A healthcare space planning simulation model for Accident and Emergency (A&E)

Anthony Virtue

School of Electronics and Computer Science

A HEALTHCARE SPACE PLANNING SIMULATION MODEL FOR ACCIDENT AND EMERGENCY (A&E)

Anthony Virtue

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Declaration

I declare that the contents of this thesis are results of my personal research.

Appropriate references have been given for works of other researchers cited.

Abstract

The National Health Service (NHS) in the United Kingdom provides a range service for its population including primary care and hospital services. The impact of the 2008 economic and financial crises prompted a tightening of public budgets including health. Over the next few years, and most likely beyond, the NHS is planning for unprecedented levels of efficiency saving in the order of £ billions. With little doubt, the NHS will need to review its way of working will need to do more with less.

Simulation is an established technique with applications in many industries including healthcare. Potentially, there are huge opportunities for simulation use to make further inroads in the field of healthcare. Despite the potential, arguably, simulation has failed to make a significant impact in health. Some evidence has tended to suggest that within health there has been poor adaption along with poor linkage to real-world problems, as perceived by healthcare stakeholders.

The aim of this thesis is to develop a model to help address real-world healthcare issues as recognised by healthcare stakeholders. In doing so, this thesis will focus on a couple of real-world problems, namely:

- What space is needed to meet service demand, when is it needed and what will it cost?

- What space do we have, how can it be used to meet service demand and at what cost?

The developed simulation space demand model will demonstrate its value modelling dynamic systems over static models. The developed models will also show its value highlighting space demand issues by groups of patients, by time of day. Real, readily available data (arrival and length of stay, by patient group) would drive the model inputs, supporting ease of use and clarity for healthcare stakeholders. The model was modular by design to support rapid reconfiguration. Dynamically modelled space information allows service managers and Healthcare Planners to better manage and organise their space in a flexible way to meet service requirements. This work will also describe how space demand can linked with building notes to determine Schedules of Accommodation which can be used to cost floor space and consequent building or refurbishment costs. Furthermore, this information could be used to drive business plans and to develop operational cost pertaining to the floor area. This body of work debates using function-to-space ratios and attaching facilities management cost. Our findings suggest great variance in function-to-space ratios. Our findings also suggest that moving to median or lower quartile function-to-space ratios could potentially save hospitals £ millions in facilities management costs.

This thesis will reflect on the level of modelling taking place in the healthcare industry by non-academic healthcare modellers, sometimes collectively known as Healthcare Planners, the Healthcare Planning role in space planning and their links with healthcare stakeholders. This reflection will also consider whether healthcare stakeholders perceive a great need for academic healthcare modelling, if they believe their modelling needs are met by Healthcare Planners. A central theme of this thesis is that academic modelling and Healthcare Planning have great synergy and that bringing together Healthcare Planners' industry knowledge and stakeholder relationships with academic know-how, can make a significant contribution to the healthcare simulation modelling arena.

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London, February 2013.

Anthony Virtue

…Essentially, all models are wrong, but some are useful…

Box, G. and Draper, N. (1987)

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List of abbreviations

A&E	Accident and Emergency
CEO	Chief Executive Officer
DES	Discrete Event Simulation
DGH	District General Hospitals
DHSS	Department of Health and Social Security
DOH	Department of Health
ED	Emergency Department
FBC	Full Business Case
FM	Facilities Management
GP	General Practitioner
GIA	Gross Internal Area
HBNs	Health Building Notes
LoS	Length of Stay (arrival to discharge)
MoC	Model of Care
NHS	National Health Service
NIA	Net Internal Area
OBC	Outline Business Case
PCT	Primary Care Trust
PFI	Private Finance Initiative
PSM	Problem Structuring Methods
SoA	Schedules of Accommodation
SOC	Strategic Outline Case

Sqm	Square metre
SHA	Strategic Health Authority
UCC	Urgent Care Centre
UK	United Kingdom

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Chapter 1: Introduction

1.1 *Background*

Over recent years, the National Health Service (NHS) in the UK has made efforts to increase its overall service level to meet increasing health demand, in part driven by lifestyle factors such as obesity and diabetes and in part driven by an ageing population. Between 1999 and 2010, real spending in the NHS in England almost doubled with the goal to address this increasing demand (Wanless et al., 2007; Appleby et al., 2009; Appleby et al., 2010). However, the impact of the economic and financial crises in 2008 prompted a fiscal tightening of future health budgets. The likely impact would be significant on all areas of public financing including the NHS (Chote et al., 2009; Crawford et al., 2009) and will probably result in lower levels of NHS funding in years to come. This financial climate prompted the NHS Chief Executive to state, in his 2008-09 annual report, that the NHS would need to plan for unprecedented levels of efficiency savings between £15 billion and £20 billion between the years 2011 and 2014 (Nicholson, 2009). Clearly, the NHS will have to get used to doing more for less. Looking forward, financial challenges within the NHS will probably intensify with issues around the management and operation of hospitals locked into Private Finance Initiative (PFI) service agreements and the impact of changing patient flows over time. For example, shifts of patients from secondary to primary care, or shifts of inpatient to day case activity could result in fewer hospital beds trending towards lower patient income increasing financial pressure on hospitals (Imison, 2011; Hurst and Williams, 2012; Hollowell and Pollock, 2009; Appleby, 2012).

1.1.1 Opportunities for simulation modelling

Simulation is an established technique widely used by a wide range of industries including healthcare. Banks et al. (2010) described simulation as the imitation of the operation of a real-world process or system over time. Banks et al. further stated that simulation involves the generation of an artificial history of a systems and that observations of that artificial history could be used to draw inferences concerning the operating characteristic of a real system. In addition, simulation models could be used both as an analysis tool for predicting changes to a system, and as a design tool to predict the performance of new systems under varying sets of circumstances. The assumptions used to create the generation of the artificial history might be described as a simulation model. These assumptions often take the form of mathematical or logical relationships, which could be used to investigate and answer questions about real-world systems.

There is evidence to suggest that productivity savings in the NHS could save £ billions. For example, the Department of Health (DoH) in the UK suggested that two areas (acute providers productivity and optimising spend within care pathways) combined could produce savings between £5.6 billion and £7.9 billion (McKinsey & Co, 2009). Similarly, a King’s Fund report suggests productivity savings could save in the order of £4.6 billion (Appleby et al., 2010).

There is a strong case for simulation modelling to help tackle productivity and optimisation challenges described above and over recent years a number of papers have been written to help address these issues.

1.2 *The problem statement and scope*

Despite the potential value of simulation within healthcare, arguably to-date, its impact resolving real-world healthcare issues has been poor. Some evidence suggests that the application of simulation to resolve real-world healthcare issues has been problematic (Taylor et al., 2009; Brailsford, 2009a; Brailsford, 2013). Poor levels of real-world simulation adoption in healthcare (as described by Eldabi, 2009) probably represent missed opportunities to increase: efficiency and delivery of healthcare; value for money spent; and clinical outcomes.

With the goal of creating focused real-world driven models, this thesis will suggest a few key issues that healthcare service managers need to address in the delivery of healthcare. Service managers need a clear understanding of:

- What space is needed to meet service demand, when is it needed and what will it cost?
- What staff are needed to meet service demand and what will it cost?

This body of work will focus on developing a model to address the first question of space requirements to meet service demand. This work will also address a corollary question of:

- What space do we have and how could it be used to meet service demand and, at what cost?

To help address these suggested real-world issues, the core focus of this thesis will be the development of space simulation models, within a hospital estate, for Healthcare Planners and estate stakeholders. A hospital estate could potentially cover a large area. If we could develop methodologies to deploy simulation methods to make better use of a healthcare estate, potentially, significant cost savings could be realised. For example the average site of a large acute Trust is 160,000 square metres (Estates Returns Information Collection, 2011-12). The provision of hospital services (including its support functions) will invariably have costs attached to providing facilities management services, such as, building maintenance cost, cleaning, catering, security, energy, information technology and management to name but a few. Therefore, if physical space could be re-organised to provide the same clinical processes and treatments in a smaller space, cost savings could be realised by the hospital. This cost savings (or proportions of it) could be used to offset against the overall cost of running the hospital estate, payment of loans or used be for reinvestment. Simulation potentially could play a key role to better optimise the use of clinical space (and clinical support space) within a hospital, as well modelling treatment pathways and flows for patients. This analysis could also be used to highlight space use at particular times of the day, suggesting an exploration into multi-purpose space use for patient treatments.

In the United Kingdom (UK), and across the globe, the provision of healthcare services within hospitals is under increasing pressure to provide more with decreasing budgets. This might sometimes result in over-crowding at the common entry point into hospitals - the emergency department (Bond, 2001; Martin et al, 2003; Sprivulis et al., 2006; Trzeciak and Rivers, 2003; Hoot et al., 2008; Boyle et al., 2012). Here too, there may be an opportunity for simulation and space planning at an operational level. For example, could space in emergency departments (commonly known in the UK as Accident and Emergency or A&E) be better used to match different cohorts of patient arrivals throughout the arrival day? Furthermore, could a model be used to predict the onset on queues (crowding)? These two questions will be explored by development of an A&E Space Simulation Model.

A&E departments (the primary term this thesis will use to describe emergency departments) are often a significant element within a hospital treating a wide range of medical conditions from minor to life threatening. The A&E is often the entry point into hospital. As a result of its position in the hospital process, over-crowding in A&E could have a severe knock-on effect on the rest of the hospital (Fletcher et al., 2007). In a way, A&E performance might be seen as a barometer to the overall operation of a hospital at any moment in time. As a result of this, and the fact they are often a relatively small unit, relatively easily observable with a relatively short throughput time (Günal and Pidd, 2010); A&Es have traditionally been a good area to perform simulation studies. Although the focus of this thesis is on A&E, healthcare and their functions in the UK, it would be hoped that concepts discussed could be applied to other areas in health and indeed other industries both in the UK and internationally.

The scope of this thesis will be limited to space planning model development with links to key facilities management costs. Capital costs and charges will be beyond the scope of this work. In addition, this model will not directly model staff or workforce or their direct costs. Although, developed length of stay analysis within the models described will encapsulate a number staffing assumptions and working patterns.

1.3 *Motivation*

A primary motivation of this thesis is to develop a simulation modelling approach to help make better use of limited resources and address real-world needs of healthcare by attaching real costs to modelled space. The primary focus here will be an exploration into simulation modelling and space use (and potential) within a hospital environment at a policy, strategic and operational levels. This thesis will explore a number of aspects around the perception of poor adoption of healthcare simulation including an exploration as to whether there has been a broad failure of academic simulation modellers to address real problems as acknowledged by healthcare stakeholders. This thesis will reflect on whether healthcare simulation modelling is fundamentally different to other industries and, if so, whether these differences impede the adoption of simulation. This reflection will also consider the influences of size, complexity and range of stakeholders and their impact on the adoption of simulation within it.

This body of work will also review the level of simulation modelling practice within the healthcare community by non-academic healthcare modellers (known as Healthcare Planners). This review will look at the historical basis for Healthcare Planners, their linkage to stakeholders at a policy and strategic level and discuss whether perhaps simulation modelling (in its widest sense) is practiced more often within healthcare than is probably recognised by papers generated by academic health modellers. Furthermore, since the early days of the NHS and continuing up to this day, there has been research into healthcare building design. As a result of this research, over the years, guidance notes have been regularly issued to help define standards on the provision of space and equipping within health facilities. This thesis will propose that simulation, working in conjunction with building guidance notes, could help meet the need for change and build better space planning models to address real healthcare issues as acknowledged by healthcare stakeholders.

1.4 *Aims*

The broad aim of this thesis is to focus on developing models to address real-world issues as recognised by real healthcare stakeholders, namely:

- What space is needed to meet service demand, when is it needed and what will it cost?
- What space do we have and how could it be used to meet service demand and, at what cost?

To help address the above issues, this thesis will:

- Develop illustrations to show the potential of simulation modelling to highlight real-world space demand issues to hospital service managers at a departmental (operational) and strategic level.
- Develop an operational A&E space simulation model to model arrival and length of stay profiles by patient group and to act as an early warning to the onset of crowding within A&E.
- Explore potential savings using smaller estates for the same provision of service.
- Use simulation modelling approaches to bring together closer working of academic healthcare modellers and healthcare stakeholders (including skills and knowledge transfer between the two) to help address real-world healthcare stakeholder issues.

1.5 *Definition of healthcare models*

For the purpose of this body of work, simulation modelling in this thesis will focus on discrete-event simulation (DES) – models created in discrete time steps. The rational for DES is its relative common use in simulation (both by modellers and healthcare), its ability to visually display patient movements in discrete steps and its relative low price to a cost conscious health sector.

As this thesis will illustrate, much of the modelling probably performed by the healthcare planning modelling community is probably deterministic or static in nature. That is to say, unlike stochastic models (models with one or more random variables as inputs); deterministic models have known inputs which result in a unique set of outputs; and static model which have no time element (Banks et al., 2010; Law and Kelton 2000). In this thesis, the term healthcare modelling will refer to deterministic, static and stochastic models. In addition, as the terms Accident and Emergency, A&E, emergency departments and ED are interchangeable, for the purpose of clarity in this thesis, A&E will be the primary descriptor used to encapsulate activity within emergency and urgent care. Furthermore, the term healthcare in this thesis will primarily be focused on hospital services.

This thesis will also use the term pathway. The use of pathways in this body of work will broadly describe cohorts of similar patients and a generalised view of their treatment and movement through a system/model. For example, elderly patients often have a set of characteristics, different, to say paediatric patient, and as such often warrant services (Models of Care) delivered in a way focused to their particular needs.

1.6 *Research contribution*

The research contributions of this thesis are as follows.

- The development of an A&E Space Simulation Model to be used as a planning tool to model space demand by patient groups and by time of day. The model showed the benefits of using simulation to more accurately model space demand in dynamic healthcare environments over static average based calculations. This information could be used by service managers and Healthcare Planners to better manage and organise space in a flexible way to meet service requirements.
- Space demand derived from simulation could be used in conjunction with health building note to develop excellence cost information. Space demand derived from simulation, used in conjunction with Schedules of Accommodation (SoA) could be used to provide high quality inputs to:
  - Clearly show space demand over time.
  - Develop capital costs of hospital building or refurbishments.
  - Develop operational running costs schedules.
  - Inform business cases.
- The A&E Space Simulation Model could be configured in a matter of hours to suit an A&E system and would be driven by real data easily recognisable to healthcare stakeholders, namely;
  - Arrival time profiles (related to distinct patient groups).
  - Length of stay profiles (related to distinct patient groups).

- The model would be modular by design thus facilitating pathway modelling (by acuity and type), speed of development (adaption to the service needs of a particular stakeholder) and speed of adaption to other service settings.
- Visible clear models to support interrogation by healthcare stakeholders, the integration of Excel tools and discrete-event simulation models and training – the ability to quickly highlight issues, with clear outputs to alert stakeholders to the onset of crowding and crowd severity.
- Development of the links between space use in a health service estate and associated facilities management costs highlighted the potential of significant cost savings (up to several £ millions) across a health estate.
- Another area of contribution of this work was the recognition of relationships between healthcare stakeholders, academic healthcare modellers and healthcare planning modellers and the mutual benefit of combining their skills and expertise to create better dynamic models more focused to the real-world requirements of healthcare stakeholders.

1.7 *Structure of this thesis*

The structure of this thesis is laid out as follows. Here in Chapter 1, the topic was introduced, setting out the problem statement, motivation, aims and research contribution of this thesis. Chapter 2 covers the literature survey, setting out the scope of the review before looking at evidence of poor simulation adoption within healthcare – covering areas such as the size and complexity of healthcare, poor linkage to real-world issues, stakeholder engagement and modelling timescales. The literature review also compares healthcare to other industries and looks at aspects of Lean in healthcare. This chapter will also discuss approaches to overcome poor simulation adoption. The review also noted the lack of recognitions of non-academic based modelling or related issues around space. Chapter 3 discusses the role of Healthcare Planners within the UK health industry and sets out the historical perspective and Healthcare Planning links with space design and building standards. Chapter 3 also narrates the significance of the Healthcare Planning role working in conjunction with healthcare stakeholders, their space planning inputs in the form of Schedules of Accommodation (SoA), and their significance with regards to Private Finance Initiative programs and business cases. This chapter also provides a brief discussion on tools and techniques used by Healthcare Planners as well as their potential to act as a link between health sector and health modelling academia. Chapter 4 describes modelling ideas and methodologies leading up to the development of the space demand model (known as the A&E Space Simulation Model) with overviews of the Generic A&E Model and a Hierarchical Clustering Model. Chapter 5 describes the A&E Space Simulation Model including its methodological overview and key inputs such as its arrivals and length of stay profiles. Chapter 5 also describes the modelling engine and modelling steps. Analysis and results of A&E Space Simulation Model are covered in Chapter 6 and this includes statistical tests to validate (and verify) the model's arrivals and length of stay profiles. A number of space resource outputs are reviewed across a number of modelling parameters, including different groups of patients and different times of day and day of the week. The outputs described will clearly show the value and benefits of space simulation modelling over a static based modelling system. This chapter also provides example how function-to-space ratios could be used and compared with different hospital sites to highlight poorly utilised space, potentially offering up significant savings in facilities management costs. Chapter 7 adds further discussion points as well as suggestions for future work, whilst Chapter 8 concludes this body of work with a short summary and detailed contribution.

Research contribution papers and their linkage by chapter are shown below:

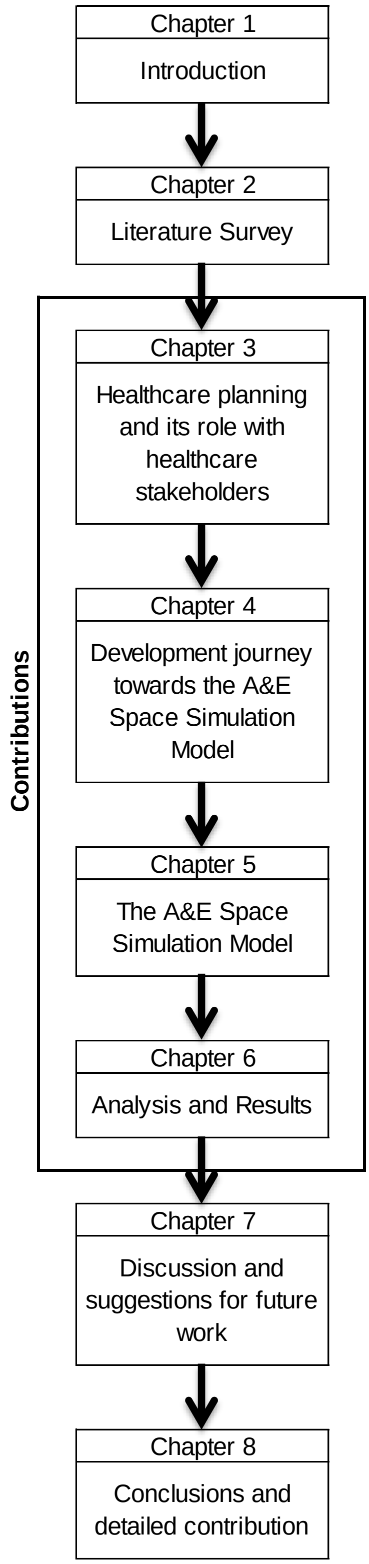
- Chapter 3
    - Virtue, A., Chaussalet, T. and Kelly, J. (2013) Healthcare planning and its potential role increasing operational efficiency in the health sector – A viewpoint, *The Journal of Enterprise Information Management*, 26(1), pp. 8-20.
- Chapter 4
    - Codrington-Virtue, A., Chaussalet, T., Millard, P., Whittlestone, P. and Kelly, J. (2006) A system for patient management based discrete-event simulation and hierarchical clustering. In: *Proceedings of the 19th IEEE International Symposium on Computer-Based Medical Systems (CBMS)*. Salt Lake City, USA, 2006. pp. 800-804.

    - Codrington-Virtue, A., Whittlestone, P., Kelly, J. and Chaussalet, T. (2005) Developing an application of an accident and emergency patient simulation modeling using an interactive framework. In: Proceedings of the 31st Annual Meeting of the EURO Working Group on OR Applied to Health Services (ORAHS). Southampton, UK, July 2005. pp. 61-76.
    - Codrington-Virtue, A., Whittlestone, P. Kelly, J. and Chaussalet, T. (2005) An interactive frame-work for developing simulation models of hospital accident and emergency services. In: Proceedings of the International Council on Medical and Care Compunetics (ICMCC). The Hague, Netherlands, June 2005, pp. 277–283.
- Chapter 3 and 5
    - Virtue, A., Chaussalet, T., and Kelly, J. (2012) Healthcare planning - the simulation perspective. In: *Proceedings of the Operational Research Society Simulation Workshop 2012 (SW12)*. Worcestershire, UK, pp. 83-91
- Chapter 5 and 6
    - Virtue, A., Chaussalet, T., and Kelly, J. (2011) Using simplified discrete-event simulation models for health care applications. In: *Proceedings of the 2011 Winter Simulation Conference*. Phoenix, AZ, USA, pp. 1154-1165.

- Virtue, A., Chaussalet, T., and Kelly, J. (2011) A case study using simplified discrete-event simulation as a tool to reconfigure health care service. In: *Proceedings of the 37th Annual Meeting of the EURO Working Group on OR Applied to Health Services (ORAHS)*. Cardiff, UK, pp. 202-213.
- Quantitative Modelling in the Management of Health and Social Care Conference, March 2013 – Poster to be submitted.

Figure 1 illustrates the linkage between the research contribution and the chapters.

Figure 1. Research Contribution Map



Chapter 2: Literature Survey

2.1 *Scope of literature review*

Many papers have been submitted covering the area of simulation modelling. Brailsford et al. (2009a) found academic health related simulation modelling papers expanding at a rate of about 30 articles per day on the Web of Knowledge bibliographic database. The same study showed that healthcare simulation modelling related search strings in 2007 resulted in around 176,000 hits. Due to the number of health related simulation modelling papers, this thesis will not attempt to perform a fully comprehensive literature review; instead it will focus on a number of relevant papers selected to enrich discussions around the aims of this thesis.

In particular, this literature review will examine evidence of poor simulation modelling adoption within healthcare focusing on issues related to:

- The size and complexity of the healthcare industry.
- DES A&E specific literature.
- Poor healthcare model linkage to real-world issues.
- Stakeholder engagement issues.
- Modelling timescales.

This literature review will also look at some evidence to question whether simulation modelling in healthcare is really unique or different compared to other industries and will include a brief exploration of the application of industrial techniques to healthcare modelling. Looking forward, the literature review will discuss some methodologies to help overcome poor healthcare implementation by exploring a number of concepts including pathway modelling and streamlined models.

2.2 *Healthcare DES models*

Within healthcare, DES is probably the most commonly used modelling technique ahead of Monte Carlo, Systems Dynamics, Agent Based Simulation and Distributed Simulation (Naseer et al. 2009; Young et al. 2009; Paul et al., 2010). Its appeal includes the ability to model quite complex systems using relatively low priced software packages. DES has studied a wide range of healthcare application and services across a range of decision levels as illustrated in Table 1. Table 1, which excludes A&E is by no means an extensive list; examples were selected to show a range of healthcare applications over a range of decision levels including tactical, operational or strategic. Applications include service such as walk-in centres, intensive care, outpatients and radiation therapy.

The focus area of this thesis is A&E and many academic papers have been generated particularly in this area. Table 2 shows a snapshot of papers related to A&E. By its nature, A&E is an operational area. As such, the majority of papers in Table 2 are tactical or operational.

Table 1. Span of DES models across healthcare applications and services

Decision level	Area	Paper
Tactical or Operational	Walk-in Centre	A simulation-based study of a NHS walk-in Centre (Ashton et al., 2005)
	Intensive Care	Modelling the requirement for supplementary nurses in an intensive care unit (Griffiths et al., 2005)
		Mixing methodology to enhance the implementation of healthcare operational research (Sachdeva el al., 2007)
		A simulation model of bed-occupancy in a critical care unit (Griffiths et al., 2010)
	Outpatients	A Simulation study of scheduling clinic appointments in surgical care: individual surgeons versus pooled lists (Vasilakis et al., 2007)
	Radiation therapy	The use of discrete-event simulation modelling to improve radiation therapy planning processes (Werker et al., 2009)
Strategic	Surgery	Graphical simulation modelling for the regional planning of oral and maxillofacial surgery across London (Harper et al., 2005)
	National and local blood supply chain	Using simulation to improve the blood supply chain (Katsaliaki and Brailsford 2007
	Disease transmission	Use of discrete-event simulation to evaluate strategies for the prevention of mother-to-child transmission of HIV in developing countries (Rauner el al., 2005)
	Health service decision making tool	Improving decision making in healthcare services through the use of existing simulation modelling tools and new technologies (Katsaliaki and Mustafee, 2010)

Table 2. A&E specific DES models

Decision level	Area	Paper
Tactical or Operational	Accident and Emergency department	The use of simulation to reduce the length of stay in an emergency department (Samaha et al., 2003)
		Discrete event simulation of emergency department activity: a platform for system-level operational research (Connelly and Bair, 2004)
		Modelling emergency departments using discrete event simulation techniques (Komanshie and Mousavi, 2005)
		Understanding accident and emergency department performance using simulation (Günal and Pidd, 2006)
		Simulation model for improving the operation of the emergency department of special health care (Ruohonen and Teittinen, 2006)
		Combining data mining and discrete event simulation for a value-added view of a hospital emergency department (Ceglowski et al., 2007)
		Modelling and improving emergency department systems using discrete event simulation (Duguay and Chetouane, 2007)
		Forecasting emergency department crowding: a discrete event simulation (Hoot et al., 2008)
		Process modelling of emergency department patient flow: effect of patient length of stay on ED diversion (Kolker, 2008)
		A generic framework for real-time discrete-event (DES) modelling (Tavakoli et al.,2008)
		Success and failure in the simulation of an Accident and Emergency (Bowers et al, 2009)
		Using simulation and goal programming to reschedule emergency department doctors' shifts: case of a Tunisian hospital (Jerbi and Kamoun, 2009)
		Reducing length of stay in emergency department: a simulation study at a community hospital (Wang at al., 2012)
		A simulation study to improve quality of care in the emergency department of community hospital (Zeng et al., (2012)
Strategic	Accident and Emergency department	The DH accident and emergency department model: a national generic model used locally (Fletcher at al., 2007)

2.2.1 Analysis of A&E DES models

Reviewing the snapshot of papers in Tables 1 and 2 it was not actually clear if any of the papers had been fully implemented. In general, the papers were case studies or examples of how DES could be made to work, or improve the area under investigation. Table 3 shows a review of DES A&E modelling features (Duguay and Chetouane, 2007).

Table 3. DES A&E model features and their usage adapted from Duguay and Chetouane (2007)

Features	Features included
Arrival process	Dependent on week days or patient type
Triage codes	Either 4, 5 or no codes
Entities	Patients, lab specimens and test results or patients only
Staff shifts	Yes or no
Service times (diagnosis or expertise based)	Yes or no
Bed ready times	Yes or no
Transfer times	Yes or no
Result transfer times	Yes or no
Lab tests	Yes or no
Teaching and collaborative aspects	Yes or no
Animation	Yes or no
Software	Either Siman-Cinema, Arena or Medmodel

Table 3 shows the variability of features modelled in A&E. These observations might raise issues with healthcare stakeholders such as:

1. As a busy A&E manager, I can see lots of case studies and theory papers out there. I can see the overall benefit, but I don't have the time/skills to improve this; or
2. As a busy A&E manager, the variances in the models don't reflect my actual unit. I need a model I can quickly tailor to my situation.

The observation of poor adoption will be discussed in greater detail below. The second bullet point captures the essence of what this thesis is trying to address.

2.3 *Evidence of poor simulation modelling adoption within healthcare*

Despite the number of healthcare related publications, there is evidence of poor adoption of simulation within healthcare (Brailsford et al., 2009a; Brailsford et al., 2013). Brailsford et al. (2009a) concluded "…*startling few studies report evidence of implementation*…" In all, 342 articles were reviewed by Brailsford et al. and rated according to 3 levels of implementation:

1. Suggested (theoretically proposed by the authors).
2. Conceptualised (discussed with the client organisation).
3. Implemented (actually used in practice).

Of the 342 total, 171 (50%) were suggested, 153 (44.7%) conceptualised and only 18 (5.3%) were implemented. As commented by Brailsford et al., the low levels of simulation and modelling implementation in healthcare were similar to previous findings (Wilson 1981; Fone et al. 2003; Jun et al. 1999) and disappointingly showed little improvement in implementation since the 1980s. Wilson (1981) surveyed over 200 papers which included examples of computer simulation applications to healthcare problems. Of the 200 papers surveyed, only 16 reported recommendations that could be acted upon. Furthermore, of the 16 reported recommendations, some of the implementation could be claimed to be incidental to simulation. Another issue highlighted was the poor follow-up rates of projects. Only 7 of the 16 projects reported any attempt to follow-up the original work. Wilson did observe a number of factors, which supported successful implementation. Factors included authors' allegiance to university or medical college. Having one or more person from the health organisation on the project team tended to ensure that projects were taken seriously and that simulated solutions were feasible.

Compared to other industries, there is evidence that healthcare has lower real-world outcomes with real-world stakeholders. Eldabi (2009) reviewed a number of publications to compare the use of modelling and simulation across three industries:

- Healthcare.
- Defence/Aerospace.
- Industry/Business.

The review classified outcomes into three classes:

- Class A - a real problem and real stakeholders.
- Class B - real-life problems, no engagement from real stakeholders.
- Class C - theoretical propositions and enhancements.

Figure 2 showed a summary of Eldabi's modelling and simulation use by industry and class.

Figure 2. Modelling and simulation use by industry and class, (adapted from Eldabi, 2009)

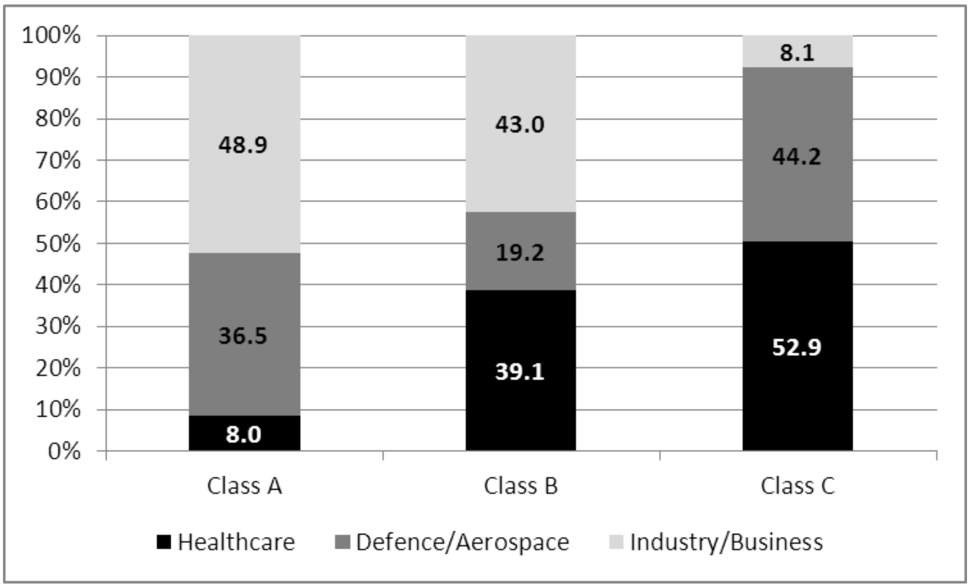


Figure 2 shows that 8.0% healthcare publications were categorised Class A, compared to 36.5% defence/aerospace and 48.9% for industry/business. In contrast, 52.9% of healthcare publications were categorised Class C, compared to 44.2% defence/aerospace and 8.1% for industry/business. Figure 2 clearly suggested that compared to defence, aerospace, industry and business, healthcare publications were underrepresented in Class A (real problems with real stakeholders) and over represented in Class C (theoretical propositions and enhancements). The poor representation of healthcare publications in real problems with real stakeholders appeared to go hand-in-hand with low levels of implementation as described by Brailsford et al. (2009a). The sections below will address further issues related to healthcare modelling adoption due the size and complexity of the healthcare industry; poor linkage of healthcare models to real-world issues; stakeholder engagement issues and healthcare modelling timescales.

2.3.1 Poor adoption due to the size and complexity of the healthcare

One explanation for poor adoption of simulation in the health industry might be related to the size and complexity of services and treatments the industry is required to deliver. Harper and Pitt (2004) noted that the health industry was complex and employed a large number of people who delivered across a wide range of services, sometimes with conflicting objectives and issues including:

- Scale.
- Complexity and changes (demographic change, social and behavioural change, organizational change, political change, strategic change, technological and clinical change).
- Diversity.
- Buy-in and credibility.

Kuljis et al. (2007) commented that simulation adoption in health was constrained due to the multitude of stakeholders involved and suggested seven axes of difference which sets health apart from other businesses (Paul and Kuljis, 2007). These seven axes were described as:

1) Patient fear of death.
2) Medical practitioners, for example approach to healing, investigation by experimentation and finance.
3) Healthcare support staff.
4) Healthcare managers.
5) Political influence and control.
6) Society view.
7) Utopia.

In their study, Kuljis el al. suggested that fear of death introduced unpredictable pressures and irrationality in to the healthcare system. Another complication they noted was that medical practitioners tended to be a diverse community with the potential to be highly opinionated, disagreeing on many issues. On the other hand, healthcare support staff had the potential to form another set of views in contrast to medical practitioners. Healthcare managers had yet another set of goals, often left with the difficult task of managing and reconciling complex issues and competing forces. Another aspect noted by Kuljis et al. was healthcare exposure to political influence and control creating their own management and control issues. Their study also further suggested a societal and utopian view in a scenario where '*nobody dies'* were other factors particularly unique to the healthcare system. Kuljis et al. captured a number of competing forces in healthcare and arguably, helped to explain some of the issues (and challenges) that simulation needs to overcome within the industry.

Eldabi (2009) discussed the wicked nature of healthcare problems and posed the question whether stakeholders, tools and complexity are central to the nature of healthcare systems, or whether they are due to modellers approach to modelling healthcare. Rittel and Webber (1973) defined '*wicked problems*' as problems impossible to solve, while solvable problems were defined as '*tame*' problems. Characteristics of wicked problems, as defined by Rittel and Webber, included:

- There is no definite formulation of a wicked problem.
- Wicked problems have no stopping rules.
- Solutions to wicked problems are not true-or-false, but better or worse.
- There is no immediate and no ultimate test of a solution to a wicked problem.
- Every solution to a wicked problem is a "one-shot operation"; because there is no opportunity to learn by trial-and-error, every attempt counts significantly.
- Wicked problems do not have an enumerable (or an exhaustively describable) set of potential solutions, nor is there a well-described set of permissible operations that may be incorporated into the plan.
- Every wicked problem is essentially unique.
- Every wicked problem can be considered to be a symptom of another wicked problem.

- The causes of a wicked problem can be explained in numerous ways. The choice of explanation determines the nature of the problem's resolution.
- With wicked problems, the planner has no right to be wrong.

Eldabi suggested that although many healthcare problems might be complex (wicked problems if not wicked puzzles) they may not be solvable using traditional scientific (linear) methods and this in itself might be a significant barrier. Eldabi stated that much of the existing healthcare simulation modelling literature focused on producing an answer. Instead, Eldabi argued that with wicked problems modellers needed to focus on resolution rather than solution and consensus rather than optimisation.

2.3.2 Poor healthcare model linkage to real-world issues

Eldabi el at (2007) suggested that the relationship between the healthcare industry and simulation should be symbiotic at the time same recognising that the impact of simulation on policy-making and management decision-making was weak. Similarly, Günal and Pidd (2010) commented that the extent to which DES models are used in healthcare for real decisions was rarely discussed and stakeholders needed to be convinced of the benefits and aware of limitations. The authors also pointed out that this was not always straightforward and that this process might not be of great interest to academic authors. Furthermore, Günal and Pidd posed the question; after 30 years use of DES in healthcare, that it might be time to look at the serious issue of model implementation and use of model. To reflect on the impact on simulation on its 50 year (or so) anniversary, in a review of around 580 papers, Taylor et al. (2009) revealed the lack of modelling publications describing real-world systems and an even greater lack of evidence of real-world benefit. Taylor et al. reviewed papers across a range of areas, including healthcare, and suggested that modelling publications were academic in nature and unengaged with the real-world. Stated reasons included:

- Many researchers misunderstand real-world problems due to lack of real-world exposure.
- Papers sometimes did not stand up to real-world tests as they studied irrelevant problems that did not reflect realistic scenarios and were full of convenient assumptions.
- The academic world had little relevance to the industrial practitioners in the real-world; and academics were rewarded for publishing in high quality journals that often were not connected to the real-world.

Proudlove et al. (2007) also considered operational research and the challenge to improve the NHS, particularly modelling for insight and improvement in inpatient flows and found it to be limited. Proudlove et al. described tensions between academic rigour and practical value, suggesting that work published by academics rewarded large complicated models with detailed statistical analysis and that this was in detriment to the requirements of the environment and the needs of the stakeholder. The Proudlove et al. study described examples of forecasting inpatient bed requirements and assumptions behind them: firstly, that they were hard forecasting problems; and secondly, that none of the inputs were within the control of local health managers. As the study highlighted, emergency admissions were not that unpredictable and elective arrivals were within the control of the clinicians and managers. The study illustrated the point that developing complex forecasting was an indication that modellers did not understand or were not interested in addressing the real problem - which actually was to manage flows rather than forecast them. Proudlove et al. also proposed the use of simpler models to gain generic understanding of a system rather than a specific very powerful model. The study concluded with a number of recommendations for more effective engagements in the NHS including:

- Focus on the people who will have to change something to make a difference, and their needs.
- Do not assume the root cause is complex or demands a complex model.
- Presentations can be as important as modelling.
- Link analysis to actions that people could take.
- Be open to insights from other disciplines.
- Providing simple tools can help local systems-owners make sense of their systems.

2.3.3 Stakeholder engagement issues

Some of the points raised above highlighted the need to focus modelling requirements on the needs of the stakeholders. However, identifying stakeholders can sometimes be challenging. For example, Brailsford et al. (2009b) identified a long list of 28 stakeholders in the NHS ranging from Parliament to the public and their influence across policy, strategy and operations - see Table 4. Brailsford et al. described a method to classify stakeholders by ownership, legitimacy, power, urgency centrality, time, money and data. However, as pointed out by Young et al. (2009), the literature offered little clarification in defining either key stakeholders or the connection between key stakeholders and simulation. Young et al. introduced the concept of the '*absent*' stakeholder. In this instance, modellers develop simple relationships with a stakeholder (or a small number of stakeholders) who act on behalf of absent stakeholders. For the purpose of clarity, in the context of this thesis, future references to stakeholders will primarily refer to managers and clinicians providing hospital services, namely, 'Public providers' and 'Professionals' (and associated managers of those services) as described in Table 4.

