DEMAND AND CAPACITY MODELLING OF ACUTE SERVICES USING SIMULATION AND OPTIMIZATION TECHNIQUES

Muhammed ORDU

University of Hertfordshire

Hertfordshire Business School

Submitted in partial fulfilment of the requirements of the University of Hertfordshire for the degree of Doctor of Philosophy

December 2018

To my lovely family…

Abstract

The level of difficulty that hospital management have been experiencing over the past decade in terms of balancing demand and capacity needs has been at an unprecedented level in the UK. Due to shortage of capacity, hospitals are unable to treat patients, and in some cases, patients are transferred to other hospitals, outpatient referrals are delayed, and accident and emergency (A&E) waiting times are prolonged. So, it's time to do things differently, because the current status quo is not an option.

A whole hospital level decision support system (DSS) was developed to assess and respond to the needs of local populations. The model integrates every component of a hospital (including A&E, all outpatient and inpatient specialties) to aid with efficient and effective use of scarce resources. An individual service or a specialty cannot be assumed to be independent, they are all interconnected. It is clear from the literature that this level of generic hospital simulation model has never been developed before (so this is an innovative DSS).

Using the Hospital Episode Statistics and local datasets, 768 forecasting models for the 28 outpatient and inpatient specialties are developed (to capture demand). Within this context, a variety of forecasting models (i.e. ARIMA, exponential smoothing, stepwise linear regression and STLF) for each specialty of outpatient and inpatient including the A&E department were developed. The best forecasting methods and periods were selected by comparing 4 forecasting methods and 3 periods (i.e. daily, weekly and monthly) according to forecast accuracy values calculated by the mean absolute scaled error (MASE). Demand forecasts were then used as an input into the simulation model for the entire hospital (all specialties).

The generic hospital simulation model was developed by taking into account all specialties and interactions amongst the A&E, outpatient and inpatient specialties. Six hundred observed frequency distributions were established for the simulation model. All distributions used in the model were based on age groups. Using other inputs (i.e. financial inputs, number

of follow ups, etc.), the hospital was therefore modelled to measure key output metrics in strategic planning. This decision support system eliminates the deficiencies of the current and past studies around modelling hospitals within a single framework. A new output metric which is called ‘demand coverage ratio’ was developed to measure the percentage of patients who are admitted and discharged with available resources of the associated specialty.

In addition, a full factorial experimental design with 4 factors (A&E, elective and non-elective admissions and outpatient attendance) at 2 levels (possible 5% and 10% demand increases) was carried out in order to investigate the effects of demand increases on the key outputs (i.e. demand coverage ratio, bed occupancy rate and total revenue). As a result, each factor is found to affect total revenue, as well as the interaction between elective and non-elective admissions. The demand coverage ratio is affected by the changes in outpatient demands as well as A&E arrivals and non-elective admissions. In addition, the A&E arrivals, non-elective admissions and elective admissions are most important for bed occupancy rates, respectively.

After an exhaustive review of the literature we notice that an entire hospital model has never been developed that combines forecasting, simulation and optimization techniques. A linear optimization model was developed to estimate the required bed capacity and staff needs of a mid-size hospital in England (using essential outputs from forecasting and forecasting-simulation) for each inpatient elective and non-elective specialty.

In conclusion, these results will bring a different perspective to key decision makers with a decision support tool for short and long term strategic planning to make rational and realistic plans. This hospital decision support system can become a crucial instrument for decision makers for efficient service in hospitals in England and other parts of the world.

Acknowledgments

During my doctoral study, a number of people have helped me with their knowledge and moral support to strengthen my motivation. I would like to take this opportunity to thank them all one more time here. First of all, I would like to express my deepest thanks to my first supervisor Dr. Eren Demir. I am grateful with his helpfulness and friendly behaviour to me, along with his patience and feedback about my research.

I surely appreciate my second supervisor Dr. Chris Tofallis. I am very pleased with his supervision. His help, support, feedback, and criticism were always with me during my research.

I would like to give many thanks to Dr. M. Murat Günal for his contribution. He joined us when I was preparing journal articles with my supervisors.

I would like to express my gratitude to the industrial engineering families, which I am always proud of being a member, in Pamukkale University and Erciyes University.

I would like to offer a great thank you to the Ministry of National Education (Republic of Turkey) for the scholarship for postgraduate study abroad. In addition, I would like to thank The Turkish Education Consultancy in London for their help and support.

I would like to thank to all my teachers, supervisors and friends who have made my life meaningful.

I would like to present the most special thanks from the bottom of my heart to my father Ali Ordu, my mother Fadime Ordu and my sisters Ayşe Uysal and Merve Nur Ordu. Their endless love and support have always been with me.

Many thanks to you all.

Hatfield, December 2018.

Muhammed Ordu

Table of contents

List of tables

List of figures

List of abbreviations

A&E : Accident and Emergency

ABS : Agent Based Simulation

AG : Age Group

AIC : Akaike's Information Criteria

ANOVA : Analysis of Variance

AR : Autoregressive

ARIMA : Autoregressive Integrated Moving Averages

BIC : Bayesian Information Criterion

BOR : Bed Occupancy Rate

CEO : Chief Executive Officer

CI : Confidence Interval

DCR : Demand Coverage Ratio

DES : Discrete Event Simulation

DNA : Did Not Attend

DoH : Department of Health

DSS : Decision Support System

ECDA : Ethics Committees with Delegated Authority

ED : Emergency Department

ES : Exponential Smoothing

FA : Forecast Accuracy

FO : Forecasting-Optimization

FS	: Forecasting-Simulation
FSO	: Forecasting-Simulation-Optimization
FTE	: Full Time Equivalent
FUP	: Follow Up
GoF	: Goodness of Fit
GP	: General Practitioner
HES	: Hospital Episode Statistics
HRG	: Healthcare Research Group
LCI	: Lower Confidence Interval
LoS	: Length of Stay
MA	: Moving Average
MASE	: Mean Absolute Scaled Error
MFF	: Market Forces Factor
NHS	: National Health Service
NICE	: National Institute for Health and Care Excellence
ONS	: Office for National Statistics
PAH	: Princess Alexandra Hospital
SD	: System Dynamics
SLR	: Stepwise Linear Regression
STL	: Seasonal and Trend Decomposition Using Loess
STLF	: The Function of Seasonal and Trend Decomposition Using Loess
TR	: Total Revenue
TS	: Training Set
UCI	: Upper Confidence Interval
UK	: United Kingdom
WT	: Waiting Time
VS	: Validation Set

CHAPTER 1

Introduction

1.1 Brief background

We begin by presenting the general background within which this project is set. High levels of hospitalisation places hospital managements under intense pressure; this is usually affected by a number of factors, such as population, alcohol and cigarette consumption and stress. The size of the population is a core factor as this is both growing and aging in the United Kingdom (UK).

Accident and emergency (A&E) units are the busiest departments within hospitals working under immense financial pressures resulting in shortages of clinicians, nurses, beds and equipment. For the last ten years, A&E departments in the UK have been struggling with issues related to increasing waiting times and length of stay, as well as lack of resources, which all have a negative impact on day to day functioning of A&E services. Increasing waiting times and length of stay have been observed and the 4-hour target, which is the percentage of patients spending 4 hours or more in hospital should be less than 5%, determined by the government has not been achieved since the financial year 2014-15 as shown in Figure 1.1 and their performance is worsening each year (National Health Services England, 2014 and 2018a). Therefore, patients are faced with low quality services from A&E departments.

The considerable increase (i.e. approximately 26% from 2006/07 to 2017/18 financial year) in the number of admissions has been observed in the UK A&E departments (National Health Services England, 2014 and 2018a).

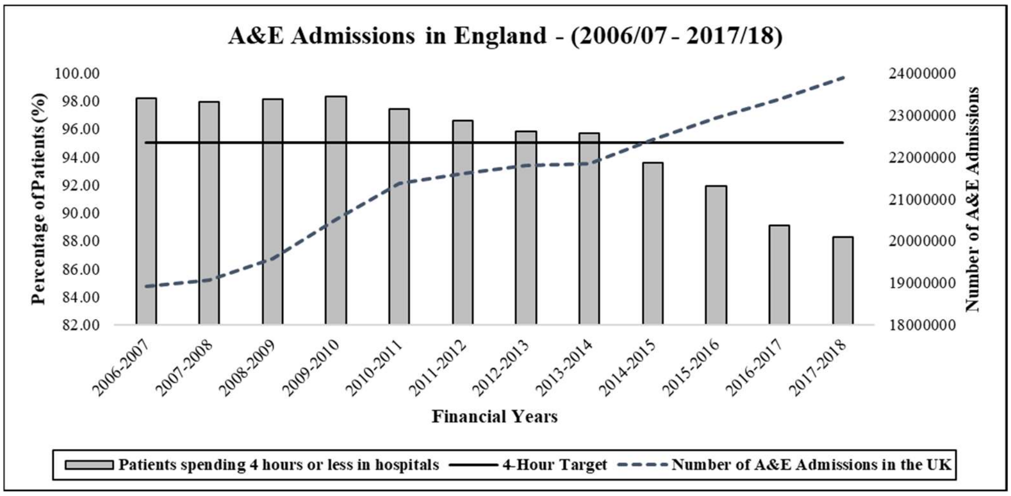

Figure 1.1: Statistical background of A&E admissions in England (National Health Services England, 2014 and 2018a). The 95% target line is shown.

In addition, over the past decade, the number of attendances and admissions to outpatient and inpatient specialties has increased by around 27% and 32%, respectively (National Health Services England, 2018b) as shown in Figure 1.2 and 1.3. The level of difficulties experienced by the hospital management around demand and capacity issues has been at an unprecedented level.

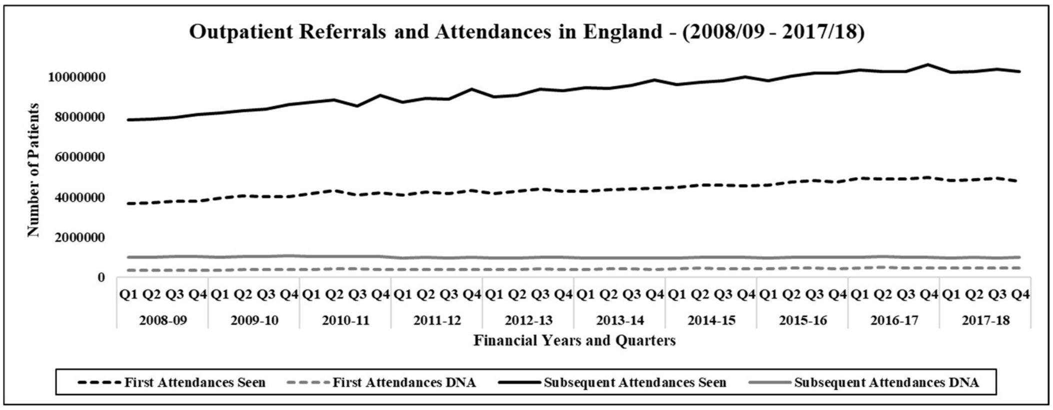

Figure 1.2: Outpatient referrals and attendances in England (National Health Services England, 2018b).

In addition, Figure 1.4 also shows that the bed occupancy rates of hospitals in the UK from financial year 2010/11 to 2017/18 have been on an upward trend for occupied beds used overnight, and day only, 6% and 13%, respectively. (National Health Services England, 2018c). The bed occupancy rate has exceeded the 85% target level in England (National Health Services England, 2018c).

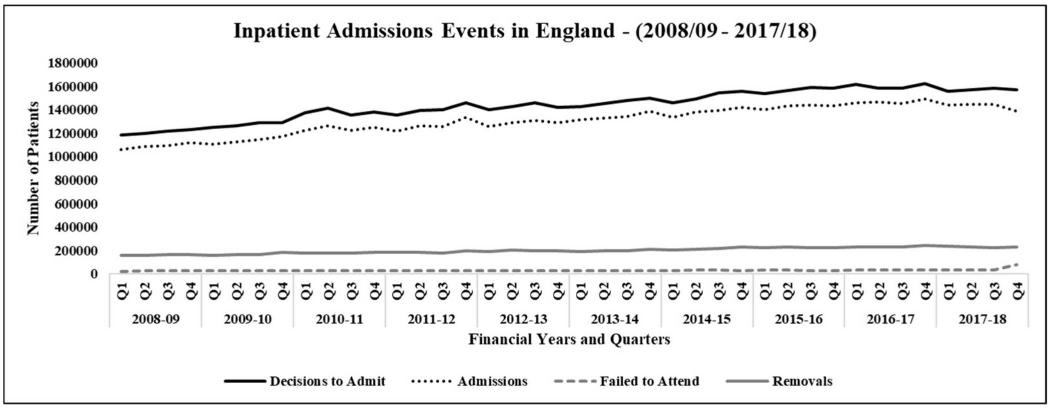

Figure 1.3: Inpatient admissions events in England (National Health Services England, 2018b).

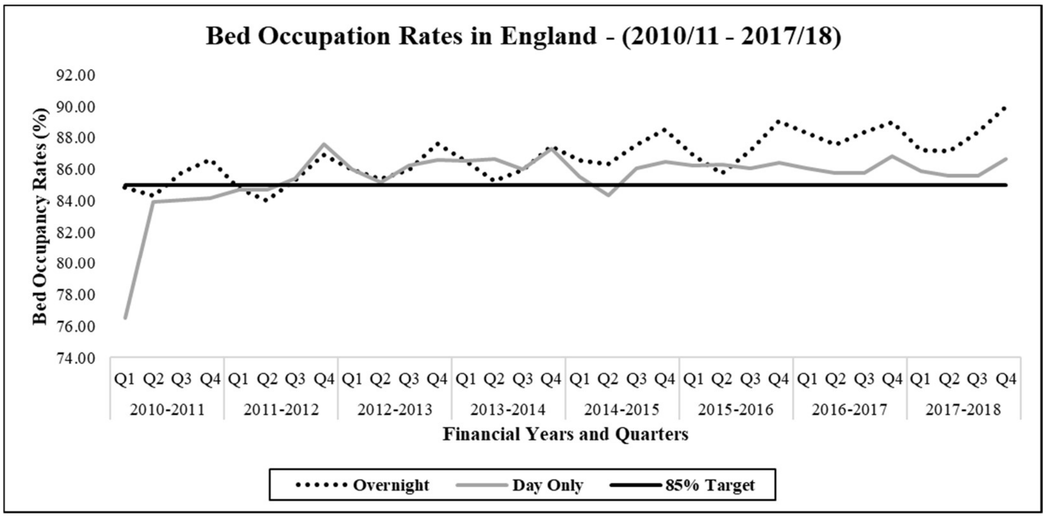

Figure 1.4: Bed occupancy rates in England (National Health Services England, 2018c). The 85% target line is shown.

