	682.57
Record Unadmitted Red Patient Journey Time	219.51	0.59	216.59	222.28	92.4165	722.36

Figure D.2: Arena Summary Output for particular Journey Time Statistics from Journey-Path Model Simulation Output

Replications: 30 Time Units: Minutes

User Specified

Tally

Between	Average	Half Width	Minimum Average	Maximum Average	Minimum Value	Maximum Value
Record Interarrival Time	5.3316	0.01	5.2950	5.3831	0.00000016	185.15

Interval	Average	Half Width	Minimum Average	Maximum Average	Minimum Value	Maximum Value
Record Admitted Amber Patient Journey Time	292.02	1.17	285.71	298.37	37.7851	1310.93
Record Admitted Blue Patient Journey Time	152.30	1.71	143.84	163.46	34.0136	956.34
Record Admitted Green Patient Journey Time	237.68	0.69	234.07	241.17	32.9577	1137.37
Record Admitted GreenMIU Patient Journey Time	223.15	1.43	213.99	231.25	42.6126	845.44
Record Admitted Red Patient Journey Time	302.15	0.92	297.14	308.21	49.7539	1196.07
Record all Admitted Patient Journey Time	270.91	0.82	266.06	274.54	32.9577	1310.93
Record all Amber Patient Journey Time	256.67	1.14	250.15	262.68	10.1918	1310.93
Record all Green Patient Journey Time	167.85	0.54	165.17	170.83	10.0298	1137.37
Record all GreenMIU Patient Journey Time	138.08	0.53	135.80	140.78	10.1996	941.53
Record all Patient Journey Time	176.03	0.61	173.10	179.26	10.0164	1310.93
Record all Red Patient Journey Time	282.00	0.93	275.83	286.76	12.8628	1196.07
Record all Unadmitted Patient Journey Time	141.59	0.56	138.66	144.44	10.0164	1226.48
Record Blue Patient Journey Time	71.5116	0.51	67.8412	74.3938	10.0164	956.34
Record Unadmitted Amber Patient Journey Time	204.16	1.01	197.79	209.97	10.1918	1226.48
Record Unadmitted Blue Patient Journey Time	68.0527	0.52	64.4966	70.9598	10.0164	839.30
Record Unadmitted Green Patient Journey Time	150.26	0.54	147.28	153.09	10.0298	1014.81
Record Unadmitted GreenMIU Patient Journey Time	134.67	0.53	132.35	137.14	10.1996	941.53
Record Unadmitted Red Patient Journey Time	212.97	1.64	205.81	226.07	12.8628	1028.47