Brailsford et al. (2009b) also raised the issue of ethics and some of the problems it may cause to academic researchers. Research within the NHS often required approval from the NHS Research Ethics Committee and to obtain approval, the exact modelling methodology, interviewees, questions they will be asked, for how long and specific data requirements should be specified in advance. In addition, obtaining ethics approval often took many months. In contrast, service evaluation often did not have this onerous requirement. Many real-world healthcare problems were often a combination of service evaluation and research. To publish, academic healthcare modellers were often forced down a research route, whereas business consultancies usually followed the less onerous service evaluation route.

Table 4. Stakeholders in the NHS and decision level influence (adapted from Brailsford et al. 2009b)

Area	Stakeholders	Policy	Strategy	Operations
Parliament	Policy committee	1	0	0
Government	Health Minister	1	1	0
	Department of Trade and Industry	1	1	0
	Treasury	1	1	0
Civil service	Social care	1	1	0
	Agencies	0	1	1
	Strategic Health Authorities (SHAs)	0	1	0
Public providers	CEOs of NHS Trust	0	1	1
	Trusts (hospitals and PCTs)	0	1	1
Private providers	Independent treatment centres	0	1	1
	Private hospitals	0	1	1
	Insurance companies	0	1	1
Professional groups	British Medical Association	1	0	1
	Royal College of Nursing	1	0	1
	Allied Health Physicians	1	0	1
	Royal Colleges	1	1	0
	NHS Confederation	1	1	0
	Educational Institutions	0	1	1
	Healthcare Commission	0	1	1
	Allied healthcare professionals	0	1	1
Professionals	General Practitioners	0	1	1
	Physicians	0	1	1
	Nurses	0	1	1
	Surgeons	0	1	1
Users	Patient interest groups	1	0	1
	Patients	0	0	1
	Families and informal carers	0	0	1
Public	Taxpayers	1	0	0

Having discussed some of the academic healthcare modelling challenges above, Fletcher et al. (2007) paper pulled together some common themes. Fletcher et al. commented that the biggest obstacles were not related to their generic model; in fact, they were related to other factors such as: data quality - cited as being poor in most

Trusts; organisational dysfunction - issues downstream of A&E affecting the patient flow through A&E; motivation – with some Trusts paying '*lip service*' to the process imposed on them by the DoH; and changes in A&E departments – different Trusts had numerous mechanisms over different time periods to improve A&E performance. This made it difficult to identify the impact of individual changes. Other challenges noted by the Fletcher et al. paper included:

- Finding the appropriate level of modelling – designing the model so that it was not over specific to a particular A&E, yet detailed enough to capture national issues. Data inputs also needed to be as simple as possible.
- Interpreting available national data, using it well and allowing for known inaccuracies.
- Communications and consultancy skills – facilitating sessions to explain and run the model, building common understanding, interpretation of results and using the model to innovate.

Whilst modelling of typical departments using a generic model with typical inputs had value, Fletcher et al. commented…"*In passing we also note that, as with much operational research, working for a client who wishes to gain general insights is a different situation from that often faced by academics who have the added challenge of trying to interest managers in the general insights provided by their models."* The comment above emphasised the issue of stakeholder management through a modelling process and indeed, one might suggest that data issues are directly linked with stakeholder engagement. As in the Fletcher et al. case, if stakeholders felt they are forced unwittingly into a process they may not feel any incentive to positively take part in the process. Similarly, if a simulation project is a ‘*pet*’ project for a particular stakeholder, unless the stakeholder has agreement from other key stakeholders, they (and any associated modeller) might encounter difficulty obtaining quality, timely data.

2.3.4 Modelling timescales for healthcare

Eldabi (2009) also commented that healthcare had additional characteristics to compound wicked problem issues. These characteristics included constantly changing behaviour due to national policies or in response to local pressures. Eldabi also highlighted that healthcare projects rarely have the time to wait until a complete resolution of a modelling project nor were healthcare institutions willing to pay to extended periods for complete resolution; problems need to be resolved with a specified time and budget. The timing of projects was also an issue noted by Wilson (1981) who highlighted that time needed to be allocated to the overall project time. Additionally, he argued, time would be required to collect enough data of sufficient accuracy to drive the simulations. Wilson commented that "… *simulation project had to be carried out fast enough for the results to be available when the necessary decisions were taken.*" The importance of timeliness of projects was further highlighted by Bowers et al. study of an A&E. The Bowers et al. study provided a major contribution to the understanding of the A&E process, but the model was delivered after the A&E system had been thoroughly investigated, changes implemented and the 4 hour target met.

The observations above tend to suggest that academic healthcare simulation modellers had broadly failed to build models that addressed healthcare problems as acknowledged by healthcare stakeholders. Earlier, we discussed Eldabi (2009) comparisons of healthcare modelling with other industries. The following section will expand the discussion whether the healthcare industry is different, or any more complicated than other industries.

2.4 *Is healthcare unique compared to other industries?*

Tako and Robinson (2012) observed a body of thought that questioned whether modelling healthcare systems was different and/or more complicated compared to other industries. Tako and Robinson surveyed authors at the 2010 Winter Simulation Conference. Of the 444 conference authors, 113 responses were analysed for the study and a summary of the survey respondents is shown in Table 5.

Table 5. Demographic data for the survey respondents (adapted from Tako and Robinson, 2012)

Experience in simulation modelling				
Less than 3 years	3-10 years	More than 10 years		
19%	36%	45%		
Split of simulation modelling activity				
Research	Teaching	Consulting	Other	
64%	20%	15%	10%	
Split of modelling work by sector				
Health	Manufacturing	Government	Service	Other
24%	33%	17%	11%	15%

Their study concluded that health modelling had less evident structures and was more complex and messier but changed no more than other industries. The Tako and Robinson study suggested that health had more difficulty collecting data, more difficulty accessing data and had more difficulty due to research ethics compared to other industries. However, health clients had no more difficulty interpreting results compared to other industries. Their study also suggested that compared to other sectors, health had higher influence of political events and results became obsolete faster and were less appropriate for simulation software. In addition, results indicated that health had less incentive to change, was more resistant to change, and it was more difficult to develop generic models with clients short of time. In contrast, health had no resistance to simulation, had no more difficulty ensuring implementation and had no more difficulty in identifying stakeholders compared to other sectors. A final survey question asking if modelling in health was different to other sectors concluded that health was indeed different to other industries. As Tako and Robinson pointed out in the paper, further investigation was required to test if these results held true if more objective measures were applied. There was also the question of the validity of modellers commenting on their non-specialist domain.

The Tako and Robinson evidence did appear to support the fact that health modelling was different compared to other industries. Despite the differences, arguably healthcare could learn from other industries.

2.5 *Lean concepts in healthcare*

Young el al. (2004) posed the question, "might industrial processes improve quality, reduce waiting times and enhance the working environment?" In their paper, Young et al. looked at three management processes: Lean Thinking; Theory of Constraints; and Six Sigma and explored how the concept of each might be applied to healthcare. The paper referred to maternity and emergency care in a lean environment and suggested it could create an interesting conundrum. Elimination of waste in those areas could free up waiting time and release staff possibly for other duties, however, in both of those areas there would be a requirement for staff to be ready to swing into action as soon as patients arrive. Overall, Young et al. made a clear argument for the adoption of Lean principles through the five key concepts of Lean thinking. These concepts were:

1) Value - products should be designed for and with customers, they should suit the purpose and they should be at the right price.
2) Value stream - Each step in the process must produce value for the customer, eliminating all sources of waste.
3) Flow - Systems must flow efficiently with materials being delivered as and when they are needed and to the quality required.
4) Pull - Processes must be flexible and be geared to customer demand.
5) Perfection - Creating an environment of constant review and learning from previous mistakes.

Young et al. also suggested adoption of Theory of Constraints in healthcare. Although the paper did concede that finding the location of a bottleneck was not obvious, it did show how finding and managing the constraint could be a valuable exercise. Once identified, the constraining flow could be monitored and elevated (other parts of the system designed to help it). The system could then be reviewed to see if another area had become the constraint and the improvement process started again. The Young et al. study also provided an argument for the adoption of Six Sigma by showing how it might be useful to help measure, analyse, improve and control critical customer requirements. This thesis does not attempt to provide an exhaustive review of management processes, but the Young et al. paper does pose an important question of whether healthcare could benefit from management processes from other industries.

The NHS and its Institute for Innovation and Improvement recognised the potential of modelling and simulation. The Modernisation Agency (the predecessor of the NHS Institute for Innovation and Improvement) developed the Big Wizard a 5-step tool to improve health services (Modernisation Agency, 2002). The 5-steps identified were:

1) How do we get started?
2) Sizing up the challenge.
3) Where are we now? Where do we want to be?
4) Managing demand.
5) How can we continue to improve?

Within step 3 (where are we now? Where do we want to be?) Lean thinking and queuing theory were identified as improvement tools. The NHS Institute for Innovation and Improvement also evaluated Lean methodology and proposed the following translation of the 7 classical Lean wastes into a healthcare context (NHS Institute of Innovation and Improvement website, 2008), namely:

1) Overproduction - undertaking activity '*just-in-case*' and / or in a batch. This also contributes to constraining steps in the patient pathway by feeding in inappropriate work or the wrong batch size. Examples include requesting tests and referrals to outpatient clinics '*just in case*'.
2) Inventory - this refers to materials but can be translated as the patient. Holding inventory works against quality and effectiveness, making it hard to identify problems. Examples include using inpatient beds for patients who are waiting for tests but could be discharged safely, or ordering excess material because the supply is unreliable.
3) Waiting - refers to a patient or material waiting, instead of moving at the pace of customer demand. Examples are waiting in queues at the surgery, waiting for tests or making sure all the equipment is ready for an operating list.
4) Transportation - any movement of a patient or material is wasteful. Although you can't fully eliminate transport, you should aim to reduce it over time. When process steps are located next to one another, it's easier for you to visualise, identify and resolve quality issues. Examples include moving a patient to an inpatient bed for review at post-op ward round and then to

another ward for discharge, moving the patient for tests or to see the physiotherapist.

5) Defects - a defect which is passed along the process can escalate the impact of the initial defect. Aim for zero defects.
6) Staff movement - unnecessary movement in the workplace relates to layout and organisation: How far do you move to get to a computer to input discharge information? Is there a better way which will minimise your wasted time?
7) Unnecessary processing - using complex equipment to undertake simple tasks. Often the equipment is large and inflexible i.e. a robot in the pharmacy. Whilst it can take hours for a patient to receive their prescription, the task of dispensing takes a matter of seconds.

From the evidence above, it is clear that the innovation and productivity arm of the NHS has looked at other industries (notably the automotive industry) and adapted Lean methodologies to healthcare. On the face of it, simulation modelling, process improvements and Lean all share similar goals. Robinson et al., (2012) noted that Lean and DES shared a similar motivation: the improvement of processes and service delivery and described the Lean/DES integration process as SimLean.

There is evidence that Lean thinking has been applied to hospitals and in particular A&E (Ben-Tovim et al., 2007; King et al., 2006; Decker and Stead, 2008; Banerjee et al. 2008; Mazzocato et al., 2012; Robinson et al., 2012). A key element in Lean is the focus on flow. In healthcare terms, this is the patient pathway. This might mean changing job roles and descriptions, work schedules changes, standardising work and connecting people that are dependent on each other (Mazzocato et al., 2012). One interesting observation was impact on regarding job changes on both managers and highly skilled staff. Managers familiar with a 'command and control' structure would be required to take on a more facilitative role in a Lean environment (Ben-Tovin et al., 2007). Whilst, under a more regulated Lean regime, clinical staff sometimes found their role too regulated (Mazzocato et al., 2012).

2.6 *Pathway modelling*

Young et al. (2004) stated there is "*a practical challenge is to disentangle actual patient pathways and obtain a clear picture of journeys that loop back on themselves and bounce across boundaries between primary and secondary care*". Interdepartmental services such as emergency departments also have challenges to disentangle pathways. Developing a rationale to model patient pathways could be very useful in a wide range of healthcare applications. For instance, clinical managers and other appropriate stakeholders could look at particular patient pathways and develop models of care focused to patients on a particular pathway (Sanchez et al. 2004). Flow and pathways are key features of Lean methodology and patient grouping (or streaming) was identified by Ben-Tovim et al. (2007), King et al. (2006), Decker and Stead (2008), Banerjee et al. (2008) and Mazzocato et al. (2012). Banerjee et al. identified 4 key patient flows through A&E:

1. Patients with minor injury or illness who, after simple diagnosis, could be treated and discharged relatively quickly – known as “See and Treat”.
2. Patients who require longer assessment and observation in addition to diagnosis or treatment.
3. Patients who require admission to medical ward with a significant length of stay.
4. Patients admitted for emergency surgery procedure.

Locker and Mason (2005) analysed the distribution of time that patients spent in emergency departments and showed that the cohort of admitted older patients had different lengths of stay profiles compared to discharged patients. Similarly, Mayhew and Smith (2008) queuing theory study of the 4 hour accident and emergency department’s target conceptualised 3 patient pathways: leave after little or no treatment; leave after a short treatment; or leave after longer treatment. Patient grouping methods were also employed by Fletcher et al. (2007) who used a national generic A&E model locally to focus on three groups of patient flows: minor, major and admitted patients. Analysis by pathways also helped to show the interactions of patient flow through an area and arguably its further development could help to open the ‘*black*’ box of modelling for stakeholders. The concept of pathway has been discussed in other areas of health modelling. For example, pathway or ‘compartmental modelling’ (Millard, 1994) showed geriatric patients could be split into two distinct pathways: one acute; the other long stay. A number of simulation papers have used compartmental methodology to model different groups of patients (El-Darzi et al, 1998; Vasilakis and Marshall, 2005).

2.7 *Approaches to help overcome poor implementation*

The previous sections described some of the issues surrounding complicated models and their failure to address real problems as acknowledged by stakeholders. To help overcome some of the issues highlighted above, Sanchez et al. (2004) argued that simulation professionals needed to improve their personal capabilities to:

- Make valid verified models.
- Better understand their customer's business needs.
- Provide customers with answers and insights to their business.

In a similar vein, Barnes et al. (1997) suggested three key elements to successful simulation in healthcare were:

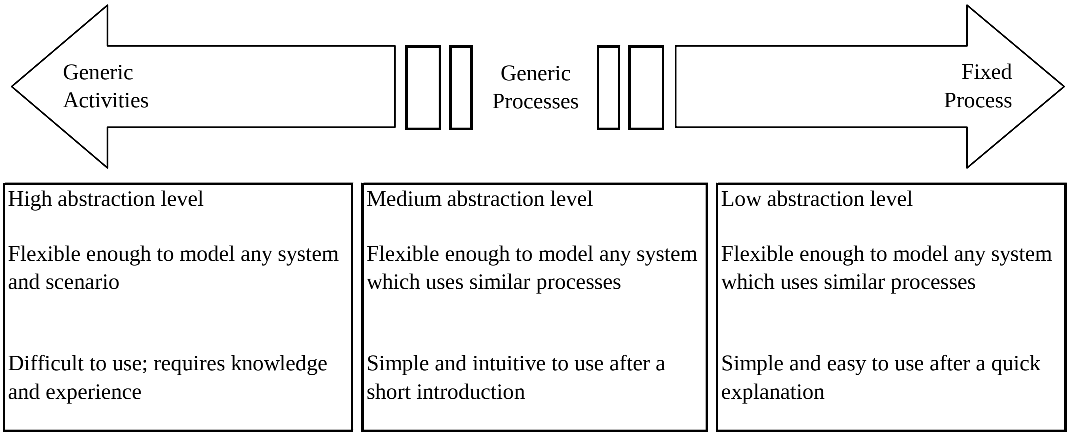
1) Communication and participation.
2) User-friendly simulation software.
3) Using simulation as a decision making tool.

Whilst, arguably, the three key elements above provided a sound basis for successful implementation of simulation in healthcare, levels of complexity and timeliness of models are also key issues that must be addressed. Models and how they are presented in the health industry was also highlighted by the Sinreich and Marmor (2004) paper looking at a simple and intuitive tool for analysing emergency department operations. Sinreich and Marmor observed a lack of acceptance from hospital management to models, especially if the suggestions appeared to have come from a black box. To simplify the process, Sinreich and Marmor suggested the desired simulation tool should be based on the following principles:

1) The simulation tool has to be general and flexible enough to model different possible emergency department settings.
2) The tool has to be intuitive and simple to use. This allows hospital managers, engineers and other non-professional simulation modellers to run simulation models with very little effort.
3) The tool has to include default values for all (or most) of the system parameters.

Although the principles were developed in an emergency department setting, arguably, they are applicable to many areas of simulation. Sinreich and Marmor also developed a range of modelling options which could be used to illustrate building blocks available to modellers - see Figure 3. For example, Generic Activities (simulation packages) usually have high levels of abstraction with enough flexibility to model a large range of systems and scenarios. However, a down-side of high levels of abstraction is often the level of skill, knowledge and experience required to develop and use these types of models. In contrast, low levels of abstraction used to model Fixed Processes are much simpler to use but limited in that they are usually only useful to analyse the model for which it was designed.

Figure 3. The range of modelling options and the building blocks used in each case (adapted from Sinreich and Marmor, 2004)



In between the Generic Activities and Fixed Processes sits Generic Processes. Generic Processes have medium levels of abstraction - flexible enough to model systems with similar processes yet intuitive and simple enough to use after brief training. Arguably, Generic Processes encapsulates a powerful concept. Once a generic process has been modelled, similar processes could be quickly developed using repeatable code - reducing both development time and code verification time.

Chick (2006) suggested six ways to improve a simulation analysis derived after two decades of personal experience of simulation modelling. The six ways were:

1) The choice of the most appropriate tool for the job.
2) Insuring that the problem statement is understood well enough.
3) The balance between the credibility of the model and its simplicity.
4) The notion that simulation does not mean emulation.

5) The influence of explicit and implicit assumptions.
6) The problem of over-analysing when parameters that describe system behaviours are unknown.

Chick also made an interesting observation regarding the understanding the language of the application domain. He suggested that in multidisciplinary applications it was critical to be precise with one's language and modellers needed to be familiar with the language of the decision maker and other stakeholders. Chick commented that it might take years to learn the language of a collaborator from another field. He highlighted the point that even if syntax and semantics of words were understood, there still might be mismatches in the importance of particular words.

With regard to wicked problems Ritchy (2005) and Rosenhead (1996) suggested methods to help tame them, namely:

- Accommodate multiple alternative perspectives rather than prescribe single solutions.
- Function through group interaction and iteration rather than back office calculations.
- Generate ownership of the problem formulation through transparency.
- Facilitate a graphical (visual) representation for the systematic, group exploration of a solution space.
- Focus on relationships between discrete alternatives rather than continuous variables.

- Concentrate on possibility rather than probability.

Eldabi's (2009) paper also referred to a number of methodologies to help frame wicked problems such as Problem Structuring Methods (PSM) (Pidd, 2007). These approaches might in themselves be an issue to healthcare stakeholders, if it appears as though more effort was put into structuring a framework rather than working to resolve real healthcare stakeholder issues. Eldabi further suggested that modellers needed to improve their modelling abilities to deal with wicked problems. Suggested improvement areas included:

- Technical modelling skills – technical skills to build models to provide answers to questions posed by stakeholders; visual and output presentations also important.
- Facilitation skills – Communication with stakeholders crucial. Modellers are required to express their view to stakeholder, but those views should not impose directions or outcomes.
- Eliciting information by all means – modellers should be equally at home extracting data from stakeholders or data sources. Lack of data should be seen as an opportunity to find innovative solutions.
- Identifying modelling values – modellers need to be able to identify interim outcome beneficial to the outcome and be able to communicate these to stakeholders.
- Communication skills – ability to extract important modelling issues, keeping stakeholders updated and interested in the model.

- Ability to manage stakeholders – managing multiple stakeholders including any political issues.

2.7.1 An argument for streamlined models

Young et al. (2009) described the challenge of matching the complexity of the model to the problem in hand and questioned whether the model could meet customer operational needs. One suggestion might be the development of generic simulation models, transparent to stakeholders, powerful enough to highlight key issues, yet simple enough to be tailored at short notice to represent a local system (Young et al., 2009; Sinreich and Marmor, 2004). Simple tools could help system-owner (stakeholders) make sense of their systems (Proudlove et al. 2007). Young et al. (2009) developed this theme by suggesting that if modelling and simulation were to make a bigger impact in healthcare, a strenuous effort needed to be made in terms of '*reducing to practice'*. Young et al. suggested that prescriptive guidelines or rules of thumb might be used to help provide results in a timeframe required by real hospitals. In this vein, Fletcher et al. (2007) simplified the A&E model by excluding processes outside of A&E control, for example, diagnostic testing. For example, if no inpatient beds are available to receive admitted patients from A&E, modelling the downstream constraints of no inpatient beds could create coding challenges. Indeed, some functions within A&E created modelling challenges, such as modelling peak activity just before the 4 hour target time from arrival to discharge out of the hospital or admission to ward (Locker and Mason, 2005; Mayhew and Smith 2008; Mason et al., 2010; Mason 2010; Günal and Pidd, 2006). Furthermore, the peak characteristic was more pronounced on admitted patients. Eatock et al. (2011) developed an innovative solution to model the 4 hour peak by attaching shelf life to modelled patients. On shelf life expiry, patients were fast-tracked with a higher priority. The Eatock et al. model supported two interesting observations. One was that subjectively, this type of behaviour was witnessed during real observational visits to A&Es by the author; and two, the fact this behaviour was able to be modelled, perhaps it was not freakish, random or uncontrollable as one might intuitively think.

Another area of modelling challenge might be the need to possibly model clinical staff possibly increasing their workload as demand increases (or patients approach their 4 hour breach) or slowing down when demands slacken. Some papers regarding human factors (Badham and Ehn, 2000; Baines and Kay, 2002; Baines et al., 2005; Baines and Benedettini, 2007) suggest a framework linking human centred factors (the individual, physical conditions and organisational environment) as a function with human performance indicators (activity time, dependability error rate, absenteeism rate, accident rate and staff turnover rate) and as such, it might be possible to add these inputs into a simulation model. As A&E departments are rarely self-contained units (A&E staff interact with other staff within hospital), this would suggest that clinical colleagues working with A&E staff would be subject to the human centred framework.

2.8 *Literature review overview*

This literature review captured a number of issues related to poor implementation of simulation models in healthcare and a broad failure of academic simulation modellers building models to reflect real healthcare problems as acknowledged by healthcare stakeholders. The evidence suggested that the size, complexity and the emotive topic of health set healthcare aside from other industries. Perhaps, the evidence of poor implementation and the relatively low levels of documented real-life problems are a symptom of modelling an industry with a high proportion of complex and wicked issues. The complex and wicked nature of modelling healthcare appeared to be an attractive area of investigation to researchers and academics and the literature review provided evidence of a high proportion of theoretical healthcare papers compared to other industries. This literature review also provided some evidence to suggest that academic researchers might be rewarded for publishing in high quality journals that often have poor connection to the real-world. Stakeholder engagement by academics was another issue highlighted in the literature review, as was modelling to resolve real issues within specific timeframes. This chapter also briefly looked at other industrial techniques, such as Lean thinking and Six Sigma. Approaches to help overcome poor simulation modelling implementation were also discussed in this chapter, as well as an argument for streamlined models.

All in all, the academic evidence appeared to highlight the fact that academic healthcare modellers have generally failed to build models to resolve healthcare problems as acknowledged by healthcare stakeholders. One observation was that academic papers appeared to show little or no recognition of the non-academic based modelling activity taking place in the healthcare industry. Also, the literature review made little mention of space demand issues with regards to modelling. The following chapter will review Healthcare Planners and discuss issues around the impact of space demand in a healthcare setting.

Chapter 3: Healthcare planning and its role with healthcare stakeholders

3.1 *Chapter outline*

The literature review found little or no mention of Healthcare Planners and their role within the UK healthcare industry. In the recent past however, Healthcare Planners have had a small but significant input during the recent wave of hospital builds and refurbishments under the Private Finance Initiative (PFI) program (circa 2000 to 2008). Moreover, Healthcare Planning historically has been a recognised function within the UK healthcare industry and throughout the life of the NHS. During that time, Healthcare Planners had developed strong relationships with architects, building research space planning and policy, and strategic stakeholders within the healthcare. This chapter will provide a brief overview of Healthcare Planners, their role and relationships with healthcare stakeholders, including their inputs into space planning. To help set the Healthcare Planning context, this chapter will describe the early years of the NHS with a particular focus on NHS building requirement and standard.

3.2 *NHS Building requirements and Building Standards*

At the birth of the National Health Service (the NHS) in 1948, hospital buildings, previously run by county and municipal authorities and voluntary bodies, were badly in need of repair. Hospital buildings incorporated into the new NHS included:

- General Hospitals.
- Cottage Hospitals.
- Workhouse infirmaries.
- Hospitals for the Armed Services, Specialist Hospitals and Convalescent Homes and Hospitals.

In this period after the Second World War, houses and schools were also in demand and their build, repair or replacement often took precedence ahead of hospitals. It was within this environment of the need to renovate hospital building stock, using scarce financial resources, that in 1949 The Nuffield Provincial Hospital (later to become the Nuffield Trust) in partnership with Bristol University initiated a major research study to examine what hospitals the country needed to support the new universal free health service.

Francis et al. (1999) suggested four broad areas shaped healthcare:

1. The practice of medicine in its widest sense; capturing new drugs, treatment, design and provision of facilities.
2. Architecture and technological ideas and how they informed our approach to healthcare buildings; such as industrial production, prefabrication used on non-healthcare buildings, natural/artificial lighting and planning the physical environment.

3. NHS buildings and how they service society; the notion that people being treated in hospital were entitled to standards at least or better than their own homes.
4. Continuing healthcare and policy; the impact of government policy.

This work resulted in the publication of Studies in the Function and Design of Hospitals in 1955 (Francis et al., 1999), which arguably had significant impact in the ideas and research on healthcare buildings over the following 30 years. A multidisciplinary group formed the nucleus of the research team which included architects, historians, physicians, nurses, statisticians and accountants.

At the time, this was pioneering work and resulted in a systematic investigation into the environment of hospital buildings and the organisation of healthcare delivery. This included statistical analysis to help plan demand of the community served by the hospital. By the 1960's, clear ideas were beginning to develop regarding the structure of NHS hospitals. In 1962 the Minister of Health's Hospital Plan proposed to replace the ageing inherited hospital buildings across the UK with 600-800 bedded District General Hospitals (DGH's), each serving a defined population. To help support the dissemination of information, standards of control and management of capital investment, the Hospital Building Division (within the Ministry of Health) created Hospital Building Notes (HBNs). HBNs built on the research of organisations like Nuffield and these de-facto national standards defined aspects such as:

- Working relationships of rooms.
- Descriptions of rooms.
- Schedules of Accommodation (SoA) which defined floor area and number of treatment spaces.

Within this environment, Healthcare Planners (sometime called Service Planners) had an important role, both in the development of HBNs and working with architects and senior hospital managers to help translate them into functional spaces within hospitals (Francis et al., 1999; Hignett and Lu, 2008). The development of Schedules of Accommodation was a key component to space planning and will be described in greater detail later in this chapter.

To keep pace with advances over the years, guidance notes were regularly updated. Guidance notes sometimes referred to calculations or 'rule-of-thumb' calculations to determine clinical space for the provision of health for patients. Examples include clinical space in emergency departments (NHS Estates, 2005b), facilities for primary and community care services (Department of Health, 2011) and facilities for surgical procedures (NHS Estates, 2004).

3.3 *Healthcare Planning and their role in Private Finance Initiative (PFI) healthcare building projects*

Healthcare planning generally started life as a centralised function within the Department of Health (DoH). During the period of the Thatcher and Major

Governments (1979 to 1997), many centralised services were decentralised and this period saw the rise of the internal markets (Gorsky, 2008; Pollock and Dunnigan, 1998; Francis et al., 1999). As a result of this decentralisation, many services like healthcare planning moved from a centralised function from the DoH to the private sector or to NHS hospitals. The years 1997 to 2008 (the Blair and Brown Governments) saw big increases in public spending in the healthcare infrastructure within the UK to meet the Government commitment to match the European level average. The primary funding vehicle used at the time to modernise health infrastructure was the Private Finance Initiative (PFI). Before PFI, the majority of physical assets (buildings) that delivered health services were owned by the health sector. Under PFI, hospitals are owned by a private sector consortium, and the consortium provides a serviced building to a hospital over an agreed period, typically 25 to 30 years. Over the agreed period, the hospital pays the consortium annual service charges. Hospitals built under PFI asset were a substantial undertaking; defining the requirements, designing the asset and managing the release of funds. The funds required to upgrade or to build new hospital facilities were significant. Funds required ranged from a few £ millions up to potentially hundreds of £ millions for a new hospital. The PFI process steps are outlined in Table 6. As illustrated in Table 6, business cases were important steps in the PFI process namely; Step 1, the Strategic Outline Case (SOC), Step 2, the Outline Business Case (OBC); and Step 5, Full Business Case (FBC). Step 1 prepared the Strategic Outline Case (SOC) which provided a broad outline of the project. Approval of the SOC was required by the Capital Advisory Group before the process moved to the next stage (Step 2), the Outline Business Case (OBC). The OBC described the project in greater detail including outlining the service requirements and option appraisals. OBCs were usually approved by the NHS regional executive. The next stage, Step 3, Preparation for Procurement, approved options and translated into detailed specifications outputs, outcomes and allocation of risk. These output specification in essence specified the clinical activity required, but not the number of beds or rooms required in delivering services specified. Steps 1 to 3 were usually prepared by the Trust and/or the Trust's advisors.

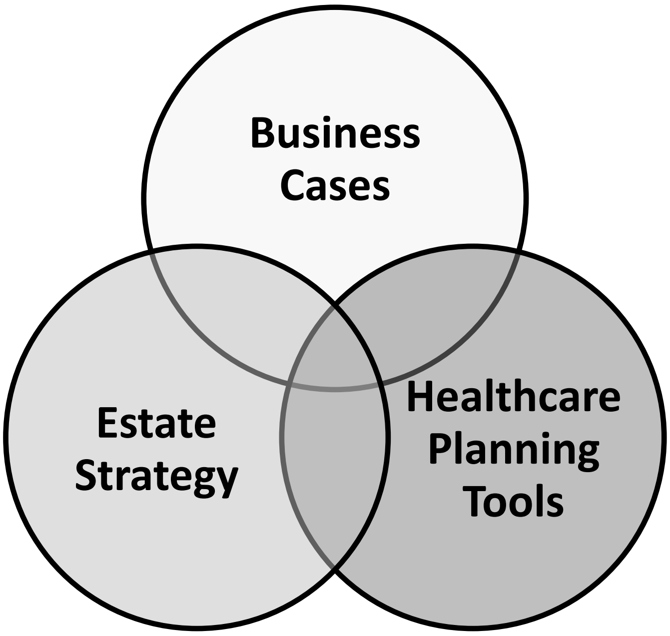
Table 6. The Private Finance Initiative (PFI) Process

The Private Finance Initiative (PFI) Process	
Step	Activity
1. Strategic Outline Case (SOC)	Prepare outline sketch of project and obtain approval to proceed from Capital Advisory Group
2. Outline Business Case (OBC)	Define service requirements; appraise the options and make the case for change in an OBC; obtain approval to process
3. Preparation for Procurement	Translate approved option into a detailed specification of outputs, outcomes and desired allocation of risks
4. Procurement Process	Already suitable providers and the best obtainable privately financed solution through a procurement process
5. Full Business Case (FBC)	Complete the definitive investment appraisal and FBC and obtain approval
6. Contracts award	Finalise, award and implement the contract

The PFI Consortia responded to the output specification (Step 4, the Procurement Process) by defining precisely how they would meet the clinical activity requirement, including the numbers of beds, rooms and physical layout of the proposed building. This process concluded with the Trust selecting its chosen PFI consortia. On selection of a consortium, a Full Business Case (FBC) was prepared (Step 5) and this pulled together all the previous documents and included relevant financial information, for example, defining how the project will be funded and how the PFI would be serviced over its lifetime. The sixth and final step saw the awarding and implementation of the contract by the PFI consortium.

The PFI programme was a significant financial undertaking. By April 2009, there were 76 operational PFI hospital contracts with a capital value of £6 billion (House of Commons Committee of Public Accounts, 2011). The PFI programme recognised that skills gaps might exist and that NHS Trust might consider using appropriate professional advisors. Healthcare Planners were often employed as healthcare advisors to assist the development of strategic context and preparation of business cases (The Department of Health 2007a; The Department of Health 2007b). Often Healthcare Planners were also used as hospital advisors on PFI contracts. Therefore, on PFI projects, Healthcare Planners frequently built working relationships with senior managers' hospitals to develop business cases. Business Cases were often supported by a range of functions such as an Estate Strategy and Healthcare Planning Tools as illustrated in Figure 4. The next two sections will describe the Healthcare Planning, their inputs into Estate Strategies and tools used.

Figure 4. Planning Model



3.4 *Estate Strategy - Healthcare Planning links*

The physical hospital estate is a crucial element in the provision of clinical services. Under the Health Service Act 2006 hospitals were encouraged to take on more self-governance by becoming Foundation Trusts (FT) (National Health Service Act, 2006). More self-governance increased the focus on the management of the physical hospital estate, which often resulted in an estate strategy (NHS Estates 2005a). An estate strategy is a high-level document, often used by a Trust board and its senior officers, to drive the broad direction of the Trust. The estate strategy usually captured the physical condition of the healthcare estate and building requirements to support the current and future healthcare needs of the local population. The service strategy is an important element of an estate strategy encapsulating: national policies and priorities; specialist services; cross boundary issues; wider health needs; and other needs identified from other health organisations and local government. Supported by other inputs such as finance and staffing, an estate strategy could provide a clear direction in:

- Premises developments that support service (including capacity requirements) to national and strategic level commitments.
- The provision of appropriate, safe and secure buildings, encouraging commitment towards sustainable development and environmental targets.
- The provision of high-quality healthcare environments, to enhance patient clinical outcomes, satisfaction and improved staff retention.
- Opportunities to dispose of poorly used or surplus assets - releasing capital for re-investment.
- A clear plan for change with measurable goals.

As such, estate strategies (or the information within them) were often used to inform business cases for the allocation of capital for building and refurbishment projects. Many Trusts developed estate strategies with their own internal staff. Sometimes, Healthcare Planners were used by Trusts to help develop estate strategies. Healthcare planning professionals used a range of analytical tools to support estate strategies and related functions. The following sections will describe a selection of tools used by Healthcare Planners.

3.5 *Healthcare planning tools*

Healthcare Planners use a range of tools and techniques to support their role. Key tools described here will include:

- Demand and Capacity analysis.
- Space planning and Schedules of Accommodation (SoA).
- Model of Care analysis.

This section will also describe other supporting functions often undertaken by Healthcare Planners supporting business cases and other ad hoc work.

3.5.1 Demand and Capacity analysis

Demand and Capacity analysis is the investigation of patient numbers and their length of stay in a particular area to help ascertain the space requirements for the provision of a service. For example, if one was able to assess the number of inpatients requiring a bed and how long they might stay in a bed, then it would be possible to calculate the number of beds required and therefore the physical space required to support those beds. Large building programs may take years to complete and may be associated with significant cost. Therefore, Demand and Capacity models often incorporate future projection scenarios. For example, demand and capacity analysis often considers future projected scenarios such as demographic, technological or service changes over time. Similarly, models might incorporate improvement analyses such as admissions avoidance for patients into hospital and shorter lengths of stay scenarios. As demand and capacity analyses were often used to help determine the physical size of buildings to provide healthcare provision, they were often a key element supporting business cases, estate strategies and a range of other related activities.

A number of relatively simple mathematical formulae often formed the heart of demand and capacity modelling and these are described here. Occupied bed days (OBDs) captured the period of time a patient is held in a hospital bed. For example, a patient stay of 5 nights in a hospital bed equated to 5 OBDs. Likewise, if say 50 OBDs were occupied by 10 patients; the average length of stay (ALoS) would be 5 days; see Formula 1.1.

$$\boldsymbol{ALoS = \frac{OBDs}{Number\ of\ admissions\ or\ discharged}} \qquad (1.1)$$

Where, OBDs = Occupied bed days

These formulae were often developed to calculate beds provided by a service such as a hospital. As an example, if we assume a patient is in bed for a whole year (365 days) and the bed was occupied 100%, they would consume a bed for a year as shown in Formulae 1.2 or 1.3.

$$\boldsymbol{Beds = \frac{OBDs}{Days * \%\ Occ}} \qquad (1.2)$$

Or

$$\boldsymbol{Beds} = \frac{\boldsymbol{Number} * \boldsymbol{ALoS}}{\boldsymbol{Days} * \% \, \boldsymbol{Occ}} \qquad (1.3)$$

Where Days were number of service days available and % Occ the occupancy rate

The bed Formulae (1.2 and 1.3 above) have commonly been applied to inpatient beds stays where patients stay in hospital for one or more nights. Day case patients used the same formula except that *Days* relate to the number of days that the Day Case unit is open with shorter OBD assumptions per patient. For example, an OBD for a day case patient may be 0.5 of a day.

The formulae described above often formed the heart of demand and capacity analysis, which in turn often fed into space planning and all its associated activity. As defined earlier, healthcare models might be static (no change over time) or to the contrary, they may be considered dynamic. For example, A&E activity could change quite dramatically over a 24 hour period. Spreadsheet based packages are commonly used and, as suggested by both the formulae above and health guidance notes, models tend to be deterministic (known set of inputs resulting in a unique set of outputs) rather than stochastic (one or more random variable inputs) in nature.

3.5.2 Schedules of Accommodation (SoA)

Often working closely with demand and capacity analysis is the development of Schedules of Accommodation (SoA). SoAs essentially defined and documented the functional content of an area. For example, the relevant HBN for a theatre might suggest an area of 55 square metres (sqm) per theatre. Working in conjunction with service stakeholders, Healthcare Planners would calculate the number of theatres required based on projected theatre demand (activity). Space to support the theatre activity would be added, for example anaesthetic space to prepare the patient for surgery, recovery space post-surgery, scrub/washroom space for clinical staff, staff changing rooms, clean and dirty storage areas, offices etc. The total space required to perform surgical activity would be added to determine the total floor area, often known as the Net Internal Area (NIA). A percentage for plant and circulation would be added to the NIA to determine the Gross Internal Area (GIA); in the example here, for theatre activity. This exercise would be repeated for all functional areas within the hospital to determine the total floor space or GIA. Service growth assumptions are often also included to future prof the proposed floor space. Using SoAs, architects working in conjunction with other specialists (such equipment specialist) would then develop detailed drawings for construction. With space requirements clearly established, costs (whether capital cost to refurbish or build, and or operational) could be attached to the assigned space and monitored. Often SoA information and their associated costs are used in the financial arguments within business cases.