The proportion of the younger population is decreasing, in contrast to the proportion of the elderly population, which is increasing. According to Cracknell (2010), the 65 years and over age group in the UK was around 10 million (1/6th of the population) in 2010 and expected to reach 19 million by 2050, which is approximately a quarter of the population. Blunt (2014) mentioned in his report that the number of elderly people who visit A&Es in the UK is much higher than other age groups. In addition, he emphasized that most elderly patients spend 4 hours or more, and thus hospitals are not able to achieve that 95% of patients are seen, treated and then admitted or discharged within four hours in A&E, as the target set by the NHS Constitution.

The NHS employs 1.3 million staff in England and Wales, caring for approximately 1 million patients every 36 hours, which is equivalent to around 243 million patients per year. This means NHS staff will continue to face challenges in terms of health and wellbeing due to severe patient demand and financial constraints (Royal College of Physicians, 2015). Therefore, resources (e.g. staff, beds) may not be sufficient to meet demand for hospitals, where doctors and nurses are sometimes forced to work flat out. Reducing the quality of hospital services may lead to loss of motivation in human resources, not to mention the negative effect it might have on service satisfaction for patients. In addition, the NHS has come up against financial constraints and it needs to generate £20 billion (equal to approximately 4% productivity annually) of net savings in the next few years (Hamm, 2010). Taking into account limited capacity (i.e. bed, staff) and financial constraints, as well as increasing patient arrivals, it is clear that hospitals will continue to struggle (i.e. longer waiting times). Due to increasing demand, hospital administrations will need to provide higher productivity rates by enhancing the match of demand and capacity of hospitals. Therefore, key decision makers would need to model the level of resources needed by patients in hospitals as a function of demand factors with a range of supply issues, thus it is crucial to understand patient pathway in order to demonstrate the full impact of change (Demir et al., 2017).

Due to severe budget cuts in the National Health Service (NHS), hospitals do not have the luxury of recruiting additional doctors and nurses or increasing bed capacity. If nothing can be done in terms of capacity, hospital management needs to find efficient and effective ways of utilising existing resources.

A hospital is a complex system and modelling each and every service (within A&E, inpatient and outpatient departments/specialties) is a huge challenge. A typical hospital is made up of 31 specialties providing treatment across inpatient and outpatient services. Each specialty has a number of departments and wards with an army of human resources, made up of consultants, doctors, nurses, healthcare assistants, technicians, radiographers, and many more. For instance, a typical hospital in England has an average of 100,000 inpatient admissions, 350,000 outpatient attendances across the 31 specialties in a year, along with 125,000 A&E admissions (National Health Services England, 2018a and 2018b).

Therefore, modelling at this level of detail is not just a challenge but extremely difficult. The literature around modelling healthcare services is vast and extremely rich. In the majority of instances (if not all) they concentrate around modelling a single disease, service, department or a specialty, and at best a few of these services combined. However, at the hospital level this can be deemed to be almost useless. A director (or a CEO of a hospital) needs a model that assists them both at strategic and operational level. A whole hospital modelling framework is an absolute necessity. For example, an increasing demand does not just happen within a single specialty, it's a phenomenon across the hospital, and thus a model examining the impact across all specialties is a must, so that the management intervenes accordingly.

At the time when this model was under development, a local nearby hospital had closed down. This is a typical example where such a model can be extremely beneficial, because the knock-on effect is on all of the services within the hospital that stayed open. Therefore, a comprehensive modelling framework is needed that brings together all specialties and services at a hospital within a single decision support system (DSS).

The DSS should guide key decision makers to ensure their system is able to cope with current and future demand, and able to stress test the system, not just focusing on a single specialty (or a service) but its impact on the hospital as a whole. No department, service or specialty is an independent entity, they are all interconnected. For example, a consultant does not just work in an outpatient setting but their expertise is utilised in inpatient too. If there are bed shortages within a specific specialty, patients are admitted to other specialties.

Amongst many modelling methods and approaches, discrete event simulation (DES) is chosen as it enables us to capture the whole hospital at a sufficient level of detail, with the flexibility of further developing a user-friendly interface to get hospital managers to engage with the model. Furthermore, unlike other methods, DES is able to simulate random behaviours of systems (i.e. length of stay, waiting time and number of follow ups) and is able to track individual patient's path in a hospital. DES can also model events occurring at any discrete point in time and takes into account different features of patients (i.e. age, gender, disease, etc.) (Demir and Southern, 2017).

The model is able to answer many key questions. For example, what will be the required number of beds by each inpatient specialty? How much consultation hours will be needed by each specialty for outpatient and inpatient services? What percentage of future demand will be met with the available resources (i.e. doctors, nurses, beds) for each specialty? Will specialties require additional resources, if yes, which one and how many? What will be the financial implications of change? What is the expected current and future levels of theatre utilization and outpatient clinic utilization?

In this study, the hospital demands are predicted using four forecasting methods (i.e. ARIMA, exponential smoothing, STLF and stepwise linear regression) under three different forecasting periods (i.e. daily, weekly and monthly) for each specialty in order to embed this into the simulation model.

A generic hospital simulation model combined with forecasting technique is developed and proposed to investigate the capacity of the hospital along with many key output metrics for future years. To develop the model, many 100's of inputs are taken into account including demographic features (age groups), staff shifts, number of resources (consultants, nurses, beds, triage rooms and clinic rooms), cost of treatment, all laboratory tests and statistical distributions. Many observed frequency distributions are established based on age groups, so that the related times vary, hence a more robust model could be built. For example, time for treatment, treatment time, time for discharge *for the A&E department*; time for first appointment, number of follow-ups, length between follow-up treatments *for outpatient specialties;* time for first admission, and length of stay *for inpatient specialties*. These observed frequency distributions were estimated depending on specialty, age group and types of attendances/admissions (first/follow up attendances for outpatient and elective/non-elective admissions for inpatient).

In addition, a full factorial experimental design with 4 factors (A&E, elective and non-elective admissions and outpatient attendance) at 2 levels (possible 5% and 10% demand increases) is carried out in order to investigate the effects of demand increases on key outputs (i.e. demand coverage ratio, bed occupancy rate and total revenue).

The increasing demand for services is closely linked to rising prevalence conditions and ageing population, who often have multiple complex conditions, such as diabetes and dementia, are the highest users of beds (The King's Fund, 2012). Advancements in technology and medicine have led to improvements in healthcare, greatly reducing length of stays in hospital and increased the number of day-cases (or outpatient), however hospital beds remain fundamental resources for all health systems.

Despite a sharp growth in demand, the number of beds has continued to decline. "In 2000 there were an average of 3.8 beds per 1,000 people, whereas this had dropped to 2.4 beds by

2015. Between 2006/07 and 2015/16 the number of overnight beds has decreased by over a fifth. As a result, the average bed occupancy rates have increased over time, with rates for general and acute wards, and mental health, now peaking at over" 91% (BMA, 2017). Hospitals are expected to aim for an 85% bed occupancy rate, whereas they are increasingly operating at very high levels of occupancy, particularly during the winter period.

The implications of high bed occupancy rates are widespread, and to name a few, 1) it creates a backlog in emergency departments (Nuffield Trust, 2016), 2) patients can be placed on clinically inappropriate wards, which may affect patients experience and the quality of care they receive (Goulding, 2015), and 3) evidence suggests that high occupancy rates increases the rate of hospital acquired infections, which may lead to temporary closure of beds or wards (Kaier, 2012).

Due to severe budget cuts in the NHS, hospitals do not have the necessary funding to increase capacity, either in the form of beds or staff. Therefore, hospital management needs to find efficient and effective ways of utilising existing resources. This may mean the management doing things differently, a shift from conventional decision-making process to a more evidence-based approach (a behavioural change).

Finally, a forecasting-simulation-optimization (FSO) approach is developed and proposed to reallocate the available number of beds and to optimize staffing levels (i.e. consultants and nurses) of the inpatient specialties for the next financial year in this study. A comprehensive entire hospital modelling framework is necessary that combines all the specialties and services within a single decision support system (DSS). No model so far has ever been developed at this scale, such that it is able to, 1) forecast demand for all specialties within inpatient, outpatient and A&E, 2) capture the entire hospital patient pathway at a sufficient level of detail, and 3) optimise the required bed capacity and the required number of consultants and nurses.

Such a DSS is able to answer many key questions beyond capacity requirements. For example, a hospital may experience a sharp increase in activity, possibly due to severe weather conditions, or a general trend. The forecasts will generate the expected activity to be integrated into the simulation model, whereas the simulation will capture all the uncertainties around the dynamics of the hospital, ranging from time related activities (e.g. length of stay, waiting times, and treatment duration) to hospital finances (revenue, cost and surplus), with the aim of testing wide range of scenarios around impact of change. The simulation has limitations around establishing the optimal capacity requirements. This is where the optimisation becomes a great tool to estimate the exact bed requirements (along with consultant and nurse hours) subject to constraints (e.g. targeted bed occupancy rate).

1.2 Aim of the thesis

This thesis aims to solve demand and capacity problems experienced by the NHS hospitals. More specifically, this thesis aims to:

- Develop a generic hospital simulation model integrated with forecasting technique for demand and capacity model for an entire hospital. Using the English Hospital Episodes Statistics (HES) dataset, demand for each specialty is predicted by comparing four forecasting methods and selecting the best model according to a forecast accuracy measure. An entire hospital is modelled through a generic hospital simulation model which eliminates the deficiencies of current and past studies in the literature.
- Develop a user-friendly decision support system to examine key performance metrics of a typical NHS trust for future planning. Decision makers will then be able to balance demand-capacity, thus an opportunity to intervene well in advance.
- Develop a forecasting-simulation-optimization (FSO) approach to solve the resource management problems in the inpatient department of the hospital using operational research techniques. Available number of beds in hospital's wards is optimally reallocated and the required numbers of human resources (i.e. consultants and nurses) are determined for projected usage.

1.3 Contributions

This thesis contributes to the knowledge of operational research techniques applied to healthcare solving the real-life problems of a National Healthcare Services (NHS) Trust. The specific contributions are presented as follows:

- Establishment of a patient pathway and the development of a generic simulation model of an entire hospital, with the aim of assisting key decision makers at a medium-sized hospital in England. The goal is to eliminate the deficiencies of the current and past studies around modelling hospitals within a single framework, which forms the basis of our contribution to knowledge.

- Development of an innovative approach combining discrete event simulation and forecasting demand and capacity in a healthcare setting. To our knowledge, the literature does not have an extensive study that forecasts demand of all types of attendances/admissions of each specialty which then integrates these demand inputs within the generic hospital simulation model. Furthermore, no study has ever compared three different forecasting periods (i.e. daily, weekly and monthly) in forecasting of hospital demand.
- Development of a new output metric: Demand coverage ratio (DCR). It measures the percentage of patients admitted to the specialty (or hospital) and discharged using the available resources of each specialty (or hospital).
- Development of a forecasting-simulation-optimization (FSO) approach which has not yet been developed in literature. The available number of beds in hospital's wards is optimally reallocated and the required numbers of human resources (i.e. consultants and nurses) are determined for projected usage well in advance.

1.4 Outline of the thesis

Figure 1.5 shows the chapters and their interdependencies of this research. These chapters are classified as four groups: literature review (Chapter 2 and 3), theoretical concept (Chapter 4 to 6), contribution (Chapter 7 to 9) and conclusion (Chapter 10).

Chapter 2: Literature review

An extensive literature review regarding the operational research techniques applied to healthcare services is presented in this chapter. This chapter is separated into five sections by five subtitles: 1) Generic hospital simulation modelling, 2) Simulation modelling of healthcare services (i.e. system analysis and demand & capacity modelling), 3) Optimization and simulation-optimization approaches on healthcare services, 4) Forecasting hospital demand and 5) Simulation studies on healthcare settings for projection.

Chapter 3: Demand and capacity modelling of acute hospital services

The research problem of this study is described. The study design, study settings and population are presented. Data sources and assumptions of this research is explained in this chapter. Furthermore, research methodologies are described, i.e. generic hospital simulation modelling, forecasting-simulation approach and forecasting-simulation-optimization approach.

Chapter 4: Forecasting time series

The processes of forecasting methods used in this study are explained in greater detail. Autoregressive integrated moving average (ARIMA), exponential smoothing, stepwise linear regression and the function of the seasonal and trend decomposition using loess (STLF) methods are methodologically described. In addition, parameters of ARIMA, which is p, d, q, types of exponential smoothing (i.e. single exponential smoothing, Holt's linear model, damped trend model and Holt-Winters' trend and seasonality method), how to use the STLF method, stepwise linear regression and its output parameters are explained. This chapter also discusses goodness of fit (GoF) and forecast accuracy (FA) measures and gives the reasons related to the selected GoF and FA for this study.

Chapter 5: Discrete event simulation modelling

The methodological concept for discrete event simulation technique is described and all steps are explained with the necessary formulae. It discusses why discrete event simulation technique is selected for hospital modelling instead of system dynamics and agent based simulation techniques. This chapter explains how to conceptualize and verify a system; how to build and verify a simulation model; how to determine optimum replication number and calculate warm up period; how to validate output parameters; description of the full factorial experimental design used in this study, and how to carry out what-if scenario analysis.

Chapter 6: Integer linear programming

This chapter covers theoretical description of integer linear programming. It explains what objective function and constraints are in an optimization model and describes the sensitivity analysis.

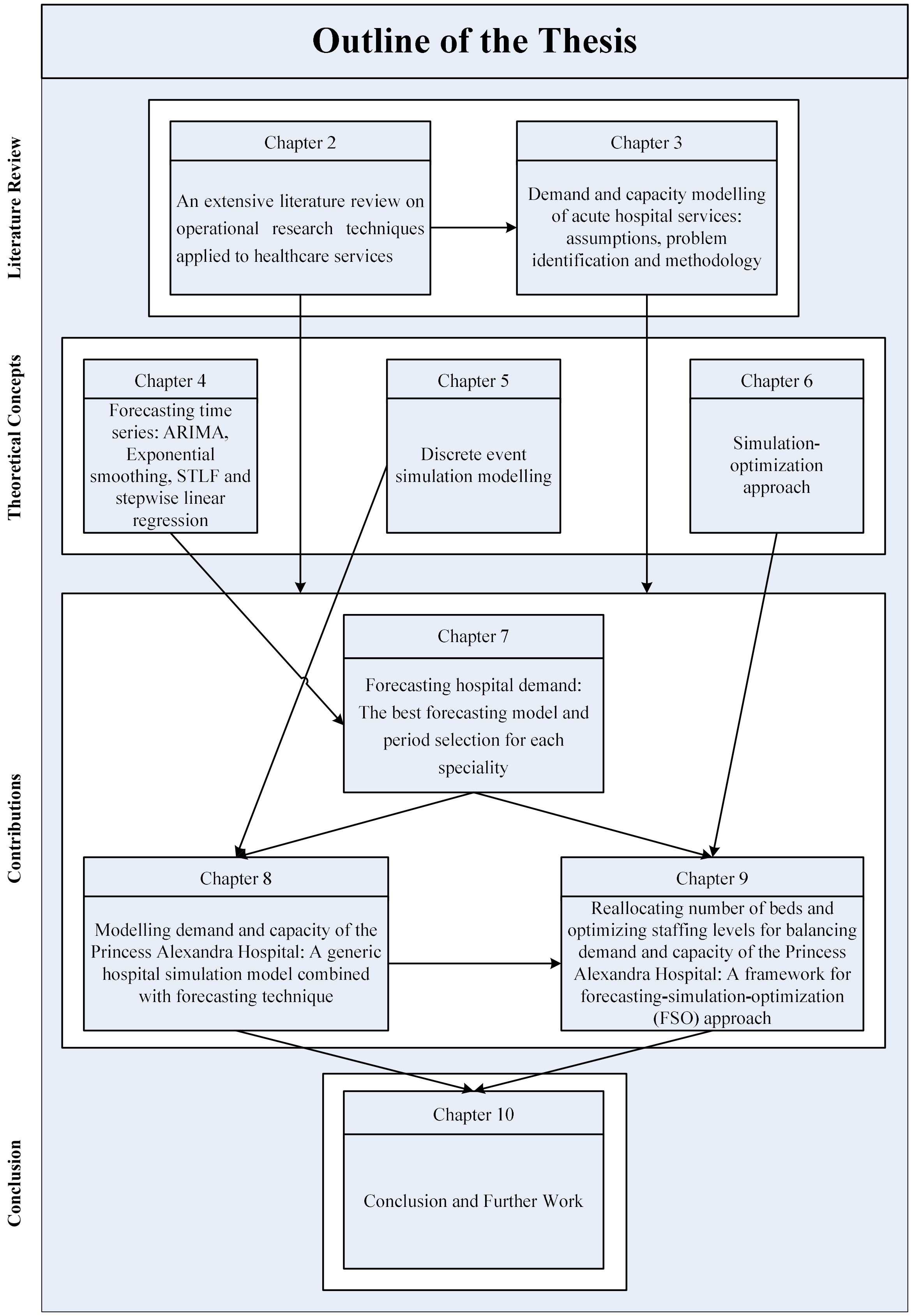

Figure 1.5: Chapters and their interdependency of this thesis

Chapter 7: Forecasting hospital demand: The best forecasting model and period selection for each specialty

The national Hospital Episodes Statistics (HES) dataset is used to extract the necessary data regarding the hospital demand for each specialty of a mid-size England hospital. The extracted data is prepared for different forecasting periods (i.e. daily, weekly and monthly). Using four distinct forecasting methods (i.e. ARIMA, exponential smoothing, STLF and stepwise linear regression), demand is estimated for A&E department, outpatient specialties (for first and follow up referrals) and inpatient specialties (for elective and non-elective admissions). The best forecasting method and period is selected for each type of attendances/admissions of each specialty by using the selected forecast accuracy method. In total 12 models are developed for A&E, 300 models for inpatient admissions and 456 for outpatient attendances.

Chapter 8: Modelling demand and capacity of the Princess Alexandra Hospital: A generic hospital simulation model combined with forecasting techniques

A generic hospital simulation model is developed by taking into account all specialties (i.e. A&E, outpatient and inpatient services) and stochastic nature of an entire hospital with the interactions amongst hospital departments. This chapter illustrates the steps of the innovative approach combining forecasting and simulation methods. Extensive data analysis is carried out for simulation modelling and all input parameters and key output metrics for each specialty are described in greater detail. This chapter also provides a step by step guide to simulating an entire hospital with real life application, explaining all steps in greater detail, including the model validation stage, warm-up period, and the optimum replication number. Finally, the full factorial experimental design is implemented to stress test the system under various what-if scenarios of interest. A full factorial experimental design with 4 factors (A&E, elective and non-elective admissions and outpatient attendance) at 2 levels (possible 5% and 10% demand increases) is carried out in order to investigate the effects of demand increases on the key outputs (bed occupancy rate, total revenue and so on).

Chapter 9: Reallocating beds and optimizing staffing levels for balancing demand and capacity: A hybrid framework for forecasting-simulation-optimization (FSO approach)

A forecasting-simulation-optimization approach is developed in line with the requirements of the hospital. This chapter presents the development of an integer linear programming integrated with forecasting and discrete event simulation techniques. The model is built to determine optimum bed capacity and staffing levels in each inpatient specialty that patients need to stay in a bed. It identifies all parameters, decision variables of the model and describes the input-output relations amongst forecasting, simulation and optimization models. A sensitivity analysis is carried out increasing the forecasted demand (i.e. the base model). The sensitivity analysis consists of 20 experiments where demand is cumulatively increased by 1%, for example, the demand increased by 1% based on forecasted demand in the first experiment, and 2%-increase on demand is used as input in the second experiment. Therefore, it models the effect of demand increases on key output metrics.

Chapter 10: Conclusion and Further Work

This chapter concludes the thesis, describes the limitations of this study, and how the research can be further improved.

1.5 Summary

In this chapter, a brief background was provided for demand and capacity modelling in healthcare management, in conjunction with the aims, contributions and outlines of the thesis. In the next chapter, an extensive literature review related to operational research techniques applied to healthcare services is presented.

CHAPTER 2

Literature review

2.1 Introduction

An extensive literature review regarding operational research techniques applied to healthcare services is presented in this chapter. The literature is reviewed in Section 2.3 to 2.7. The findings which have been deduced from the literature are clarified in Section 2.8. Research gaps in this field are identified in Section 2.9. This chapter is concluded in Section 2.10.

2.2 Background

In this study, a systematic literature review was carried out. The literature was exhaustively investigated from 1998 to 2019 by searching many databases related to healthcare and operational research, for example, HealthSTAR, Medline, INFORMS Online, CINAHL, INSPEC, Science Citation Index, Embase, SIGLE and MathSci databases. Our supervision team has had comprehensive experiences and published high quality paper in this research area. Along with their experience, we determined and listed a number of keywords related to healthcare modelling, simulation, scheduling, forecasting, optimization, mathematical modelling, heuristic, experimental design and so on. More than 200 papers met our inclusion criteria, 1) Simulation models in healthcare context (discrete event simulation, system dynamics and agent based simulation), 2) Forecasting hospital demand (A&E, outpatient and inpatient specialties), 3) Mathematical modelling in healthcare settings, 4) Hybrid studies in healthcare modelling, 5) Other topics (i.e. scheduling) in Operational Research/Operations Management in healthcare. In addition, we contacted a number of researchers found on ResearchGate and Academia. Papers were requested from these researchers via these websites. After that, we removed duplicates and eliminated a number of papers by examining the studies in greater detail. We then classified and categorized all the remaining articles accordingly. There are many articles published in other sectors e.g. supply chain, manufacturing, logistics and so on. These studies were not considered as interest lies in healthcare only.

Many reasons such as population growth, ageing population, infectious diseases and lack of education increase hospital demands. Healthcare services which have limited resources and capacities need to meet these demands. Within this framework, several methodologies (e.g. simulation, optimization) have been developed to improve health systems. From the literature we found that forecasting, simulation methods and mathematical models are heavily utilized to find short, medium and long term solutions to healthcare systems working under extreme pressure with limited resources. These studies can be split into five subheadings as shown in Figure 2.1, 1) Generic entire hospital simulation modelling (Section 2.3), 2) Simulation modelling of healthcare services (i.e. system analysis and demand & capacity modelling) (Section 2.4), 3) mathematical modelling and simulation-optimization approaches on healthcare services (Section 2.5), 4) forecasting hospital demand (Section 2.6) and 5) Simulation studies on healthcare settings for projection (Section 2.7).

Simulation modelling of healthcare services (Section 2.4) and Simulation studies on healthcare settings for projection (Section 2.7) are different sections. Section 2.4 focuses on development of simulation models using historical demand inputs and tests the improvement through scenarios. On the other hand, Section 2.7 concentrates on simulation modelling using demand for the future. These demands are used as an input in the simulation models. The demands are generated for the projected usage by assuming that demand is increased by a rate which represents increases on demand in the past) or using basic forecasting approach (i.e. moving average or using the population growth rates estimated by the Office for National Statistics).

Note that ED is widely used in other countries (particularly USA) whereas A&E in the UK. For consistency, ED is only used in the literature review section of the thesis, whereas A&E in all the other parts of this research.

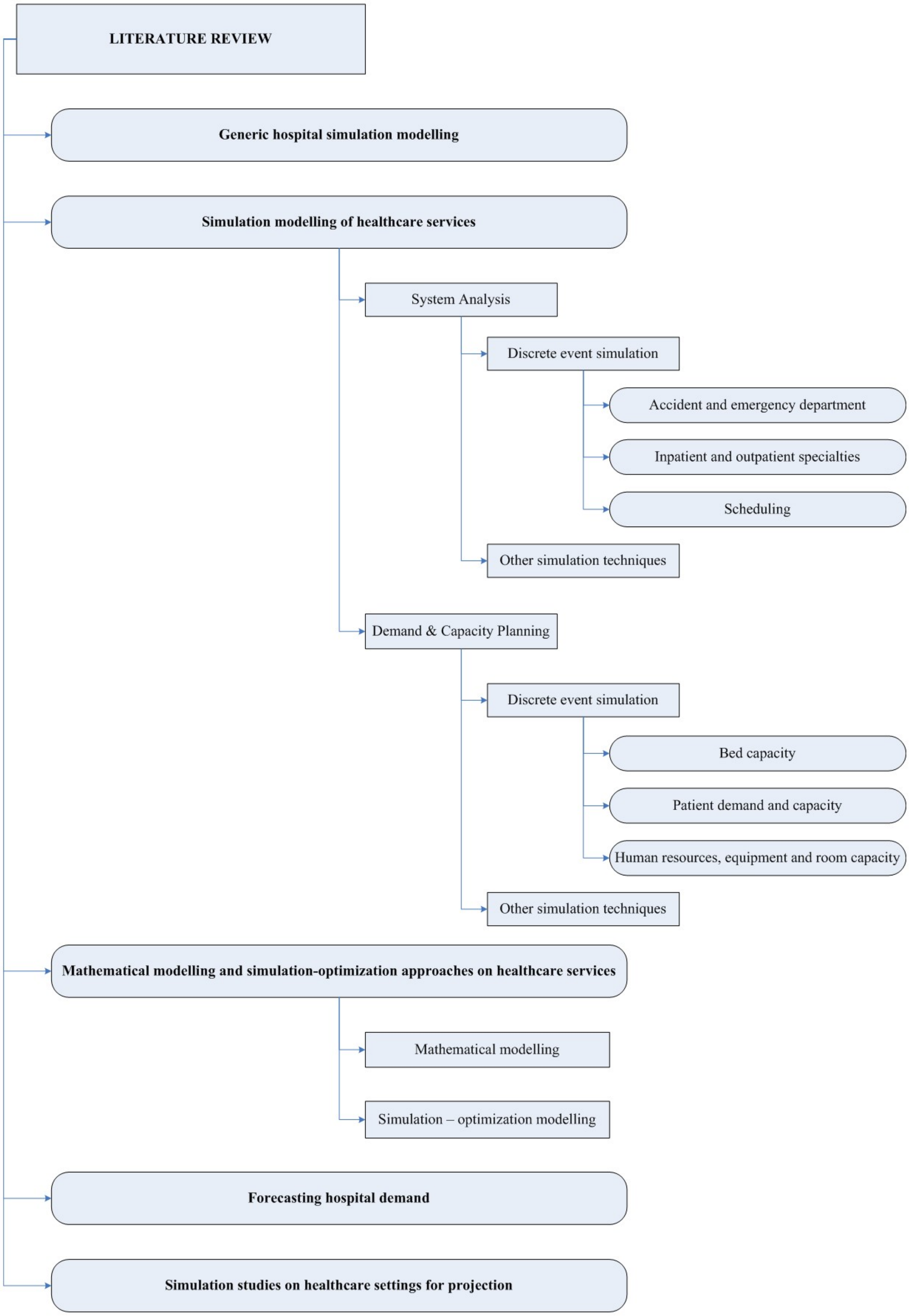

Figure 2.1: The structure of literature review

2.3 Generic entire hospital simulation modelling

The literature around modelling healthcare services is vast and extremely rich. In the majority of instances (if not all) they concentrate around modelling a single disease, service, department or a specialty, and at best a few of these services combined (Gunal and Pidd, 2010). It is difficult to develop a generic simulation model imitating everything belonging to an entire hospital (Pidd, 2003). In the literature, there are very few studies that have developed simulation models for an entire hospital where all the relevant data are collected and analysed for each specialty within an inpatient and outpatient setting. These studies have been reviewed in greater detail. For example, Harper (2002) developed a generic framework to model level of resources (i.e. beds, staff and operating theatre) by capturing variability, uncertainty, limited resources and complexity of a hospital. This study focused on modelling only inpatient beds and theatre processes and therefore other components of the hospital are not included, for example, A&E department, outpatient services and referrals between and within each other. Patient activities for length of stay and operation times are modelled based on demographic features (i.e. age). The best fitting distributions for only length of stay and operation times are estimated depending on each patient group.

Brailsford et al. (2004) model a whole hospital system (including two hospitals) using system dynamics technique which is not an ideal method for queueing networks with resources as they emphasized in their research. They did not model every main specialty individually, instead a submodel is used to represent all main specialties. In addition, only admission wards are taken into account in the model instead of all main specialty wards. They did not measure bed occupancy rates of each inpatient specialty, but bed occupancy is calculated at the hospital level. Moreover, the interactions between departments (i.e. referrals from A&E to outpatient and inpatient specialties) are not considered in the simulation modelling.

Gunal and Pidd (2007) model a whole hospital which is composed of A&E, inpatient, outpatient departments and waiting list generating four simulation models. There are some limitations in the models. For example, non-elective inpatient admissions who are referred from only both GPs and A&E are not exhaustively modelled, and fixed distributions are used instead. But non-elective admissions are also referred from outpatient specialties or other hospitals. Inpatient elective referrals are made from only outpatient departments in the model, however, in the reality, elective patients are referred from different sources (i.e. GPs).

In addition, outpatient attendances are referred from GPs and inpatient departments in the simulation model. However, outpatients are referred from other referral sources (i.e. A&E and self-referrals) in real world. The model does not include theatre processes. It focuses only on inpatient wards and ignores other inpatient specialties which do not have wards. The model takes into account outpatient clinic slots. In outpatient modelling, percentages are used for number of follow ups instead of using more realistic one (i.e. observed frequency distributions extracted from the HES dataset). Using frequency distributions for number of follow ups enables the model to be more realistic. The simulation model generates a limited number of key outputs, for instance, number of patients treated, number of cancellations, bed occupancy and 'outlier' which represents patients that are not admitted in appropriate wards and who stay in inappropriate wards.

Holm et al. (2013) developed a generic hospital simulation model using discrete event simulation technique for the purpose of allocating beds in a hospital. However, they focused on only inpatient specialties, and ignored A&E department, outpatient specialties and interactions amongst each other's. Non-elective patient admissions are considered in a stochastic nature taking into account arrival time with theoretical distributions. On the other hand, elective patient arrivals are planned and known beforehand for each day specifically. In addition, length of stay for each ward is modelled with theoretical distributions instead of using frequency observed distributions. They avoid to model theatre process and measure theatre utilization along with financial inputs and required consultant and nurse hours.