3.5.3 Model of Care Analysis

Guidance notes often provided useful information on the physical location of clinical services and their associated pathways. For instance, where possible, it is good practice to separate adult and children flows or pathways. In the similar way, sterile and dirty products or material should, where possible, have separate pathways and flows. As such, the Healthcare Planning function has a natural synergy with Lean methodologies. In a similar vein, it is good practice to physically locate theatres, theatre recovery suites and intensive care units adjacent to each other to minimise travel time for very ill patients. With their skills and experience, Healthcare Planners were often used by health stakeholders to provide Model of Care (MoC) guidance on refurbishments and new builds during the recent wave of PFI projects.

3.5.4 Business cases, strategic reviews and function timelines

As described above, the generation of an estate strategy was often the precursor to a business case. In addition to estate strategies and business cases, Healthcare Planners might also work with healthcare stakeholders to generate focused strategic reviews or ad hoc investigations and reports as required. Ad hoc investigations might include, for example, a detailed analysis of theatre activity, outpatient room utilisation or a focused review of imaging requirements. The scope of healthcare planning horizons ranged from long term (strategic), medium term (tactical) and short term (operational) as shown in Table 7. Furthermore, this planning activity might be applied to new buildings, refurbishment or reconfiguration of buildings. As one might guess, the range of horizons and associated decision levels spanned a wide range of healthcare stakeholders: including executive directors and senior managers within the Trust, estate managers, departmental service managers, informatics and clinical staff.

Table 7. Healthcare planning function time horizons

Horizons	Decision levels	Examples
Long term	Strategic	• Estate Strategy • Strategic planning • Business cases • Demand and Capacity planning
Medium term	Tactical	• Demand and Capacity planning • Improvement analysis • Model of Care analysis • Schedules of accommodation • Room output specifications • Operational policies
Short term	Operational	• Demand and Capacity planning • Improvement analysis • Model of Care analysis • Operational policies

3.6 *Review of Healthcare Planning inputs*

Pollock et al. (1997) highlighted the fact that as PFIs were private commercial agreements, due to commercial confidentially, Full Business Cases (FBCs) were not readily available for public scrutiny. Pollock and Dunnigan (1998) suggested this lack of public scrutiny of FBCs could be problematic especially as costs often showed significant increases from the Outline Business Case (OBC). In addition, Pollock et al. stated that activity projections and bed modelling assumptions were rarely tested or evaluated and that PFIs would lead to a "*...shrunken NHS that will not be able to provide a comprehensive range of health services to all sections of the community*". The value for money for PFIs debate is outside the scope of this thesis. However, on the question of a shrunken NHS, with the benefit of hindsight (at the time of writing), there is little evidence of a shrunken NHS (in terms of beds and facilities) wholly unable to provide a comprehensive health service. In fact, there is evidence that hospitals in the UK (in line with international trends) have reduced hospital bed numbers (to match inpatient bed demand) in light of technological advances and efficiency improvements and this trend is likely to continue (Imison 2011; Hurst and Williams 2012). This is not to say there are not difficult areas or challenges ahead within the service, especially in light of increasing demands and constrained finances.

As such, this would suggest that the number of hospital beds (and facilities) planned during the PFI period was not wholly unreasonable. It may well be the case that as healthcare planning inputs appeared to meet healthcare stakeholder requirements, healthcare stakeholders may not have perceived a great additional need for academic modelling of healthcare. However, as highlighted earlier, healthcare planning inputs tend to be deterministic (and static) and arguably would benefit from using more stochastic methodologies with a greater understanding of modelling variance over time. For example, OBDs historically are derived from a bed count at a point of time in the day (say midnight). It may well be the case that during the peak of a working day, the beds in use might be significantly higher than indicated by a midnight count. Arguably, both healthcare stakeholders and health planning relationship could benefit from academic inputs with a goal to better manage wicked problems. The health community already has a great precedence related to academic input shrinking a wicked problem. Bagust et al. (1999) stochastic simulation modelling paper suggested that if average bed occupancy rose above 85% in an acute hospital setting, this increased the risk of bed shortages for emergency admissions. Arguably, the

85% bed occupancy rate has almost become a de facto occupancy target for many hospitals in the UK.

3.7 *Do healthcare stakeholders see a need for academic modellers?*

The healthcare planning role is rarely mentioned in academic health modelling literature. However, as outlined above, healthcare planning demand and capacity analysis has provided a level of modelling, and as such, non-academic healthcare modelling methods have probably been more widely used in real-world healthcare modelling than suggested by academic literature. In the UK, hospitals built under the PFI schemes almost certainly had a level of hospital modelling to support their business case development. However, as PFI contracts historically have been private commercial agreements, they are rarely in the public domain (Pollock and Dunnigan, 1998). We have also seen healthcare planning supporting a range of other healthcare stakeholder functions. Therefore, it could well be the case that healthcare stakeholders do not see a need for healthcare modelling from the academic community, if they perceived their modelling methods were being met by Healthcare Planners. That does not mean that healthcare stakeholders should rest on their laurels with their relationships with Healthcare Planners and vice versa. In the main, Healthcare Planners probably need to improve their modelling capabilities and this theme will be developed throughout this thesis.

It is probably the case that simplified prescriptive guidelines are more widely used in real-world healthcare modelling than suggested by academic health modelling literature. Therefore, it could well be the case that if healthcare stakeholders do not perceive a need for academic simulation modellers (over Healthcare Planners), this too could account for poor acceptance of academic healthcare simulation models.

3.8 *Stakeholder engagement*

As discussed earlier, stakeholder engagement on any healthcare modelling assignment is crucial. This chapter also described the role of Healthcare Planners and provided examples of their strong historical links with a range of healthcare stakeholders. Furthermore, compared to the academic community, private sector healthcare simulation modelling engagements have many advantages, such as:

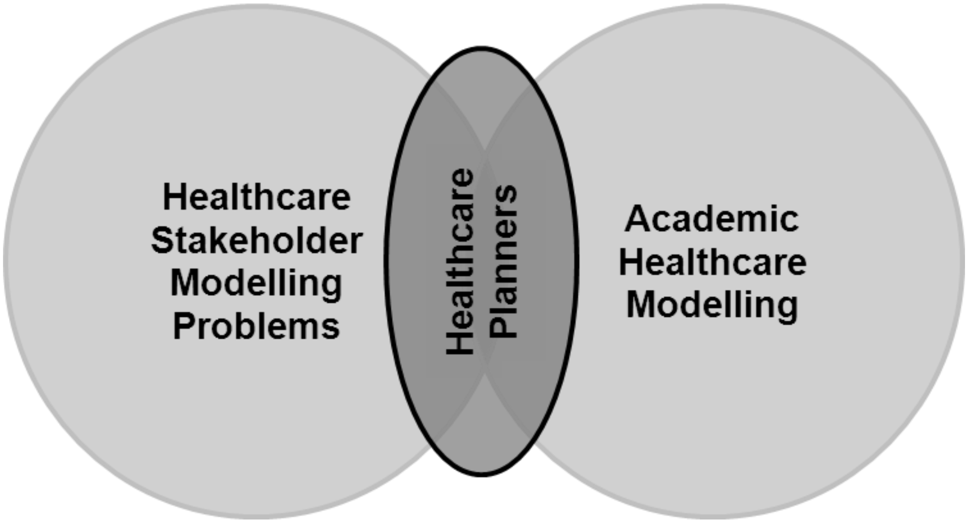
- Engagements are often agreed by contract, so there tends to be strong commitment by all relevant parties.
- Timescales and costs are contractually agreed.
- The key stakeholder(s) often acts the champion for the project.

By engaging in contractual agreements, stakeholders by definition were usually convinced of the value of modelling. Also, contractual agreements tend to have clearly stated aims and objectives bound by time and cost parameters. These elements help to focus the modelling activities towards a stated goal. Often, many issues such as ethics and lack of data encountered by academic researchers are not encountered by their non-academic modelling (Healthcare Planning) counterparts. For example, the modelling process cannot begin until data has been provided, as such, the onus is on stakeholders (or a key stakeholder) to facilitate the supply of data to initiate the modelling process. Frequently within contractual agreements a key stakeholder took on a role as project champion and acted as a link to other stakeholders – taking on the linking role with absence stakeholders (Young et al., 2009).

Another key factor of the contractual process was the provider selection process. The process of selection in itself frequently satisfied stakeholders of the provider's capability to meeting the requirements of the contract. As described, Healthcare Planners have experience providing a range modelling services in healthcare and working in conjunction with a range of stakeholders within healthcare. In building that experience, Healthcare Planners have also become familiar with the language of stakeholders (Chick 2006). As such, the design of the models developed in this thesis focused strongly on the needs of the healthcare stakeholders, namely: streamlined models developed to help tame wicked problems as recognised by the stakeholder(s); within a timescale and budget agreeable to stakeholders; clearly communicating relevant information to those stakeholders.

Arguably, Healthcare Planners could play a pivotal role bringing together (conceptually, if not physically) healthcare stakeholder modelling problems with academic healthcare modelling. This prospective Healthcare Planner role is illustrated in Figure 5. This view of the Healthcare Planner role could work well in conjunction with other academic/industry healthcare modelling initiatives such as MASHnet (2005) and the Cumberland Initiative (2010).

Figure 5. Healthcare planning acting as a link between healthcare and simulation



3.9 *Healthcare Planning overview*

As an overview, this chapter provided examples of Healthcare Planners' roles and their inputs across a wide range on healthcare activities including strategic PFI business cases, estate strategies and related functions. This chapter also described Healthcare Planners and their strong historical links to a range of healthcare related stakeholders. For example, Healthcare Planners often assisted in the development of service plans within PFI business cases and estate strategies. This section also provided illustrations of the scope of healthcare planning tools and their contribution to service planning over a span of time horizon. This chapter illustrated Healthcare Planners’ knowledge and understanding of space guidance notes and their connections to health architects and designers. Due to the increase in importance and number of business cases, Healthcare Planners became well practiced in the art of communicating informatics within business cases to healthcare stakeholders. Healthcare Planners were often employed as external consultants on healthcare projects, so their objectivity and ability to critically challenge was often seen as a valuable input to health projects. Healthcare Planners’ experience within the health industry and their ability to understand the nuances of health and the language of healthcare added their ability to communicate with a wide range of healthcare stakeholders. As such, the relationships between Healthcare Planners and healthcare stakeholders arguably grew, lowering communication barriers between these groups; perhaps in contrast to relationships between academic healthcare modellers and healthcare stakeholders. On this evidence, it would appear that healthcare stakeholders generally believed that Healthcare Planners often had the ability to address real problems as acknowledged by them. However, it is also probably the case that the healthcare planning modelling is predominately deterministic and static; as such, it could benefit from greater use of stochastic modelling and better capability to model variance over time.

Chapter 4: Development journey towards the A&E Space Simulation Model

4.1 *Chapter outline*

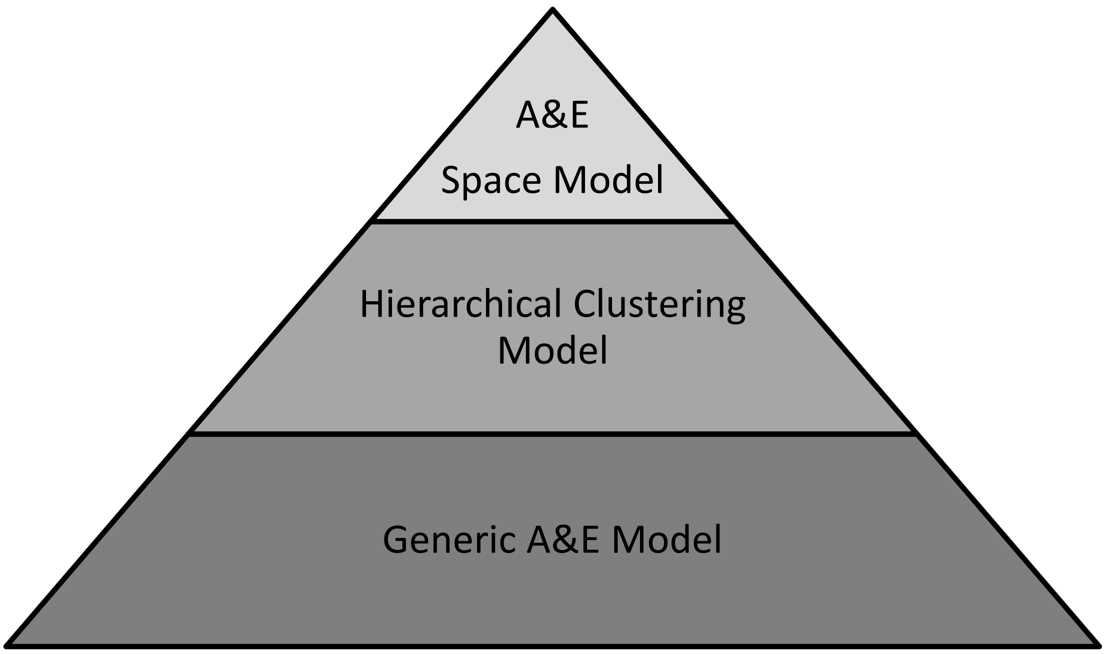
The chapters above have reviewed a perceived lack of the academic modelling community in building models to address real-world problems. The previous chapter reviewed the role of Healthcare Planners within the healthcare sector and the active role they played within the healthcare community; notionally it would appear, to the satisfaction of healthcare stakeholders. The hypothesis of this body of work is that the healthcare planning community can work as an active agent to bring together the worlds of academic healthcare modelling and healthcare stakeholder to address real-world healthcare problems as perceived by healthcare stakeholders. By bringing together these two areas and helping the transference of skill and knowledge between them, there is the opportunity to increase the simulation application on real problems resulting in better hospital management and performance world-wide.

Working towards these broad goals described above, this chapter will describe the development journey towards an A&E Space Simulation Model, namely by:

- Development of a Generic A&E model.
- Development of a Hierarchical Clustering Model.

Figure 6 describes the model development pyramid. Figure 6 also shows the Generic A&E Model as the first step in the development A&E Space Simulation Model. The Generic A&E Model primarily provided the opportunity to develop modelling capability. This step was used as an element to better understand DES capabilities (and limitations) and to develop interfaces with other systems (spreadsheets and databases). Lessons learned from the Generic A&E Model were built on and applied to the Hierarchical Clustering Model, in particular pathway modelling. The development of both the Generic A&E Model and the Hierarchical Clustering Model is described below.

Figure 6. Model Development Pyramid



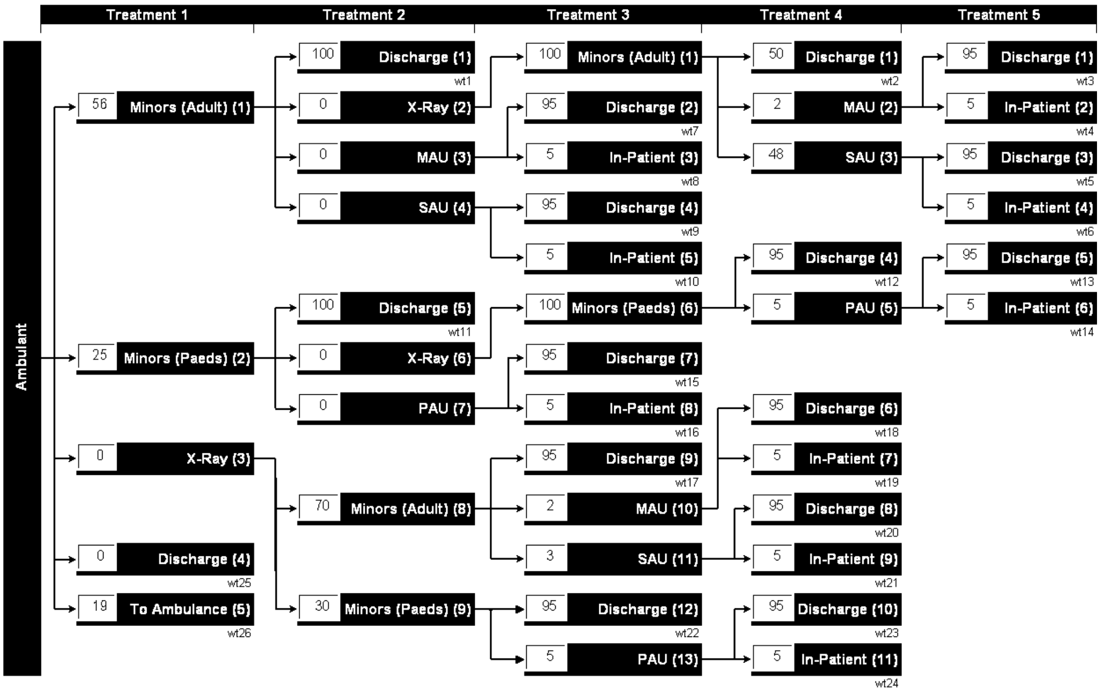
4.2 *Development of the generic A&E model*

Sinreich and Marmor (2004) proposed that medium abstraction level models supported:

- Flexibility to model any systems which use similar processes.
- Simple and intuitive to use after a short introduction.

The rationale of medium abstraction levels was used at the initial stage of this study to develop flexible, easy to use generic A&E models. In addition, developed generic models could be quickly reconfigured and applied to different A&E applications. The generic model was designed to analyse adult and paediatric patients flowing through triage, minor injuries, major injuries (shown in the model as Rapid Assessment) and a resuscitation unit. Major adults were further divided into two groups: medical; and surgical and orthopaedics. Additionally, the model was coded to further direct, if required, adult patients towards a medical assessment unit or a surgical assessment unit (although this area was not fully developed or tested). The model had two arrival points: one for ambulance; the other ambulant, (also known as walk-in) arrivals. This model was also designed to be user-friendly (to help minimise user resistance) as well acting as a communication and decision making tool. The flow through the model was dictated by pathway routers; one each for ambulance and ambulant arrival. The Ambulant Pathway Router (shown in Figure 7) both managed the movement of the modelled patients through the treatment areas and the numbers moving through the treatment areas. Working in conjunction with subject-matter experts to define the pathway routing, Figure 7 shows, 56% of ambulant arrivals defined as minor adults, 25% of ambulant arrivals defined as minor paediatrics and 19% redirected to ambulance arrivals. After treatment in their respective treatment adult and paediatric treatment areas, all patients were discharged.

Figure 7. Ambulant Pathway Router



The Ambulance Pathway Router followed a similar methodology. The pathway routers directed the simulated patient icons over a bitmap of a generic A&E layout. In this way, users (stakeholders) could see patient icons moving through the A&E area in simulation time.

The proposed admissions for a new A&E hospital build are shown in Table 8. The percentages by admissions and arrival route are shown in brackets. The split by area and admission method were defined in conjunction with subject-matter experts. Note that the ambulant arrival percentages correspond to the per cent routing values shown in Figure 7. Table 8 also shows the number of cubicle/beds allocated to the modelled A&E area (as defined by the proposed A&E build). Within the model, cubicle/beds were used as constraints. That is to say, they were assigned on patient arrival and released on exit. Unavailability of cubicle/beds would result in patients queuing in the model.

Table 8. Generic A&E Model Cubicle/Beds and admissions by area

Area	Cubicle/beds	Admissions	Ambulance	Ambulant
Resuscitation Room	8	5,408 (8)	5,408 (28)	0 (0)
Rapid assessment – Medicine	18	12,832 (19)	7,699 (40)	5,133 (19*)
Rapid assessment – Surgery and Orthopaedics	12	6,826 (10)	4,096 (21)	2,730 (19*)
Rapid assessment – Paediatrics	6	3,641 (5)	2,185 (11)	1,456 (19*)
Minor Injuries – Adult	10	28,000 (40)	0 (0)	28,000 (56)
Minor Injuries – Paediatrics	8	12,600 (18)	0 (0)	12,600 (25)
Total	62	69,307 (100)	19,388 (100)	49,919 (100)

The model’s time based functions were defined as follows; Average hourly arrival Data derived from a London based hospital was used as the arrival inputs generator into the model. Process times were defined by subject-matter experts as described by

Law and Kelton, (2001). Process times for the triage, resuscitation, major adults, major paediatrics, minor adults and minor paediatrics functions are shown in Table 9.

Table 9. Process times for the triage, resuscitation, major adults, major paediatrics, minor adults and minor paediatrics

Parameter	Triage	Resuscitation	Major adults	Major paediatric	Minor adults	Minor paediatric
Most optimistic time (minutes)	5	30	60	30	5	5
Most likely time (minutes)	10	30	180	120	90	90
Most pessimistic time (minutes)	15	300	240	150	240	240
Distribution	Normal	Triangular	Beta	Beta	Beta	Beta
Distribution parameters	$\mu=10$, $\sigma=1.67$	a=30, b=30, c=300	$\alpha 1=1.67$, $\alpha 2=1.33$	$\alpha 1=1.75$, $\alpha 2=2.18$	$\alpha 1=1.36$, $\alpha 2=1.64$	$\alpha 1=1.36$, $\alpha 2=1.64$

Where:

- μ was the mean
- σ was the standard deviation
- a, b and c respectively represented the left limit, the mode and the right limit of the triangular distribution
- $\alpha 1$ and $\alpha 2$ represented the shape parameters of the beta distribution.

For a typical simulation run, the generic A&E model collected data over a whole day (24 hours commencing at midnight) after a warm-up period of a day. The typical run cycle was 50 runs. The input and parameters above were loaded into the model and the modelled outputs compared against Scottish national data. Summary results are shown in Table 10.

Table 10. Generic A&E Summary Results

Parameter	Scottish data	Generic A&E Model
Rapid assessment – Medicine (average time to discharge in minutes)	164	163
Rapid assessment – Surgical (average time to discharge in minutes)	164	162
Minors Adult	89	128
Minors Paediatric	89	117
Resuscitation - Paediatrics (median time to discharge in minutes)	72	80
Rapid assessment - Paediatrics (median time to discharge in minutes)	91	86
Minors - Paediatrics (median time to discharge in minutes)	90	104
Resuscitation - Adult (median time to discharge in minutes)	100	80
Rapid assessment - Adult (median time to discharge in minutes)	130	170
Minors - Adult (median time to discharge in minutes)	106	113

Looking at the average and median point comparisons between the Scottish data and the Generic A&E models, the average rapid assessment times showed similar results. It was also interesting to observe that the modelled resuscitation (a combination of adult and paediatric) was between the Scottish adult and paediatric values. Although other comparisons were not as close, this model did serve a purpose to test the modelling philosophy. For example, the model showed poor utilisation of rapid assessment medical bed and that reducing the number of beds from 18 to 10 had a minor impact on the average queue time for treatment or average time to discharge, but a great improvement in the utilisation.

Critically reviewing the Generic A&E Model the positive elements may be defined as follows:

- The model demonstrated the potential of a generic model in an A&E environment at a high level.
- The visual element of the model acted as a good communication tools. Stakeholders could visually see the impact of patient flows through the A&E at different times of the day.
- The development process provided model building experience/expertise, including the linkage of the simulation software to Microsoft based spreadsheet and database packages.

Negative aspects of the model development included:

- Not all elements of the A&E pathway were modelled (for example imaging for patients). This might have left some doubt that the model developed was an oversimplification of the real process.
- Staff and their variability were not modelled.

- Even using a modular methodology of model development, arguably, the model development time was too long.
- Data used from a variety of different sources did not facilitate good statistical testing.

4.3 *Development of a Hierarchical Clustering Model*

Building on the Generic A&E Model, in an effort to facilitate ease and speed of data entry into the model, a Hierarchical Clustering Model was developed to group patients by diagnosis groups. The goal of this development was to:

- Model length of stay profiles, (in relation their 4 hour target).
- Model nurses and bed/cubicle resource usage.
- Develop a pathway modelling methodology.

The hierarchical clustering model was built on concepts discussed by:

- Walczak et al, (2003) which used data set variables, patient groupings and neural networks as a tool to derive bed resources in an intensive care unit and
- Isken and Rajagopalan (2002) which used K-means clustering to model obstetrics and gynaecological flows in hospital.

Within the hierarchical model, patient arrival modes (ambulance or ambulant) and patient pathways were similar to the Generic A&E Model. However, instead of using the pathway routers for ambulance arrivals, clustered groups were used to define ambulance patient pathways. The clustering process is described below. Patients admitted to A&E were assigned a diagnosis code and the length of stay (the difference between their arrival and discharge time) recorded. A hierarchical cluster was performed of length of stay distributions to group together diagnosis with similar lengths of stay. Figure 8 shows the average linkage by Euclidian distance (Everitt and Dunn, 2001; Venables and Ripley 2002). The clustering process was the sole criteria for grouping patients. No attempt was made to group or link diagnosis by treatment activity or intensity.

Figure 8. Hierarchical Cluster Groups

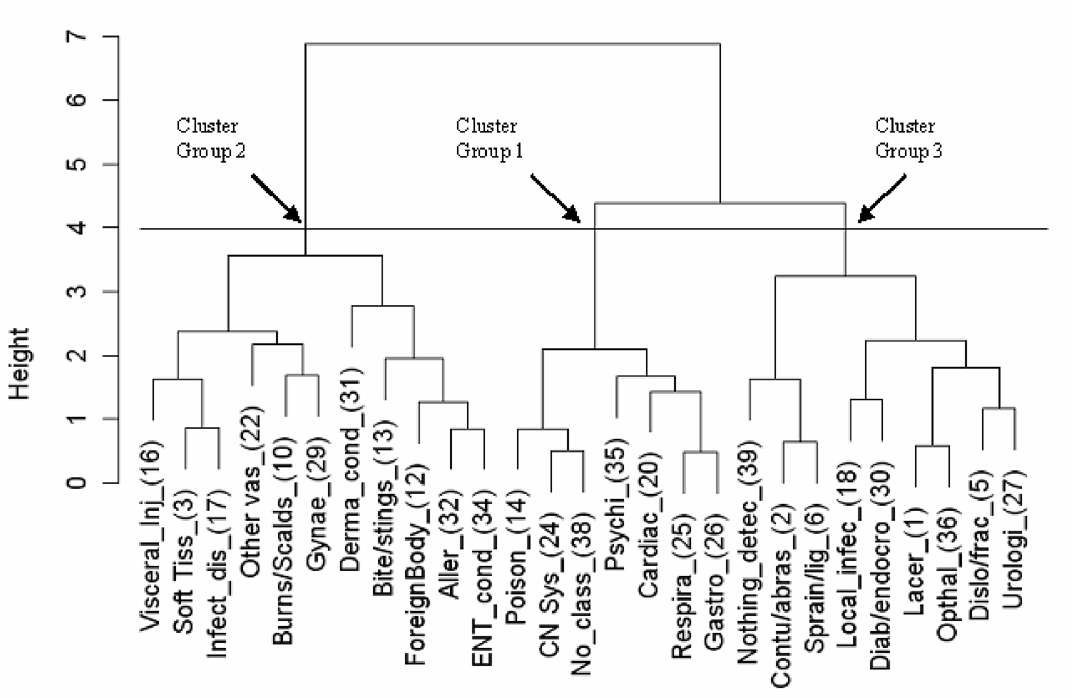


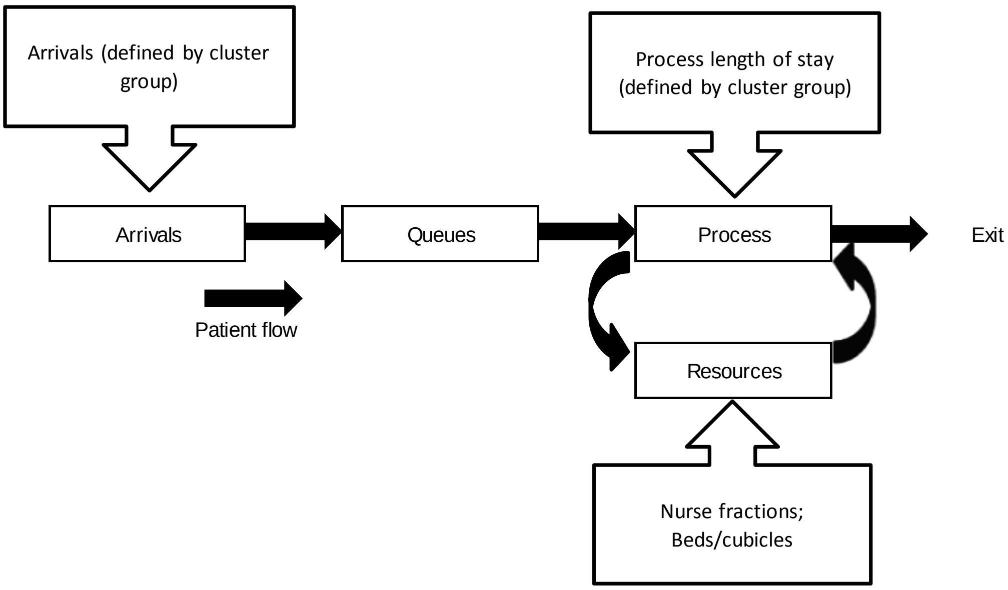
Figure 8 illustrates the three clustered groups, where:

1. Cluster Group 1 comprised of poisoning, central nervous system conditions – excluding strokes, no classification, psychiatric conditions, cardiac conditions, respiratory conditions and gastrointestinal conditions.
2. Cluster Group 2 comprised of visceral injury, soft tissue inflammation, infectious disease, other vascular conditions, burns/scalds and gynaecological conditions.
3. Cluster Group 3 comprised (nothing abnormal detected, contusions and abrasions, sprain and ligament injury, local infection, diabetes and other endocrinological conditions, lacerations, ophthalmological conditions, dislocations/fracture/joint injury/amputation and urological conditions.

A review of the clustered groups with subject-matter experts concluded that the clustered groups made intuitive sense. Cluster Group 1 contained a number of diagnoses that could likely result in extended lengths of stay within A&E. For example, poisoning, central nervous system conditions, cardiac and respiratory conditions often require periods of investigation, monitoring and stabilisation in A&E before further treatment. In contrast, Cluster Groups 2 and 3 contained a cohort of diagnoses that, whilst no less serious, generally were easier to detect and treat (for example, lacerations, dislocations/fracture/joint injury/amputation and burns/scalds. With this confidence, each cluster group had their length of stay homogenised to derive a single length of stay profile for the entire group. The group length of stay profile acted as the process time generator in the model.

The arrival profile of the clustered groups was also homogenised and averaged over a 24 hour day. For each cluster group, the homogenised arrival profile acted as the inputs into the model. Bed/cubicles and nurse fractions (a proportion of a nurse) resources were attached to patient at the start of the process and released at the end of the process. Nurses were allocated to patient independent of cluster or diagnosis coding. A model overview is illustrated in Figure 9.

Figure 9. Hierarchical Cluster Model Overview.



A summary of the model outputs are shown in Table 11.

Table 11. Hierarchical Cluster Model Summary.

Ambulance arrivals (%)	Cluster Group	% of patients meeting 4 hour target	98% target in hours
7,124 (55.3%)	1	89.1	8.2
535 (4.2%)	2	95.3	5.3
5,222 (40.5%)	3	93.3	5.9
12,881 (100.0%)	1, 2 & 3	91.1	7.2
47,018 (-----)	Total A&E	96.1	5.3

The model output appeared to support the observation that Cluster Group 1 contained more conditions with extended length of stay as this group had the lowest proportion of patients meeting 4 hour target (89.1%) with 98% of patients treated within 8.2 hours. Cluster groups 2 and 3 performed better than Cluster Group 1, however, they too fell short of 98% leaving the area within 4 hours. Cluster Group 2 (a relatively small group) showed around 3% of patients missed the 4 hour target, whilst Cluster Group 3 showed around 5% of patients missed the 4 hour target. The 98% target for Cluster Group 2 and Cluster Group 3 was 5.3 and 5.9 hours respectively. The combined clusters (cluster groups 1, 2 and 3) showed around 91% of patients met the 4 hour target, with 98% of patients treated in 7.2 hours. The whole A&E (ambulance clustered groups, plus ambulant arrivals) showed 96% of patients met the 4 hour target, with 98% of patients treated in 5.3 hours.

The pros and cons of the hierarchical clustering model were as follows. On the positive:

- The model demonstrated the potential of a generic model in an A&E environment at a high level.
- The visual element of the model acted as a good communication tools. Stakeholders could visually see the impact of patient flows through the A&E at different times of the day.
- The development process provided model building experience/expertise, including the linkage of the simulation software to Microsoft based packages
- Provided a high level overview for stakeholders.

Negative aspects of the model development included:

- Not all elements of the A&E pathway were modelled (for example imaging for patients). This might leave some doubt that the model developed was an oversimplification of the real process.
- Only nursing staff was modelled in any way.
- Hierarchical clustering took too long, was too complicated and the technique would probably be unfamiliar to many stakeholders.
- No statistical validation of the model.

4.4 *Modelling goals*

Lessons learned from the development of the generic and hierarchical models were used to develop modelling goals for the A&E Space Simulation Model. These goals included:

- Models focused towards resolution and consensus (rather than solution and optimisation).
- Modular pathways modelling methodology.
- Models designed to be user-friendly to encourage stakeholder adoption and to facilitate communications and training.
- Timely models for speed of use and to support rapid reconfiguration.

4.4.1 Models focused towards resolution and consensus

Due to the vagaries of real-world healthcare delivery, healthcare stakeholders are usually more interested in pragmatic resolutions and consensus as opposed to solution and optimisation (Eldabi 2009). This thesis will illustrate below, demand requirements within A&E often varied at different times of the day. Healthcare stakeholders generally (where applicable) desire flexible, generic space. Flexible space, along with service variance information, help stakeholders to better manage their services. Many clinical services are arranged around clinical groups and as described earlier, a better understanding and management of those patient treatment pathways could prove very useful to stakeholders.

4.4.2 Modular Pathways modelling methodology

Developed model components were modular by nature to optimise repeatable code wherever possible. A benefit of using repeatable code was reduced model development time as a result of less time spent on code writing. Another benefit of using repeatable code was reduced code verification time (Law and Kelton, 2000; Sargent, 2011). Yet another benefit of modular model components was the effect of '*opening-up*' models and making them more transparent, thus helping to overcome the '*black box*' model syndrome as described by Sinreich and Marmor (2004). As described earlier in this thesis, within a clinical area, patients may have different pathways dependent on their clinical need.

This thesis proposes that modelling patient pathways are often important requirements to stakeholders in a real-world environment and, as illustrated earlier, pathway analysis and planning is an important element in a healthcare planning role. As such, the models developed in this thesis effectively capture a number of patient pathways from arrival to discharge, using arrival patterns derived from real data recognisable to stakeholders. The pathways developed in this thesis are a development on Mayhew and Smith (2008) ideas, but used DES instead of queuing theory. DES was chosen as the modelling tool as it is commonly used in A&E (Nasser et al. 2009; Young et al. 2009; Paul et al., 2010), its visual communications capability for stakeholders (Barnes et al., 1997; Eldabi, 2009; Proudlove, 2007) and its ability to model in discrete steps. To improve the user-friendliness of the models, Excel spreadsheets were used to configure and input arrival and process parameters. By design, pathway inputs could be quickly configured to real arrival profiles – directly focused towards the local requirements of the stakeholder (Barnes et al., 1997; Sinreich and Marmor, 2004; Ben-Tovim et al., 2007; King et al., 2006; Decker and Stead, 2008; Banerjee et al., 2008; Mazzocato et al., 2012). In addition, pathways could be overlaid to provide a high-level picture of combined pathways (processes). Another prime objective of the modular pathway model was to '*reduce to practice'* (Young et al., 2009) using average process treatment times to determine patient length by patient group.

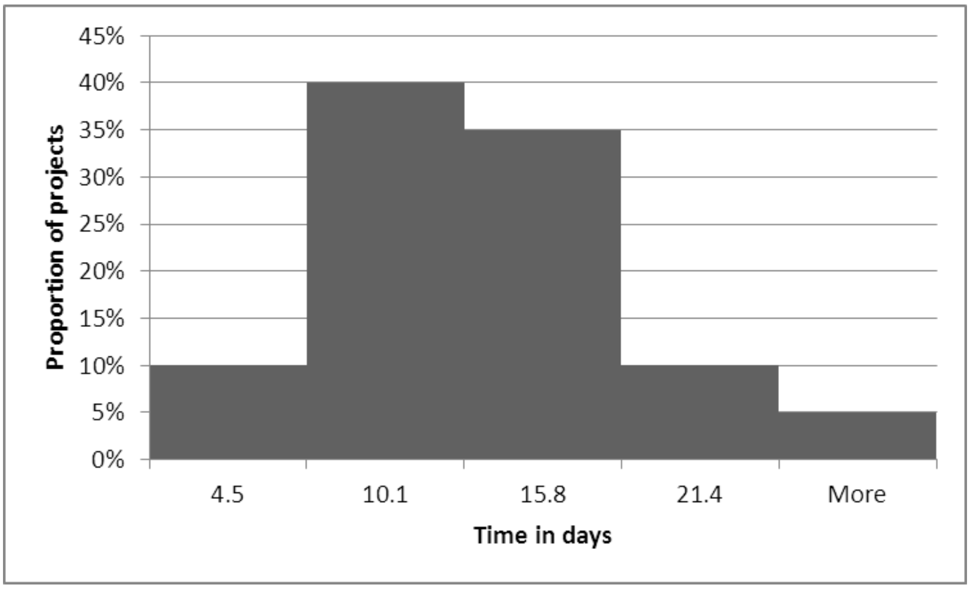
4.4.3 Communications and training

Barnes et al. (1997) and Proudlove (2007) highlighted the importance of communications and training in bringing simulation closer towards the health sector and once again healthcare planning professionals could play a key role. Eldabi et al. (2007) noted communication as a barrier commented "…*it is likely that few modellers really understand healthcare 'from the inside' and few clinicians or healthcare managers really understand simulation*…" As illustrated earlier, Healthcare Planners have a rather unique position in that they understand the healthcare industry rather well and they understand the language of healthcare stakeholders.

4.4.4 Timely models

Timeliness of model development was a factor noted by Eldabi (2009) and Bowers et al. (2009) to name but a few. Figure 10 shows a sample of healthcare planning assignments and a histogram of time proposed to perform the initial modelling exercise. The range of modelling assignments captured in Figure 10 includes strategic planning, estate planning and demand and capacity planning. The average time initially allocated to healthcare modelling proposals was 10.9 days (median 11 days), with the majority (95%) within 22 days. As stated above, many healthcare planning arrangements were contractually agreed and usually funded by stakeholders. As described here, the time (and money) that stakeholders were often prepared to allocate to healthcare modelling was not particularly generous. This necessitates the development of efficient, concise models in compressed timescales using reusable code wherever possible. Models developed would be generic in nature, both to reduce as much as possible the development time and to optimise the model verification process (Sargent, 2011). The allocated time shown in Figure 10 reflected the initial allocated time; often, after an initial analysis, the data and modelling scope expanded to an agreed wider remit. Even so, the deployment of modular, simplified models was used as a key element to support the development of timely models.