Demir et al. (2017) developed a decision support tool to better understand future key performance metrics of a hospital. They assume this project was carried out in an entire hospital by focusing on only 10 main specialties (i.e. general surgery, ophthalmology and trauma & orthopaedics) along with A&E department. These specialties represent 85% of all inpatient specialties and 51% of all outpatient specialties and majority of total revenue from patient care is obtained from these specialties. The developed simulation model is rather simple, for example, all specialties are modelled by using single processes in the simulation model. However, the specialties have many complex processes, for example, registration, pre-assessment, waiting process, consultations, staying in a bed, laboratory processes, triage process, diagnostics tests, daycase process and so on. None of these vital elements of a hospital system have been considered. The model also takes into consideration the interactions between the A&E and inpatient so that non-elective admissions are assumed to arrive from the A&E department. However, non-elective patients are not only referred from

A&E, but also, they might be referred to inpatient specialties from outpatient specialties or other hospitals. The modelling approach are conducted for each patient type (i.e. retinal vascular occlusions, diabetic retinopathy and macular degeneration) and type of attendances (i.e. first and follow up attendances). Theoretical distributions are estimated for some parameters (i.e. length of stay). Number of follow ups is one of crucial parameters, so that unique patients attend in the related outpatient clinic as much as number of follow ups assigned to them. In this study, average number of follow ups is used for each patient. However, number of follow ups is not fixed, and varies according to the patient. Therefore, frequency distributions should be estimated and can be assigned to individual patient by using label in the simulation model.

There are a number of healthcare simulation case studies (i.e. Bed P.A.C.) provided by Simul8 (Simul8, 2019). It is an excellent resource with wide range of applications for beginners to better understand the use of Simul8 in practice. Each model tackles a single disease, pathway or a specific problem in hand (e.g. bed capacity/management, operating rooms). However, further details about the individual models in the form of a publication or a report are not available, thus it is not possible to find out the inner workings of the model, such as the care setting, input parameters (data collection and analysis), verification, and the validation process. It is therefore not possible to check the validity and reliability of these presented models.

Furthermore, none of the models developed by Simul8 tackles an entire hospital's services as presented in this study, including all specialties within inpatient, outpatient and A&E. Our model does not just deal with a specific element of a hospital (e.g. bed management) but it considers an array of issues at specialty level, including theatres, outpatient clinic slots, bed management, staff management, patient readmissions, laboratory, tariff per diagnostic and so on. More importantly we provide all the relevant details for hospitals to be able to replicate this within their own setting.

2.4 Simulation modelling of healthcare services

In literature, studies related to simulation modelling of healthcare services can be split into two types: "system analysis" and "demand & capacity planning". System analysis aims at determining current values of performance criteria such as length of stay and waiting time and makes changes by means of what-if analysis in order to optimize these criteria values. Therefore, it is provided that productivities of hospitals are developed. On the other hand, demand and capacity planning targets specifying optimum levels of beds and other resources required by hospitals. The major distinction is that system analysis focuses on productivity while demand & capacity planning determines the optimum required number of beds, staffs, equipment or rooms at hospitals.

2.4.1 System analysis

System analysis is an important decision support tool to determine and solve problems emerging in systems. As shown in Table 2.1, performance criteria such as length of stay and waiting time are taken into account in this study area where statistical techniques have also been utilised.

2.4.1.1 Discrete event simulation

Discrete event simulation has been used in many departments of hospitals in order to analyse systems of healthcare services. Studies with regard to system analysis are examined in three groups: emergency department, inpatient and outpatient department and scheduling.

2.4.1.1.1 Accident and emergency (A&E) department

One of the most widely used areas of simulation methods is the emergency department (ED). System analysis and development is crucial for this kind of department where limited resources are used, and emergency medical interventions are necessary. In addition, most studies have examined current performances of EDs by means of triage systems which classify patients according to their urgency case at emergency departments. Some researchers compare existing triage system with new approaches while others just benefit from triage system in simulation models. In the literature, Connelly and Bair (2004) compare the existing triage system with 'acuity ratio triage (ART)' (the ART allows an initial assessment relevant to input-output (patient) and resources utilization). The authors state the advantages and disadvantages of ART on performance criteria, such as service time and treatment time. On the other hand, Medeiros et al. (2008) improve a new simulation approach called PDQ which refers patients who need an emergency intervention to a room without any registration at busy times of days. The model compares the performance criteria's, such as length of stay and patient flow time, taking differences between the base model and the new approach. Ruohonen and Teittinen (2006) create a triage-team approach where patients are referred for basic tests, such as blood pressure before seen by a healthcare provider, which results in better process times. While in other cases, Gunal and Pidd (2006) readjust the existing triage system and proposed a model where performances are measured using triage system converted from 5-colour to 3-variable. The new classification tool (to classify patients in the ED) outperformed previous triage systems by decreasing length of stay.

On the other hand, some studies focus on classifying and prioritizing patients, for instance, Ozdagoglu et al. (2009) noticed a significant improvement by considering various patient types according to their diagnosis, sex and age. A limitation of this study is that the number of resources are fixed where in reality EDs can be extremely dynamic in terms of staff and equipment. Virtue et al. (2011) use a simplified discrete-event simulation model with the aim of illustrating whether the average simulation times correctly estimate length of stay and use a 2-scale triage system instead of a 6-scale triage system for classifying patients.

A number of studies in the literature have developed systems of EDs by means of scenarios. Alternative scenarios are generated and compared by measuring the performances of EDs. Komashie and Mousavi (2005) analysed to improve an ED through six scenarios which are created by taking key resources, (e.g. beds, nurses and doctors) into account with a number of limitations that some parameters such as triage and lab tests are not considered. In contrast, Duguay and Chetouane (2007) focus on decreasing waiting times in an emergency department taking into account a number of scenarios involving additional nurse, physician and room. Additional nurse and physician are considered to be tested in different shift time. Meng and Spedding (2008) are interested in revealing the impact of eight scenarios on key performance metrics (i.e. waiting time and service time). They determine arrival times of patients and reduce significantly waiting times developing a number of scenarios related to changes in the A&E department. Gul et al. (2012) generated 10 alternative scenarios to reduce length of stay, increase patient productivity, develop resource utilization rates and specify optimum number of staff members at an ED. In this study, number of staffs are not changed for each shift. That is to say that fixed staff schedule is used. Similarly, Wang et al. (2012) test to observe whether the generated scenarios has made an impact on length of stay.

In addition, the simulation input parameters are mainly based on averages as opposed to determining their relevant statistical distributions, such as the arrival process, service times and length of stay.

Emergency departments have been exhaustively investigated by many researchers around the world, with the aim of assisting key decision makers find the most effective and efficient way of running an ED. Researchers have conducted many studies, creating new triage systems, tackling the issues by means of what-if analysis and prioritizing patients according to their health status. These studies have a number of limitations, firstly the numbers of staff in each shift are generally assumed to be fixed. Secondly, lack of availability of real data to capture reality within ED. In some cases, data are obtained through observations while others are able to access limited datasets, and thus without real data no simulation model can be deemed to be accurate, robust and reliable.

2.4.1.1.2 Inpatient and outpatient specialties

Researchers consider simulation modelling as an alternative solution method in different departments of hospitals as well as modelling a whole hospital. Within this framework, inpatient and outpatient departments such as radiology and orthopaedic have been considered as study areas. Cote (1999) developed a simulation model to determine the interaction between room capacity and resource occupancy rates. Swisher et al. (2001) constructed a model to investigate the functionality of a family practice clinic. The DES model considered the mutual effects of several clinics, including weekdays weekends, and hours of days at intraday. The average interarrival times of the clinic were assumed to be fixed values. The study suggests that clinics are able to be redesigned without having any financial difficulties. Coelli et al. (2007) conduct performance assessment in a mammography clinic evaluating the effects of variable parameters (i.e. technician and physician) step by step. Strengths of the study is for the inclusion of the clinical examination and maintenance planning of equipment into the scenarios. Moreover, periodic breaks such as lunch and patient walking speed and time are considered. It is mentioned as limitation that capacities of all rooms are fixed. VanBerkel and Blake (2007) are interested in researching a general surgery's performance indicators. Their modelling approach is based on generating many scenarios in order to reduce waiting times and operation room times. Key result of the study is that long waiting times are dependent on numbers of beds. In the study, it is suggested that alternative scenarios must be combined to decrease patient waiting times. Komashie et al. (2008) simulate orthopaedic theatre of a hospital and compare occupancy rates and throughputs of theatres under some scenarios. When modelling theatres, patients are classified according to lengths of operations and scenario-based studies are utilised. Eventually, it is found that utilization rates of theatres are different from each other. Aksarayli et al. (2009) found that waiting times are reduced when beds are effectively used at a urology clinic. In this study, patient classification is carried out in two steps. Firstly, patients are assigned as urgent or non-urgent. Secondly, patients who undergo hospitalization are divided into three: surgery patient, non-surgery patient and emergency surgery patient. The system is modelled by scenarios under the limitation of limited numbers of beds and theatre rooms. It is found that more patients can be treated without additional costs and the main factor which affects the performance of the clinic is limited numbers of beds. Werker et al. (2009) conduct a study focusing on exploring how changes on inputs of the system affect the planning times related to a radiation therapy which is tested by 'what-if analysis'. As in many studies, fixed numbers of staffs work in the clinic and clinicians are assumed as full-time employees in the simulation model, although they do not work during lunch breaks. Villamizar et al. (2011) took five different options into account in order to assess the system at a physiotherapy centre. The model has fixed parameters such as numbers of rooms, treatment types, staffs and patient walking speed. Therefore, it is clear that the model is created under restrictions. Furthermore, patient pathways and procedures are determined by making interviews with staffs before developing the model. Rohleder et al. (2011) measure performance of outpatient pathway at an orthopaedic department where suggested changes are experienced, and improvements are reported. During modelling, assumptions are made, for instance a doctor can be available when a patient is not treated although a doctor normally has a short free time in between treatments. In modelling process, a combination of optimum number of staff, patient schedules and punctual staff is applied. Hence, significant reductions on waiting times and total patient times emerge as key results.

2.4.1.1.3 Scheduling

A service manager at a hospital department may seek help to find ways of treating more patients with limited resources. In this respect, scheduling is a widely used technique with the objective to enhance provision of care efficiently and effectively. Resources such as staff, equipment and room are needed to be optimally used for increasing performances of healthcare services. In this context, researchers employ simulation modelling in solving of scheduling problems. Bowers and Mould (2004) schedule only elective patients and simulate to increase utilization rates of theatre at an orthopaedic trauma theatre. In the model which scheduling is made weekly, preparation times of patients are included and patients who turn up to appointments are considered as ‘did not attend’. This study recommends that increased utilization rates on theatres can be provided by means of scheduling. Wijewickrama (2006) focused on finding the lowest waiting times at an outpatient department by considering four scheduling approaches called ‘B2’, ‘Rising’, ‘15MIN’ and ‘SPTBEG’. Moreover, it is attempted that a better solution is found by combining some of considered scheduling approaches.

In some scheduling problems, better solutions have been generated by classifying patients. In the studies carried out by Everett (2002), Harper and Gamlin (2003) and Yeh and Lin (2007), patients are categorised in order to minimize waiting times. Everett (2002) developed a simulation model to help an elective surgery department by means of a scheduling approach, where patients are classified with respect to their situation of urgency. In the study, a waiting area is created, and few hospitals are simulated. In addition, three icons in the simulation model are used to represent admission, theatre and beds. Harper and Gamlin (2003) who categorised patients in their study discuss nine schedules which additional resources are not used. The results from the scheduling are compared in terms of average time, percentage of waited patients and utilization rates of staffs. Unlike others, Yeh and Lin (2007) schedule nurses without additional staffs by means of genetic algorithm which is one of the heuristic research methods. In the study three different patient groups are used, the researchers took into account patient arrival rates differently for every time zone during the weekdays and weekends.

Table 2.1: Detailed information about studies related to discrete event simulation in system analysis

Authors	Year	Department	What-if Analysis	Performance Criteria	Triage	Scheduling	Software
Cote	1999	Outpatient	N	LoS, QL, UR	N	N	SIMAN
Switcher et al.	2001	Physician Clinic	Y	LoS, TP, UR	N	N	VSE
Everett	2002	Elective surgery	N	WT	N	Y	EXTEND
Harper and Gamlin	2003	Ear, Nose & Throat	Y	LoS, WT	Y	Y	SIMUL8
Bowers and Mould	2004	Orthopaedic Trauma	Y	UR, ST	N	Y	SIMUL8
Connelly and Bair	2004	Emergency	Y	ST, TT	Y	N	EDSIM
Komashie and Mousavi	2005	Emergency	Y	LoS, UR, WT	N	N	ARENA
Wijewickrama	2006	Outpatient	Y	IT, WT	N	Y	ARENA
Ruohonen and Teittinen	2006	Emergency	Y	ST	Y	N	MEDMODEL
Gunal and Pidd	2006	Emergency	Y	LoS	Y	N	MICRO SAINT SHARP
Duguay and Chetouane	2007	Emergency	Y	TP, UR, WT	Y	N	ARENA
Yeh and Lin	2007	Emergency	Y	LoS, WT	Y	Y	eM-PLANT
Gunal and Pidd	2007	Hospital	N	WT	Y	N	MICRO SAINT SHARP
Coelli et al.	2007	Mammography Clinic	Y	LoS, UR	N	Y	MEDMODEL
VanBerkel and Blake	2007	General Surgery	Y	LoS, TP, WT	N	N	ARENA
Meng and Spedding	2008	Emergency	Y	WT	Y	N	MEDMODEL
Komashie et al.	2008	Hospital	Y	UR	N	N	ARENA
Medeiros et al.	2008	Emergency	Y	LoS, PFT	Y	N	ARENA
Ozdagoglu et al.	2009	Emergency	Y	LoS, WT	Y	N	ARENA
Aksarayli et al.	2009	Urology Clinic	Y	AoP, ST, UR	Y	N	PROMODEL
Werker et al.	2009	Radiation Theraphy	Y	PT	N	N	ARENA
Rohleder et al.	2011	Orthopaedic Clinic	Y	LoS, ST, WT	N	N	ARENA
Villamizar et al.	2011	Physiotherapy Clinic	Y	LoS, ST, WT	N	Y	MEDMODEL
Virtue et al.	2011	Emergency	N	LoS	Y	N	SIMUL8
Gul et al.	2012	Emergency	Y	LoS, UR	N	N	SERVICEMODEL
Wang et al.	2012	Emergency	Y	LoS	Y	N	SIMUL8

N: No, Y: Yes, AoP: Arrival of Patient; IT: Idle Time; LoS: Length of Stay; PFT: Patient Flow Time; PT: Planning Time; QL: Queue Length; ST: Service Time; TP: Treated Patient; TT: Treatment Time; UR: Utilization Rate; WT: Waiting Time.

Table 2.1 (cont.): Detailed information about studies related to other simulation techniques in system analysis

Authors	Year	Department	What-if Analysis	Performance Criteria	Triage	Scheduling	Software
Frank et al.	2015	Geriatric	Y	OR, WT, LoS, PN	N	N	Arena
Oh et al.	2016	Emergency	Y	WT, QL, LoS, UR	Y	N	Arena
Hussein et al.	2017	Emergency	Y	WT, UR	N	N	Simul8
Babashov et al.	2017	Radiotherapy	Y	LoS, UR, CL	Y	N	Simul8

N: No, Y: Yes, CL: Congestion Level; LoS: Length of Stay; OR: Occupancy Rate; PN: Number of Patient; PT: Procedure Time; QL: Queue Length; UR: Utilization Rate; WT: Waiting Time.

2.4.1.2 Other simulation techniques

It is clear that there are simulation techniques other than discrete event simulation. To give an example, system dynamics and agent based simulation are used by researchers. These simulation methods are explained and compared in Section 5.3 and Chapter 5. In addition, studies related to these simulation methods are summarized in Table 2.2. Lane et al. (2000) use system dynamics to model an emergency department, on the other hand, Jones and Evans (2008) and Wang (2009) carry out their studies by using agent based simulation. Lane et al. (2000) and Wang (2009) benefit from scenarios while Jones and Evans (2008) aim was to reduce waiting times by means of scheduling approach. Lane et al. (2000) measure the performance of an emergency department by generating scenarios which are created by different values of bed numbers and patient demands. Moreover, influences of additional increases on patient demands in crisis days on the performance are calculated. One scenario which consists of less bed capacity and more patient demand is developed and tested. Jones and Evans (2008) present a study that schedules staff and examines the impact on waiting times in an emergency department. As distinct from other studies, Wang (2009) examines how performance criteria are changed in an emergency department according to two alternatives, i.e. triage vs. non-triage systems.

Table 2.2: Detailed information about studies related to other simulation techniques in system analysis

Authors	Year	Department	What-if Analysis	Performance Criteria	Triage	Type of Simulation	Software
Lane et al.	2000	Emergency	Y	WT, OR, UR	Y	System Dynamics	ITHINK
Jones and Evans	2008	Emergency	Y	WT	Y	Agent Based	NETLOGO
Wang	2009	Emergency	Y	PN, PT	Y	Agent Based	NETLOGO
Kaushal et al.	2015	Emergency	Y	WT, LoS	Y	Agent Based	NG

N: No, Y: Yes, LoS: Length of Stay; NG: Not Given; OR: Occupancy Rate; PN: Number of Patient; PT: Procedure Time; UR: Utilization Rate; WT: Waiting Time.

2.4.2 Demand and capacity planning

Many operational research techniques such as simulation method and mathematical modelling have been considered for demand and capacity planning of hospitals. Simulation has become a common method in this area. In this context, it is clear that many simulation modelling approaches are available: Discrete Event Simulation (DES), System Dynamics (SD) and Agent Based Simulation (ABS).

2.4.2.1 Discrete event simulation

Discrete event simulation (DES) is an influential analytical approach to be applied in order to plan capacities of healthcare services as understood from the literature (see Table 2.3). In this section, studies are examined in three different categories: bed capacity, patient demand and capacity, and human resources, equipment and room capacity.

2.4.2.1.1 Bed capacity

Bed capacity problems of healthcare services are directly proportional to hospital demands. In addition, increases on hospital demands make bed planning difficult. Accordingly, healthcare managements take precautions such as reallocation of beds, building new departments and increasing of capacities. Many researchers have developed their studies with regard to bed capacities in intensive care units and all have aimed at finding optimum bed numbers. Ridge et al. (1998) suggest a model that allows to investigate whether or not a relation exists among capacity, transfer and bed utilization rates at an intensive care unit and finds that as capacity increases, transfer and utilization rates decrease. Costa et al. (2003) and Zhu et al. (2012) try different numbers of beds in order to get optimal bed numbers in their simulation models. For this purpose, Costa et al. (2003) examines intensive care unit of a hospital and a critical care unit of another hospital by creating simulation model. Unlike this study, Zhu et al. (2012) analyse how two growth rates on demand change optimum bed numbers. Apart from these studies, Antmen and Ogulata (2012) also conduct a research in an intensive care unit in Turkey. They propose a simulation model to specify bed capacities that meet demands of three hospitals' intensive care units. Intensive care is defined as a patient with multi-organ failures, and according to their findings, additional life support systems are required. In one of these hospitals, intensive care unit has two departments, one for adults and another for children. In addition, intensive care units of these hospitals have fixed number of staff and equipment.

Vasilakis and El-Darzi (2001), Bowers and Mould (2005), Cochran and Bharti (2006) and Levin et al. (2008) are interested in solving bed capacity problems at different outpatient departments. Vasilakis and El-Darzi (2001) analyse crises coming in sight during winter seasons and reveal available bed capacity *'before crisis'* and *'during crisis'*. Bowers and Mould (2005) concentrate on calculating theatre occupancy and examine changes on the capacity at an orthopaedic clinic by evaluating five scenarios relevant to ambulatory care. Cochran and Bharti (2006) provide that beds are reallocated to more patients by a small increase in the bed capacity at an obstetrics hospital. Levin et al. (2008) find that determining optimal capacity of cardiology reduces admission times at the ED.

2.4.2.1.2 Patient demand and capacity

Researchers have focused on solving problems around patient demands and capacities. Patient demand means the number of patients who are admitted to healthcare services while patient capacity represents numbers of people who are treated with available resources under current conditions. Again, simulation modelling attracts the attention of researchers as a preferred method as it allows you to observe the impact of change on key metrics and easily understood by everyone, in the safety of a validated model, without any costing implications.

Brailsford et al. (2004) conduct a research investigating changes on demands of two hospitals using simulation methods: a whole hospital is modelled by system dynamics method and the emergency department of other hospital is analysed by discrete event simulation technique. Gupta et al. (2007) examine the system of a cardiac unit in order to plan the capacity by classifying patient arrivals, separated into three groups, using a simulation modelling approach which measures the influence of increases on the capacity over the waiting times. Elkhuizen et al. (2007) generate a model to analyse demand and capacity required and decrease *'access time'* from engagement to the first seen by a medical staff in a medical centre. Within this framework, two models which are analytical, and simulation are developed to be implemented in neurology and gynaecology departments. The capacity is increased to obtain an adequate utilisation percentage and remove *'backlog'*. As a result, capacity of the neurology department needs to be increased and gynaecology department has enough capacity. Khadem et al. (2008) reorganize the layout of an ED and use a simulation model to measure effects of this alteration in the ED. Consequently, a significant increase occurs on patient capacity. Ahmad et al. (2012) develop a simulation model which explores how possible increases on patient demand effect the ED where three different triage zones are used. Since patient arrivals to the ED has risen approximately 30% in last 6-year, it is assumed that patient arrivals to each triaged zone for each scenario will separately increase by 30%. Thus, influences of this assumption on the performance criteria of the system are observed and additional capacity needs are determined.

2.4.2.1.3 Human resources, equipment and room capacity

Equipment, staff and room are capacity parameters of healthcare services. These capacity parameters have been investigated scientifically. Martin et al. (2003) specify utilization rates of human resources at a geriatric department and required human resources' capacities are calculated for each developed what-if scenarios. Ballard and Kuhl (2006) illustrate how to use simulation in order to calculate maximum capacity and compare the differences between current situation and maximum capacity of a surgical suite in terms of key performance measurement criteria such as utilization rates. Brenner et al. (2010) fix capacities needed related to human resources and equipment for an ED through what-if analyses.

Table 2.3: Detailed information about studies related to discrete event simulation in demand and capacity planning

Authors	Year	Department	Major Problems	Performance Criteria	Software
Ridge et al.	1998	Intensive Care Unit	Bed Capacity	Length of Stay	PASCAL
Vasilakis and El-Darzi	2001	Surgery	Bed Capacity	Number of Available Beds	MICROSAINT
Costa et al.	2003	Intensive Care Unit, Critical Care Unit	Bed Capacity	Bed Occupancy, Admissions	CCUSIM
Martin et al.	2003	Geriatric	Human Resources Capacity	Utilization Rates	PROMODEL
Brailsford et al.	2004	Emergency	Patient D&C	Utilization Rates	SIMUL8
Bowers and Mould	2005	Orthopaedic	Bed Capacity	Utilization Rates	SIMUL8
Ballard et al.	2006	Surgical Suite	Theatre Capacity	Utilization Rates, Operating room Time, Service Time	ARENA
Cochran and Bharti	2006	Obstetrics	Bed Capacity	Number of Beds, Bed Utilization Rate	ARENA
Gupta et al.	2007	Cardiology	Patient D&C	Waiting Time	Not Given
Elkhuizen et al.	2007	Neurology, Gynaecology	Patient D&C	Utilization Rates, Length of Queue, Access Time	Not Given
Khadem et al.	2008	Emergency	Patient D&C	Waiting Time, Service Time	MEDMODEL
Levin et al.	2008	Cardiology	Bed Capacity	Admission Time	MEDMODEL
Brenner et al.	2010	Emergency	Human and Equipment Resources Capacity	Arrival of Patient, Utilization Rates, Waiting Time, Service Time	SIMUL8
Ahmad et al.	2012	Emergency	Patient D&C	Waiting Time, Length of Stay, Treatment Time, Utilization Rates	ANYLOGIC
Zhu et al.	2012	Intensive Care unit	Bed Capacity, Patient D&C	Occupation Rate	Not Given
Antmen and Ogulata	2012	Intensive Care unit	Bed Capacity	Waiting Time, Length of Stay	SIMAN
Landa et al.	2014	Inpatient	Bed Capacity, Patient D&C	Number of Patient Misallocated, Waiting Time, Occupation Rate	Witness

D&C: Demand and Capacity

2.4.2.2 Other simulation techniques

System dynamics and agent based simulation have been applied to solve capacity problems as shown in Table 2.4. Exadaktylos et al. (2008) and Kumar (2011) conducted research to establish the number of beds by using system dynamics, while Cabrera et al. (2012) optimize numbers of staffs in an emergency department by using agent based simulation. Exadaktylos et al. (2008) specify required additional bed numbers by system dynamics method in an emergency department. The simulation model is built by taking into account the assumption that more outpatients in surgical side of the emergency department exist than in medical side. Furthermore, the system is tested by altering the number of beds, length of stay and patient arrivals. It is determined as a key result that required additional bed numbers increase year on year. On the other hand, Kumar (2011) focuses on numbers of beds and patient activities at a surgery department. The researcher models the system by means of scenarios which are based on capacity optimization generated with respect to parameters such as numbers of beds, waiting list and length of stay. In the study, two patient admissions, namely emergency and routine are admitted, demand from emergency is more dynamic than others. With the differences of studies described above, Cabrera et al. (2012) focus on optimizing the numbers of staffs such as doctors, nurses and admission staff in an emergency department of a hospital.

Table 2.4: Detailed information about studies related to other simulation techniques in demand and capacity planning

Authors	Year	Department	Major Problems	Performance Criteria	Type of Simulation	Software
Exadaktylos et al.	2008	Emergency	Bed Capacity	Waiting Time	System Dynamics	ITHINK
Kumar	2011	Surgery	Bed Capacity	Length of Stay, Numbers of Patients, Waiting Time	System Dynamics	POWERSIM
Cabrera et al.	2012	Emergency	Human Resources Capacity	Length of Stay	Agent Based	NETLOGO
Rashwan et al.	2015	Hospital for Elderly Patients	Bed Capacity	Length of Stay, Percentage of Bed Blockage	System Dynamics	NG
Mathews and Long	2015	Intensive Care Unit	Bed Capacity	Waiting Time, Length of Stay, Bed Occupancy	Queuing Theory	NG
Lane et al.	2016	Emergency	Bed Capacity	Waiting Time, Bed Occupancy, Resource Utilization	System Dynamics	ITHINK
German et al.	2018	Hospital	Bed Capacity	Hospital Bed Ratio	System Dynamics	POWERSIM

NG: Not Given

2.5 Mathematical modelling and simulation-optimization approaches in healthcare services

Mathematical modelling is a popular technique to investigate healthcare issues (i.e. bed capacity, performance analysis, etc.). Recently, simulation and mathematical modelling have been integrated for demand and capacity planning of hospitals. Articles related to capacity planning generally focus on finding the optimum numbers of beds and resources. This section has been examined by splitting into two parts in demand and capacity planning of healthcare: “mathematical modelling” and “simulation optimization”. These sections are exhaustively explained as follows and summarized in Table 2.5 and 2.6.

2.5.1 Mathematical modelling

Mathematical modelling is a method applied to examine performances of healthcare services. It is aimed to obtain optimum values under constraints, such as budget and capacity. Mulholland et al. (2005) formulated a mathematical model that maximized the financial results of a surgery department. In the model, bed days, operating, recovery and preoperative rooms times are considered as constraints. In addition, there is an assumption where volumes of each procedure can be reduced or increased by 15%. Moreover, impact of changes (5%, 10% and 15%) about procedure volume on the assumption are assessed. Mazier et al. (2010) formulate two linear programming with the aim of minimizing ‘transfer’ and appointment costs and waiting times through their objective function. Constraints including non-adherence between patients, capacities of rooms are added to the model. Two models are compared in terms of their performances. Unlike others, in this study, simulation approach for the selected model is improved and applied by means of scenarios which consist of different patient arrivals under capacities of the units in a hospital.

As can be understood from the literature, one of the most common methods is mathematical optimization in capacity planning problems. Healthcare services as well as other industries have applied mathematical optimization. Linear integer programming and mix integer programming are given as samples of optimization techniques which are used in solutions of these problems. Vissers et al. (2005) determine the needed capacities of related departments by scheduling the operating theatre by an integer linear programming model. Adan et al. (2009) further developed their previous study, which focused on scheduling the operating theatre, by taking into account a stochastic variable relevant to length of stay and compared the capacities with respect to stochastic and deterministic variables.

In some studies, healthcare services have been considered in terms of bed capacity problems. Akcali et al. (2006) focuses on determination of bed capacity while Wang et al. (2009) and Abdelaziz and Masmoudi (2012) are interested in bed capacity by allocating available beds. Akcali et al. (2006) calculate numbers of beds required by a hospital under restrictive parameters by experimenting different scenarios which are improved by considering indicators, such as demand rate, waiting cost and patient delay. The researchers generate patient arrival rates by simulating the scenarios instead of using statistical forecasting techniques. Moreover, in the study, only bed capacity of a whole hospital is calculated instead of each department. Wang et al. (2009) provide the best distribution of beds by calculating values of objective functions by means of scenarios which are created by assigning different numbers of available beds to each department. A restrictive point of this study, five major departments of a hospital is selected instead of considering all departments. In addition, only elective and urgent patients from the emergency department are taken into account in the study even if non-elective patients are also admitted to the inpatient specialties from different referral sources (i.e. other hospitals). Likewise, Abdelaziz and Masmoudi (2012) focus on allocating beds by using optimization technique. Distinctively, all hospitals in Tunisia are counted in the study. Beds of each hospitals are reallocated to their departments through a goal programming and therefore, supplementary bed requirements across the country are determined for each department.