Figure 10. Time allocated to simulation modelling proposals



4.5 *Development of streamlined pathway overview*

By way of a recap, this chapter defined the A&E Space Simulation Model development journey by describing the building blocks, namely:

- Development of a Generic A&E model.
- Development of a Hierarchical Clustering Model.

The models developed used repeatable code focused towards addressing real-world modelling needs as acknowledged by healthcare stakeholders, looking to tackle wicked healthcare issues by resolution and consensus. Stakeholder engagement, modular pathways models, timely model development, communications and training were key elements in the model. A key element would be the model's ability to '*reduce to practice'* using real data to determine patient LoS by patient group – with the added ability to gather together numerous pathway to provide stakeholder insights into overall performance. The following chapter will describe the A&E Space Simulation model and how it built on previous work.

Chapter 5: The A&E Space Simulation Model

5.1 *Model introduction*

The previous chapter described the development journey towards the A&E Space Simulation Model. This chapter builds on that work and will outline the design and construction of the A&E Space Simulation Model. A key element would be the model's ability to '*reduce to practice'* using real arrival and LoS by patient groups. The model outputs would facilitate stakeholders and Healthcare Planners ability to model a range of scenarios/parameters, such as, time in the system, space usage and the onset of crowding in specific A&E pathways or the whole system.

This model will build upon of principles discussed earlier, namely:

- Pathways modelling to provide useful information on particular patient groups for stakeholders.
- Modular structure to reduce model development time and ease stakeholder interpretation.
- Use of real arrival and LoS data by pathway to drive the model.
- Reducing to practice; by developing a modelling methodology to model a standard day.

The following sections will describe the A&E Space Simulation Model in greater detail, including a methodological overview, use of real hospital data to define a standard A&E day, patient pathways and resource space.

5.2 *Model methodological overview*

A methodological overview of the model is shown in Figure 11. Figure 11 shows 3 distinct inputs into the model; all easily recognisable to stakeholders, namely:

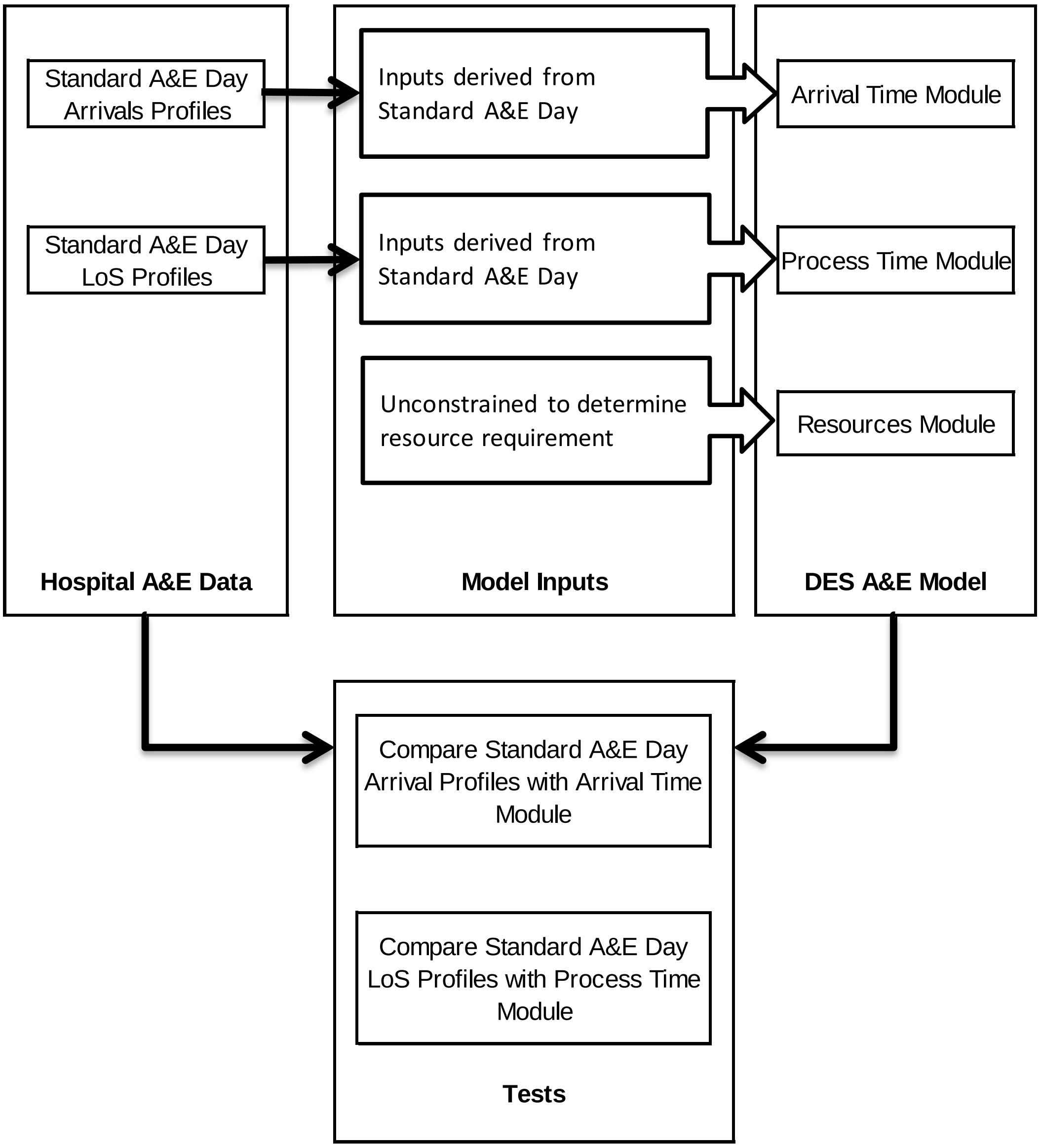
1. Pathway arrival time profiles.
    - Derived from a standard A&E day.
2. Pathway LoS profiles.
    - Derived from a standard A&E day.
3. Resource space (clinical area to treat or hold the patient).
    - This was unconstrained in the model to determine resources required.

The following describes the model in greater detail. The term ‘Standard Day’ was used to generalise both arrivals and length of stay (LoS) activity and represented one year of A&E data from a hospital Trust averaged over a 24 hour day. The data was used to derive 2 distinct profiles:

1. Standard A&E Day Arrival Profiles.
2. Standard A&E Day LoS Profiles.

Using this method of a standard day would allow comparison of the model to actual data. Standard A&E Day Arrival Profiles defined the arrival profile for each pathway and this fed the Arrival Time Modules in the Model. The Process Time Module was driven by LoS profiles by each pathway, whilst the Resources Module was allowed to pull space resources in an unconstrained manner to determine space requirements.

Figure 11. Model Methodological Overview



As illustrated by Figure 11, standard arrival and LoS profiles were tested against modelled arrival and LoS profiles. On this basis, the Model could act as a high level patient pathway Healthcare Planning tool to test space requirements. The processes to extract the Standard A&E Day Arrivals Profile and Standard A&E Day LoS Profiles from the hospital A&E data are described below.

5.3 *The Standard A&E Day Arrivals Profiles*

This section outlines the generation of the Standard A&E Day Arrivals Profiles used to drive the Arrival Time Module in the Model. The pathways selected for this model were:

- Adult major patients – described as Adult-A&E.
- Adult minor patients – described as Adult-UCC (Urgent Care Centre).
- Elderly patients – described as Elderly.
- Paediatric patients – described as Paediatrics.

The rational for the pathway splits were as follows. The triaged data (in the Hospital A&E Data) showed that a large cohort of patients in A&E had non-urgent illnesses or injuries. Some of the earlier discussion around Lean and pathways showed it was good practice to separate major and minor A&E patients. In the UK, it is not uncommon for A&E arrivals to be split into two streams:

1. Stream 1 for major illnesses or injuries (often called A&E).
2. Stream 2 for minor illnesses or injuries (sometimes called Urgent Care Centres or UCC).

Another group of interest were the elderly. The hospital A&E data showed the elderly, although a relatively small group they had longer lengths of stay compared to other groups. Typically up to 2 weeks LoS, 37% of patients are 65 years of age or older. In contrast for LoS over 2 weeks, 71% of patients are 65 years of age or older (Poteliakhoff and Thompson, 2011). Another group of interest were paediatrics. Within healthcare, it is common practice to separate adult and paediatric patient flows. Furthermore, the paediatric profile showed arrivals generally later in the day than adults. In the hospital data, the triage code and age were used to create the pathway data. This process is described below.

5.3.1 Patient Pathways - by acuity

Table 12 illustrates the triage codes for the one year hospital A&E data. Table 12 shows the triage code, triage description, the number of arrivals and percentage by triage code. Referring to Table 12, the triage codes (1 to 6) related to triage description by severity; where code 1 related to patients requiring immediate treatment (for example resuscitation) whereas code 6 related to non-urgent treatment.

Table 12. A&E triage codes by description, arrivals and % of arrivals

Triage codes	Triage description	Number of arrivals	%
1	Immediate	875	0.7
2	Very urgent	11,860	9.7
3	Urgent	38,626	31.5
4	Standard	69,464	56.6
5	Non-urgent 1	372	0.3
6	Non-urgent 2	1,530	1.2
-	Total	122,727	100.0

If we assume that triage codes 1, 2 and 3 captured major illnesses and injuries and triage codes 4, 5 and 6 captured minor illnesses and injuries we could assign triage codes 1, 2 and 3 to model A&E treatment and triage codes 4, 5 and 6 to model UCC. Table 13 describes the triage codes reflecting the A&E and UCC models of care.

Table 13. A&E triage codes re-assigned to A&E and UCC codes

<table>
<tr><th>Triage codes</th><th>Triage description</th><th>New model</th><th>%</th></tr>
<tr><td>1</td><td>Immediate</td><td>A&E</td><td rowspan="3">42</td></tr>
<tr><td>2</td><td>Very urgent</td><td>A&E</td></tr>
<tr><td>3</td><td>Urgent</td><td>A&E</td></tr>
<tr><td>4</td><td>Standard</td><td>UCC</td><td rowspan="3">58</td></tr>
<tr><td>5</td><td>Non-urgent 1</td><td>UCC</td></tr>
<tr><td>6</td><td>Non-urgent 2</td><td>UCC</td></tr>
<tr><td>-</td><td>Total</td><td>-</td><td>100</td></tr>
</table>

Table 13 also highlights that the UCC codes (our minor illnesses and injury assumptions) represents 58% of activity versus 42% of our assumptions for major illnesses and injuries.

5.3.2 Patient Pathways - by acuity and age

In the same way above that we have described patient pathways by acuity; we could further define patient groups by age. In this dataset, all patients 16 or under were defined as Paediatric and all adults over the age of (75) were defined as Elderly. The remaining adult patients were grouped into A&E or UCC dependent on their triage code. The update patient pathways are shown in Table 14.

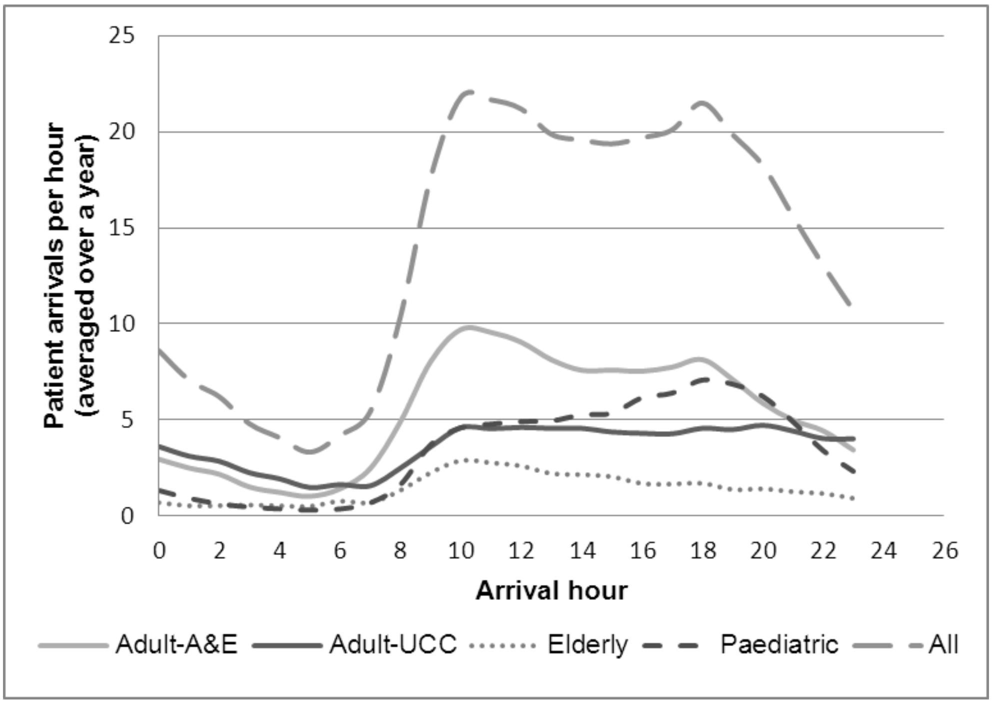
Table 14. Patient pathway by type and acuity

Pathway	Number of patients	Percentage (%)
Adult-A&E	31,641	25.8
Adult-UCC	47,135	34.4
Elderly	12,538	10.2
Paediatric	30,538	24.9
Resuscitation	875	0.7
Total	122,727	100

5.3.3 The Standard A&E Day – Arrivals Profile

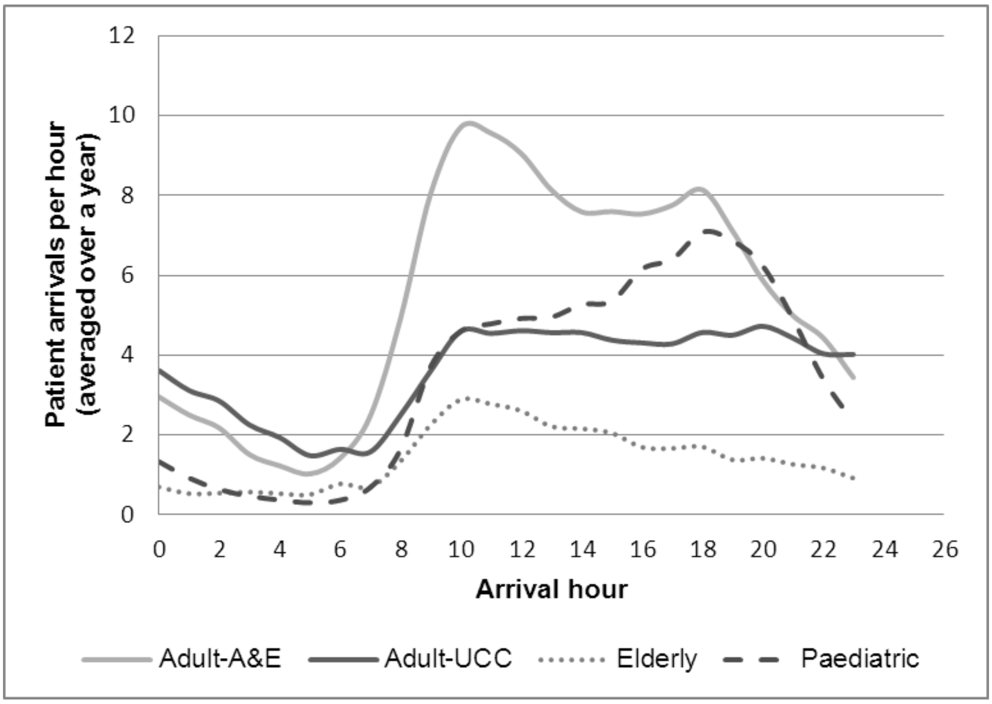
With patient groups defined in this manner, their arrival profiles and length of stay data was extracted from the A&E dataset. Figure12 shows hourly arrival profiles for each pathway (Adult-A&E, Adult-UCC, Elderly and Paediatrics) averaged over the dataset year. Figure 12 describes the overall impact of all the combined pathways – where the sum of the combined pathways arrivals shown as ‘All.’ The ‘All’ data showed the steep rise in the activity around 8:00 and 12:00 hours.

Figure 12. Patient arrivals per hour by type and acuity - All



The activity remained high throughout the day (around 20 arrivals per hour) before reducing at around 20:00 hours. For example, Adult-A&E and Elderly arrivals appeared to peak mid-morning, in contrast to Paediatrics whose arrivals peaked in the evening, whilst Adult-UCC patients showed relatively flat arrivals between 10:00 and 20:00 hours. This information could be very useful to local managers (stakeholders) to plan resources to match arrival demand. Figure 13 is essentially a copy of the Figure 12 plots excluding the '*All*' information to illustrate the individual pathways in greater detail.

Figure 13. Patient arrivals per hour by type and acuity - Detail



Section 3.5 highlighted the importance of modelling variance over time and the example here will emphasise the point. Referring to Table 14, we saw a combined total of 122,727 A&E and UCC patients. If we assume the emergency facilities were open 24 hours a day, 365 days a year, we have 8,760 hours per year. Therefore, the average number of patients per hour was around 14 as shown in Formula 1.4:

$$\boldsymbol{Average\ patients\ per\ hour} = \frac{\mathbf{122,727}}{\mathbf{8,760}} \approx \mathbf{14} \qquad (1.4)$$

The overall average of around 14 patients per hour is clearly below the average peak '*All'* levels over 20 shown in Figure 12. As such, if service provision was provided to meet the average of 14 patients per day, service delivery would probably struggle trying to meet the demand of around 20 patients in the day. This quick example clearly highlights the benefits and necessity of simulation modelling in dynamic situations and the deficiency of average data based models which might be used by unwitting Healthcare Planners or healthcare stakeholders.

5.3.4 The Standard A&E Day – LoS Profiles

The methodology described above to extract the Standard A&E Day Arrival Profiles was also used to extract the Standard A&E Day LoS Profiles. Figure 14 illustrates length of stay (LoS) profiles for the individual patient pathways and the overall impact of the combined pathways – the sum of the combined pathways shown as '*All*'.

Figure 14. Length of stay (LoS) profiles by patient type and acuity - All

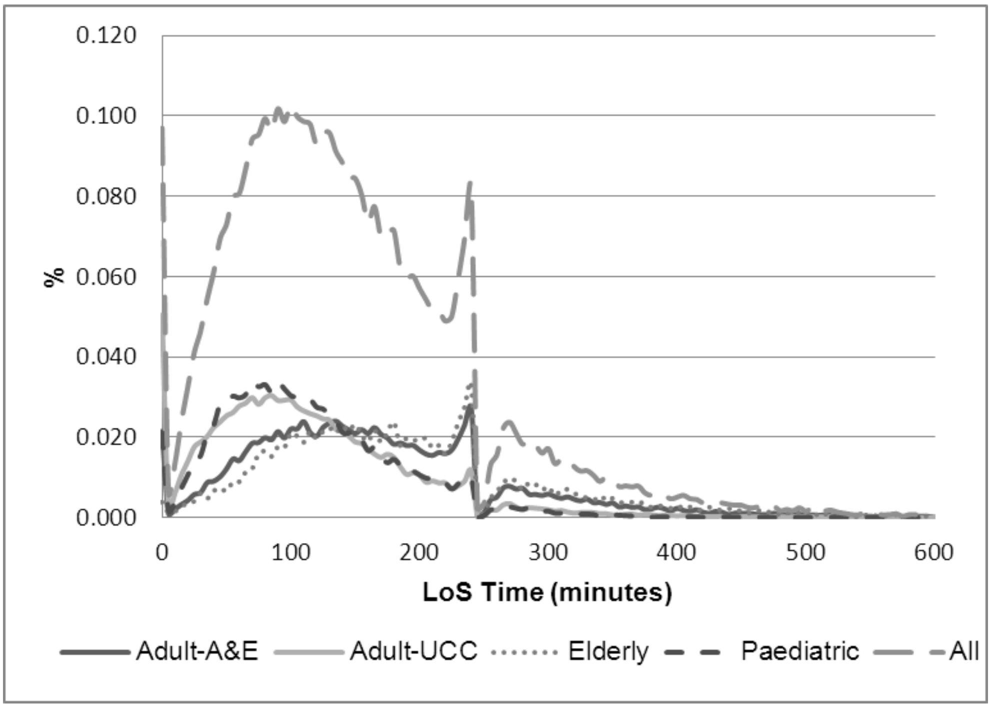
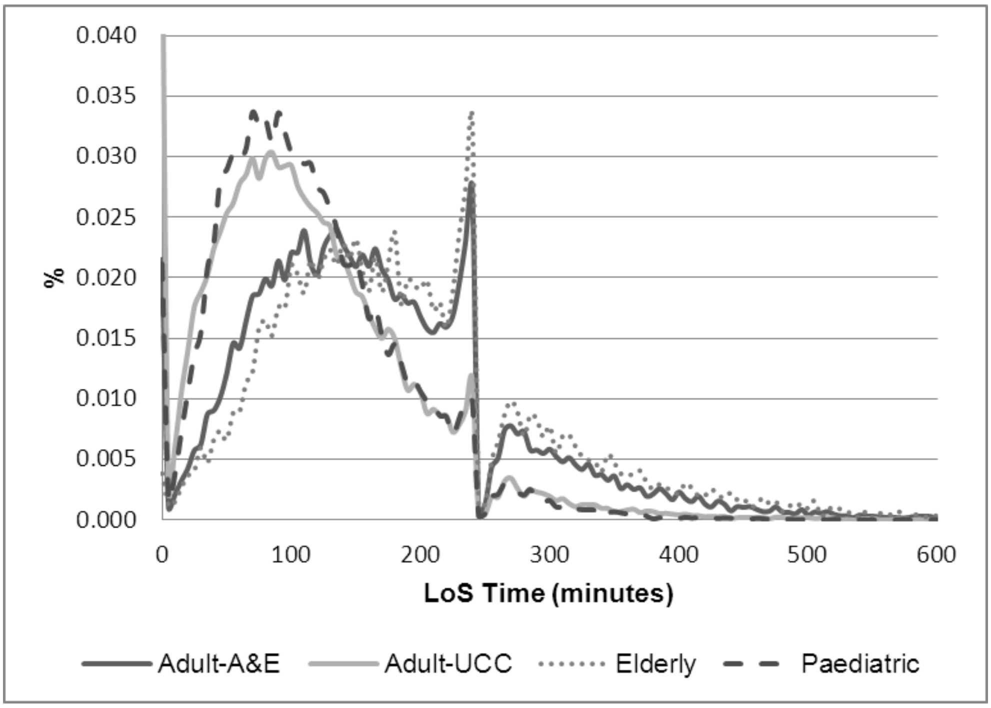


Figure 15 (excluding All data) shows in greater detail the variance of individual length of stay profiles for Adult-A&E, Adult-UCC, Elderly and Paediatric patients. The information in Figure 15 suggests that Adult-UCC and paediatric patients had similar LoS profiles with their median length of stay around 100 minutes. In contrast, Adult-A&E and Elderly showed their median length of stay around 160 minutes. This knowledge could also be very useful to stakeholders (local managers) in the quest for better management of the emergency department area. During the time of the core data collection, 4 hour A&E waiting targets were in place in the NHS. The target meant that after arrival in an emergency care environment, patients had a target time of 4 hours to discharge or to be admitted into hospital as an inpatient.

Figure 15. Length of stay (LoS) profiles by patient type and acuity - Detail

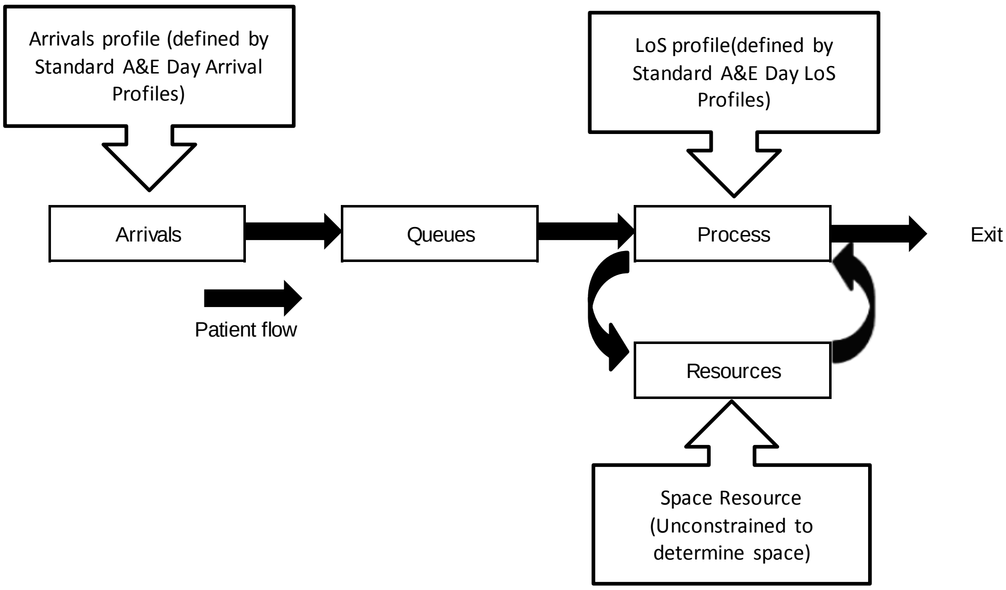


The LoS outputs in Figure 15 show a steep rise and fall around the 240 minutes (4 hours) LoS. The highest peaks at 240 minutes relate to the Elderly pathway and are probably linked to the high proportion of hospital admissions. This characteristic has been noted in a number of other papers, for example: Locker and Mason, 2005; Mayhew and Smith 2008; Mason et al., 2010; Mason 2010; and Günal and Pidd, 2006.

5.4 *The A&E Space Simulation Model process flow*

A schematic of the A&E Space Simulation Model is shown in Figure 16. The schematic shows the first step in the model as the arrivals. After arrivals (using inputs from the Standard A&E Day Arrivals Profile), simulated patients pass through queue area (Queues) before being treated in Process using process times defined Standard A&E LoS Profiles. On arrival at the Process, resources are freely assigned, without any constraints, to determine space resource requirements. Completion of the treatment (process) patients marked the end of their LoS time in the model before exit and the end of the overall process. The completion of the treatment (process) also releases the resources for a future arrival. This model made no attempt to model patient movements (or any other sub-system) within the emergency area, for example, movement to and from a plaster room, imaging, pathology etc. Nor did the model attempt to model staffing in any way; use of space resource was the primary focus. Therefore the pathway process time and the room resources acted as a proxy for all the clinical processes and activities required during the patient stay, for example plaster room, imaging, pathology etc.

Figure 16. Schematic of simulation model process flow.



Several modelled pathways were configured to replicate a number of real pathways. In terms of modelling, a pathway process flow might be expressed as an *M/M/c* queue where the inter-arrival time and service times were exponentially distributed and c represented the number of parallel servers. The model modules are described below.

5.4.1 Arrival Time Module

By way of an example, Table 15 shows the Adult-UCC Standard A&E Day Arrival Profile. The first three columns, extracted from the source data, shows the arrival hour, average LoS and total attendance by hour ('ArrivalHr', 'Sum of LoS ave' and 'Sum of attn' respectively). For the hourly arrivals, row 0 represents 00:00 hrs to 00:59 hrs, 1 represents 01:00 hrs to 01:59 hrs and so on.

Table 15. Pathway arrivals profile - Adult-UCC arrival input example

Disp Code 02	(All)
Triage Desc 03	Adult - UCC

Arrivals per day
129.14

	Data				
ArrivalHr	Sum of LoS ave	Sum of attn	percent	patients per hr	Int arrival time
0	313.07	1,079	2.29%	2.96	20.30
1	337.82	913	1.94%	2.50	23.99
2	346.79	794	1.68%	2.18	27.58
3	300.90	551	1.17%	1.51	39.75
4	328.61	449	0.95%	1.23	48.78
5	318.29	375	0.80%	1.03	58.40
6	315.50	518	1.10%	1.42	42.28
7	312.97	904	1.92%	2.48	24.23
8	305.45	1,792	3.80%	4.91	12.22
9	289.70	2,934	6.22%	8.04	7.46
10	330.26	3,543	7.52%	9.71	6.18
11	355.63	3,488	7.40%	9.56	6.28
12	356.23	3,302	7.01%	9.05	6.63
13	329.62	2,969	6.30%	8.13	7.38
14	313.59	2,769	5.87%	7.59	7.91
15	336.92	2,772	5.88%	7.59	7.90
16	334.14	2,750	5.83%	7.53	7.96
17	323.08	2,829	6.00%	7.75	7.74
18	344.71	2,971	6.30%	8.14	7.37
19	317.77	2,595	5.51%	7.11	8.44
20	321.09	2,143	4.55%	5.87	10.22
21	324.50	1,822	3.87%	4.99	12.02
22	310.83	1,618	3.43%	4.43	13.54
23	336.62	1,255	2.66%	3.44	17.45
Grand Total	7804.07	47,135			

Also note the '*Sum of Attn'* equalled 47,135 matching the total Adult-UCC shown in Table 14. The other columns prepared the source data for the simulation input. The stages were as follows. The attendance by hour was used to calculate the % by hour, patient arrivals by hour and inter-arrival times (columns 'per cent', 'patient per hr' and 'Int arrival time' respectively). As an example, the 0 hour calculations are shown in Formulas 1.5 to 1.7.

$$\frac{\boldsymbol{Average\ arrivals\ per\ hour}}{\boldsymbol{Grand\ Total}} = \frac{\mathbf{1,079}}{\mathbf{47,135}} = \mathbf{2.29}\% \qquad (1.5)$$

$$\mathbf{2.29\% * 129.14 = 2.96} \qquad (1.6)$$

Finally, the inter-arrival time (‘*Int arrival time’*) was calculated as shown in Formula 1.7:

$$\frac{\mathbf{60}}{\boldsymbol{Patients\ per\ hr}} = \frac{\mathbf{60}}{\mathbf{2.96}} = \mathbf{20.30} \qquad (1.7)$$

Formulae 1.5 to 1.7 were used to calculate the average inter-arrival time for each hour over the 24 hour period, for each of the patient group pathways. Also note, the hourly average patient by hour (i.e. ‘*patients per hr’*) and pathway (reference Formula 1.6) were the data used to plot Figures 14 and 15. Standard A&E Day LoS Profiles for Adult-A&E, Elderly and Paediatric are shown in Appendix A1. The real arrival profiles as described (and illustrated in Table 15) above were exported into the simulation model and was used as the source data to generate patient arrivals by pathway.

5.4.2 Process Time Module

Once generated, the patient icons moved through the pathway queues area into their Process area. In the simulation model, the pathway process area was a work centre and patient icons were processed in accordance to their LoS profile. Similar to arrival methodology, patient icons were processed in accordance to their real pathway LoS distributions. Using real LoS distributions captured 4 hour peak profiles and other staffing characteristics and interactions. The use of real LoS data was a neat resolution to the 4 hour peak and staffing issues, eliminating the need for data pre-processing or data assumptions around those inputs. Table 16 illustrates an extract of the real Adult-UCC LoS profile which was exported into the simulation model to drive its LoS pathway profile.

Table 16. LoS Distribution Profile – Adult-UCC example

ProbColNo	Bin	Frequency	UCC%	UCC%100
1	0	2,379	0.050	5.047
2	30	3,273	0.069	6.944
3	60	6,864	0.146	14.562
4	90	8,292	0.176	17.592
5	120	7,722	0.164	16.383
6	150	6,197	0.131	13.147
7	180	4,572	0.097	9.700
8	210	2,973	0.063	6.307
9	240	2,504	0.053	5.312
10	270	529	0.011	1.122
11	300	636	0.013	1.349
12	330	395	0.008	0.838
13	360	253	0.005	0.537
14	390	190	0.004	0.403
15	420	114	0.002	0.242
16	450	66	0.001	0.140
17	480	54	0.001	0.115
18	510	44	0.001	0.093
19	540	24	0.001	0.051
20	570	18	0.000	0.038
21	600	6	0.000	0.013
22	630	30	0.001	0.064
Totals		47,135	1.000	100.000

In Table 16 the column ‘Bin’ reflected the LoS in minutes; ‘Frequency’ the number of occurrences assigned to the Bin time; ‘UCC%’ the percentage proportion of the total occurrences at the Bin time; and ‘UCC%100’ was ‘UCC%’ time 100. The key fields were the ‘Bin’ and ‘UCC%100’ columns which were used by the model to define the actual LoS profile. For the purpose of the model, any occurrences over

600 minutes were allocated to the 630 minute bin. The process described here was used to generate the LoS distribution profiles for the other pathways.

5.4.3 Resources Module

In the model, on arrival at a work centre, a space resource was assigned to a patient icon and released on completion of their LoS. To fully assess demand requirement, resources were unconstrained in this model. In a real A&E, this treatment space could be a cubicle, a room or even a seat. For the purpose of describing this model this allocated treatment space resource was called a space.

5.5 *Using readily available data*

As demonstrated above, this model used real A&E arrival and LoS data to generate stochastic arrival and LoS profiles in the model. Another benefit is that it is a relatively quick process (no further processing required to define distributions) and that real parameters such as the 4 hour peak could be captured and modelled. In the UK, A&E data is routinely collected and the processes described here, shows how that information recognisable to stakeholders, could be quickly manipulated and readily fed into the model. Therefore, this model provides the opportunity for healthcare stakeholders to (relatively quickly) model their own activity or to vary parameters to run and compare a range of scenarios.

5.6 *The DES engine*

This section will describe, in a greater detail, the DES elements with the model, outlining the arrivals sub-model, the process sub-model and coding steps, including input and output interfaces. The A&E Space Simulation Model was created in Simul8 (2011) (a DES package) in conjunction with input and output spreadsheets used to transfer data to and from Excel. For example, the Arrival Process and Process Modules were input data using Excel. On completion of a modelling run, outputs were exported into Excel. The DES modelling steps are shown in Table 17. At the start of each model run (Step 0), the DES data logging sheets were cleared, headers reset and the pathway arrival and LoS profiles were uploaded from Excel. As stated earlier, resources were freely drawn, unconstrained to determine space requirements. At each discrete step during a model run, the simulation clock was checked against the simulation hour and the inter-arrival rate adjusted accordingly (Step 1). For example, at hour 0, the work entry points picked up their appropriate pathway inter-arrival time for hour 0; at hour 1 the work entry points picked up their appropriate pathway inter-arrival time for hour 1 and so on through the remaining hourly periods of the standard simulation day. Once generated, patient icons flowed through their queue area (Step 2), into their respective process areas to start their process time - reference Step 3, where patients were modelled in accordance to their real LoS distribution profile.

Table 17. DES Modelling Steps

Step	Location	Virtual Logic	Sub-routine	Function
0	-	Reset Logic	----	Clear DES data sheet; reset headers, import arrivals profile and LoS profiles from Excel; define run trial parameters
1	Arrivals	Time check logic	----	Set inter-arrival time by matching *'ArrivalHr'* to simulation hour
		----	----	Attach unique ID, pathway ID and simulation start (arrival) time to patient icon
2	Queues	----	----	Patient icons pass through unconstrained to determine resources
3	Process	wc_Grp1 Route In Logic	Sub Set Work Start	Set simulation start work time
4		wc_Grp1 Work Complete Logic	Sub Calc LoS	Set simulation end work time; calculate LoS (simulation end work time – simulation start work time; calculate queue time (simulation start work time – simulation start time)
5	----	----	----	Patient icon splitter to individual and combined profiles in Simul8
6	----	Work Center 13 Route In Logic	Sub Results Log	Log run number, unique ID, pathway ID, simulation start time, simulation start work time, simulation end work time, queue time, LoS, resource free count
7	Exit	----	----	----
8	----	End Run Logic	----	Export results log to Excel

On completion of their processes at Step 4 (the end time of their LoS), the patient icons exited their process area on route to the work exit points. Step 5 describes a splitter process to record individual and combined pathways in Simul8. At key steps throughout the model, namely the time of patient icon generation, their start process time and their end process times were recorded and logged against each patient icon. This facilitated an easy calculation of the process (treatment) time, queue time and overall LoS as described in Formulae 1.8 to 1.10 respectively. Note, using unconstrained resources as described would result in zero queues. However, this feature was designed in to allow the modelling of constrained resources if ever required.

$$\boldsymbol{Process\ time} \quad \boldsymbol{= end\ process\ time - start\ process\ time} \tag{1.8}$$

$$\boldsymbol{Queue\ time} \quad \boldsymbol{= start\ process\ time - arrival\ time} \tag{1.9}$$

$$\boldsymbol{LoS} \quad \boldsymbol{= end\ process\ time - arrival\ time} \tag{1.10}$$

Step 6 logged all the patient parameters in Simul8, ready for export into Excel. Parameters included simulation start time, process start time, process end time and a snap shot of resource use at the point in the simulation run. Step 7 completed the patient icon process; whilst Step 8 marked the end of the '*run'* (Step 8) where patient parameters logged in Simul8 were downloaded into Excel. In this model, a '*run'* was 24 hours of data collection. The '*run*' also included a 24 hour model warm-up period where no data was collected. If multiple runs (a trial) were requested, the process would repeat, cycling from Step 1 through to Step 7. For the model analysis, a trial run size of 50 (50 simulation '*run*' days) was typical.

Tables 18 shows sampled extracts of the first 50 lines of the run log downloaded into Excel.