A number of studies have been interested in scheduling problems in healthcare settings. Mathematical models have been developed for efficient human resources planning. For example, staff scheduling conducted by Guler (2013), Satheesh Kumar et al. (2014), Wang et al. (2014), Cetin and Sarucan (2015), and Bagheri et al. (2016). In addition, operating room have been scheduled by Zhang et al. (2009), Yahia et al. (2014), Bouguerra et al. (2015), Wang et al. (2015), Maaroufi et al. (2016) and Yahia et al. (2016).

Table 2.5: Detailed information about studies related to optimization in demand and capacity planning

Authors	Year	Department	Objective Function	Method	Software
Vissers et al.	2005	Cardiothoracic Surgery	**Min:** Deviation at Utilization of Resources	Mixed Integer Linear Programming	MOMIP
Mulholland et al.	2005	Surgery	**Max:** Financial Outcomes	Linear Programming	MS Excel
Akcali et al.	2006	Hospital	**Min:** Costs	Nonlinear Zero-One Integer Programming	C++
Adan et al.	2009	Cardiothoracic Surgery	**Min:** Under & Over-Utilization of Resources	Mixed Integer Linear Programming	CPLEX
Wang et al.	2009	Hospital	**Max:** Incomes **Min:** Costs	Mixed Integer Linear Program	LINGO, CPLEX
Mazier et al.	2010	Emergency	**Min:** Transfer Cost, Assignment Cost, Waiting Time	Linear Programming	CPLEX
Abdelaziz and Masmoudi	2012	Hospital	**Min:** Costs and Numbers of Nurses and Physicians	Goal Programming	WHAT'S BEST
Bachouch et al.	2012	Hospital	**Min:** Cost	Integer Linear Programming	GLPK, LINGO, CPLEX
Shapoval and Lee	2017	Inpatient	**Min:** Worst Blocking Probability	Mixed Integer Nonlinear Programming	NG
Sitepu et al.	2018	Hospital	**Min:** Total Operating Cost	Integer programming	NG

NG: Not given

2.5.2 Simulation-optimization modelling

In some studies, optimization and simulation methods have been combined in solving capacity problems of healthcare services, where effective solutions have been investigated (see Table 2.6).

Kokangul (2008), Oddoye et al. (2009), Zhang et al. (2012), Ma and Demeulemeester (2013) and Holm et al. (2013) are interested in bed capacity problems, whereas Zhang et al. (2009) conducted a study related to operating room capacity. Kokangul (2008) determines maximum patient demand by means of simulation. The researcher assumes that this maximum demand causes the required maximum bed capacity in paediatric intensive care. The simulation model is rerun using the maximum bed capacity and it is tested that neither rejection nor transfer is possible for any patient. The optimum bed capacity is found by using parameter values such as maximum bed capacity by a mathematical modelling which targets maximum patient admission and has service and occupancy levels constraints. Oddoye et al. (2009) simulate a medical assessment unit in order to get five performance criteria values coupled with lengths of queues, numbers of beds and waiting times. The researchers establish the required resources of the unit by using a goal programming approach, where the results from the simulation is used as input into the mathematical model. Zhang et al. (2009) who benefit from a mixed integer programming in distributing hours of operating room to departments and simulate the room in order to specify lengths of stay. In their mathematical model, there are assumptions such as fixed patient demands for every week, fixed numbers of staffs and considers only weekdays (although patients can also stay during weekends). On the other hand, Ma and Demeulemeester (2013) aim to effectively allocate the available beds. To this, the researchers conduct a study which consists of three steps and plans capacity of a hospital. In the first step of the study, an integer linear programming model is developed to efficiently use resources and maximize the financial situation of the hospital. Moreover, constraints such as bed capacity and bed utilization are taken into account. In the second step, the objective is to allocate the beds effectively, therefore a mix integer linear programming model is developed. In the final step, a performance measurement is successfully completed by using the results obtained from the mathematical models through a discrete event simulation model.

Simulation-optimization studies have been utilised in resource optimization as well as bed capacity problems. In this context, human resources and hospitals' rooms have been evaluated in the scope of these problems. Ahmed and Alkhamis (2009), Cabrera et al. (2011), Cabrera et al. (2012), Ghanes et al. (2015) and Uriarte et al. (2017) investigated human resources of healthcare services. Ahmed and Alkhamis (2009) determined the staffing level from optimization model by considering budget constraint, patient arrivals and waiting times. These optimum numbers of staffs are used as inputs in the simulation model and therefore measure the system performance.

Scheduling problems were solved using simulation-optimization approach by Lamiri et al. (2009), Cappanare et al. (2014), Saodouli et al. (2015). Lamiri et al. (2009) developed a simulation-optimization method to plan elective surgery cases since operating rooms are used by both elective and non-elective patients. A mixed integer programming was developed with objective functions minimizing patients' related to costs and overtime costs. A Monte Carlo simulation was developed to find a reasonable solution for elective surgery cases and compared the developed simulation-optimization method with a number of heuristic and meta-heuristic methods (i.e. sequential improvement, local optimization, and taboo search heuristics). Cappanare et al. (2014) compared different scheduling policies by developing a mixed integer programming and then, combined this with a discrete event simulation model. They tested the schedules generated by optimization method in a stochastic nature of the hospital provided by the simulation model with the parameters (i.e. surgical time and length of stay) which have the features of variability.

Table 2.6: Detailed information about studies related to mathematical modelling in demand and capacity planning

Authors and Year	Methods	Objective Function	Main constraints	Inputs (from to)	Software
Kokangul (2008)	**S:** DES **O:** INLP	**Max:** Number of admissions	Service level, Occupancy level	S to O	**S:** Matlab **O:** Lingo
Zhang et al. (2009)	**S:** DES **O:** MIP	**Min:** Length of stay	OR capacity, emergency demand to be met, postponed demand, unmet demand	O to S	**S:** Awesim **O:** CPLEX
Oddoye et al. (2009)	**S:** DES **O:** GP	**Min:** Deviations from queues, waiting times, beds	Queue length, waiting time, number of beds	S to O	**S:** Micro saint **O:** NG
Ahmed and Alkhamis (2009)	**S:** DES **O:** IP	**Max:** Throughput **Min:** Cost	Budget, average waiting time, staffing level	S to O	**S:** Simiscript **O:** MS Excel solver
Lamiri et al. (2009)	**S:** MCS **O:** MIP	**Min:** Overtime cost, Patients' related costs	Assignment of elective case once	O to S	**S:** C#.NET **O:** CPLEX
Cabrera et al. (2011)	**S:** ABS **O:** O	**Min:** Waiting time	Cost of staff configuration	S to O	**S:** Netlogo **O:** NG
Zhang et al. (2012)	**S:** DES **O:** SSA, SBSA	-	-	S to O	**S:** Arena **O:** VBA
Cabrera et al. (2012)	**S:** ABS **O:** O	**Min:** Length of stay	Cost of staff configuration	S to O	**S:** Netlogo **O:** NG
Ma and Demeulemeester (2013)	**S:** DES **O:** ILP, MIP	**Max:** Total financial contributions	Bed shortage, BDU, OR blocks, total surgery time, admission volume bound	O to S	**S:** Arena **O:** CPLEX
Holm et al. (2013)	**S:** DES **O:** PIOA	-	-	S to O	**S:** FlexSim **O:** R
Cappanera et al. (2014)	**S:** DES **O:** MIP	1st **Min:** Max ORs and BDU 2nd **Min:** Gaps between max and min ORs and BDU 3rd **Min:** Sum of quadratic positive deviations of ORs and BDU from a fixed threshold	Daily utilization of ORs, maximum BDU	O to S	**S:** Arena **O:** CPLEX
Ghanes et al. (2015)	**S:** DES **O:** O	**Min:** Length of stay	Staffing budget, Door-to-door time	S to O	**S:** Arena **O:** OptQuest
Saadouli et al. (2015)	**S:** DES **O:** MIP	**Min:** Maximum completion time and total waiting time of operations	Completion times, waiting times, assignment of operations	O to S	**S:** Arena **O:** CPLEX
Uriarte et al. (2017)	**S:** DES **O:** NSGA II	-	-	S to O	**S:** FlexSim **O:** ModeFRONTIER

ABS: Agent based simulation, BDU: Bed daily utilization, DES: Discrete event simulation, GP: Goal programming, ILP: Integer linear programming, INLP: Integer nonlinear programming, IP: Integer programming, Max: Maximization, Min: Minimization, MIP: Mixed integer programming, NG: Not given, NSGA II: Non-dominated sorting genetic algorithm II, O: Optimization, OR: Operating room, PIOA: Prevalence and incidence optimization algorithm, S: Simulation, SSA: Simultaneous search algorithm, SBSA: Sequential bisection search algorithm, VBA: Visual basic for application

2.6 Forecasting hospital demand

Many studies have been conducted using time series analysis to forecast patient demand (see Table 2.7). Some of these studies focused on comparing different forecasting methods. For example, Champion et al. (2007) compared two forecasting techniques to estimate future admissions. Jones et al. (2008) used regression models including climate variables to compare a number of forecasting methods to estimate A&E demand. Sun et al. (2009) forecasted daily admissions to A&E by autoregressive integrated moving average (ARIMA) and generalized linear model (GLM), including weather variables for planning resources and staff. Kam et al. (2010) used a variety of ARIMA techniques (SARIMA and multivariate SARIMA) and compared them with moving averages to calculate daily demand. Marcilio et al. (2013) found generalized estimating equation and generalized linear model as successful methods against seasonal ARIMA. On the other hand, Aboagye-Sarfo et al. (2015) used a new technique (Vector-ARMA) to compare with ARMA and exponential smoothing methods on estimating A&E demand.

Instead of comparing different forecasting methods, some researchers estimated hospital demand by using one or a few methods. Batal et al. (2001), who estimated demand for an urgent care clinic, used stepwise linear regression model in order to optimize staffing levels for patient demand. Boutsioli (2010) carried out a study on forecasting A&E demand of 10 hospitals in Greece using a time series method and determined the amount of unforeseen admissions using the residuals generated by the regression model. In another study, Boutsioli (2013) investigated the unpredictable hospital demand variations by using two types of forecast errors (firstly, only positive errors and secondly, both positive and negative forecast errors).

In addition, a number of studies used forecasting methods for different aims. For example, Blaisdell et al. (2002) and Moustris et al. (2011) forecasted hospitalizations for the paediatric patients with asthma. Moreover, Joy and Jones (2005) was interested in forecasting hospital bed demands, whereas Toerper et al. (2016) predicted required hospital beds for patients admitted from cardiac catheterization laboratory. Schweigler et al. (2009) focused on estimating bed occupancy rate in an A&E department, whereas length of stay was predicted by Hussey and Guo (2005) in a child residential treatment, Wrenn et al. (2005) in an emergency department, Garg et al. (2011) in a hospital, Levin et al. (2012) for paediatric intensive care unit, Li et al. (2013) for Cholecystitis patients, Hachesu et al. (2013) for cardiac patients, Combes et al. (2014), Gul and Guneri (2015) in an A&E department, Papi et al. (2016) in a hospital and Barnes et al. (2016) for discharge prioritization.

Table 2.7: A literature review on forecasting hospital demands using time series analysis

Authors and Year	Goodness of fit and forecast accuracy	Method/s used, Best method (*)	Independent variables
Batal et al. (2001)	**GoF:** BIC **FA:** R^2	Stepwise linear regression	Days, months, seasons, holidays, after and before days of a holiday
Reis and Mandl (2003)	**GoF:** MAPE **FA:** MAPE	ARIMA	-
Champion et al. (2007)	**GoF:** RMSE, R^2, BIC **FA:** SD	ARIMA Single exponential smoothing (*)	-
Jones et al. (2008)	**GoF:** AIC_c, R^2 **FA:** MAPE	Artificial neural network Exponential smoothing Seasonal ARIMA Time series regression (TSR) (*) Time series regression with climate variables (TSRCV)	Days, months, holiday, near-holiday, interaction terms (for TSR), in addition to these daily min – max temperature, daily precipitation (for TSRCV)
McCarthy et al. (2008)	**GoF:** OD, AC, SP **FA:** PC	Poisson Regression	Temporal, climatic and patient factors
Sun et al. (2009)	**GoF:** Least error **FA:** MAPE	ARIMA (*) General linear model	Days, months, public holidays, weather factors
Boutsioli (2010)	**GoF:** Adjusted R^2 **FA:** -	Multivariate regression model	Weekends, summer holidays, official holidays, duty
Kam et al. (2010)	**GoF:** AIC, BIC **FA:** MAPE	Moving average Seasonal ARIMA Multivariate seasonal ARIMA (*)	Days, months, quarters of years, seasons, weather factors, daily temperature, holidays, near-holidays
Wargon et al. (2010)	**GoF:** MAPE **FA:** MAPE	Generalized Linear Model	Calendar variables
Boyle et al. (2012)	**GoF:** - **FA:** MAPE	ARIMA Exponential smoothing Multiple linear regression	Days, months and public holidays
Marcilio et al. (2013)	**GoF:** QIC, AIC **FA:** MAPE	Generalized estimating equation (*) Generalized linear model (*) Seasonal ARIMA	Days, months, public holidays, after and before days of a holiday, temperature
Boutsioli (2013)	**GoF:** AIC, BIC, Adjusted R^2 **FA:** SD	ARMA Multiple linear regression	Weekends, summer holidays, official holidays, duty
Bergs et al. (2013)	**GoF:** MAE, MAPE, MASE **FA:** MAE, MAPE, MASE	Exponential smoothing	-
Aboagye-Sarfo et al. (2015)	**GoF:** AIC, BIC **FA:** MAE, MAPE, RMSE	ARMA Vector-ARMA (*) Exponential smoothing	Time *Dependent Variables:* Age group, place of treatment, triage category, disposition

AC: Autocorrelation, AIC: Akaike's Information Criterion, AIC_c: Corrected Akaike's Information Criterion, ARMA: Autoregressive moving average, ARIMA: Autoregressive integrated moving average, BIC: Bayesian Information Criterion, FA: Forecast accuracy, GoF: Goodness of fit, MAPE: Mean absolute percentage error, OD: Overdispersion, PC: Percentage Change, RMS: Root mean square, RMSE: Root mean square error, QIC: Quasi-likelihood under the independence model criterion, SD: Standard deviation, SP: Skewness present

Table 2.8 gives detailed information of the literature related to forecasting hospital demand. The literature has been drawn on to select forecasting methods to be used in the study. Three forecasting methods (ARIMA, exponential smoothing and multiple linear regression) have been widely used as seen in Table 2.8 and 2.9.

Table 2.8: Studies related to forecasting methods applied in hospital demand

Forecasting methods	References
Artificial Neural Network (ANN)	Blaisdell et al. (2002), Jones et al. (2008), Moustris et al. (2011)
Autoregressive Integrated Moving Average (ARIMA)	Reis and Mandl (2003), Champion et al. (2007), Sun et al. (2009), Boyle et al. (2012), Boutsioli (2013), Kim et al. (2014), Aboagye-Sarfo et al. (2015)
Exponential Smoothing (ES)	Champion et al. (2007), Jones et al. (2008), Boyle et al. (2012), Bergs et al. (2013), Kim et al. (2014), Aboagye-Sarfo et al. (2015)
Generalized Autoregressive Conditional Heteroskedasticity (GARCH)	Kim et al. (2014)
Generalized Estimating Equations (GEE)	Marcilio et al. (2013)
Generalized Linear Model (GLM)	Sun et al. (2009), Wargon et al. (2010), Marcilio et al. (2013)
Moving Average (MA)	Kam et al. (2010)
Multiple Linear Regression (MLR)	Jones et al. (2008), Boutsioli (2010), Boyle et al. (2012), Boutsioli (2013), Cote and Smith (2018)
Poisson Regression (PR)	McCarthy et al. (2008)
Seasonal ARIMA (SARIMA)	Jones et al. (2008), Kam et al. (2010), Marcilio et al. (2013), Kim et al. (2014), Zinouri et al. (2018)
Stepwise Linear Regression (SLR)	Batal et al. (2001)
Vector-Autoregressive Moving Average (VARMA)	Aboagye-Sarfo et al. (2015)

Studies regarding hospital demand were conducted in different periods (i.e. hourly, daily, weekly and monthly) as given in Table 2.9. However, no study compared these periods to determine the best period that actually forecasts A&E demand.

Boyle et al. (2012) used three forecasting periods (i.e. hourly, daily and monthly) but did not compare these periods to select the most appropriate one. However, it’s not always wise to make use of the same period to forecast demand for all specialties. There are variations between and within A&E departments, outpatient and inpatient services around the world. Daily forecasts can be more accurate for some, whereas weekly or monthly for others.

Table 2.9: Different periods considered in forecasting studies applied in hospital demand

Periods	References
Hourly	McCarthy et al. (2008), Boyle et al. (2012), Kim et al. (2014)
Daily	Batal et al. (2001), Reis and Mandl (2003), Jones et al. (2008), Sun et al. (2009), Wargon et al. (2010), Boutsioli (2010), Kam et al. (2010), Boyle et al. (2012), Marcilio et al. (2013), Boutsioli (2013), Kim et al. (2014), Zinouri et al. (2018), Cote and Smith (2018)
Weekly	Blaisdell et al. (2002), Moustris et al. (2011)
Monthly	Champion et al. (2007), Boyle et al. (2012), Bergs et al. (2013), Aboagye-Sarfo et al. (2015)

2.7 Simulation studies on healthcare settings for projection

Demand increases for future years have been taken into account in a limited number of studies as seen in Table 2.10. These studies are typically based on assumptions or associated with data published by the Office for National Statistics. Brailsford et. al (2004) developed a whole hospital simulation model integrated with the primary care sectors (i.e. GPs for in-hours and out-of-hours). The number of referrals from GPs to inpatient services are investigated in terms of bed occupancy. 5-year projection is considered in the study and 3% year-on-year increase in referrals from GPs to inpatient elective admissions is assumed as demand increase in scenario testing.

Ahmad et al. (2012) developed a simulation model which explores how possible increases on the patient demand effect the ED where three different triage zones are used. Since patient arrivals to the ED has risen approximately 30% in last 6-year period, it is assumed that patient arrivals to each triaged zone for each scenario will separately increase by 30%. Thus, the impact of this assumption on the performance criteria of the system are observed and additional capacity needs are determined.

Holm et al. (2013) use discrete event simulation technique to model all inpatient specialties in a hospital to allocate beds. Arrival rates of inpatient admissions are expected to be augmented by 40% depending on empirical data after the hospital locations are restructured. They therefore increased demand of the hospital modelled in the study by 40% for projection.

Demir et al. (2017) develop a decision support tool to better understand future key performance metrics of 10 specialties of a hospital. Monthly hospital demands for the next year are estimated using forecasting techniques (i.e. exponential smoothing and ARIMA). Depending on the forecasted demands, the next 5-year monthly demands are adapted by linking with the population growth rates of the catchment area which the hospital serves. Forecasting models for all types of patient activity (i.e. elective and non-elective admissions, DNA, cancellations, outpatient attendances and A&E admissions) are developed based on age groups in all specialties.

Harper et al. (2017) used a simple regression model to forecast a temporary 10-year demand of an endoscopy service. The percentages of demand within the population in each year are calculated using historical data. These proportions of demand for the projected years are calculated taking into account the estimated number of population provided by the Office for National Statistics. An adjustment ratio is calculated dividing the proportion of demand by the proportion of the last year of the historical data period. The forecasted demand is obtained multiplying by the temporary demand (with regression) and the adjustment ratio. This process is carried out for each procedures and age groups. At the end, all forecasted demands for each year are aggregated. The estimated demands are fed into the simulation model.

Demir et al. (2018) develop a discrete event simulation model to enable better managements of a retinal service in the UK. The service is modelled for better understanding of both current and future key performance metrics (i.e. resources utilization and financial outputs). To capture future patient activity, they develop a series of forecasting model (not determined specifically). After that, using the population growth rates estimated by the Office for National Statistics, the forecasted activities are adjusted for the projected year. Forecasting processes are conducted for each patient type (i.e. retinal vascular occlusions, diabetic retinopathy and macular degeneration) and type of attendances (i.e. first and follow up attendances). These forecasted demands are embedded in the simulation model.

Table 2.10: Simulation studies on healthcare settings for projection

Authors and Year	Department	Demand for Projection
Brailsford et al. (2004)	Inpatient (from GP)	Assumption
Ahmad et al. (2012)	Emergency	Assumption
Holm et al. (2013)	Inpatient	Expectation
Demir et al. (2017)	Hospital	Forecasting and integrated with ONS
Harper et al. (2017)	Endoscopy service	Integrated with ONS
Demir et al. (2018)	Retinal service	Forecasting and integrated with ONS

ONS: Office for National Statistics

2.8 Conclusion

Operational research and statistical techniques have been widely applied to healthcare systems around the world. In this study, an extensive literature review has been carried out in the area of operational research techniques (i.e. specifically forecasting, simulation modelling and optimization methods) in terms of problems emerged in healthcare systems. In conclusion, the following findings are deduced from the literature:

- Triage system is used as a system improvement tool in emergency departments.
- It is aimed that better solutions are obtained by means of what-if scenarios.
- Validation and verification are made by comparing simulation results with actual data even if different statistical methods (i.e. paired t test) are used in some studies.
- Healthcare services are effectively analysed by classifying and prioritizing patients.
- Capacities are generally planned by reallocating beds to departments, building new departments, making decision about increasing the capacities in both simulation and mathematical modelling.
- Results of performance criteria, which are calculated through scenarios, become more of an issue in decision-making periods.
- Mathematical modelling generally has financial objectives. These objectives aim at either cost minimization or outcome maximization.
- Mathematical modelling is improved by considering constraints and opportunities of hospitals.

- In mathematical modelling, some performance criteria such as revenue and patient numbers admitted are considered as a maximization issue while others such as length of stay, waiting time and cost are taken into account as a minimization parameter.
- In simulation-optimization approaches, optimization techniques are generally used for obtaining inputs of simulation models or vice versa.
- Departments of healthcare services are typically assessed for both system analysis and demand & capacity planning. A whole hospital has rarely been examined in terms of system analysis and demand & capacity planning.
- In the majority of hospital simulation modelling (if not all) they concentrate around modelling a single disease, service, department or a specialty, and at best a few of these services combined.
- A whole hospital simulation modelling has been developed but incomplete. These studies have assumed important points related to hospital systems, for example, focusing on only inpatient specialties instead of all specialties (including outpatient and A&E), ignoring the interactions between all specialties (i.e. referrals from A&E to inpatient and outpatient specialties), using theoretical distributions or average numbers for stochastic events (i.e. length of stay) instead of using real hospital data (i.e. observed frequency distributions), focusing on specific outputs (e.g. bed occupancy rate), rather than wide range of key outputs of interest.
- Forecasting has been widely used for A&E departments and demand for inpatient and outpatient services has been neglected.
- Hospital demands are mostly forecasted in daily period.
- Forecasting methods have been compared using forecast accuracy measurements such as MAPE, MAE, and RMSE.

2.9 Research Gap

Hospitalization has been increasing in all areas of hospitals in the UK, including A&E admissions, elective and non-elective admissions, and outpatient attendances with every passing year. Service managers and other key decision makers need to better understand the likely impacts of increasing demand on key performance metrics (e.g. waiting time targets, resource utilization, budget estimates and requirements) in the upcoming years. The objective is therefore to better manage services, increase quality and achieve NHS standards and targets. Consequently, the following research gaps have been identified and urgently needs to be tackled to balance the current and future demand & capacity needs of hospitals:

- In the literature, there are no study that has developed a simulation model for an entire hospital, where all the relevant data are collected and analysed for each specialty within A&E, inpatient and outpatient settings. Within this framework, a patient pathway in hospital level should be established, and a generic simulation model of an entire hospital should be developed, which eliminates the deficiencies of the current and past studies around modelling hospitals within a single framework.
- Past and current models measure limited number of key output metrics or have focused on specific output metrics (e.g. bed occupancy). A user-friendly decision support system should be developed to examine wide range key performance metrics of A&E and all outpatient and inpatient specialties in a typical NHS Trust (i.e. flexible for all NHS Trusts) for future planning. Decision makers should then be able to balance demand-capacity, thus an opportunity to intervene well in advance.
- In the literature, a significant number of past studies have estimated demand for a specific department (mostly A&E department). Patient visits in consideration of each specialty and types of arrivals have not been forecasted at a hospital level. Each specialty should be estimated for better understanding of patient volume of an entire hospital for projected usage.
- In addition, the majority of past studies have preferred daily period to estimate hospital demand. However, it’s not always wise to make use of the same period to forecast demand for all specialties. There are variations between and within each specialty in the hospital. Daily forecasts can be more accurate for some, whereas monthly for others. The hospital managements should take into consideration different forecasting periods to better estimate hospital demands.
- For many years, two distinct methodologies (i.e. forecasting and simulation) have been used in isolation for health systems. A major gap is therefore identified in the literature, i.e., the lack of use of comparative forecasting and simulation techniques within the healthcare context. These two distinct methodologies should be integrated by conducting an interdisciplinary study.
- Many simulation-optimisation methods have been developed with the aim of determining optimal solutions for their decision variables (e.g. number of operating

rooms and beds or staffing cost). In the majority of instances these models have focused on modelling a service, department or a specialty, however no models have tackled current and future bed occupancy (and other key metrics of interest) at the entire hospital level. A model for a single service (or few) would not be inadequate to determine the required capacity for all specialties within a hospital. A comprehensive entire hospital modelling framework is necessary that combines all the specialties and services within a single decision support system (DSS). No model so far has ever been developed at this scale, such that it is able to, 1) forecast demand for all specialties within inpatient, outpatient and A&E, 2) capture the entire hospital patient pathway at a sufficient level of detail, and 3) optimise the required bed capacity and the required number of consultants and nurses.

2.10 Summary

In this chapter, the structure of the literature review is outlined, with. an extensive literature review is explained. In this respect, the developed generic whole hospital simulation models are criticized, and disadvantages and characteristic features of these models are presented. How simulation and optimization models are integrated is also explained. Comparative forecasting studies are discussed. Simulation studies in healthcare settings for demand projection are investigated. After an exhaustive review of the literature, research gaps in healthcare simulation and optimization modelling has been identified (with relevant evidence) and specified accordingly. The next chapter explains demand and capacity modelling of acute hospital services, and important issues are explained, for example, definition of the research problem, data source, assumptions and the proposed methodologies.

CHAPTER 3

Demand and capacity modelling of acute hospital services

3.1 Introduction

In this chapter, the developed approaches regarding demand and capacity modelling of an entire hospital are presented. In Section 3.2, the research problem of this thesis is identified. Section 3.3, 3.4 and 3.5 presents the study design, study settings and population, and study protocol, respectively. Section 3.6 describes data sources used in this study. Section 3.7 explains the assumptions. Section 3.8 clarifies the proposed methodologies. Section 3.8.1 describes the comparative forecasting process. Section 3.8.2 introduces the developed generic hospital simulation model integrated with forecasting technique. Section 3.8.3 summarises the forecasting-simulation-optimization (FSO) approach.

3.2 Problem identification

According to NHS statistical data, the number of patient activities in A&E departments (see Figure 1.1), outpatient services (see Figure 1.2 for first and follow up attendances and DNAs) and inpatient services (see Figure 1.3) in England has been on the rise. In addition, the NHS statistical data show that the A&E admissions spending at least four hours from arrival to admission, transfer or discharge has increased in England. In addition, number of patients in outpatient and inpatient services have increased significantly. Moreover, bed occupancy level has exceeded the target level (85%). This situation means that acute services are faced with serious problems (i.e. increasing waiting times, lack of resources, etc.) having a negative effect on hospital performances.

High levels of hospitalisation place the management under intense pressure. This is due to multiple factors, such as population expansion, alcohol and cigarette consumption, and stress. The size of the population is a core factor as this is both growing and aging in the UK. Coupled with limited capacity (i.e. bed, staff) and financial constraints as well as increasing demands of patients, it is clear that acute services will continue to struggle (i.e. longer waiting times) to use their resources efficiently. Due to increasing numbers of patients, hospital managements will need to provide higher productivity rates of acute services by enhancing the matching demand and capacity of hospitals.

A comprehensive modelling framework is needed that brings together all specialties and services at a hospital within a single decision support system (DSS). The DSS should guide key decision makers to ensure their system is able to cope with current and future demand, and able to stress test the system, not just focusing on a single specialty (or a service) but its impact on the hospital as a whole. Therefore, they should better understand patient pathway and simulate current systems for projection and model the level of resources needed by patients in acute services in future. Thus, hospital key decision makers can generate efficient solutions about problems related to demand and capacity of acute services and have better management skills.

3.3 Study Design

This study uses the vast majority of the inputs are provided locally by Princess Alexandra Hospital, e.g., number of beds, number of outpatient clinics, number of theatres, staff availability, etc. In addition, the National Hospital Episode Statistics (HES) in England is used. Required hospital data are extracted from this 'big data' corresponding to the hospital of interest, i.e., 248,910 A&E arrivals (with 86 variables), 996,134 outpatient attendances (with 130 variables) and 191,462 inpatient admissions (with 414 variables) over the period of the study between 1 February 2010 – 31 January 2013.

This study is accepted and approved by the Ethics Committees with Delegated Authority (ECDA) in the University of Hertfordshire with the protocol number 'BUS/PGR/UH/02715' under date of 21.11.2016. The Ethic Approval Notification given by the University of Hertfordshire Social Sciences, Arts and Humanities ECDA is presented in Appendix 1.