Table 18. Run Log extract – modelled system times

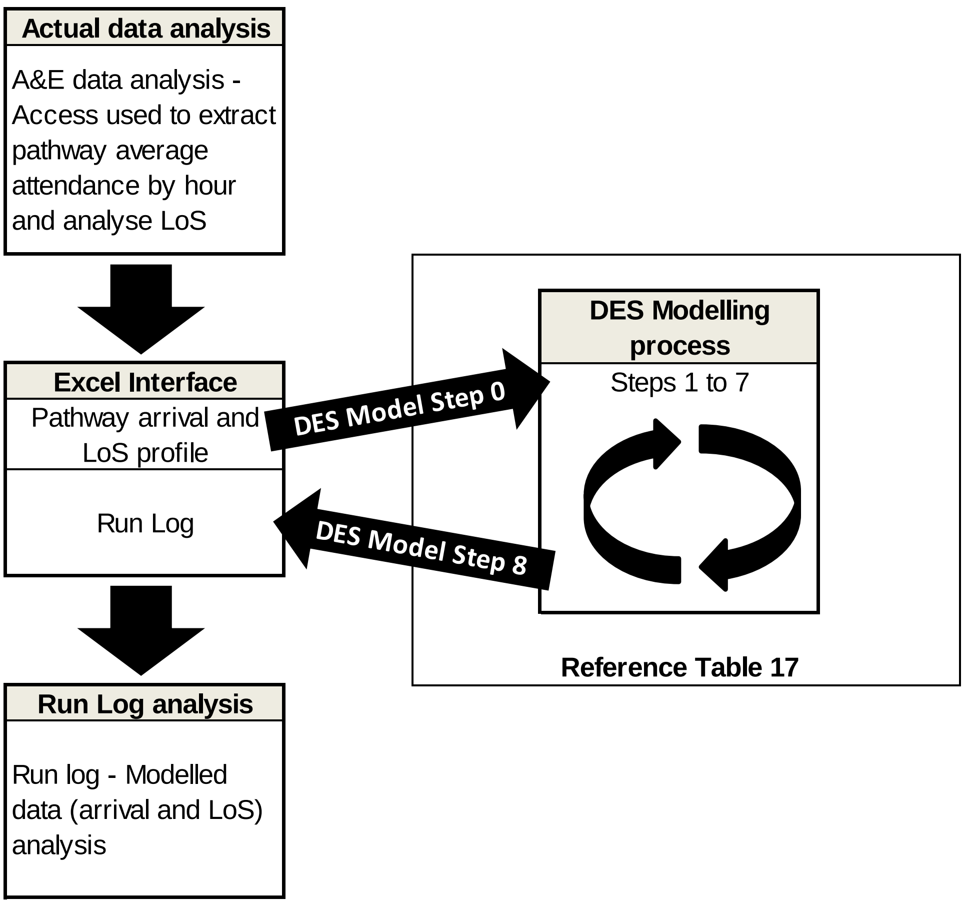
Line No	Trial run No	Unique ID	Route	StartTime	EndTime	StartWork	TreatmentTime	Qtime	LoS
1	1	363	Grp2	1,438	1,440	1,438	2.5	-	2.5
2	1	284	Grp4	1,118	1,465	1,118	347.3	-	347.3
3	1	356	Grp2	1,424	1,470	1,424	46.2	-	46.2
4	1	347	Grp2	1,370	1,471	1,370	100.8	-	100.8
5	1	345	Grp4	1,360	1,473	1,360	112.5	-	112.5
6	1	362	Grp2	1,438	1,474	1,438	36.3	-	36.3
7	1	327	Grp4	1,287	1,477	1,287	190.6	-	190.6
8	1	355	Grp2	1,419	1,481	1,419	62.9	-	62.9
9	1	306	Grp2	1,213	1,497	1,213	284.4	-	284.4
10	1	369	Grp4	1,500	1,500	1,500	-	-	-
11	1	328	Grp1	1,292	1,508	1,292	216.4	-	216.4
12	1	350	Grp1	1,394	1,509	1,394	115.5	-	115.5
13	1	341	Grp4	1,319	1,512	1,319	193.1	-	193.1
14	1	352	Grp2	1,398	1,515	1,398	116.2	-	116.2
15	1	346	Grp1	1,360	1,520	1,360	159.5	-	159.5
16	1	351	Grp1	1,396	1,521	1,396	124.3	-	124.3
17	1	342	Grp4	1,329	1,524	1,329	194.9	-	194.9
18	1	344	Grp4	1,346	1,528	1,346	182.4	-	182.4
19	1	360	Grp1	1,432	1,540	1,432	107.3	-	107.3
20	1	354	Grp2	1,418	1,543	1,418	124.9	-	124.9
21	1	364	Grp1	1,466	1,565	1,466	99.0	-	99.0
22	1	330	Grp1	1,293	1,573	1,293	280.7	-	280.7
23	1	353	Grp2	1,404	1,575	1,404	171.0	-	171.0
24	1	367	Grp4	1,497	1,578	1,497	81.3	-	81.3
25	1	359	Grp4	1,429	1,588	1,429	159.1	-	159.1
26	1	371	Grp2	1,511	1,589	1,511	77.9	-	77.9
27	1	358	Grp2	1,428	1,594	1,428	166.0	-	166.0
28	1	378	Grp4	1,564	1,598	1,564	34.1	-	34.1
29	1	368	Grp2	1,500	1,602	1,500	102.2	-	102.2
30	1	372	Grp3	1,512	1,602	1,512	89.9	-	89.9
31	1	340	Grp4	1,318	1,615	1,318	297.1	-	297.1
32	1	373	Grp2	1,525	1,616	1,525	90.3	-	90.3
33	1	241	Grp2	1,016	1,626	1,016	610.4	-	610.4
34	1	374	Grp1	1,529	1,631	1,529	101.9	-	101.9
35	1	357	Grp1	1,426	1,643	1,426	217.4	-	217.4
36	1	348	Grp1	1,378	1,657	1,378	279.6	-	279.6
37	1	361	Grp1	1,435	1,661	1,435	226.4	-	226.4
38	1	381	Grp2	1,652	1,668	1,652	16.0	-	16.0
39	1	377	Grp2	1,550	1,673	1,550	123.4	-	123.4
40	1	370	Grp2	1,501	1,682	1,501	181.5	-	181.5
41	1	365	Grp1	1,474	1,702	1,474	227.4	-	227.4
42	1	376	Grp2	1,548	1,741	1,548	192.5	-	192.5
43	1	375	Grp1	1,547	1,747	1,547	199.1	-	199.1
44	1	383	Grp4	1,728	1,757	1,728	29.0	-	29.0
45	1	382	Grp2	1,673	1,764	1,673	91.2	-	91.2
46	1	380	Grp1	1,651	1,783	1,651	132.4	-	132.4
47	1	386	Grp2	1,835	1,836	1,835	0.3	-	0.3
48	1	385	Grp3	1,746	1,873	1,746	127.2	-	127.2
49	1	379	Grp1	1,647	1,887	1,647	240.9	-	240.9
50	1	392	Grp1	1,930	1,930	1,930	-	-	-

The 50 lines were an arbitrary choice to demonstrate the working of the model. Each line represented a patient icon. Table18 illustrates the icon data tags and modelled system times parameters, namely: the logged line number, trial run number, the unique patient icon ID and the pathway route. Columns 'StartTime', 'EndTime' and 'StartWork' respectively show the simulation arrival time, process end time (also the end of the LoS) and process start time. Whilst columns 'TreatmentTime', 'QTime' and 'LoS' respectively show the calculated process time, queue time and LoS (all in minutes) for each patient icon.

As illustrated by the '*Virtual Logic*' column in Table 17, throughout the model, programming sub-routines (written in Simul8 Virtual Logic) were used to trigger repeat activity; the Virtual Logic used codes are listed in Appendix A2 along the model schematic. Using verified code (has the programming been correctly translated? - as defined by Law and Kelton, 2000) in this repeatable way both reduced development (model design time) and model testing time. In addition, the visual nature of Simul8 made it an ideal tool with which stakeholder could see the flow of patients (and queues) by pathway, at different times of day throughout the model process.

A schematic of the input/output interfaces model is shown in Figure 17. The '*Actual data analysis'* box captured the analysis of the core data where extracted pathway average attendance by hour was used to create pathway arrival profiles. Box '*Manual data entry*' shows the manual inputs of the average process times and resources. At the start of the '*DES modelling process'* (DES Model Step 0) (reference Table 17), pathway arrival profiles were loaded into Simul8. Using the inter-arrival times within the pathway arrival profiles, patient icons were generated and processed through the model. At the end of each '*run'*, (DES Model Step 8) patient parameters (start time, queue time, process time, LoS and resources) were logged. At the end of the trial, the run results (Run Log analysis) were uploaded into the Excel interface. The Excel interface was used to facilitate the analysis of the trial results. The analysis of the modelled data is described in the following chapter.

Figure 17. A schematic of the model input/output interfaces



5.7 *A&E Space Simulation Model overview*

This chapter conceptualised the model and described distinct model inputs recognisable to stakeholders namely:

- The use real arrival and LoS data by pathway to drive the model focused on specific patient pathways, both of which are easily recognisable to stakeholders.
- Reducing to practice; by developing a modelling methodology to model a standard day; real arrival data eliminates the requirement to develop input and process profiles to drive the model; all of which greatly shortens model development and encourages model re-use.
- Running the model with real inputs could help to identify space demand issues and effects of crowding of an area under investigation.

This chapter also discussed the coding methodology, to streamline the model, as well as the distinct modelling steps within the model. The act of model streamlining, for example using sub-routines and a repeatable code, potentially opened up the model in the eyes of the stakeholders, in addition to reducing the model development and testing time. The graphical nature of Simul8 also supported visual analysis of the model – which allowed stakeholders to observe patient flows and space resource use within the model to gain greater insights in their processes. The following chapter will analyse the results of the simulation model.

Chapter 6: Analysis and Results

6.1 *Chapter overview*

This chapter will review the analysis and results from the A&E Space Simulation Model including its validation and verification. Specifically, this review will take a two-pronged approach looking at:

1. How the model might support operational aspects of an A&E environment.
2. How the thinking developed in this work might be useful to provide some insight at strategic level using function-to-space ratios to highlight potential cost savings.

With regards to operational aspects, this chapter will take a focused look at comparisons between the actual and modelled arrival and LoS profiles by pathways, using statistical tests to compare significant between real and modelled data. In addition to the significance testing the data used to develop the model (known as the primary dataset), a secondary dataset (data from another UK hospital) was also significance tested. Additionally, Friday to Saturday data from the primary dataset was also tested for significance. The purpose of the secondary and the Friday to Saturday analysis was to both test the significant and modelled outputs and to demonstrate how quickly and effectively the model could be adapted to other applications. The operational analysis will also include a number of graphical outputs to demonstrate space demand within the model A&E area. Using this information, service managers can, hopefully, better plan their provision of services at an operational level.

At a strategic level, this section will examine at a high level function-to-space ratios with a view to attach operational costs per unit space. The hospitals within this study showed a significant variance in the space per bed ratio and suggested that moving to the mean (or even lower quartile) space per bed ratios could result in significant savings in facilities management operational costs.

6.2 *Modelled and Actual arrival data comparisons*

As described earlier, the Standard A&E Day Arrival Profiles acted as the arrivals driver in the A&E Space Simulation Model. Therefore an intuitive test was to test the model's Arrival profiles with the Standard A&E Day Arrivals profiles. Figures 18 to 21, respectively show the comparison of actual (real) to modelled arrival profiles (average arrivals per hour) for the Adult-A&E, Adult-UCC, Elderly and Paediatric patients groups. For reference the Standard A&E Day Arrival profiles and the A&E Space Simulation Model Arrival profiles are shown in Appendix A1 and A3 respectively.

Figure 18. Adult-A&E arrival profile - actual and modelled

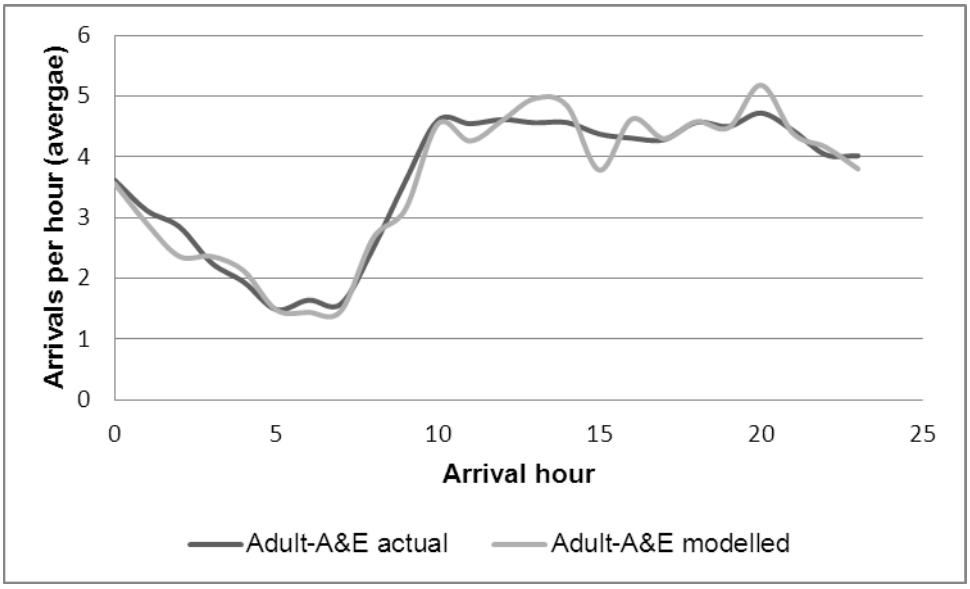


Figure 19. Adult-UCC arrival profiles - actual and modelled

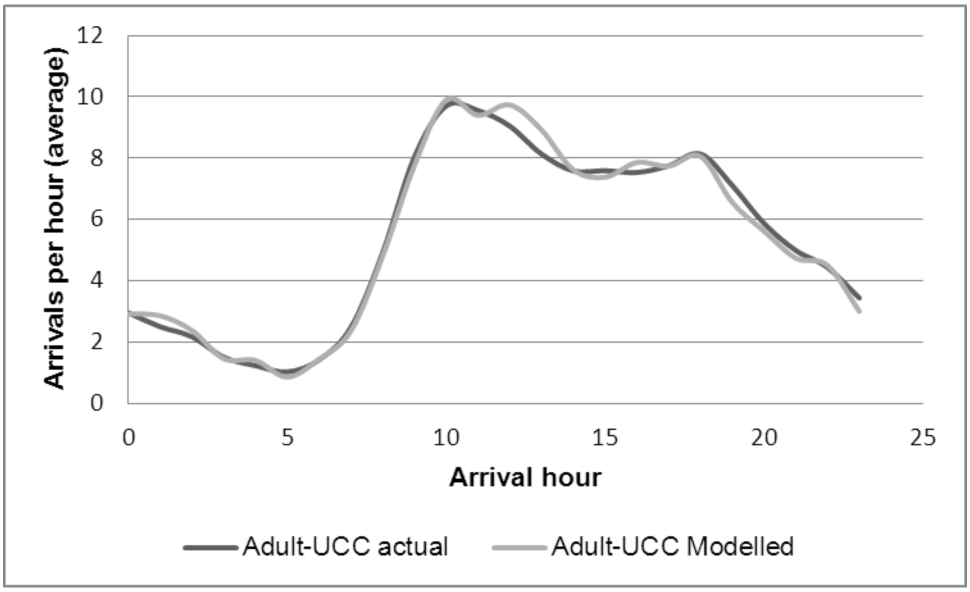


Figure 20. Elderly arrival profiles - actual and modelled

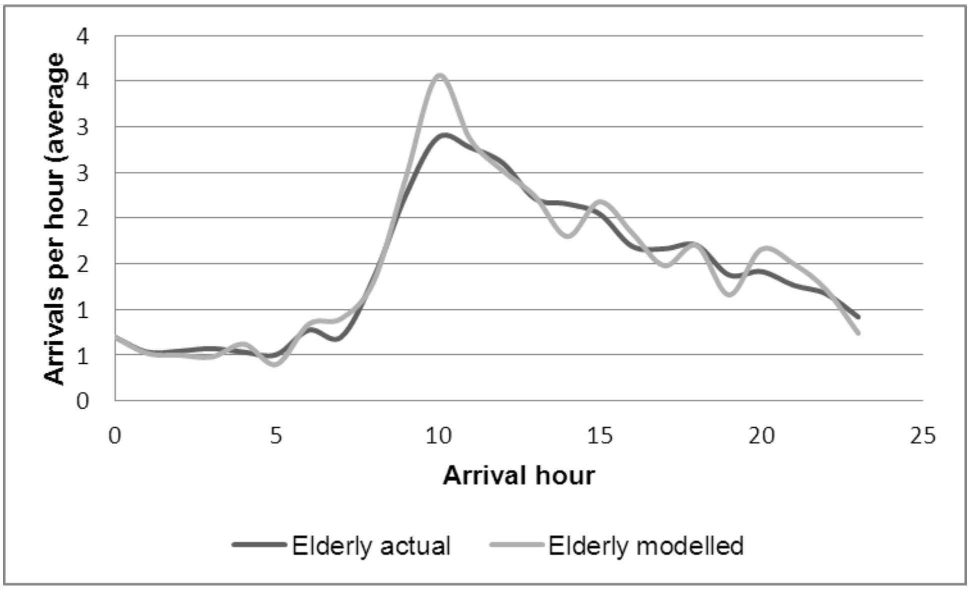
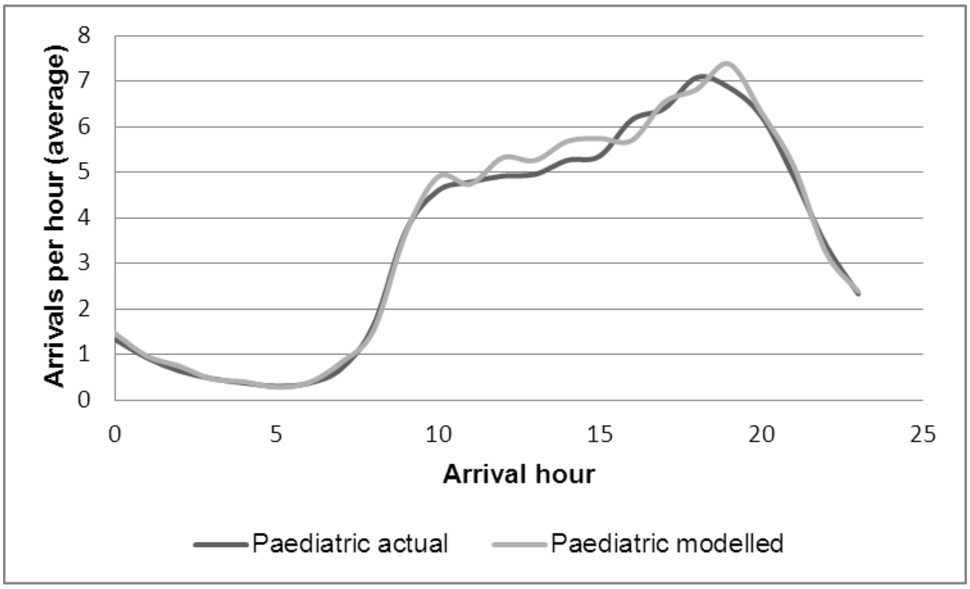


Figure 21. Paediatric arrival profiles - actual and modelled



Subjectively, comparing the actual arrivals (Standard A&E Day Arrival Profiles) with the modelled arrivals, the results look similar. However, to objectively test the relationships between the actual and modelled arrivals, the non-parametric Wilcoxon signed-rank test was selected. The rational for using this non-parametric test was that it is distribution-free and makes no assumption about populations or distribution (Miller and Miller, 2004; Johnson 1994). This would be an important criterion for the development of this model as we do not need to make any assumptions or test the distribution functions of the model's input or output data. Table 19 shows the Adult-A&E arrival comparisons. The first column 'Input dataset' refers to the hours of the standard day, where 1 represents 00:00 hours (midnight) and 24 represents 23:00 hours. The second and third columns respectively show the standard day arrivals per hour for the Standards A&E Day and the Model. The fourth column shows the difference in arrivals per hour between the Standards A&E Day and the model. Arrival comparison for Adult-UCC, Elderly and Paediatrics are shown in Appendix A4.

The difference values, in conjunction with the signed-rank test, were used to test at a 0.05 level of significance whether there was a difference between the Standards A&E Day and the modelled arrival profiles using the test criterion:

- Null hypothesis: populations were identical.
- Alternative hypothesis: populations not identical.

Table 19. Adult-A&E arrival comparisons

Input dataset	Arrivals per hour – Adult-A&E		Difference
	Standard A&E Day Arrival	A&E Space Simulation Model	
1	3.62	3.56	0.06
2	3.12	2.9	0.22
3	2.85	2.36	0.49
4	2.25	2.36	-0.11
5	1.94	2.12	-0.18
6	1.48	1.48	0
7	1.64	1.44	0.2
8	1.58	1.46	0.12
9	2.5	2.66	-0.16
10	3.6	3.14	0.46
11	4.6	4.54	0.06
12	4.55	4.26	0.29
13	4.61	4.6	0.01
14	4.56	4.96	-0.4
15	4.56	4.84	-0.28
16	4.38	3.78	0.6
17	4.31	4.62	-0.31
18	4.28	4.3	-0.02
19	4.57	4.58	-0.01
20	4.5	4.48	0.02
21	4.72	5.18	-0.46
22	4.43	4.38	0.05
23	4.04	4.16	-0.12
24	4.02	3.8	0.22

The signed-rank test confirmed the null hypothesis, indicating no difference between the Standards A&E Day and A&E Space Simulation Model arrivals profiles. For this test, the test statistic was $z = +/- 1.96$. Table 20 shows the signed-rank test results for all pathways arrival profiles.

Table 20. Pathway Signed-Rank Test Results - Arrivals

Pathway	Test statistic z
Adult-A&E	0.54
Adult-UCC	0.43
Elderly	-0.74
Paediatric	-1.74

Figure 22 shows the plot of Standards A&E Day Arrivals and modelled arrival differences in arrivals per hour over the standard 24 hour day. The spread of differences around 0 visually appear random, supporting the signed-rank test findings of no difference between the real and modelled Adult-A&E arrival profiles. Figures 23 to 25 show the similar difference plots for Adult-UCC, Elderly and Paediatric arrival comparison. These difference plots also support the assumption of no differences between the real and modelled Adult-UCC, Elderly and Paediatric arrival profiles. On the basis of these results, we could conclude that the Standard A&E Day Arrivals profiles matched the arrivals profiles generated by the Arrivals Module in the A&E Space Simulation Model.

Figure 22. Plot of differences in arrivals per hour between the Standards A&E Day and A&E Space Simulation Model arrival profiles – Adult-A&E

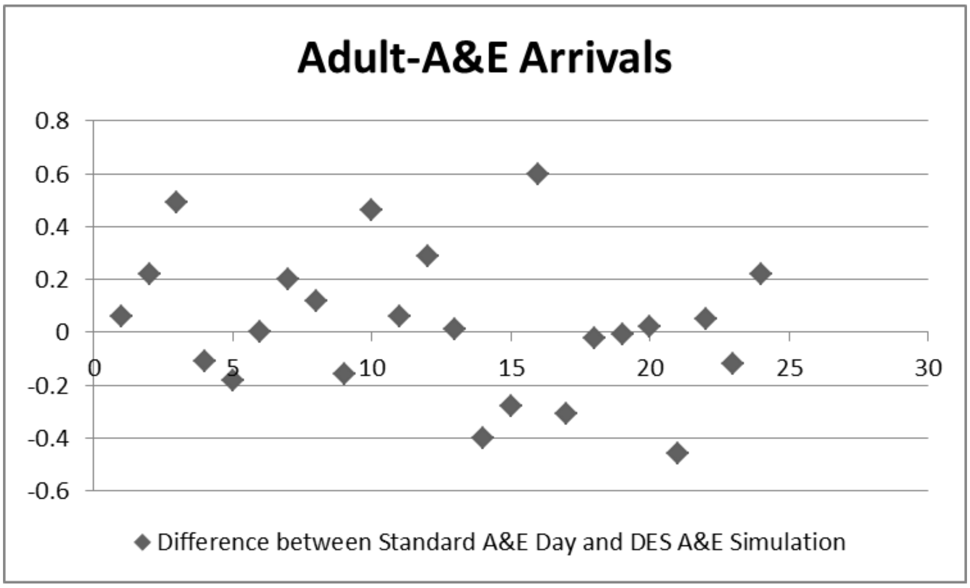


Figure 23. Plot of differences in arrivals per hour between the Standards A&E Day and A&E Space Simulation Model arrival profiles – Adult-UCC

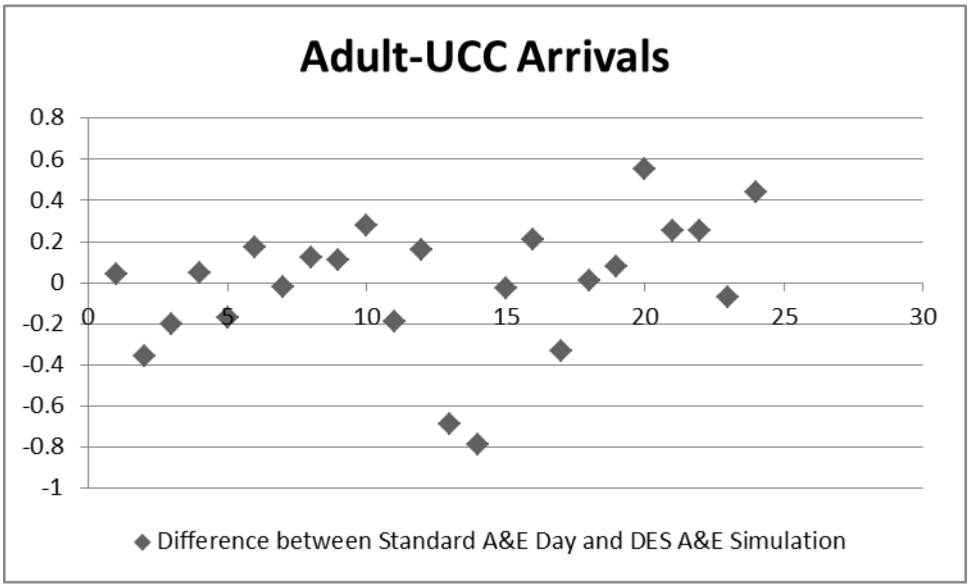


Figure 24. Plot of differences in arrivals per hour between the Standards A&E Day and A&E Space Simulation Model arrival profiles – Elderly

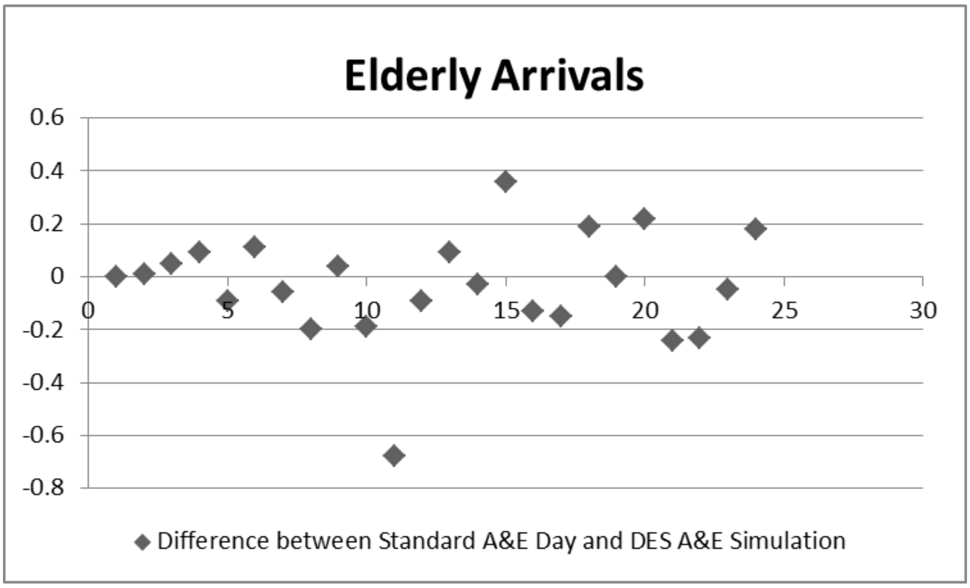
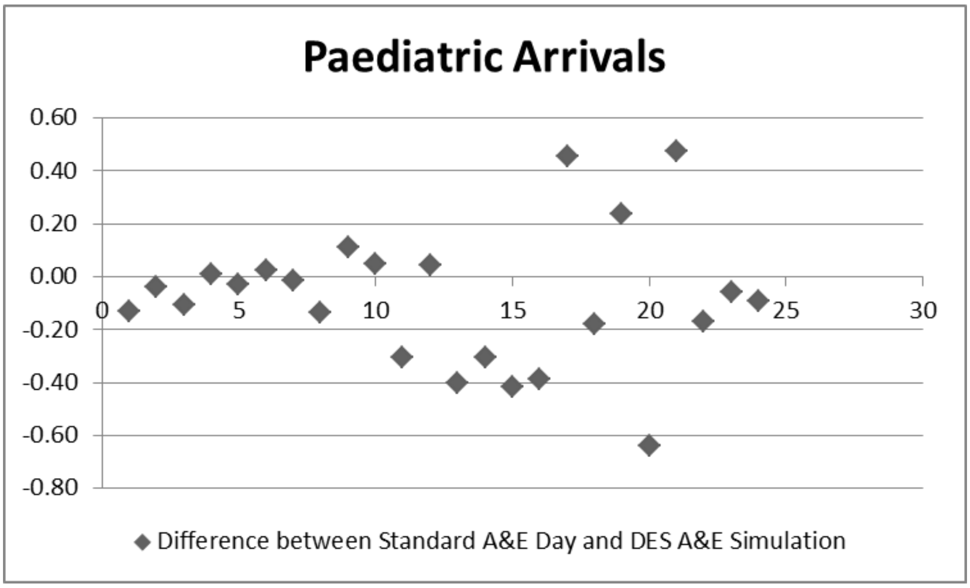


Figure 25. Plot of differences in arrivals per hour between the Standards A&E Day and A&E Space Simulation Model arrival profiles – Paediatric



6.3 *Modelled and Actual LoS data comparisons*

Figures 26 to 29 show comparative outputs between the Standard A&E Day LoS profiles and the A&E Space Simulation Model for the Adult-A&E, Adult-UCC, Elderly and Paediatric pathways. Visually, the modelled data shows similar LoS to standard day LoS profiles, including modelling of 4 hour peaks.

Figure 26. Adult-A&E LoS profiles – Actual (Baseline) and Modelled outputs

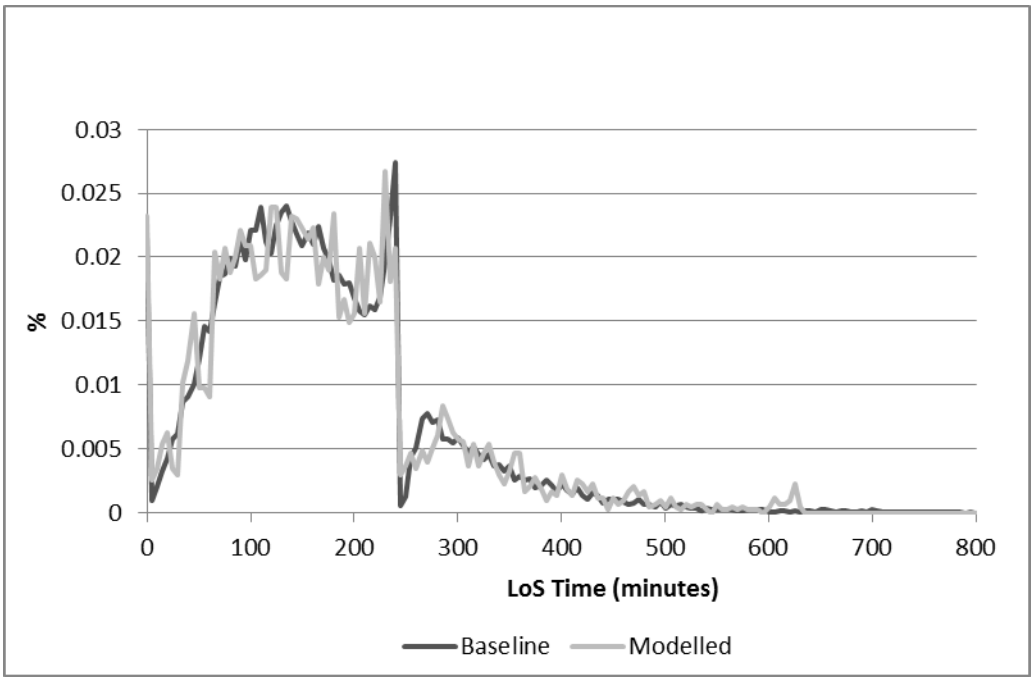


Figure 27. Adult-UCC LoS profiles – Actual (Baseline) and Modelled outputs

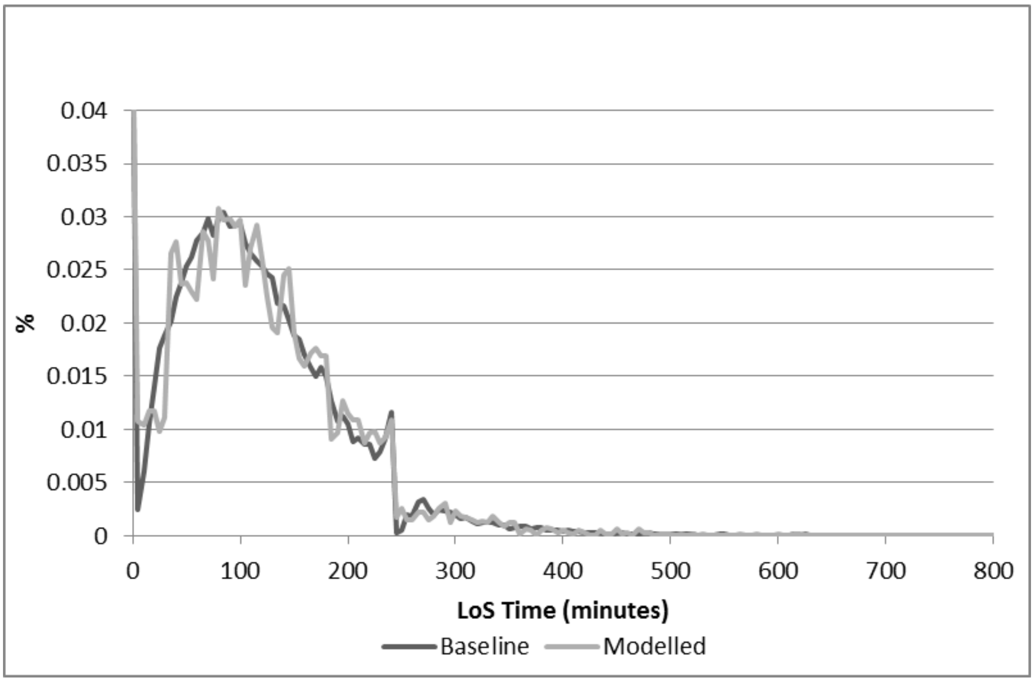


Figure 28. Elderly LoS profiles – Actual (Baseline) and Modelled outputs

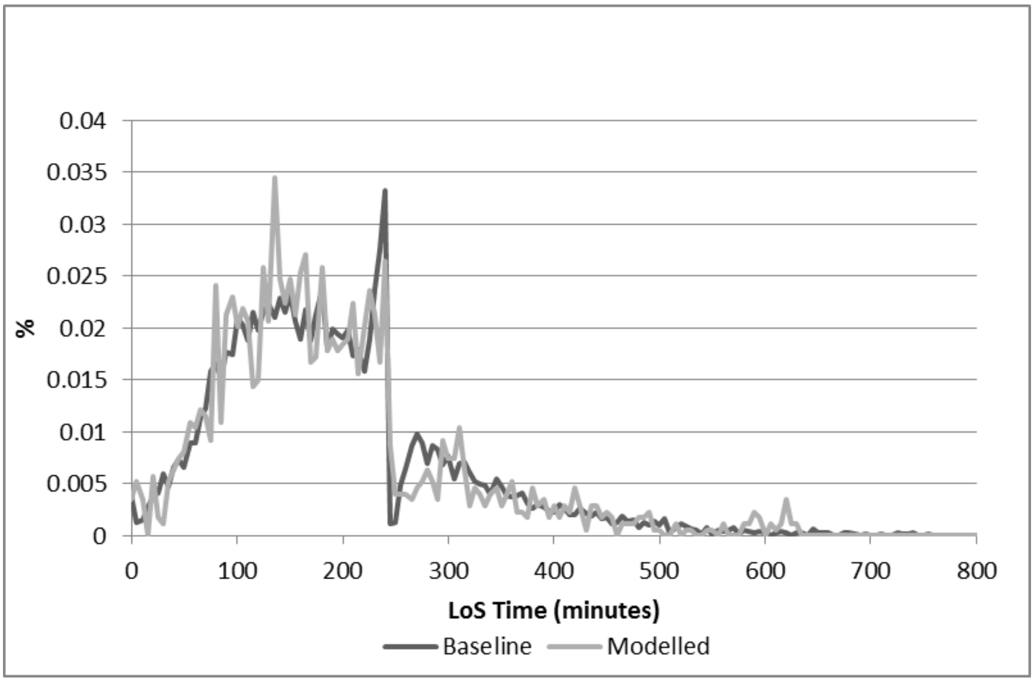
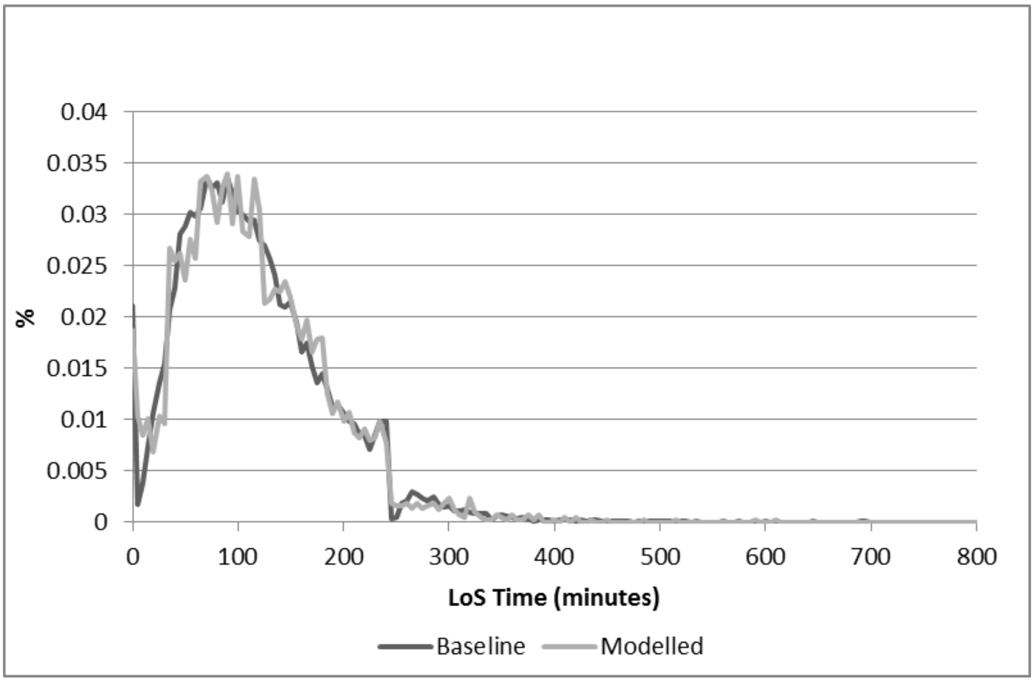


Figure 29. Paediatric LoS profiles – Actual (Baseline) and Modelled outputs



As an example, Table 21 shows the Adult-A&E LoS comparisons. The first column shows the LoS time bands, columns 2 and 3 the standard day and modelled LoS respectively, whilst column 4 shows the difference standard day and modelled profiles. Columns 2, 3 and 4 reflect the percentage proportion of the total occurrences at the LoS time. LoS comparisons for Adult-UCC, Elderly and Paediatrics are shown in Appendix A5. Similar to the arrivals, the signed-rank test was also used to test the differences between the standard LoS and modelled LoS profiles using the test criterion:

- Null hypothesis: populations were identical.
- Alternative hypothesis: populations not identical.

Table 21. Adult-A&E LoS Comparisons

LoS Time	LoS – Adult-A&E		Difference
	Standard A&E Day LoS	DES Space Simulation Model	
0	2.15	2.32	-0.17
30	2.26	2.41	-0.15
60	6.87	6.62	0.26
90	11.42	12.03	-0.61
120	12.93	12.17	0.76
150	13.55	12.96	0.59
180	12.40	12.40	0.01
210	10.26	9.87	0.39
240	11.90	12.31	-0.40
270	2.65	2.37	0.28
300	3.73	3.90	-0.17
330	2.85	2.83	0.02
360	1.99	2.18	-0.19
390	1.41	1.09	0.32
420	1.06	1.25	-0.20
450	0.69	0.77	-0.08
480	0.52	0.84	-0.32
510	0.36	0.42	-0.05
540	0.25	0.30	-0.06
570	0.15	0.19	-0.03
600	0.14	0.16	-0.02
More	0.46	0.63	-0.16

The LoS signed-rank test confirmed the null hypothesis, indicating no difference between the pathway Standard A&E LoS and modelled LoS profiles. Table 22 shows the signed-rank test results for all pathways LoS profiles. Figures 30 to 33 illustrate the spread of differences over LoS. By observation, the percentage differences appear to be randomly distributed around 0, with the maximum error at any test point just over 2 % (shown in the Elderly analysis).

Table 22. Pathway Signed-Rank Test Results - LoS

Pathway	Test Statistic z
Adult-A&E	-0.60
Adult-UCC	-0.31
Elderly	0.60
Paediatric	0.73

Figure 30. Plot of differences in arrivals per hour between the Standards A&E Day and A&E Space Simulation Model LoS profiles – Adult-A&E

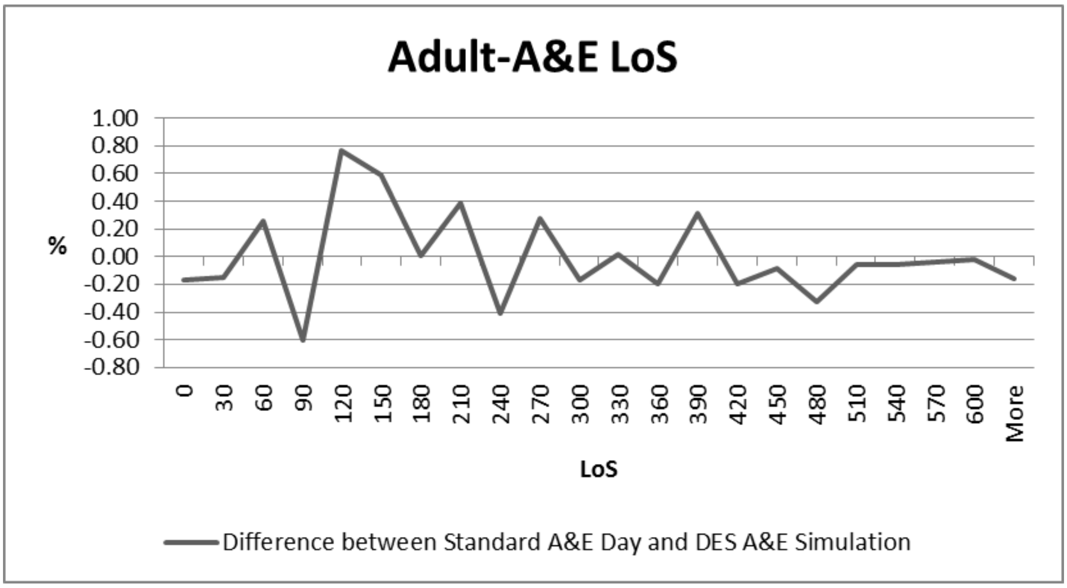


Figure 31. Plot of differences in arrivals per hour between the Standards A&E Day and A&E Space Simulation Model LoS profiles – Adult-UCC

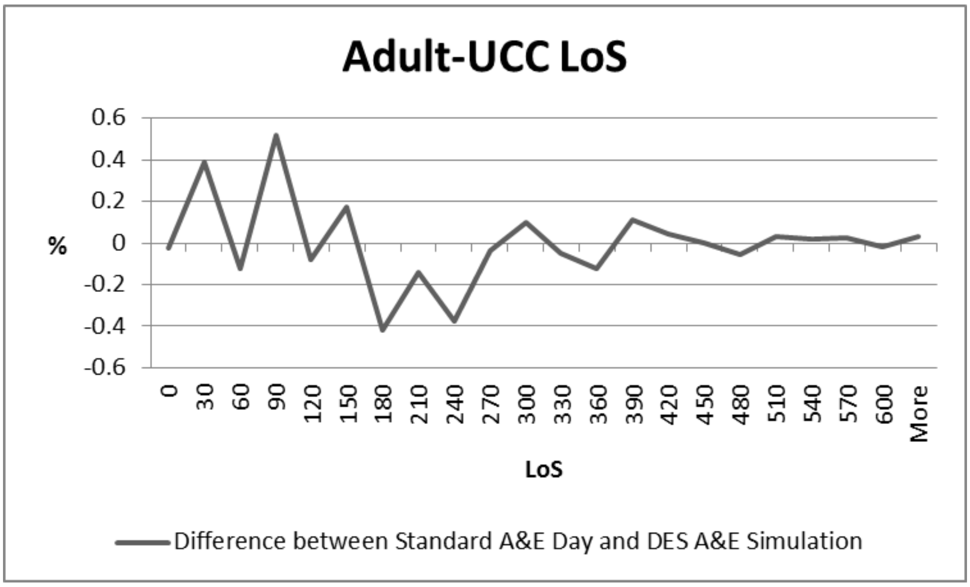


Figure 32. Plot of differences in arrivals per hour between the Standards A&E Day and A&E Space Simulation Model LoS profiles – Elderly

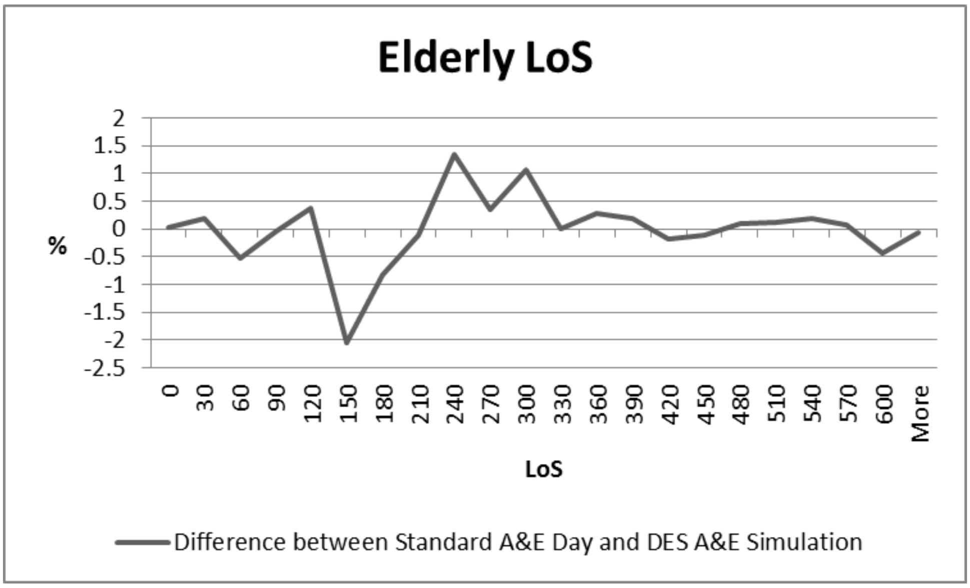
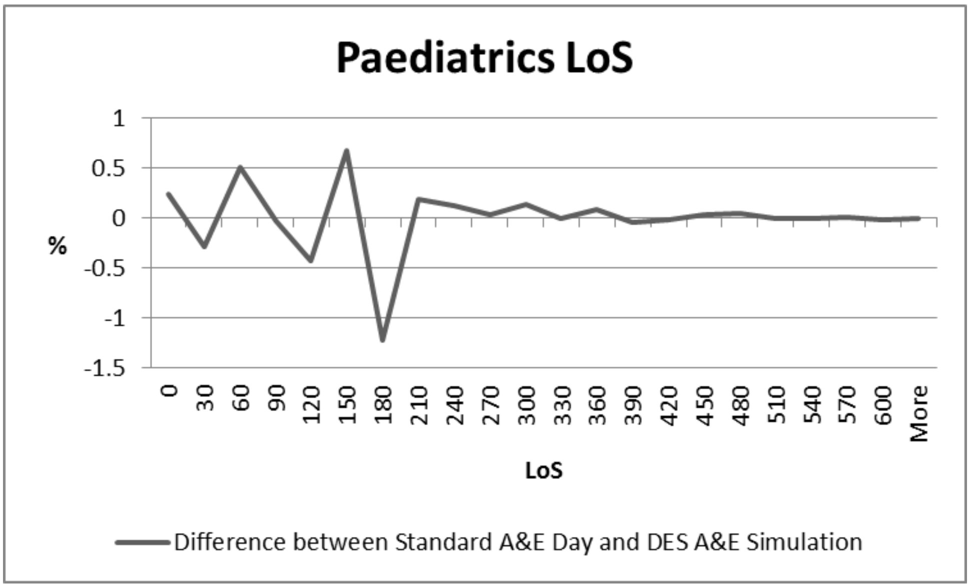


Figure 33. Plot of differences in arrivals per hour between the Standards A&E Day and A&E Space Simulation Model LoS profiles – Paediatrics



6.4 *Model validation and verification*

Acceptance of the hypothesis test comparing both the standard day and modelled profiles for arrivals and LoS served to both validate and verify the A&E Space Simulation Model. The visual nature of Simul8 provided further validation of model – visually observing patient icon flows and resources throughout model runs. 'Visual' testing was widely used to assist the verification of coding throughout the development phase of the coding.

6.4.1 Secondary input data test

The model was tested against using a second input dataset. This secondary dataset was obtained from another UK hospital. This would serve as test of the model to see how quickly new data could be fed into the model and outputs analysed. Due to the simplicity of the model new data could be fed in very quickly. Essentially, once real data was formatted as described in Tables 15 and 16, this information could entered into the model, the model re-run and the outputs analysed. Once the raw A&E data is available, the process of reconfiguring the input data, re-running and analysing the model outputs would take a matter of hours. The secondary data reflected three groups of patients: Adult (non-Elderly); Elderly; and Paediatric arrivals. Figures 34 to 36 illustrate Adult, Elderly and Paediatric average real and modelled arrivals per hour profiles. Whilst Figures 37 to 39 show the Adult, Elderly and Paediatric real and modelled LoS profiles.

Figure 34. Secondary Input Data: Adult (non-Elderly) Arrival Profiles - Actual and Modelled

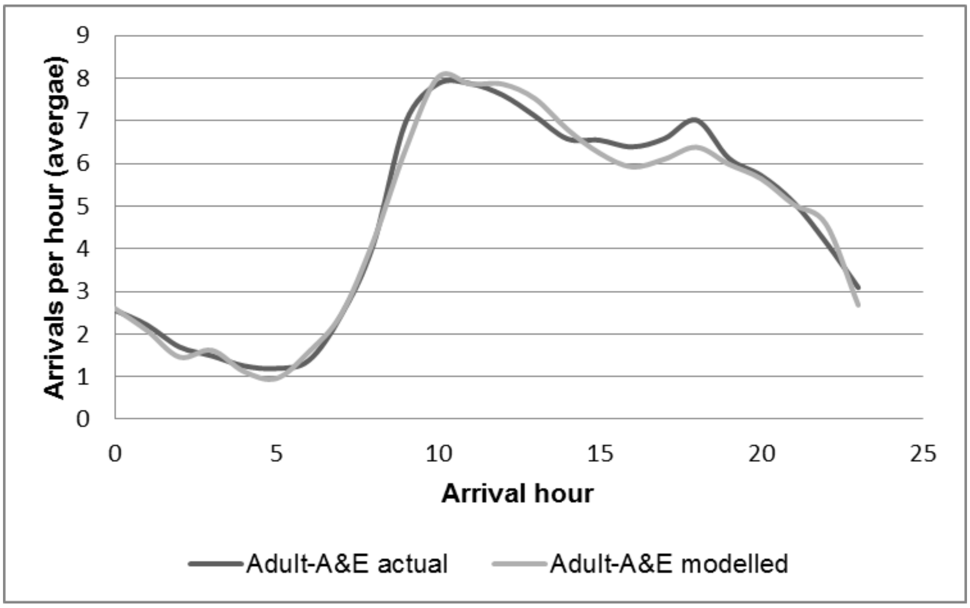


Figure 35. Secondary Input Data: Elderly Arrival Profiles - Actual and Modelled

Figure 36. Secondary Input Data: Paediatric Arrival Profiles - Actual and Modelled

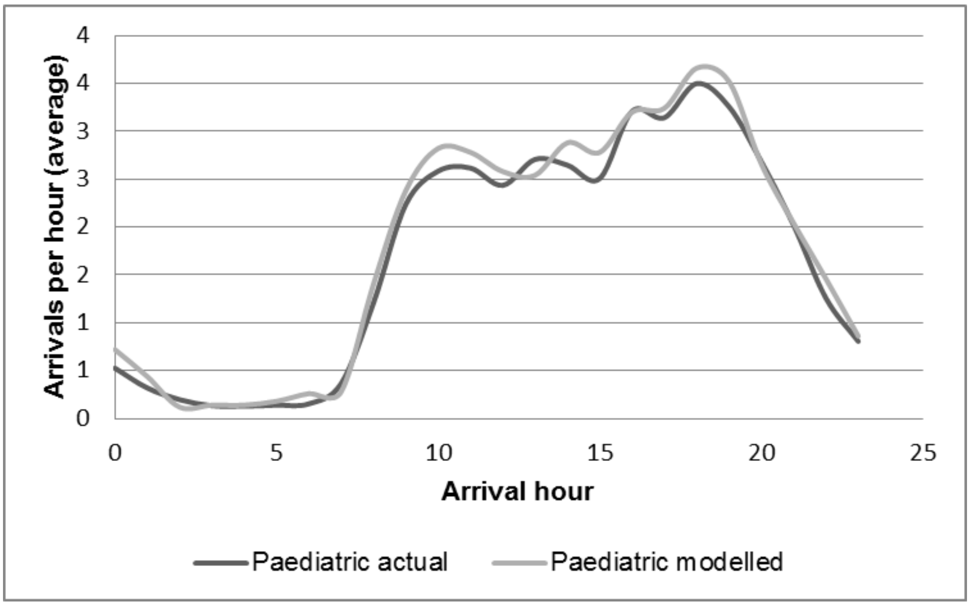


Figure 37. Secondary Input Data: Adult LoS Profiles – Actual (Baseline) and Modelled outputs

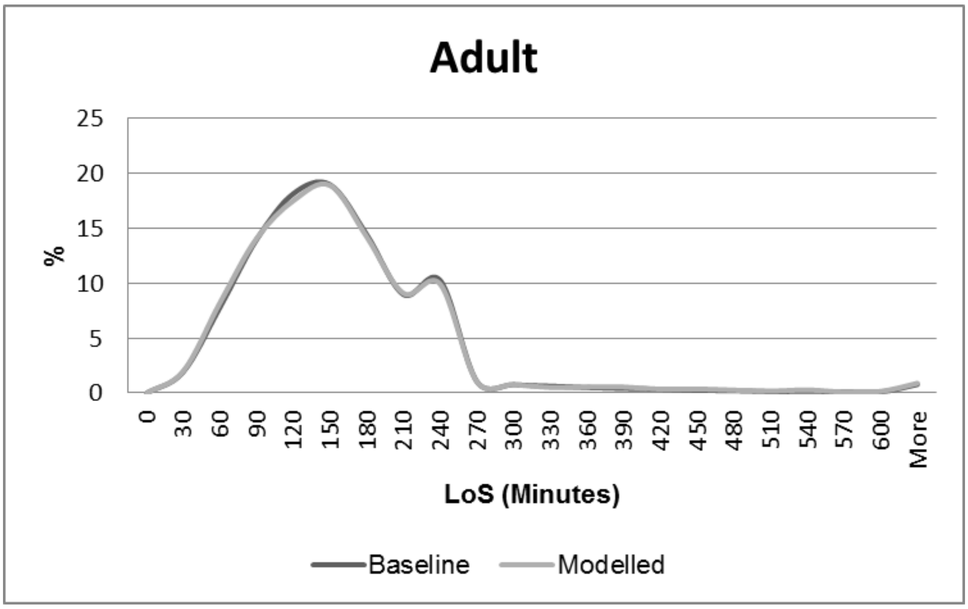


Figure 38. Secondary Input Data: Elderly Profiles – Actual (Baseline) and Modelled outputs

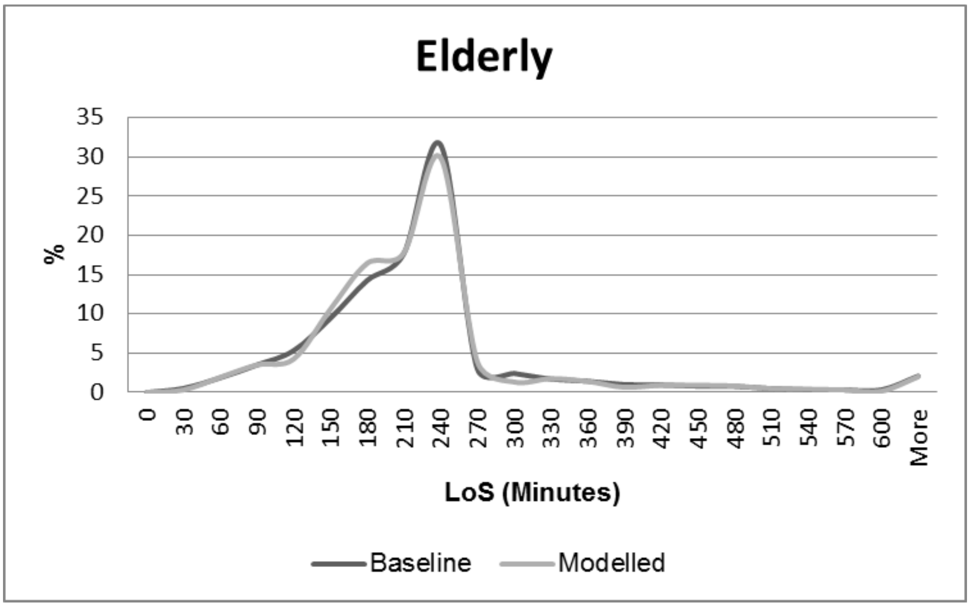
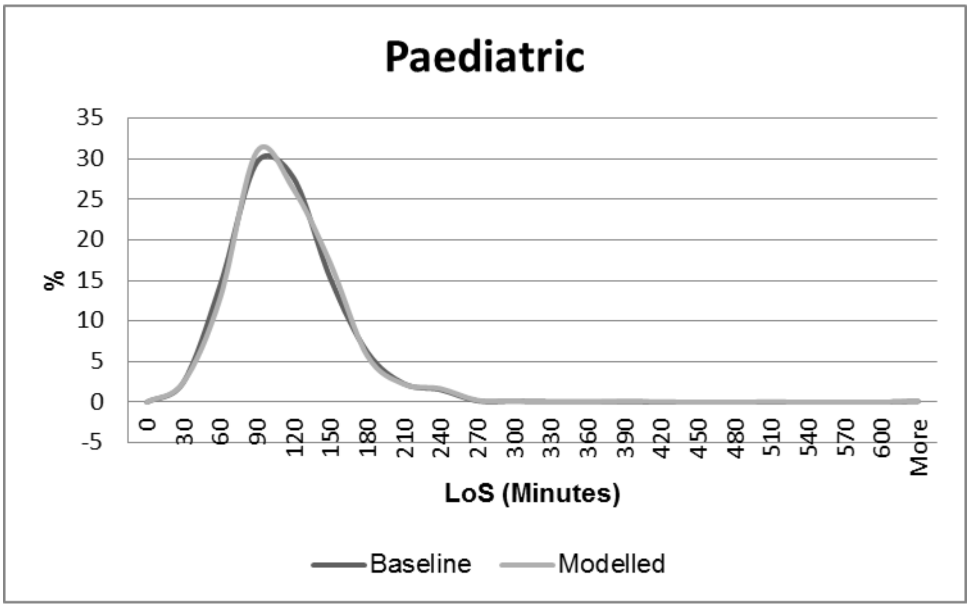


Figure 39. Secondary Input Data: Paediatric LoS Profiles – Actual (Baseline) and Modelled outputs



Using the same criteria as described previously, the secondary data showed all the tests accepted the null hypothesis (no difference between actual and modelled data) except for the Paediatric arrivals test – see Table 23.

Table 23. Secondary Signed-Rank Test Statistics

Pathway	Test Statistic z	
	Arrivals	LoS
Adult	1.17	-1.05
Elderly	-1.37	0.11
Paediatric	-3.11	-0.47

The failure of the Paediatric arrivals test statistic appeared to be due a higher number of arrivals per hour for the modelled data, i.e., actual and modelled arrival profiles had a similar profile except for higher values. Reassigning the modelled arrivals per day to the actual arrivals per day resulted in the Paediatric test passing the null hypothesis.

6.4.2 Primary input data – Friday to Saturday modelling

The model was also tested modelling day periods. The period from midday Friday to midday Saturday was selected for analysis. Arrival and LoS profiles are shown in Figures 40 to 47. As above, the actual and modelled data visually showed good correlation.

Figure 40. Primary Input Data: Friday to Saturday Adult-A&E Arrival Profiles - Actual and Modelled

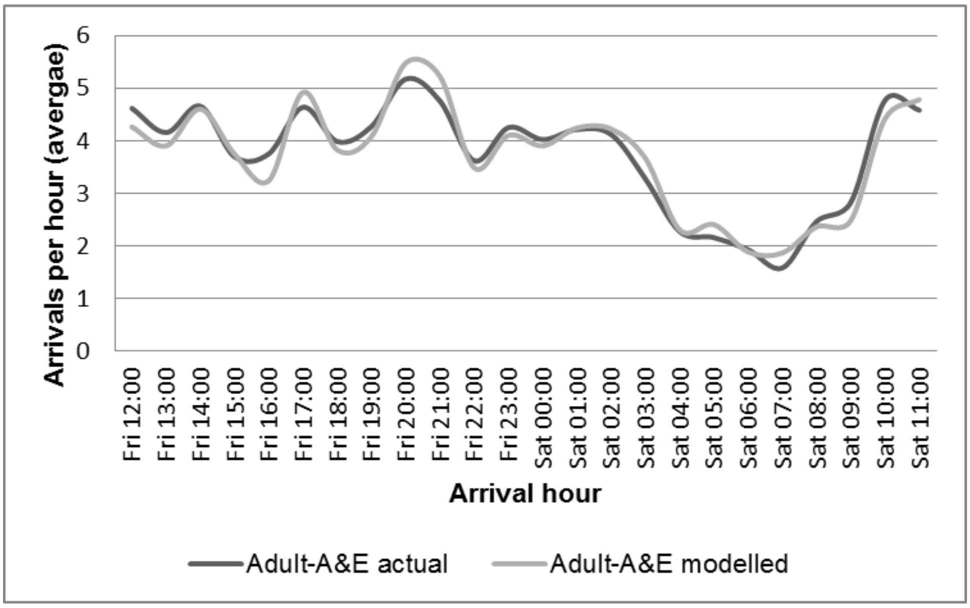


Figure 41. Primary Input Data: Friday to Saturday Adult-UCC Arrival Profiles - Actual and Modelled

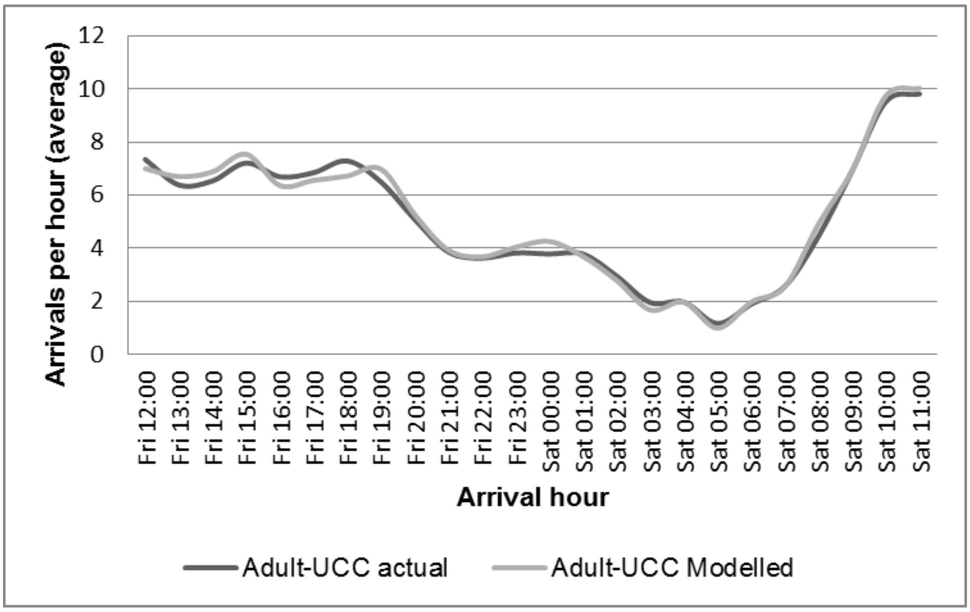


Figure 42. Primary Input Data: Friday to Saturday Elderly Arrival Profiles - Actual and Modelled

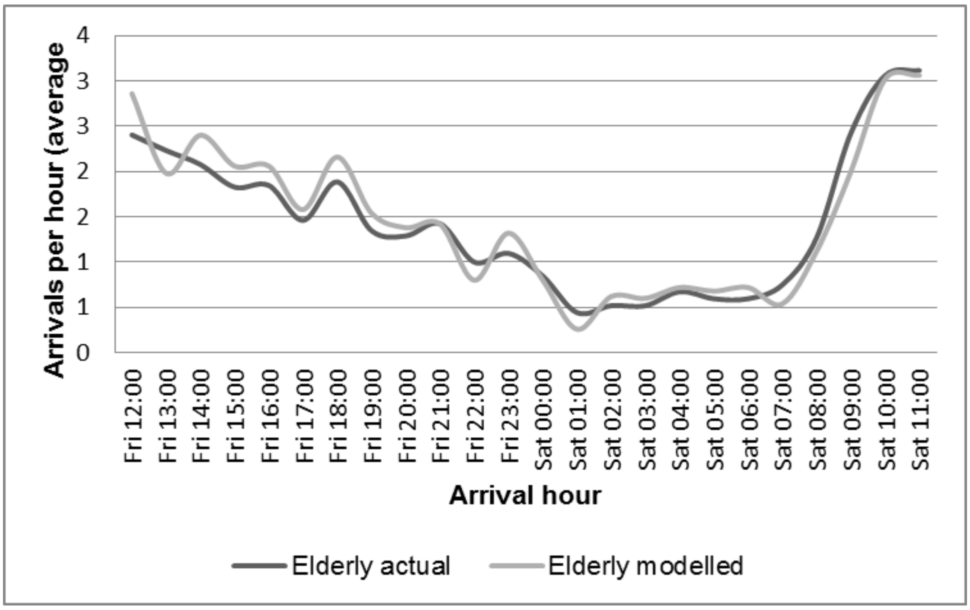


Figure 43. Primary Input Data: Friday to Saturday Paediatrics Arrival Profiles - Actual and Modelled

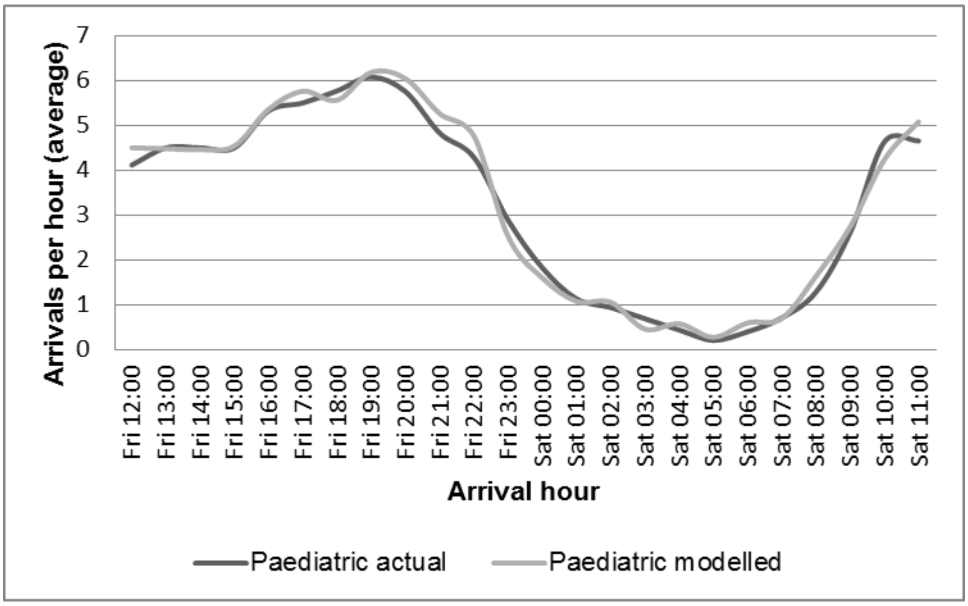


Figure 44. Primary Input Data: Friday to Saturday Adult-A&E LoS Profiles - Actual and Modelled

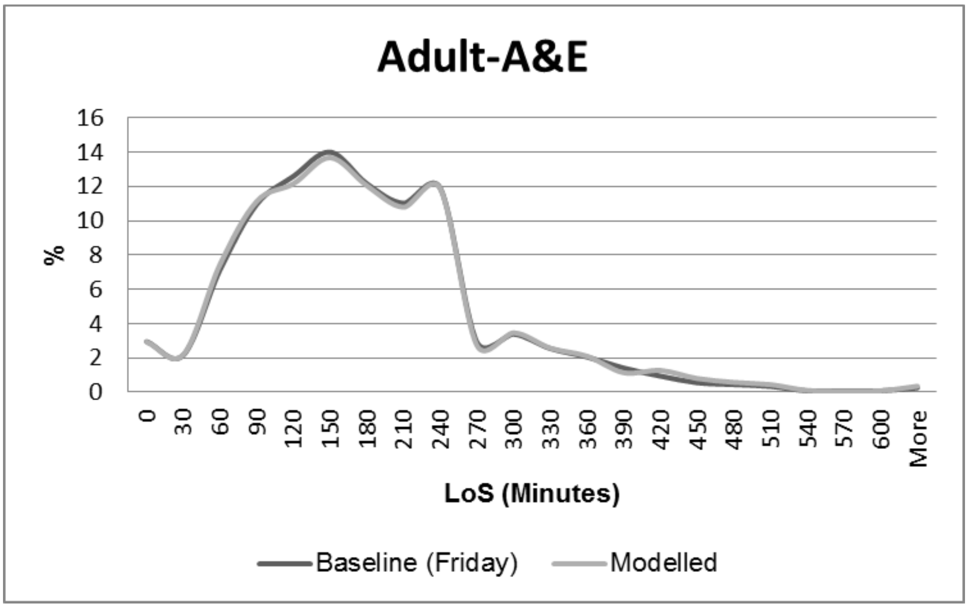


Figure 45. Primary Input Data: Friday to Saturday Adult-UCC LoS Profiles - Actual and Modelled

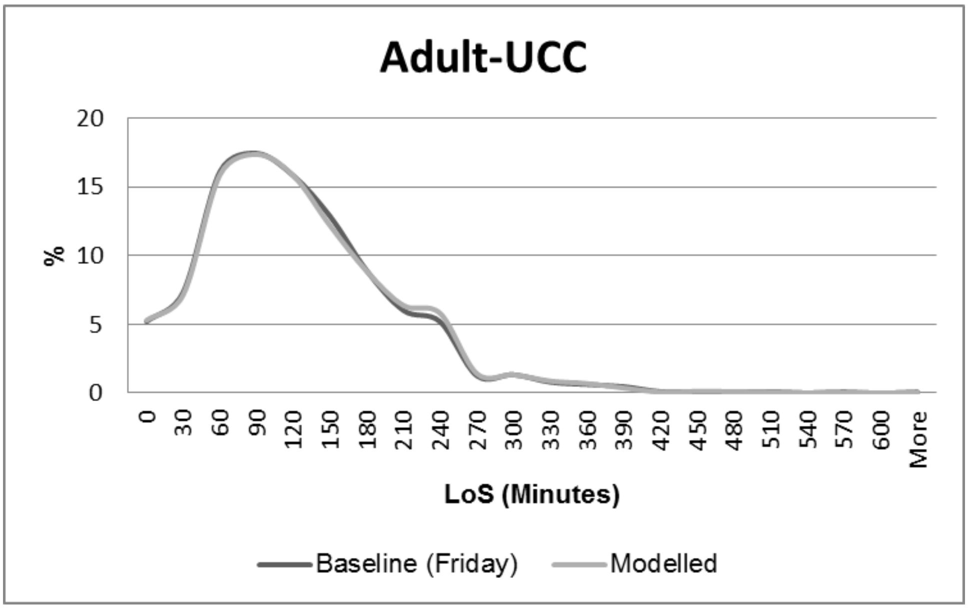


Figure 46. Primary Input Data: Friday to Saturday Elderly LoS Profiles - Actual and Modelled

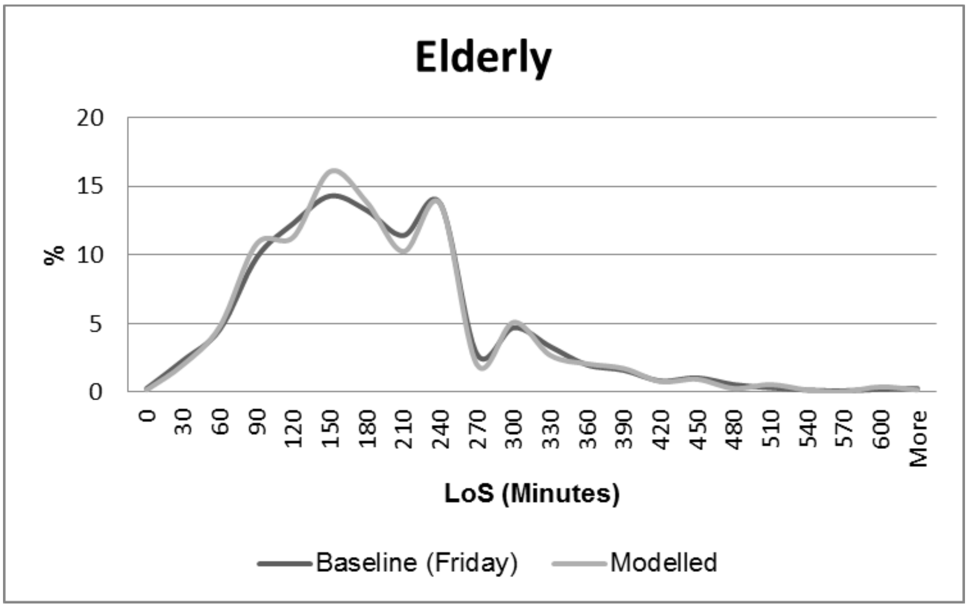
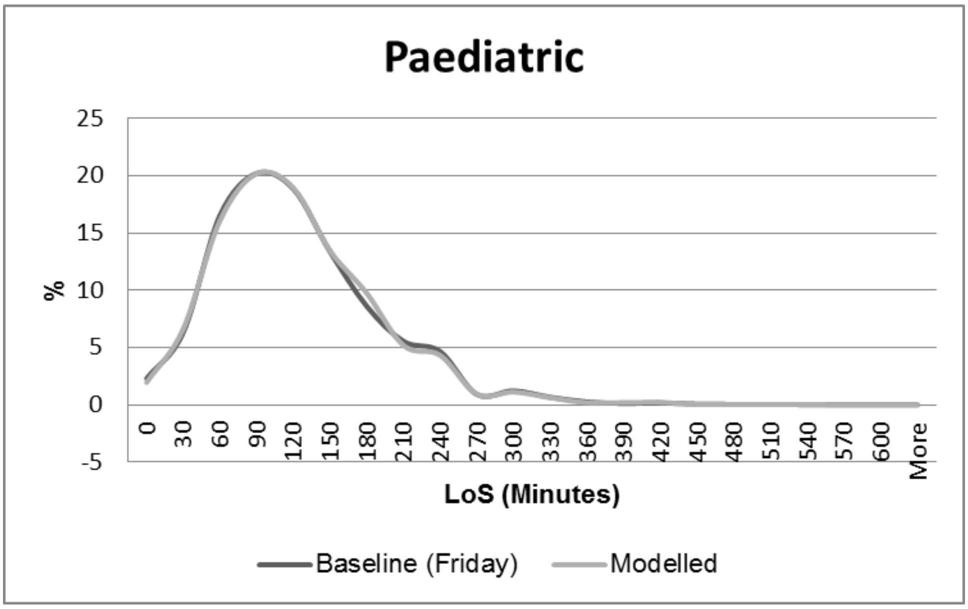


Figure 47. Primary Input Data: Friday to Saturday Paediatric LoS Profiles - Actual and Modelled



Comparisons with real and modelled Friday to Saturday (arrival and LoS) data showed acceptance of the null hypothesis test (the test statistic less than z = +/- 1.96) as illustrated in Table 24.

Table 24. Friday to Saturday Signed-Rank Test Statistics

Pathway	Test Statistic z	
	Arrivals	LoS
Adult-A&E	0.37	-0.34
Adult-UCC	-0.91	0.11
Elderly	-1.14	0.14
Paediatric	-1.57	0.34

6.4.3 All data – Primary and Secondary input data

The following charts show the total (combined pathway inputs) for both the primary and secondary datasets. Figures 48 and 49 illustrate the real and modelled primary arrivals and LoS respectively, whilst Figures 50 and 51 illustrate the real and modelled secondary arrivals and LoS. Visually, the similarities provided further evidence to indicate the model was a good representation of a real A&E. The signed-rank test statistic was also applied to total primary and secondary real and modelled arrival and LoS data. The results shown in Table 25 showed acceptance of the null hypothesis (the test statistic less than z = +/- 1.96) indicating no difference between the real and the modelled datasets.

Figure 48. Primary Input Data: All Arrivals

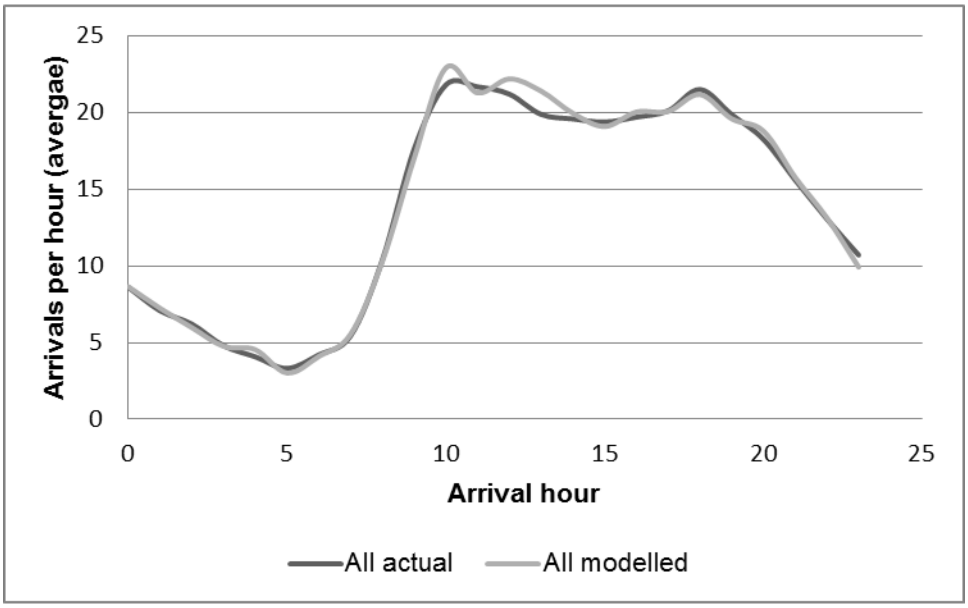


Figure 49. Primary Input Data: All LoS

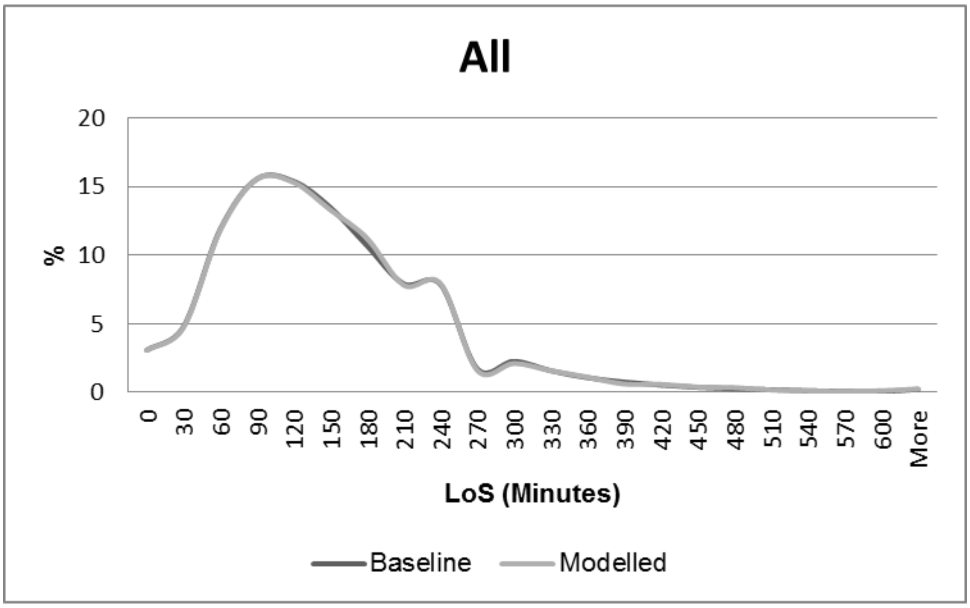


Figure 50. Secondary Input Data: All Arrivals

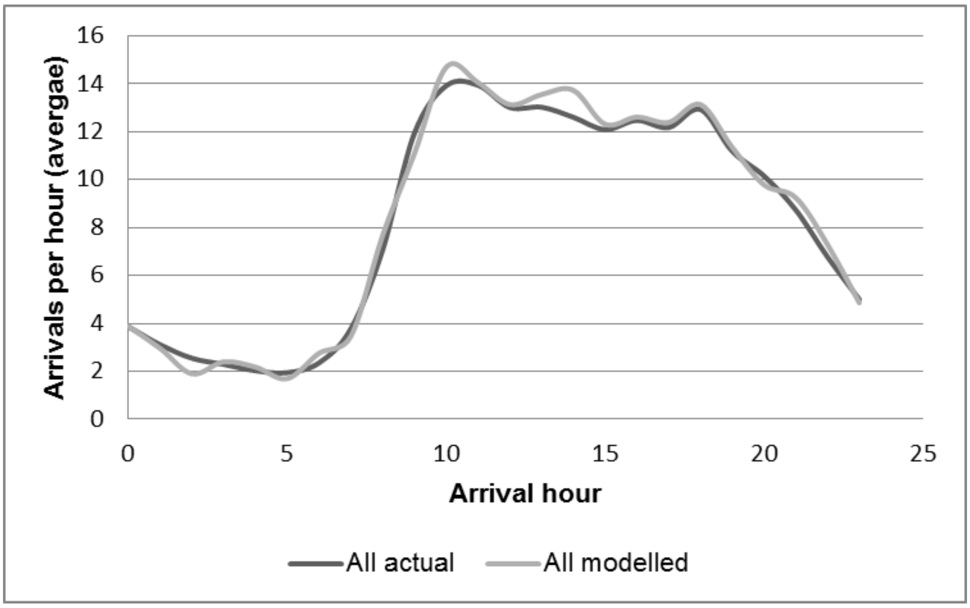


Figure 51. Secondary Input Data: All LoS

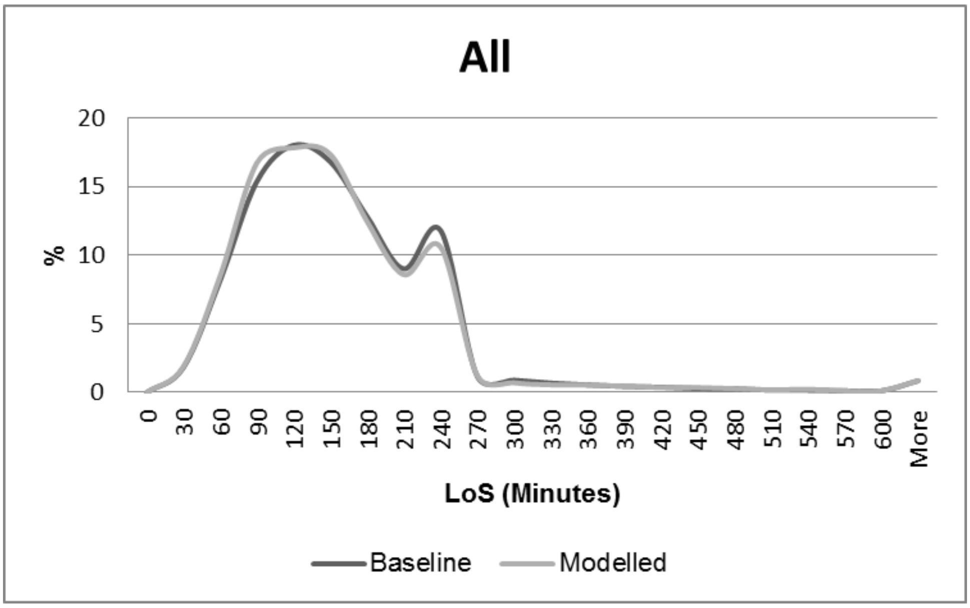


Table 25. All data Signed-Rank Test Statistics

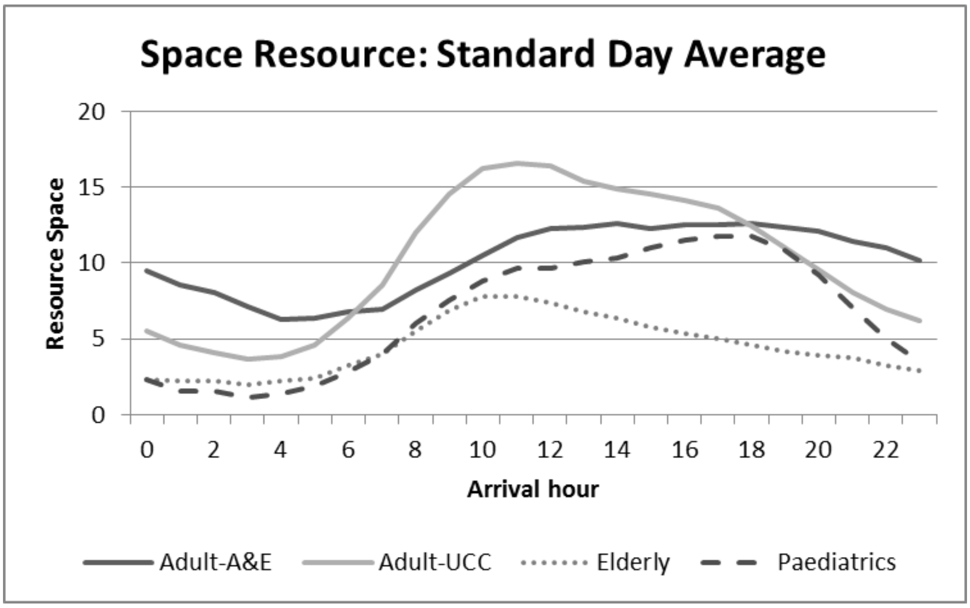
Pathway	Test Statistic z	
	Arrivals	LoS
Primary dataset	-0.46	0.86
Secondary dataset	-1.46	0.11

6.5 *Space Resources*

6.5.1 Modelled Space Resource

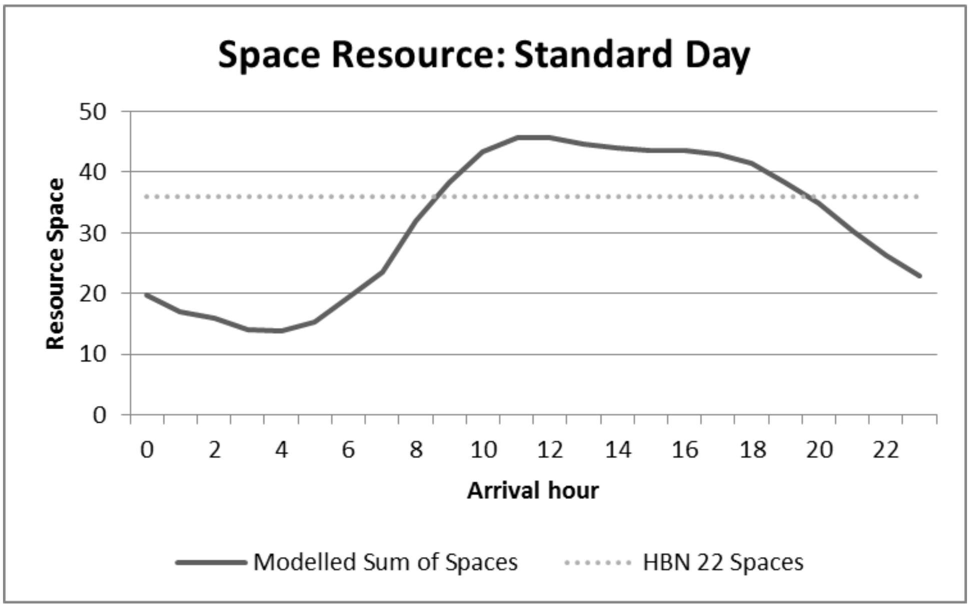
Earlier work in this and the previous chapter described the A&E Space Simulation Model and how real arrival and LoS data could be used to model space demand. Figure 52 shows the average modelled space resource by pathway by hour for the primary dataset. Looking at the Figure 52, over a standard 24 hour day, one could observe different space demand dependent on the pathway. For example, Adult-UCC and Elderly showed peak demand late morning; Adult-A&E showed their peak early in the afternoon; whilst Paediatrics showed their peak early evening.

Figure 52. Demand of Space Resource: Average by Pathway



As stated earlier, guidance notes sometimes referred to calculations or 'rule-of-thumb' calculations to determine clinical space for the provision of health. HBN 22 the building guidance for an emergency department (NHS Estates, 2005b) suggested activity space based on attendance. The A&E Space Simulation Model was designed around an initial attendance of 122,727. Referring to HBN 22, a 122,727 attendance suggests an activity space of 36 rooms/places (24 rooms for 90,000 attendances plus 12 rooms for 40,000 attendances). Figure 53 shows the modelled sum of spaces (average) and the HBN suggested 36 spaces.

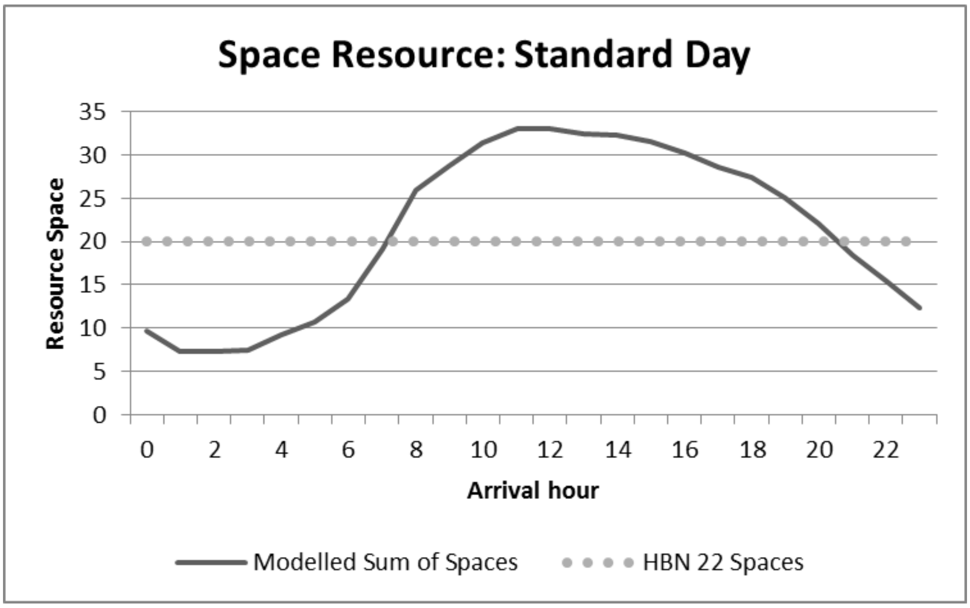
Figure 53. Demand of Space Resource: Sum of Average Spaces



Clearly, the 46 modelled places are in excess of 36 places suggested by HBN 22. In addition, the excess is over a period of around 11 hours. This excess suggests crowding issues within the emergency department area over a significant time due to lack of space. One might assume that if patients are not physically located in the emergency area, they might possibly be located in waiting areas or in corridors. From a planning point of view, having patients located in areas other than where they should be, will probably have an adverse effect on pathway flows with additional travel time for patients and staff locating those patients.

For the secondary data and their 64,352 arrivals, HBN 22 suggests 20 places. Figure 54 indicated on average the 20 HBN places would be exceeded between mid-morning and late evening.

Figure 54. Secondary Data Demand of Space Resource: Sum of Spaces



The examples above reflect average demand over a standard day. If we focus back on the primary dataset, Figure 55 shows the maximum modelled space demand by pathway. Once again, we see different pathways have different characteristics, for example, Elderly maximum demand peaks around mid-morning whilst the maximum Paediatric demand peaked in the early evening. Around the mid-morning peak period (11:00hrs), Figure 56, shows the total 94 spaces respectively represented by Adult-A&E (24 spaces, 26%); Adult-UCC (29 space, 31%); Elderly (21 spaces, 22%); and Paediatrics (20 spaces, 21%). In contrast, Figure 57 showed the combined modelled mid-evening peak period of 91 spaces represented by Adult-A&E (28 spaces, 31%); Adult-UCC (25 space, 28%); Elderly (13 spaces, 14%); and Paediatrics (25 spaces, 27%).

Figure 55. Demand of Space Resource: Maximum by Pathway

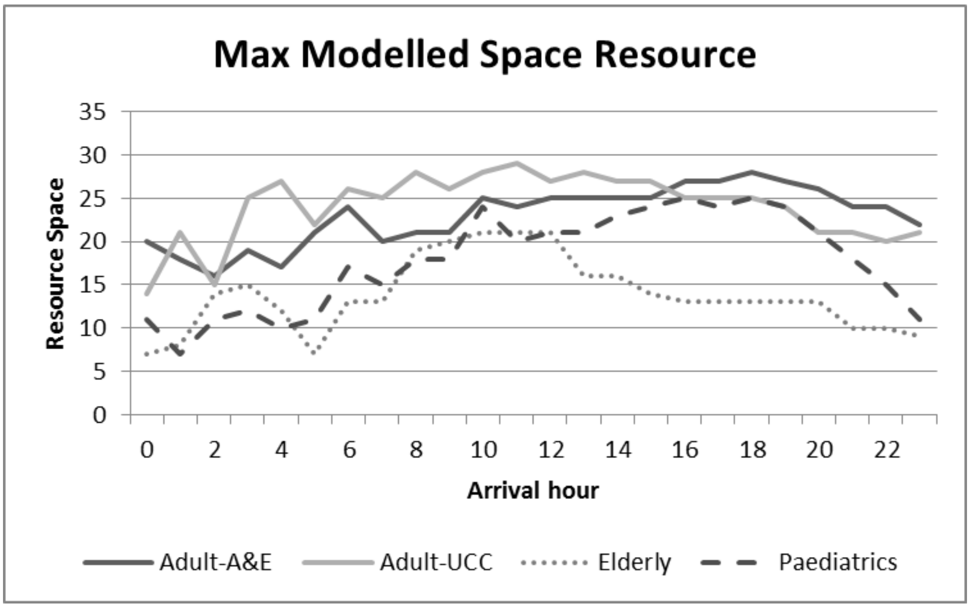


Figure 56. Max Space Demand at Mid-morning Peak Period

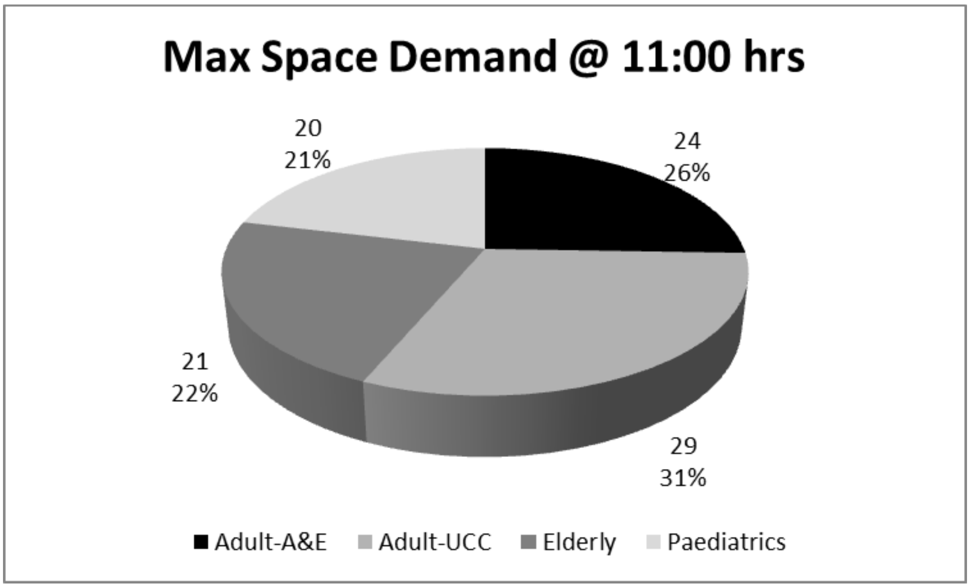


Figure 57. Max Space Demand at Mid-evening Peak Period

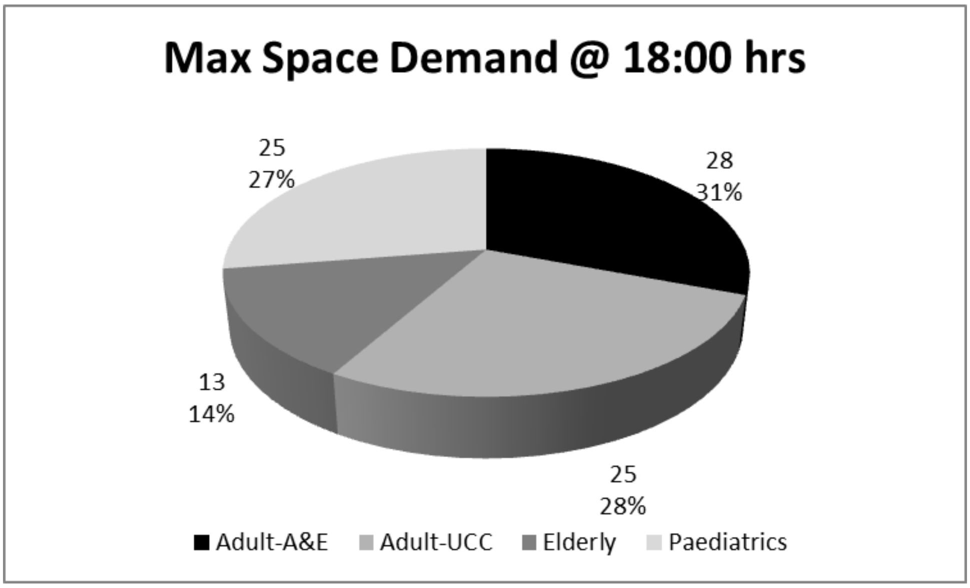
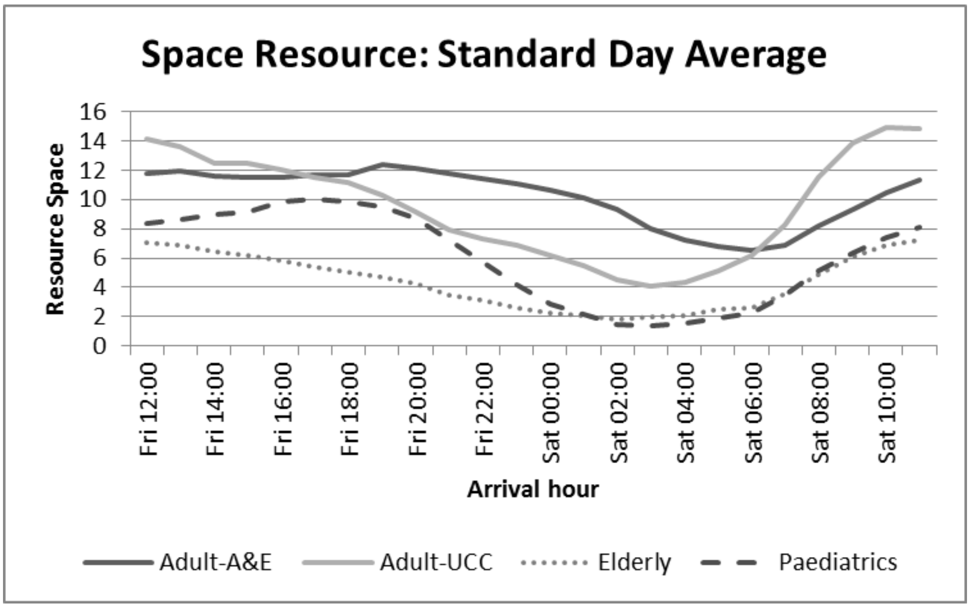


Figure 58 showed the Friday to Saturday modelled space demand. One interesting visual observation was similarity of the Friday to Saturday modelled day to the standard modelled day. The examples above demonstrate that simulation models used in this way could be of great benefit to Healthcare Planners and stakeholders in the allocation of space in a healthcare environment. The modelled examples above showed, by pathway, space demand requirements by time of day. A number of discussion points could be drawn from these observations. Firstly, the modelled maximum was just that; a maximum representing the worst of the modelled conditions. Of course (although not analysed here) further analysis could be conducted on the likelihood of occurrences of the worst conditions in each of the individual pathways and pathway combinations.

Figure 58. Demand of Space Resource: Average by Pathway Friday to Saturday



Another point of interest was the difference between the HBN suggested spaces and the modelled spaces. Availability of treatment within a hospital emergency environment is often limited by staff availability (not specifically modelled here but embedded within a real LoS); rarely by space. Arrangement might be made for patients to wait in corridors or waiting areas. Nevertheless, armed with this information, waiting spaces might be better managed and organised to at least minimise pathway and service disruption. Furthermore, the simulation model has the ability to analyse space demand specifically by pathway.

Over the years, HBN have moved towards standardised, flexible generic space where possible. With the type of analysis shown here for example, the same generic treatment areas could be used in the morning for Elderly services; then switched to Paediatric services in the evening. The modelled insights into space demand could also be used to better manage staff planning and workforce rota to meet services. Furthermore, demand information could work closely in conjunction with space guidance at the early stage of any service design and construction. For example, if the guidance notes suggest 16 square metres (sqm) for an emergency treatment area space, as described earlier Schedules of Accommodation (SoAs) could be developed (in conjunction with other support areas) to calculate the total area needed to provide health services.

Activity and space modelling concepts could be taken further. For example, ratios of activity to space may be used in conjunction with simulation modelling to establish the space effectiveness of the larger health estate. Some of these ideas will be discussed in the next section.

6.6 *The potential for function-to-space ratios to better manage space*

Table 26 shows seven UK and two international (Australian) hospitals by their number of beds and their total area (Gross Internal Area or GIA) in metres square (sqm). Australia was chosen as an international comparator due to its similarity to the UK hospital system. Table 26 shows the space per bed, calculated by the GIA divided by the number of beds. Although the term space per bed here is used, it actually reflects beds and all the supporting services required to support those bed as well surplus space not necessarily required to support the bed. The space per bed variation shown in Table 26 was ranged from around 122 sqm to almost double at around 237 sqm. An obvious question here is why a hospital could operate at 122 sqm per bed, whilst another had much greater space, up to 237 sqm. The hospitals represented a range of hospital builds. There was no clear picture that newer hospital builds had lower space per bed ratios compared to older hospital buildings.

Table 26. Space Per Bed Comparisons of UK and International Hospitals

Hosp. ID	Beds	Total Area (sqm)	Space Per Bed (sqm)
UK7	514	121,640	236.7
UK6	481	96,328	200.3
International 2	736	141,348	192.0
UK 5	900	170,000	188.9
UK 4	170	30,000	176.5
UK 3	396	66,185	167.1
UK 2	591	87,949	148.8
UK 1	712	102,000	143.3
International 1	922	112,451	122.0

Table 27 shows space per bed information by quartiles, where the lower quartile space per bed was around 149 sqm, the median space per bed was around 176 sqm and the upper quartile space per bed was around 192 sqm. Using the median and lower quartile as reference points for the space per bed, we could calculate target median and lower quartile by multiplying these reference points by bed numbers by hospital.

Table 27. Space Per bed By Quartile

Quartiles	Space Per Bed (sqm)
Max	236.7
Upper quartile	192.0
Median	176.5
Lower quartile	148.8
Min	122.0

Table 28 shows the calculated space per bed using the number of beds from our reference hospitals multiplied respectively by their median space per bed and the lower quartile space per bed of the whole group. Table 28 also shows the potential space savings: the difference between the current space and the respective median and lower quartile space calculations.

Table 28. Median and Upper Quartile Space Per Beds

Hosp ID	Beds	Total Area (sqm)	Space: Median Space (sqm) Per Bed * Beds	Median Space Saving (sqm)	Space: Lower Quartile Space (sqm) Per Bed * Beds	Lower Quartile Space Saving (sqm)
UK7	514	121,640	90,706	30,934	76,490	45,150
UK6	481	96,328	84,882	11,446	71,579	24,749
International 2	736	141,348	129,882	11,466	109,527	31,821
UK 5	900	170,000	158,824	11,176	133,932	36,068
UK 4	170	30,000	30,000	0	25,298	4,702
UK 3	396	66,185	69,882	-3,697	58,930	7,255
UK 2	591	87,949	104,294	-16,345	87,949	0
UK 1	712	102,000	125,647	-23,647	105,955	-3,955
International 1	922	112,451	162,706	-50,255	137,206	-24,755

Table 28 revealed that hospital ID UK7 could save nearly 31,000 sqm moving from its current space per bed to the median space per bed. Looking at Hospital ID UK7, 31,000 square metres is in the order of 25 % of the current GIA, or the equivalent of around 175 beds based on median space per bed. Even greater savings could be achieved moving to lower quartile space performance. For example, moving from its current space per bed to the lower quartile space per bed could save Hospital ID UK7 over 45,000 sqm. For Hospital ID UK7, 45,000 square metres is in the order of 37% of the current GIA, or the equivalent of around 300 beds based on lower quartile space per bed.

Running an NHS estate has real monetary value attached to it in terms of facilities management (FM) cost. FM costs relate to range of activities such as building and maintenance, cleaning, catering, waste and security. The NHS collects hard and soft FM cost information (Estates Returns Information Collection known as ERIC) (Estates Returns Information Collection, 2011-12). Therefore, if we could attach FM costs per unit area of hospital estate, and we could provide the same hospital services over a smaller area, as indicated above, there would be a resultant lower spend on FM. An example is shown here focused on solely two key FM costs; building and engineering maintenance costs (hard FM); and cleaning services cost (soft FM). ERIC for the year 2011-12 showed across all acute Trusts the median building and engineering maintenance costs per sqm was £24.81 and median cleaning services cost per sqm was £35.01 respectively. Table 29 shows Hospital ID UK7 cost savings based on the median hard (building and engineering maintenance) FM and the median soft (cleaning services). Table 29 captured the Hospital ID UK7 FM services (building and engineering maintenance and cleaning services) with their costs per sqm (£/sqm). The table also reflected their total areas and the total area cost (the £/sqm multiplied by the total area or GIA). Note that the cleaning services total area represented the net internal area which was 80% of the GIA. This was to take into account area such as plant rooms that do not require a regular cleaning schedule. Table 29 also shows the median space saving (calculated in Table 28) and the median space saving cost (the £/sqm multiplied by the median space saving). As illustrated by Table 29, Hospital ID UK7 moving from its current space per bed to the median space per bed could reduce its building and engineering maintenance and cleaning services) costs by £1.6 million, which represented a savings of around 25% of the current building and engineering maintenance and cleaning services of £6.4 million.

Table 29. Cost savings based on selected median FM cost and median space saving

Hospital ID UK7					
FM Service	£/sqm	Total Area (sqm)	Total Area Cost (£)	Median Space Saving (sqm)	Median Space Saving Cost (£)
Building and Engineering Main.	24.81	121,640	3,017,888	30,934	767,473
Cleaning Services	35.01	97,312	3,406,893	24,747	866,399
Total	59.82		6,424,782		1,633,872

In contrast, lower quartile space saving costs is shown in Table 30. Table 30, suggests that Hospital ID UK7 moving from its current space per bed to the median space per bed could reduce its building and engineering maintenance and cleaning services) costs by £2.4 million, which represented a savings of around 37% of the current building and engineering maintenance and cleaning services of £6.4 million.

Table 30. Cost savings based on selected median FM cost and lower quartile space saving

Hospital ID UK7					
FM Service	£/sqm	Total Area (sqm)	Total Area Cost (£)	Lower Quartile Space Saving (sqm)	Lower Quartile Space Saving Cost (£)
Building and Engineering Main.	24.81	121,640	3,017,888	45,150	1,120,172
Cleaning Services	35.01	97,312	3,406,893	36,120	1,264,561
Total	59.82		6,424,782		2,384,733

The examples above suggests that hospitals with high space per bed ratios compared to its peers could release significant savings moving to a median or lower quartile space per bed ratio In real terms, adjusting to a smaller estate may actually incur costs, for example moving services and staff. The wider message perhaps is the opportunity to use modelling in its widest sense to better match space provision in the delivery of health services at operational and strategic levels.

6.7 *Analysis and results overview*

This chapter has provided numerous examples of the A&E Space Simulation Model and how it modelled patient space demand over a standard A&E day. Specifically, examples showed how the model could be quickly configured using real patient pathway arrival profiles and real patient pathway LoS to model patient pathway space demand. Simulation modelling suggested that space demand had the potential to be quite dynamic with space demand varied by pathway and by time of day. As such rules of thumb suggested by HBNs could be misleading. In fact, in the examples shown, HBN suggested space was significantly lower than modelled space. Modelled outputs illustrated how information might be configured to provide valuable insight into planning space demand by Healthcare Planners and health service providers to support their planning of pathway specific services.

At a strategic level, this chapter also provided evidence of large variance of space per bed ratios across different hospital sites. Analysis suggested that hospitals with large space per bed ratios could potentially achieve significant saving in FM costs moving towards lower space per bed ratios. Using the example provided, moving to a median space per bed ratio could save £1.6 million (25%) in building and engineering maintenance and cleaning services cost alone. Whilst moving to a lower quartile could save around £2.4 million (37%) in building and engineering maintenance and cleaning services cost. If these potential saving are fully realised, they would make a significant contribution in savings and or reallocation of funds for hospital services.

Chapter 7: Discussion and suggestions for future work

The rationale behind the A&E Space Simulation Model developed in this thesis was to overcome a number of aspects associated with poor adoption of simulation highlighted in the literature review. With this in mind, the modelling philosophy focused on: working towards resolution and consensus; modular and user-friendly models to encourage stakeholder adoption; and timely models for speed of use and rapid reconfiguration. From the outset, the modelling aim was to develop models focused around real-world space demand issues in a hospital environment, both at an operational and strategic level, namely:

1. What space is needed to meet service demand, when is it needed and what will it cost?
2. What space do we have and how could it be used to meet service demand and, at what cost?

This focus of space modelling appeared in contrast to the wealth of other papers viewed which tended to be applied to non-space related analysis. Focused at the operational level, addressing real-world current issues, the model used two key inputs: arrival profiles and LoS profiles. Both these inputs were obtained from information readily collected within an A&E and as such, both are clearly recognisable the A&E service managers. The arrival profiles captured the dynamic patient arrival patterns (patients per hour) over a 24 hour period and needed little interpretation. Likewise, LoS profiles represented the time patients actually stayed within A&E (arrival to discharge). This information too needed little interpretation. From a modelling point of view, using real data, especially LoS profiles, provides an elegant solution to model input assumption. No real processing, curve fitting or distribution assumptions, all of which might consume development time, was necessary. Features such as the LoS 4 hour peak could be fed directly into the model. These attributes of using real, readily available data meant that the model could be quickly configured to different A&E settings, which satisfied another modelling goal; timely models with shortened development/configuration times. Running the model with these input parameters could show modelled space demand over a 24 hour day.

In a real A&E, the LoS profile would capture all the staffing and operational efficiency, such as waiting for doctors, patients having imaging procedures and waiting for test results etc. In this sense, the modelled space demand could give a realistic picture of the actual space demand requirements and where that space was needed. Dependent on the availability and access of clinical staff, is for example, space needed for clinical treatment or for waiting? The recorded LoS did raise a number of issues. One issue was what actually happens around the 4 hour peak? Was it a real peak in patient activity, was it a recorded peak (to meet operational targets) or was it a hybrid of the two? The question of the 4 hour peak and associated staff working characteristics is probably worthy of further investigation in its own right as an area for future work. As described earlier, Lean methodologies seem to make an ideal candidate to further investigate, or unravel key elements within the LoS profile.

Lean could almost certainly be used in conjunction with simulation to help resolve a real-world question:

- How much staff do I need and what would they cost?

Using Lean in this way would represent a step change in the current activity and or their assumptions. New LoS profiles based on Lean practises could be tested by the A&E Space Simulation Model to assess their impact on space demand. Similarly, the A&E Space Simulation Model could be used to test incremental improvements in the LoS profile. For example, one could create LoS profiles with say a 7% reduction in the LoS times. This profile could also be tested by the A&E Space Simulation Model to assess their impact on space demand.

Another goal of the model was the ability to model groups of patients, described in the model as pathways. Often within health service delivery, service managers are concerned with distinct groups of patients. A&Es receives the complete spectrum of illness and injuries from life threatening to minor, across the complete range of ages. Many A&E departments in the UK now stream patients into major and minor categories to more effectively manage their treatment. Legislation means that paediatrics needs to be separated from adults, as such, patient flows need to be managed. As the young have particular needs, there is a growing view that the elderly should have their own patient flows managed within a hospital environment. The design of the A&E Space Simulation Model allows for cohorts of patient to be grouped - known as pathways. Within the model, each pathway could be assigned their own arrival and LoS profile which could predict space demand by profile, by time of day. As an example in the analysis chapter showed, the model has enough flexibility to analyse particular days of week. This could be extended further to model particular times of the year. For example, we know that winters might place A&E under increased pressure. Therefore the model could be used to assess space demand for using winter adjusted profiles for arrival and LoS.

The aim of these modelled outputs was to provide key stakeholders with dynamic profiles of space demand requirements, by pathway, by time of day and even time of year. Healthcare stakeholders need to broadly know their space demand requirements so they might manage their flexible space up or down as required. For example hospital managers often required more inpatient beds available over the winter period, or generic outpatient rooms that might serve as consultation or examination rooms. The modelled examples showed the elderly space use peaks mid-morning, whilst paediatric space used peak-mid evening, suggesting flexible space might be shared. Interestingly, modelled outputs suggested peak demand in excess of the suggested HBN space allowance. This would suggest that in the real-world, as well as patients being treated in cubicle spaces, they are also in other locations, such as waiting areas or perhaps corridors. From a patient flow point of view, it is important for service managers to be aware of where patients are located so that their treatment flows might be better managed for efficient services (clinical staff know where patients are) and safety and legislation (for example, separation of adult and paediatric patient flows).

The model illustrated the ability to model maximum space demand. An area of further development could be the probability or likelihood of maximum space requirement. Healthcare Planners and key stakeholders could then design accommodation space based on the probability of that space being used, whilst building contingency plans for exceptional periods of demand. Another area for further investigation/development could be constraining space resource to test the modelled impact on LoS profiles. Arguably, constraining space resource would mimic crisis mode (no available space to locate patients), which in itself might change working patterns and thus LoS profiles. However, this type of modelling might produce some useful insights in crisis mode operations.

This developed space model could potentially be used in other health delivery environments, for example outpatient and theatres services. Within the NHS, historically, outpatient services and theatres often book time blocks and specific (rooms or theatres respectively) to treat patients. Particularly in the case of outpatient appointments which usually take place in generic rooms, there is an opportunity to test whether pools of rooms could be used. This could be an area of further investigation.

Much of the discussion above has been related to operational functional units. The A&E space Simulation model is equally adaptable to service design and as such, could be used to provide strong strategic inputs. Once arrival and LoS profiles are entered and run, space demand could be determined. Having a clear understanding of space requirements (whether at design stage, or a fully functioning unit) means that costs could be attached. Without doubt, the A&E Space Simulation Model could play an active role modelling space demand to inform Schedules of Accommodation (SoA) and consequently be used in business cases to advise the functional content, with valuable inputs into capital building and refurbishment costs as well as running costs. The model also lends itself to testing future scenarios, again by changing input parameters.

At a strategic level, this thesis discussed the function-to-space ratios and this initial study suggested significant variation in space per bed across the hospitals reviewed. The hospital of the lowest space per bed was around half that of the hospital with the largest space per bed. Arguably, one might expect more recent builds to have lower (more optimised) space per bed compared to older builds. However, viewing the raw data there appeared to be little correlation between age of build and space per bed. Our findings found that if the hospital with largest space per bed moved to the median or the lowest space per bed quartile, significant space savings could be achieved. If we attached median building and engineering maintenance and cleaning facilities management (FM) costs to the surplus estate, savings were in the order of £1.6 million moving to the median space per bed. Moving to lower quartile space per bed showed savings in the order of £2.3 million. The savings represented 25% and 37% respectively of the total median and total lower quartile building and engineering maintenance and cleaning costs. This is without doubt a very high level assessment, as it assumed that the savings could be realised at no cost. Reclaiming any part of a health estate will almost undoubtedly incur a cost of moving services. That said, the other side of the argument is that, whilst FM cost used to state the case are key cost, other FM costs (for example energy costs) could contribute to even greater savings. Furthermore, the FM costs used were median cost. Moving to, say, lower quartile FM costs would result in even greater savings. Also, the commercial income from land sale of surplus estate could also be significant. As stated at the outset, the function-to-space ratio and linkage to cost was at a high level to highlight potential saving and definitely worthy of further investigation. So far we have focused on potential saving, but of course, any potential release of funds could be used in reinvest in other service. The discussion here is focused on health. However, attaching cost to space-to-function ratios could be applied to number of other industries other than health. This too could be a rich area for exploration.

In the early days of the NHS, as described, research was conducted to analyse the types of hospitals and services needed. At the time, under great financial constraints, the research was seen as world leading and set a clear heritage of space planning for health services. At the time of writing, the NHS is once again under great financial constraint and as tools such as simulation modelling become more accessible, perhaps the time is now right to better implement these tools to help meet challenges of healthcare delivery in the 21st century. A premise behind the thesis is that Healthcare Planning can play a key role, using its current relationships with healthcare stakeholders, to bring in sound academic health modelling techniques to help develop an even more effective health services. The A&E Space Simulation Model attempted to address many of the lessons of poor simulation adoption. The developed model was focused on real-world application, in particular the wicked problems of dynamic space demand management. The modelled outputs has also shown its value as a health planning tool in a dynamic environment (in contrast to average based models), supporting and extending valuable information in health building guidance notes at both operational and strategic levels, with valuable inputs to both Healthcare Planners and healthcare stakeholders.

Chapter 8: Conclusions and detailed contribution

This thesis has focused on the development of models to address real-world issues as recognised by real stakeholders, namely:

- What space is needed to meet service demand when is it needed and what will it cost?
- What space do we have and how could it be used to meet service demand and, at what cost?

A two-pronged approach was deployed to address the issues above. The first step was to develop a simulation model to support space demand operational aspects in an A&E environment. The A&E was selected as it provided a good example of how simulation modelling could provide insightful space demand information to healthcare stakeholders in a dynamic environment. With this aim in mind and to help overcome poor aspects of modelling adoptions, the developed A&E Space Simulation Model had clear modelling goals, namely:

- Models focused towards resolution and consensus (rather than solution and optimisation).
- Modular pathways modelling methodology.
- Models designed to be user-friendly to encourage stakeholder adoption and to facilitate communications and training.
- Timely models for speed of use and to support rapid reconfiguration.

The functions of the A&E Space Simulation Model included:

- The use real arrival and LoS data by pathway to drive the model focused on specific patient pathways, both of which are easily recognisable to stakeholders.
- Reducing to practice; by developing a modelling methodology to model a standard day; real arrival data eliminates the requirement to develop input and process profiles to drive the model; all of which greatly shortens model development and encourages model re-use.
- Running the model with real inputs can help to identify space demand issues and effects of crowding of an area under investigation.

Evidence showed the model produced similar arrival and LoS pathway profiles compared to real data. As such, the model could be used to provide useful insight into the real space demand by patient pathway, by hour. At an operational level, knowledge of space demand could be used by local service managers to better organise the use of space to enhance treatment and patient flow pathways. At a design (strategic level) knowledge of space demand could be used by Healthcare Planners and estate managers to create Schedules of Accommodation (SoA). Building and operational costs could then be attached to SoAs. This information provides valuable information to healthcare stakeholder and goes some way to answer the question:

- What space is needed to meet service demand when is it needed and, what will it cost?

The second step was development of methodologies to provide some insight at strategic level using function-to-space ratios to highlight potential cost savings. Analysis of space per bed ratios across a range of hospitals should significant variation. The findings showed that in the worst case example moving from the worst space per bed ratio in the group to the median space per bed, or better still, the lower quartile space per bed of the group, thousands of square metres could be saved. Buildings on health estate have a cost associated with their operation and upkeep. The example analysis in this thesis showed that attaching median key FM costs (building and engineering maintenance and cleaning) alone potentially could save up to £2.3 million in operational cost. This too is valuable real-world information to healthcare stakeholder and goes some way to answer the question:

- What space do we have and how could it be used to meet service demand and, at what cost?

The function per space analysis represented a very high level overview and made some sweeping assumptions with regards to reclaiming estate; the reclaiming process itself could incur high costs. However, it did suggest some significant savings, which even if they are half reclaimable, was still significant.

The outputs of the A&E Space Simulation Model provided examples of its value (over average based models) as health planning tool in a dynamic environment. This thesis has also showed how the A&E Space Simulation Model could be used in conjunction with health building guidance notes adding key operational and strategic insights to Healthcare Planner and healthcare stakeholders. This body of work also proposed how Healthcare Planner could act as a catalyst to bring closer the worlds of health and academic healthcare modelling as well as suggestions how Lean methodologies could be linked into the A&E Space Simulation Model.

In summary, the contribution to the research community of this thesis is as follows:

- The development of an A&E Space Simulation Model to be used as a planning tool to model space demand by patient groups and by time of day. The model showed the benefits of using simulation to more accurately model space demand in dynamic healthcare environments over static average based calculations. This information could be used by service managers and Healthcare Planners to better manage and organise space in a flexible way to meet service requirements.
- Space demand derived from simulation could be used in conjunction with health building note to develop excellence cost information. Space demand derived from simulation, used in conjunction with Schedules of Accommodation (SoA) could be used to provide high quality inputs to:
    - Clearly show space demand over time.
    - Develop capital costs of hospital building or refurbishments.

    - Develop operational running costs schedules.
    - Inform business cases.
- The A&E Space Simulation Model could be configured in a matter of hours to suit an A&E system and would be driven by real data easily recognisable to healthcare stakeholder, namely;
    - Arrival time profiles (related to distinct patient groups).
    - Length of stay profiles (related to distinct patient groups).
- The model would be modular by design thus facilitating pathway modelling (by acuity and type), speed of development (adaption to the service needs of a particular stakeholder) and speed of adaption to other service settings.
- Visible clear models to support interrogation by healthcare stakeholders, the integration of Excel tools and discrete-event simulation models and training – the ability to quickly highlight issues, with clear outputs to alert stakeholders to the onset of crowding and crowd severity.
- Development of the links between space use in a health service estate and associated facilities management costs highlighted the potential of significant cost savings (up to several £ millions) across a health estate.
- Another area of contribution of this work was the recognition of relationships between healthcare stakeholders, academic healthcare modellers and healthcare planning modellers and the mutual benefit of combining their skills and expertise to create better dynamic models more focused to the real-world requirements of healthcare stakeholders.

Publications during research

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Appendix A1 – Standard A&E Day Arrivals profile examples: Adult-A&E; Adult-UCC; Elderly; and Paediatrics

Disp Code 02	(All)
Triage Desc 03	Adult - A&E

Arrivals per day
86.69

	Data				
ArrivalHr	Sum of LoS ave	Sum of attn	percent	patients per hr	Int arrival time
0	401.27	1,320	4.17%	3.62	16.59
1	417.03	1,137	3.59%	3.12	19.26
2	413.82	1,040	3.29%	2.85	21.06
3	414.74	822	2.60%	2.25	26.64
4	422.54	707	2.23%	1.94	30.98
5	390.78	542	1.71%	1.48	40.41
6	440.41	599	1.89%	1.64	36.56
7	449.46	575	1.82%	1.58	38.09
8	440.36	911	2.88%	2.50	24.04
9	456.04	1,315	4.16%	3.60	16.65
10	466.07	1,679	5.31%	4.60	13.04
11	513.41	1,659	5.24%	4.55	13.20
12	458.17	1,684	5.32%	4.61	13.00
13	467.17	1,665	5.26%	4.56	13.15
14	465.76	1,666	5.27%	4.56	13.15
15	465.01	1,597	5.05%	4.38	13.71
16	436.65	1,572	4.97%	4.31	13.93
17	426.85	1,563	4.94%	4.28	14.01
18	459.92	1,667	5.27%	4.57	13.14
19	435.09	1,643	5.19%	4.50	13.33
20	463.28	1,723	5.45%	4.72	12.71
21	415.06	1,616	5.11%	4.43	13.55
22	423.35	1,473	4.66%	4.04	14.87
23	401.78	1,466	4.63%	4.02	14.94
Grand Total	10544.03	31,641			

Disp Code 02	(All)
Triage Desc 03	Adult - UCC

Arrivals per day
129.14

	Data	
ArrivalHr	Sum of LoS ave	Sum of attn
0	313.07	1,079
1	337.82	913
2	346.79	794
3	300.90	551
4	328.61	449
5	318.29	375
6	315.50	518
7	312.97	904
8	305.45	1,792
9	289.70	2,934
10	330.26	3,543
11	355.63	3,488
12	356.23	3,302
13	329.62	2,969
14	313.59	2,769
15	336.92	2,772
16	334.14	2,750
17	323.08	2,829
18	344.71	2,971
19	317.77	2,595
20	321.09	2,143
21	324.50	1,822
22	310.83	1,618
23	336.62	1,255
Grand Total	7804.07	47,135

percent	patients per hr	Int arrival time
2.29%	2.96	20.30
1.94%	2.50	23.99
1.68%	2.18	27.58
1.17%	1.51	39.75
0.95%	1.23	48.78
0.80%	1.03	58.40
1.10%	1.42	42.28
1.92%	2.48	24.23
3.80%	4.91	12.22
6.22%	8.04	7.46
7.52%	9.71	6.18
7.40%	9.56	6.28
7.01%	9.05	6.63
6.30%	8.13	7.38
5.87%	7.59	7.91
5.88%	7.59	7.90
5.83%	7.53	7.96
6.00%	7.75	7.74
6.30%	8.14	7.37
5.51%	7.11	8.44
4.55%	5.87	10.22
3.87%	4.99	12.02
3.43%	4.43	13.54
2.66%	3.44	17.45

Disp Code 02	(All)
Triage Desc 03	Elderly (all)

Arrivals per day
34.35

	Data	
ArrivalHr	Sum of LoS ave	Sum of attn
0	591.96	255
1	534.04	195
2	662.09	199
3	646.24	209
4	604.41	195
5	698.84	185
6	564.62	283
7	494.65	255
8	472.06	489
9	448.50	822
10	489.40	1,053
11	490.43	1,012
12	555.07	951
13	492.71	808
14	597.40	787
15	513.38	747
16	559.65	618
17	618.28	608
18	480.07	622
19	549.95	503
20	542.32	517
21	455.11	462
22	497.26	428
23	509.68	335
Grand Total	13068.11	12,538

percent	patients per hr	Int arrival time
2.03%	0.70	85.88
1.56%	0.53	112.31
1.59%	0.55	110.05
1.67%	0.57	104.78
1.56%	0.53	112.31
1.48%	0.51	118.38
2.26%	0.78	77.39
2.03%	0.70	85.88
3.90%	1.34	44.79
6.56%	2.25	26.64
8.40%	2.88	20.80
8.07%	2.77	21.64
7.58%	2.61	23.03
6.44%	2.21	27.10
6.28%	2.16	27.83
5.96%	2.05	29.32
4.93%	1.69	35.44
4.85%	1.67	36.02
4.96%	1.70	35.21
4.01%	1.38	43.54
4.12%	1.42	42.36
3.68%	1.27	47.40
3.41%	1.17	51.17
2.67%	0.92	65.37

Disp Code 02	(All)
Triage Desc 03	Paeds ex resus

Arrivals per day
83.67

	Data				
ArrivalHr	Sum of LoS ave	Sum of attn	percent	patients per hr	Int arrival time
0	268.97	486	1.59%	1.33	45.06
1	256.19	337	1.10%	0.92	64.99
2	277.11	232	0.76%	0.64	94.40
3	266.26	171	0.56%	0.47	128.07
4	401.04	136	0.45%	0.37	161.03
5	309.80	111	0.36%	0.30	197.30
6	286.84	134	0.44%	0.37	163.43
7	312.71	250	0.82%	0.68	87.60
8	273.65	596	1.95%	1.63	36.74
9	285.98	1,353	4.43%	3.71	16.19
10	320.08	1,678	5.49%	4.60	13.05
11	316.69	1,746	5.72%	4.78	12.54
12	322.48	1,795	5.88%	4.92	12.20
13	327.46	1,808	5.92%	4.95	12.11
14	297.75	1,921	6.29%	5.26	11.40
15	294.67	1,954	6.40%	5.35	11.21
16	327.48	2,246	7.35%	6.15	9.75
17	309.41	2,336	7.65%	6.40	9.38
18	317.12	2,584	8.46%	7.08	8.48
19	308.31	2,505	8.20%	6.86	8.74
20	316.52	2,275	7.45%	6.23	9.63
21	300.94	1,792	5.87%	4.91	12.22
22	286.90	1,242	4.07%	3.40	17.63
23	267.07	850	2.78%	2.33	25.76
Grand Total	7251.42	30,538			

Appendix A2 – Virtual Logic Code – reference Table 18

Step 0: Reset Logic

(This logic clears all the record sheets, before refreshing sheet headers and arrival profiles)

```
Reset Logic
 -Obeyed just after all simulation objects are initialized at time zero
 -Obeyed just after all simulation objects are initialized at time zero
 -'This routine clear spredsheets and resets initial parameters
 -'*****************************************************************************************
 -Clear Sheet Data Only   iss_Arrivals1[1,1]
 -Clear Sheet Data Only   iss_Arrivals2[1,1]
 -Clear Sheet Data Only   iss_Arrivals3[1,1]
 -Clear Sheet Data Only   iss_Arrivals4[1,1]
 -Clear Sheet Data Only   iss_Arrivals5[1,1]
 -Clear Sheet Data Only   iss_Arrivals6[1,1]
 -Clear Sheet Data Only   iss_Headers[1,1]
 -Clear Sheet Data Only   iss_Results[1,1]
 -'************** Reset results table header **************
 -'*****************************************************************************************
 -SET iss_Headers[1,1]  =  "Line No"
 -SET iss_Headers[2,1]  =  "Trial run No"
 -SET iss_Headers[3,1]  =  "Unique ID"
 -SET iss_Headers[10,1]  =  "LineCount"
 -SET iss_Headers[11,1]  =  "Route"
 -SET iss_Headers[12,1]  =  "StartTime"
 -SET iss_Headers[13,1]  =  "EndTime"
 -SET iss_Headers[14,1]  =  "StartWork"
 -SET iss_Headers[15,1]  =  "TreatmentTime"
 -SET iss_Headers[16,1]  =  "Qtime"
 -SET iss_Headers[17,1]  =  "LoS"
 -SET iss_Headers[18,1]  =  "res_Grp1"
 -SET iss_Headers[19,1]  =  "res_Grp2"
 -SET iss_Headers[20,1]  =  "res_Grp3"
 -SET iss_Headers[21,1]  =  "res_Grp4"
 -SET iss_Headers[22,1]  =  "res_Grp5"
 -SET iss_Headers[23,1]  =  "res_Grp6"
 -SET iss_Headers[24,1]  =  "Hour_EndTime"
 -SET iss_Headers[25,1]  =  "Hour_Arrival"
 -Get data from Excel spreadsheets and load into internal Simul8 spreadsheets at start of run
 -reference Column22 = column V
 -Get from EXCEL   iss_Arrivals1[1,1] , "ArrGrp1" , 1 , 1 , 8 , 31
 -Get from EXCEL   iss_Arrivals2[1,1] , "ArrGrp2" , 1 , 1 , 8 , 31
 -Get from EXCEL   iss_Arrivals3[1,1] , "ArrGrp3" , 1 , 1 , 8 , 31
 -Get from EXCEL   iss_Arrivals4[1,1] , "ArrGrp4" , 1 , 1 , 8 , 31
 -Get from EXCEL   iss_Arrivals5[1,1] , "ArrGrp5" , 1 , 1 , 8 , 31
 -Get from EXCEL   iss_Arrivals6[1,1] , "ArrGrp6" , 1 , 1 , 8 , 31
 -'*****************************************************************************************
 -'************** Get trial number **************
 -Get Trial Run Number   gisv_TrialNumber
 -'************** Read Line end in LineLog to determine line to start **************
 -IF gisv_TrialNumber > 1
    -Get from EXCEL   lisv_LineEnd , "LineLog" , 3 , gisv_TrialNumber-1 , 1 , 1
```

Step 1: Time Check logic

(Used to update the arrivals pathway profile on an hourly basis)

```
Time Check Logic
  ************************************************************************************
  The line below returns the simulation hour. Midnight is returned as 0 with 23:59 returned as 23. Ref The complete guide 2nd ed page 408
  In summary lisv_Hour runs from 0 to 23
  SET lisv_Hour = HOUR[Simulation Time]
  ************************************************************************************
  Load arrival patterns
  Note column 8 links to interarrival time, whilst column 7
  lisv_Hour+6 links to iss_Arrivals1 row
  ************************************************************************************
  Set Object Distribution Parameters   wep_Arrivals1 , Interarrival Time , Exponential , iss_Arrivals1[8,lisv_Hour+7] , 0 , 0 , 0
  ReSchedule Arrival   wep_Arrivals1
  Set Object Distribution Parameters   wep_Arrivals2 , Interarrival Time , Exponential , iss_Arrivals2[8,lisv_Hour+7] , 0 , 0 , 0
  ReSchedule Arrival   wep_Arrivals2
  Set Object Distribution Parameters   wep_Arrivals3 , Interarrival Time , Exponential , iss_Arrivals3[8,lisv_Hour+7] , 0 , 0 , 0
  ReSchedule Arrival   wep_Arrivals3
  Set Object Distribution Parameters   wep_Arrivals4 , Interarrival Time , Exponential , iss_Arrivals4[8,lisv_Hour+7] , 0 , 0 , 0
  ReSchedule Arrival   wep_Arrivals4
  Set Object Distribution Parameters   wep_Arrivals5 , Interarrival Time , Exponential , iss_Arrivals5[8,lisv_Hour+7] , 0 , 0 , 0
  ReSchedule Arrival   wep_Arrivals5
  Set Object Distribution Parameters   wep_Arrivals6 , Interarrival Time , Exponential , iss_Arrivals6[8,lisv_Hour+7] , 0 , 0 , 0
  ReSchedule Arrival   wep_Arrivals6
```

Step 3: wc_Grp1 Route In Logic

(Similar code for Grp2, Grp3 and Grp4. This calls the sub-routine to set the start work time)

```
wc_Grp1 Route In After Logic
  CALL Sub Set Work Start
```

Step 3: Sub-routine – Sub Set Work Start

(This sub-routine used by all Grps. This sub-routine used to set patient icon start time)

```
Sub Set Work Start
  SET lbl_TimeWorkStart = Simulation Time
```

Step 4: wc_Grp1 Work Complete Logic

(Similar code for Grp2, Grp3 and Grp4. This calls the sub-routine to calculate the LoS)

```
wc_Grp1 Work Complete Logic
  CALL Sub Calc LoS
```

Step 4: Sub-routine – Sub Calc LoS

(This sub-routine used by all Grps. This sub-routine used to calculate patient LoS time)

```
Sub Calc LoS
  ******************************************************
  SET lbl_TimeSimEnd = Simulation Time
  SET lbl_TreatTime = lbl_TimeSimEnd-lbl_TimeWorkStart
  *********************************
  v1.1
  SET lbl_QueueTime = lbl_TimeSimStart-lbl_TimeWorkStart
  *********************************
  SET lbl_QueueTime = lbl_TimeWorkStart-lbl_TimeSimStart
```

Step 6: Work Centre 13 Route In Logic

(This calls the sub-routine to log the results)

```
Work Center 13 Route In After Logic
  CALL Sub Results Log
```

Step 6: Sub Results Log

(This sub-routine used to log run data in Simul8)

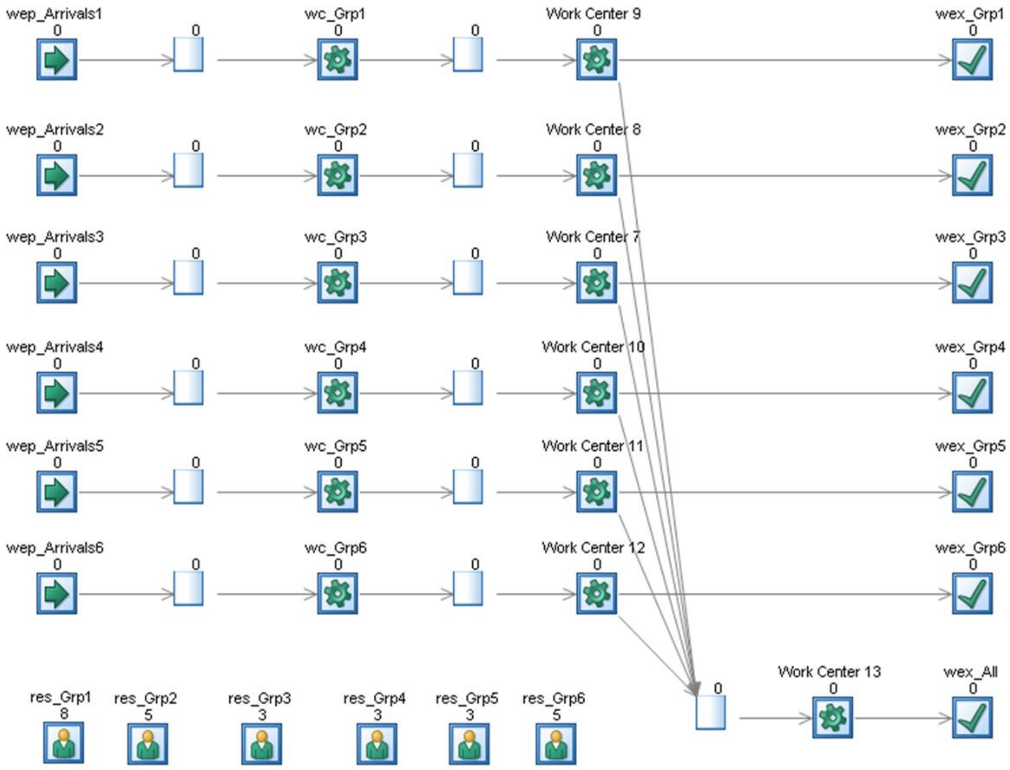
```
Sub Results Log
  Results Log *************************************
  IF Simulation Time >= Warm Up Period
    SET iss_Results[1,lisv_LineNo] = lisv_LineNo
    SET iss_Results[2,lisv_LineNo] = gisv_TrialNumber
    SET iss_Results[3,lisv_LineNo] = lbl_Unique
    SET iss_Results[10,lisv_LineNo] = 1
    SET iss_Results[11,lisv_LineNo] = lbl_Route
    SET iss_Results[12,lisv_LineNo] = lbl_TimeSimStart
    SET iss_Results[13,lisv_LineNo] = lbl_TimeSimEnd
    SET iss_Results[14,lisv_LineNo] = lbl_TimeWorkStart
    SET iss_Results[15,lisv_LineNo] = lbl_TreatTime
    SET iss_Results[16,lisv_LineNo] = lbl_QueueTime
    !************** Resources **************
    SET iss_Results[17,lisv_LineNo] = lbl_TreatTime+lbl_QueueTime
    SET iss_Results[18,lisv_LineNo] = [res_Grp1.Max Available]-[res_Grp1.Current Available]
    SET iss_Results[19,lisv_LineNo] = [res_Grp2.Max Available]-[res_Grp2.Current Available]
    SET iss_Results[20,lisv_LineNo] = [res_Grp3.Max Available]-[res_Grp3.Current Available]
    SET iss_Results[21,lisv_LineNo] = [res_Grp4.Max Available]-[res_Grp4.Current Available]
    SET iss_Results[22,lisv_LineNo] = [res_Grp5.Max Available]-[res_Grp5.Current Available]
    SET iss_Results[23,lisv_LineNo] = [res_Grp6.Max Available]-[res_Grp6.Current Available]
    SET iss_Results[24,lisv_LineNo] = HOUR[lbl_TimeSimEnd]
    SET iss_Results[25,lisv_LineNo] = HOUR[lbl_TimeSimStart]
    !************** Add line **************
    SET lisv_LineNo = lisv_LineNo+1
```

Step 8: End Run Logic

(This sub-routine used to export log run data from Simul8 to Excel)

```
End Run Logic
    Obeyed when the simulation reaches end of "Results Collection Period"
    !*************** Trial Run Number logic ***************
    This section defines the line number (row) for excel
    LineNumber parameters defined by the end run logic.
    Run number -1 = end of trial, 0 = no trial.
    !*************** Trial section ***************
    !*************** 1st run in trial ***************
    IF gisv_TrialNumber  =  1
        !****************************************
        !*************** Store header then results in excel ***************
        Set in EXCEL    iss_Headers[1,1] , "Results" , 1 , 1 , 30 , lisv_LineNo
        Set in EXCEL    iss_Results[1,1] , "Results" , 1 , 2 , 30 , lisv_LineNo
        !*************** Store line info into LineLog ***************
        !*************** Column 1 is line no '***************
        Set in EXCEL    lisv_LineNo , "LineLog" , 1 , 1 , 30 , lisv_LineNo
        !*************** Column 2 is line start '***************
        !*************** Make line end = line no '***************
        SET lisv_LineEnd  =  lisv_LineNo
        Set in EXCEL    lisv_LineStart , "LineLog" , 2 , gisv_TrialNumber , 30 , lisv_LineNo
        !*************** Column 3 is line end '***************
        Set in EXCEL    lisv_LineEnd , "LineLog" , 3 , gisv_TrialNumber , 30 , lisv_LineNo
        !*************** Column 4 is trial number '***************
        Set in EXCEL    gisv_TrialNumber , "LineLog" , 4 , gisv_TrialNumber , 30 , lisv_LineNo
        !*************** Column 5 is block '***************
        Set in EXCEL    "Block =1" , "LineLog" , 5 , gisv_TrialNumber , 30 , lisv_LineNo
    !*************** appended runs in trial ***************
    ELSE IF gisv_TrialNumber  >  1
        !*************** Make line start = line end ***************
        SET lisv_LineStart  =  lisv_LineEnd
        !*************** Store results in excel. Note start from LineStart ***************
        Set in EXCEL    iss_Results[1,1] , "Results" , 1 , lisv_LineStart , 30 , lisv_LineNo
        !*************** Store line info into LineLog ***************
        !*************** Column 1 is line no '***************
        Set in EXCEL    lisv_LineNo , "LineLog" , 1 , gisv_TrialNumber , 30 , lisv_LineNo
        !*************** Column 2 is line start '***************
        Set in EXCEL    lisv_LineStart , "LineLog" , 2 , gisv_TrialNumber , 30 , lisv_LineNo
        !*************** Column 3 is line end '***************
        !*************** Make line end = line start + line no '***************
        SET lisv_LineEnd  =  [lisv_LineStart+lisv_LineNo]-1
        Set in EXCEL    lisv_LineEnd , "LineLog" , 3 , gisv_TrialNumber , 30 , lisv_LineNo
        !*************** Column 4 is trial number '***************
        Set in EXCEL    gisv_TrialNumber , "LineLog" , 4 , gisv_TrialNumber , 30 , lisv_LineNo
        !*************** Column 5 is block '***************
        Set in EXCEL    "Block >1" , "LineLog" , 5 , gisv_TrialNumber , 30 , lisv_LineNo
    ELSE
        !*************** Run section ***************
        !*************** Store header then results in excel ***************
        Set in EXCEL    iss_Headers[1,1] , "Results" , 1 , 1 , 30 , lisv_LineNo
        Set in EXCEL    iss_Results[1,1] , "Results" , 1 , 2 , 30 , lisv_LineNo
```

Model Schematic



Appendix A3 – A&E Space Simulation Model Arrivals: Adult-A&E; Adult-UCC; Elderly; and Paediatrics

Adult-A&E (Grp1)

Route	Grp1	Arrivals per day
		85.96

Count of LoS			
Hour_Arrival	Total	Percent	patients per hr
0	178	4.14%	3.56
1	145	3.37%	2.9
2	118	2.75%	2.36
3	118	2.75%	2.36
4	106	2.47%	2.12
5	74	1.72%	1.48
6	72	1.68%	1.44
7	73	1.70%	1.46
8	133	3.09%	2.66
9	157	3.65%	3.14
10	227	5.28%	4.54
11	213	4.96%	4.26
12	230	5.35%	4.6
13	248	5.77%	4.96
14	242	5.63%	4.84
15	189	4.40%	3.78
16	231	5.37%	4.62
17	215	5.00%	4.3
18	229	5.33%	4.58
19	224	5.21%	4.48
20	259	6.03%	5.18
21	219	5.10%	4.38
22	208	4.84%	4.16
23	190	4.42%	3.8
Grand Total	4298		

Adult-UCC (Grp2)

Route	Grp2

Arrivals per day
129.28

Count of LoS			
Hour_Arrival	Total	Percent	patients per hr
0	146	2.26%	2.92
1	143	2.21%	2.86
2	119	1.84%	2.38
3	73	1.13%	1.46
4	70	1.08%	1.4
5	43	0.67%	0.86
6	72	1.11%	1.44
7	118	1.83%	2.36
8	240	3.71%	4.8
9	388	6.00%	7.76
10	495	7.66%	9.9
11	470	7.27%	9.4
12	487	7.53%	9.74
13	446	6.90%	8.92
14	381	5.89%	7.62
15	369	5.71%	7.38
16	393	6.08%	7.86
17	387	5.99%	7.74
18	403	6.23%	8.06
19	328	5.07%	6.56
20	281	4.35%	5.62
21	237	3.67%	4.74
22	225	3.48%	4.5
23	150	2.32%	3
Grand Total	6464		

Elderly (Grp3) and Paediatric (Grp4)

Route	Grp3

Arrivals per day
35.16

Count of LoS			
Hour_Arrival	Total	Percent	patients per hr
0	35	1.99%	0.7
1	26	1.48%	0.52
2	25	1.42%	0.5
3	24	1.37%	0.48
4	31	1.76%	0.62
5	20	1.14%	0.4
6	42	2.39%	0.84
7	45	2.56%	0.9
8	65	3.70%	1.3
9	122	6.94%	2.44
10	178	10.13%	3.56
11	143	8.13%	2.86
12	126	7.17%	2.52
13	112	6.37%	2.24
14	90	5.12%	1.8
15	109	6.20%	2.18
16	92	5.23%	1.84
17	74	4.21%	1.48
18	85	4.84%	1.7
19	58	3.30%	1.16
20	83	4.72%	1.66
21	75	4.27%	1.5
22	61	3.47%	1.22
23	37	2.10%	0.74
Grand Total	1758		

Route	Grp4

Arrivals per day
85.84

Count of LoS			
Hour_Arrival	Total	Percent	patients per hr
0	73	1.70%	1.46
1	48	1.12%	0.96
2	37	0.86%	0.74
3	23	0.54%	0.46
4	20	0.47%	0.4
5	14	0.33%	0.28
6	19	0.44%	0.38
7	41	0.96%	0.82
8	76	1.77%	1.52
9	183	4.26%	3.66
10	245	5.71%	4.9
11	237	5.52%	4.74
12	266	6.20%	5.32
13	263	6.13%	5.26
14	284	6.62%	5.68
15	287	6.69%	5.74
16	285	6.64%	5.7
17	327	7.62%	6.54
18	341	7.95%	6.82
19	369	8.60%	7.38
20	316	7.36%	6.32
21	257	5.99%	5.14
22	162	3.77%	3.24
23	119	2.77%	2.38
Grand Total	4292		

Appendix A4 – Arrivals Profile Comparisons

Input dataset	Arrivals per hour – Adult-UCC		Difference
	Standard A&E Day Arrival	A&E Space Simulation Model	
1	2.96	2.92	0.04
2	2.5	2.86	-0.36
3	2.18	2.38	-0.2
4	1.51	1.46	0.05
5	1.23	1.4	-0.17
6	1.03	0.86	0.17
7	1.42	1.44	-0.02
8	2.48	2.36	0.12
9	4.91	4.8	0.11
10	8.04	7.76	0.28
11	9.71	9.9	-0.19
12	9.56	9.4	0.16
13	9.05	9.74	-0.69
14	8.13	8.92	-0.79
15	7.59	7.62	-0.03
16	7.59	7.38	0.21
17	7.53	7.86	-0.33
18	7.75	7.74	0.01
19	8.14	8.06	0.08
20	7.11	6.56	0.55
21	5.87	5.62	0.25
22	4.99	4.74	0.25
23	4.43	4.5	-0.07
24	3.44	3	0.44

Input dataset	Arrivals per hour – Elderly		Difference
	Standard A&E Day Arrival	A&E Space Simulation Model	
1	0.7	0.7	0
2	0.53	0.52	0.01
3	0.55	0.5	0.05
4	0.57	0.48	0.09
5	0.53	0.62	-0.09
6	0.51	0.4	0.11
7	0.78	0.84	-0.06
8	0.7	0.9	-0.2
9	1.34	1.3	0.04
10	2.25	2.44	-0.19
11	2.88	3.56	-0.68
12	2.77	2.86	-0.09
13	2.61	2.52	0.09
14	2.21	2.24	-0.03
15	2.16	1.8	0.36
16	2.05	2.18	-0.13
17	1.69	1.84	-0.15
18	1.67	1.48	0.19
19	1.7	1.7	0
20	1.38	1.16	0.22
21	1.42	1.66	-0.24
22	1.27	1.5	-0.23
23	1.17	1.22	-0.05
24	0.92	0.74	0.18

Input dataset	Arrivals per hour – Paediatric		Difference
	Standard A&E Day Arrival	A&E Space Simulation Model	
1	1.33	1.46	-0.13
2	0.92	0.96	-0.04
3	0.64	0.74	-0.10
4	0.47	0.46	0.01
5	0.37	0.4	-0.03
6	0.30	0.28	0.02
7	0.37	0.38	-0.01
8	0.68	0.82	-0.14
9	1.63	1.52	0.11
10	3.71	3.66	0.05
11	4.60	4.9	-0.30
12	4.78	4.74	0.04
13	4.92	5.32	-0.40
14	4.95	5.26	-0.31
15	5.26	5.68	-0.42
16	5.35	5.74	-0.39
17	6.15	5.7	0.45
18	6.40	6.58	-0.18
19	7.08	6.84	0.24
20	6.86	7.5	-0.64
21	6.23	5.76	0.47
22	4.91	5.08	-0.17
23	3.40	3.46	-0.06
24	2.33	2.42	-0.09

Appendix A5 – LoS Profile Comparisons

LoS Time	LoS – Adult-UCC		Difference
	Standard A&E Day LoS	DES Space Simulation Model	
0	5.05	5.07	-0.03
30	6.94	6.56	0.39
60	14.56	14.69	-0.13
90	17.59	17.07	0.52
120	16.38	16.46	-0.08
150	13.15	12.98	0.17
180	9.70	10.12	-0.42
210	6.31	6.45	-0.14
240	5.31	5.69	-0.37
270	1.12	1.16	-0.04
300	1.35	1.25	0.10
330	0.84	0.89	-0.05
360	0.54	0.66	-0.12
390	0.40	0.29	0.11
420	0.24	0.20	0.04
450	0.14	0.14	0.00
480	0.11	0.17	-0.05
510	0.09	0.06	0.03
540	0.05	0.03	0.02
570	0.04	0.02	0.02
600	0.01	0.03	-0.02
More	0.06	0.03	0.03

LoS Time	LoS – Elderly		Difference
	Standard A&E Day LoS	DES Space Simulation Model	
0	0.38	0.34	0.04
30	1.91	1.72	0.19
60	4.31	4.83	-0.52
90	8.88	8.91	-0.03
120	11.87	11.49	0.37
150	13.24	15.29	-2.05
180	12.50	13.33	-0.84
210	11.33	11.44	-0.11
240	13.71	12.36	1.35
270	3.22	2.87	0.35
300	4.75	3.68	1.07
330	3.57	3.56	0.01
360	2.64	2.36	0.28
390	1.92	1.72	0.20
420	1.42	1.61	-0.19
450	1.21	1.32	-0.11
480	0.78	0.69	0.09
510	0.65	0.52	0.13
540	0.41	0.23	0.18
570	0.30	0.23	0.07
600	0.20	0.63	-0.43
More	0.80	0.86	-0.06

LoS Time	LoS – Paediatrics		Difference
	Standard A&E Day LoS	DES Space Simulation Model	
0	2.12	1.87	0.24
30	5.26	5.55	-0.29
60	16.07	15.56	0.51
90	19.49	19.52	-0.03
120	17.87	18.30	-0.43
150	14.05	13.38	0.67
180	9.70	10.92	-1.22
210	6.58	6.40	0.18
240	5.24	5.11	0.13
270	1.06	1.03	0.03
300	1.17	1.03	0.14
330	0.61	0.61	0.00
360	0.34	0.26	0.08
390	0.17	0.21	-0.04
420	0.10	0.12	-0.02
450	0.08	0.05	0.03
480	0.05	0.00	0.05
510	0.02	0.02	0.00
540	0.02	0.02	-0.01
570	0.00	0.00	0.00
600	0.01	0.02	-0.02
More	0.02	0.02	-0.01