3.4 Study Settings and Population

This study is carried out using the data belonging to the Princess Alexandra Hospital located in Harlow, England. Also, we worked with a number of people, i.e., Director of Service Redesign and Transformation, Director of Planning, Director of Clinical Services, Director of Finance, Assistant Director of Finance, and Finance Consultant. The average number of A&E admissions at PAH is around 82,970; 332,045 attendances to outpatient services, and 63,821 for the inpatient services over the study period. The A&E department operates 7 days a week and 24 hours a day. In addition, the A&E is a 22-bed department and treats approximately 227 patients per day (mean 226.99, standard deviation [SD] ± 28.71). All the hospital wards used for inpatient admissions consists of 557 beds. In addition, the hospital serves 25 specialties for the outpatient services and 26 specialties for inpatient services.

3.5 Study Protocol

In this study, 36-months of data are used for the period 1 February 2010 – 31 January 2013. The data covering the period between 1 February 2010 and 31 January 2012 are used for the purpose of training set in forecasting and for the purpose of establishing the required observed frequency distributions and percentage of patient referrals in simulation modelling. The period (1 February 2012 – 31 January 2013) is used to validate the forecast accuracies of out-of-samples of the models and the simulation results for the validation of the simulation model.

3.6 Data Sources

The Department of Health in the UK releases annually its national database, the Hospital Episode Statistics (HES). The HES data set contains personal, medical, and administrative details of all patients admitted to, and treated in, NHS hospitals in England (Demir and Chaussalet, 2009). There are more than approximately 80 million records for each financial year. A financial year is from 1 April to 31 March the following year. The HES data set captures all the consultant episodes of patients during their stay in hospital. During a hospital stay, a patient might encounter several successive episodes, collectively known as a spell.

The data were provided in a txt format and "necessary steps were taken to import the data into Microsoft SQL Server version 12.0, so that database programming could be carried out to prepare the data for analysis. Initial checks were made to ensure that the data sets provided contained encrypted NHS numbers for matching purposes" (Demir, 2014). The data period is from 01/04/10 to 31/03/13 (three financial years).

The total number of observations in the A&E dataset over the data period in England is 65m records, 15m inpatient admissions, and 175m outpatient attendances as seen in Table 3.1. We extracted all inpatient, outpatient and A&E data sets corresponding to the hospital of interest, i.e., 248,910 A&E arrivals (with 86 variables), 996,134 outpatient attendances (with 130 variables) and 191,462 inpatient admissions (with 414 variables).

Table 3.1: Number of patient activities in England per financial year

Specialty	2010/11	2011/12	2012/13	Total
A&E department	21,380,985	21,605,067	21,802,377	64,788,429
Outpatient service	57,728,023	58,204,060	59,382,240	175,314,323
Inpatient service	4,954,622	5,071,890	5,140,044	15,166,556
Total	84,063,630	84,881,017	86,324,661	255,269,308

Number of A&E arrivals, number of outpatient activities (i.e. first and follow up attendances and DNAs) and number of inpatient admissions

The inpatient and outpatient datasets were further partitioned into 28 distinct specialties (e.g. cardiology, ophthalmology, trauma and orthopaedics). This is to ensure all specialties within the hospital are considered as part of our forecasting and simulation modelling. For each specialty activity related data (daily, weekly, and monthly inpatient admissions and outpatient attendances) along with 100's of other variables (see Table 3.2) were extracted and analysed, and distributions were established as part of input parameters into our simulation model.

Where required data are not available in HES, local data were provided by the hospital for inpatients and outpatients for each specialty, including, number of inpatient beds; number of doctors and nurses; inpatient annual theatre capacity; percentage of patients having a surgery; outpatient clinic slots; A&E shifts, number of A&E triage rooms, and A&E clinic room availability (a comprehensive list of input parameters extracted from HES and local data are explained in Chapter 8 for a single specialty).

Table 3.2: Activity related data in trauma and orthopaedics outpatient and inpatient specialty over the data period

Patient Activity					
Trauma & orthopaedics outpatient specialty					
	Age groups	**Attendance**	**DNA**	**Cancellation**	**Total**
First attendances	Age group 1 (0 - 15)	6,070	472	1,401	7,943
	Age group 2 (16 - 35)	5,435	864	1,161	7,460
	Age group 3 (36 - 50)	5,910	602	1,590	8,102
	Age group 4 (51 - 65)	6,567	339	1,730	8,636
	Age group 5 (65+)	7,385	326	1,965	9,676
Follow up attendances	Age group 1 (0 - 15)	7,174	1,132	2,169	10,475
	Age group 2 (16 - 35)	8,126	1,855	2,120	12,101
	Age group 3 (36 - 50)	12,019	1,741	3,419	17,179
	Age group 4 (51 - 65)	15,823	1,336	4,602	21,761
	Age group 5 (65+)	20,263	1,439	6,313	28,015
Trauma & orthopaedics inpatient specialty					
Age groups		**Elective**		**Non-elective**	**Total**
Age group 1 (0 - 15)		310		640	950
Age group 2 (16 - 35)		1,231		805	2,036
Age group 3 (36 - 50)		2,210		824	3,034
Age group 4 (51 - 65)		3,121		826	3,947
Age group 5 (65+)		3,655		2,144	5,799

DNA: Did not attend

3.7 Assumptions

During the forecasted and simulation period (namely the next 12 months), we confirm that the hospital has not changed in any fundamental way.

The specialties with less than 1% patients of total patient activity in the hospital are considered as “other specialty” and therefore all specialties of the hospital are taken into account. “Other specialty” for outpatient services (see Table 3.3) consists of orthodontics, plastic surgery, medical oncology, geriatric medicine, radiology, chemical pathology and allied health professional episode. “Other specialty” for inpatient elective services (see Table

3.4) is composed of plastic surgery, anaesthetics, dermatology, neurology, rheumatology, geriatric medicine and obstetrics whereas it for inpatient non-elective services (see Table 3.5) involves ear, nose and throat (ENT), ophthalmology, oral surgery, accident and emergency, anaesthetics, gastroenterology, endocrinology, clinical haematology, medical oncology, neurology, rheumatology, general medical practice, clinical oncology, radiology and allied health professional episode.

Table 3.3: Number of patient activity in outpatient services in the hospital

Main specialty	Number of patient activity	Percentage (%)
General surgery	64,471	6.87%
Urology	43,012	4.58%
Trauma & orthopaedics	131,433	14.00%
Ear, nose and throat (ENT)	49,916	5.32%
Ophthalmology	101,116	10.77%
Oral surgery	24,922	2.65%
Orthodontics	3,384	0.36%
Plastic surgery	2,194	0.23%
Anaesthetics	55,530	5.91%
General medicine	59,608	6.35%
Gastroenterology	14,522	1.55%
Clinic haematology	27,399	2.92%
Cardiology	38,291	4.08%
Dermatology	36,739	3.91%
Medical oncology	5,332	0.57%
Neurology	13,857	1.48%
Rheumatology	24,893	2.65%
Paediatrics	42,713	4.55%
Geriatric medicine	8,780	0.93%
Obstetrics	92,027	9.80%
Gynaecology	66,516	7.08%
Clinical oncology	25,773	2.74%
Radiology	127	0.01%
Chemical pathology	1,835	0.20%
Allied health professional episode	4,719	0.50%
Total	939,109	100.00%

Table 3.4: Number of patient activity in elective inpatient services in the hospital

Main specialty	Number of patient activity	Percentage (%)
General surgery	10,612	12.26%
Urology	10,121	11.69%
Trauma & orthopaedics	10,526	12.16%
Ear, nose and throat (ENT)	2,650	3.06%
Ophthalmology	4,923	5.69%
Oral surgery	4,360	5.04%
Plastic surgery	273	0.32%
Anaesthetics	389	0.45%
General medicine	7,021	8.11%
Gastroenterology	3,825	4.42%
Clinic haematology	7,867	9.09%
Cardiology	3,161	3.65%
Dermatology	1	0.00%
Medical oncology	2,316	2.68%
Neurology	1	0.00%
Rheumatology	847	0.98%
Paediatrics	1,344	1.55%
Geriatric medicine	164	0.19%
Obstetrics	278	0.32%
Gynaecology	4,604	5.32%
Clinical oncology	6,638	7.67%
Radiology	4,642	5.36%
Total	86,563	100.00%

Table 3.5: Number of patient activity in non-elective inpatient services in the hospital

Main specialty	Number of patient activity	Percentage (%)
General surgery	11,213	10.18%
Urology	1,048	0.95%
Trauma & orthopaedics	5,243	4.76%
Ear, nose and throat (ENT)	58	0.05%
Ophthalmology	21	0.02%
Oral surgery	495	0.45%
Accident and emergency (A&E)	490	0.44%
Anaesthetics	5	0.00%
General medicine	24,815	22.52%
Gastroenterology	552	0.50%
Endocrinology	8	0.01%
Clinic haematology	249	0.23%
Cardiology	4,006	3.64%
Medical oncology	1	0.00%
Neurology	3	0.00%
Rheumatology	7	0.01%
Paediatrics	6,816	6.19%
Geriatric medicine	24,092	21.87%
Obstetrics	24,567	22.30%
Gynaecology	6,389	5.80%
General medical practice	24	0.02%
Clinical oncology	29	0.03%
Radiology	21	0.02%
Allied health professional episode	30	0.03%
Total	110,182	100.00%

3.8 Proposed methodology

In this study, three methodologies are proposed. The first proposed methodology is to establish a decision support system (DSS) for comparative forecasting to select the best forecasting method and forecasting horizon. The second proposed methodology is to build a DSS for developing a generic hospital simulation model integrated with the first proposed methodology. The DSS eliminates the deficiencies of the current and past studies around modelling hospitals within a single framework. In addition, to our knowledge, the literature does not have an extensive study that forecasts demand of all types of attendances/admissions of each specialty which then integrates these demand inputs within the generic hospital simulation model. Finally, the third proposed methodology is to integrate an integer linear programming with the second proposed methodology to reallocate the available number of beds and optimize the staffing levels of the inpatient services in the hospital. After an exhaustive review of the literature we notice that an entire hospital model has never been developed that combines forecasting, simulation and optimization techniques. All these proposed methodologies are explained in greater detail as follows.

3.8.1 Forecasting hospital demand

In this study, a decision support system (DSS) is developed to identify better forecasting methods and prediction frequency for each specialty of the hospital. The forecasted demand is used as an input in the simulation and optimization models, instead of using presumptive demand (i.e. assuming that demand will be increased by a rate which represents increases on demand in the past) or using basic forecasting approach (i.e. moving average or using the population growth rates estimated by the Office for National Statistics). Such this study which forecasts hospital demands for each specialty has never been carried out before. The structure of the DSS is presented as a flow diagram in Figure 3.1. All required hospital data are derived from the HES dataset after an extensive data preparation process. The time series patterns (i.e. daily, weekly and monthly) are established after extracting the required data. The data are divided into two sets: training set (the first 24-month data) and validation set (the last 12-month data). The best model parameters for each forecasting method are determined respectively. The mean absolute scaled error (MASE) is obtained for the goodness of fit (in sample) and the forecast accuracy (out-of-sample). The forecasting models are assessed according to the results of the goodness of fit, whereas the best forecasting method and prediction frequency are selected by taking into account the results of the forecast accuracy. Finally, the demands of each specialty are estimated by using the forecasting results and these demand inputs are embedded into the generic hospital simulation model. Theoretical concepts of quantitative forecasting techniques are explained in Chapter 4 and the results of the proposed methodology are presented in Chapter 7 in greater detail. In total 768 forecasting models were developed, made up of the following:

- 19 outpatient specialties x 2 (first and follow up referrals separately) x 3 periods (daily, weekly and monthly) x 4 forecasting methods, which is 456 models for outpatients.
- 16 inpatient specialties (for elective admissions) x 3 periods (daily, weekly and monthly) x 4 forecasting methods, which is 192 models for inpatients.
- 9 inpatient specialties (for non-elective admissions) x 3 periods (daily, weekly and monthly) x 4 forecasting methods, which is 108 models for inpatients.
- 1 A&E department x 3 periods (daily, weekly and monthly) x 4 forecasting methods, which is 12 models for A&E.

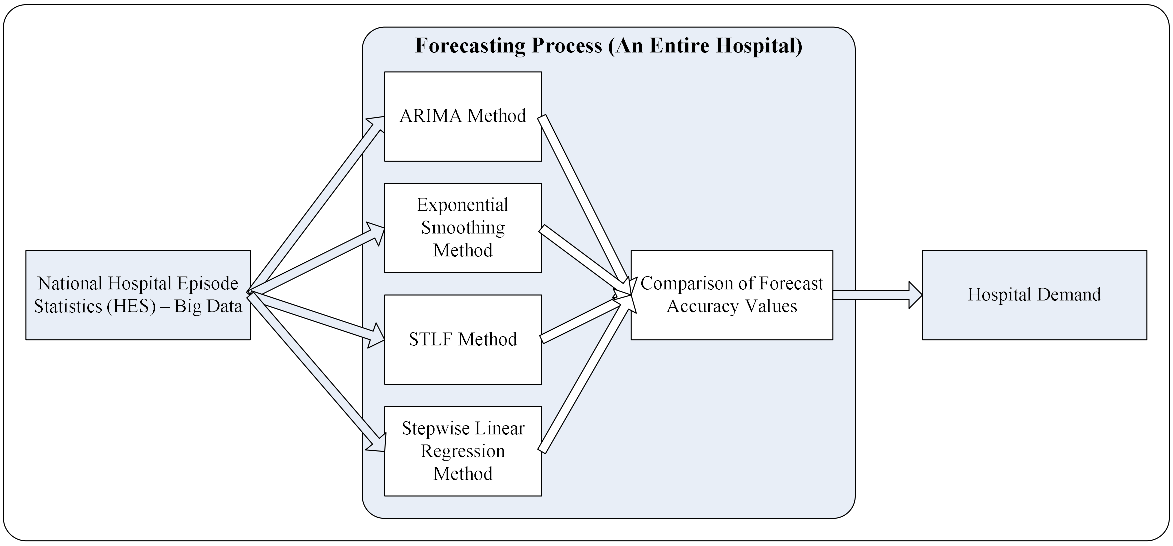

Figure 3.1: The structure of the decision support system for the comparative forecasting method

3.8.2 Generic hospital simulation modelling integrated with forecasting technique

In this study, a decision support system (DSS) is developed by combining comparative forecasting techniques and discrete event simulation for demand and capacity planning in the hospital. For this, the predicted demand is obtained from forecasting techniques instead of using presumptive demand to embed it as input in the simulation model. A step by step guide is presented as a flow diagram illustrating how the two techniques are combined in Figure 3.2. All required hospital data are extracted from the HES dataset over the period of the study. The required data are used in both demand forecasting and parameter estimation of the statistical distributions for the simulation model. These inputs along with model parameters, financial inputs and local data provided by the hospital are embedded into the generic hospital simulation model. The model then generates current and future levels of key output metrics for each specialty as seen in Figure 3.2. Theoretical concept of discrete event simulation is explained in Chapter 5 and the results of the proposed methodology are presented in Chapter 8 in greater detail.

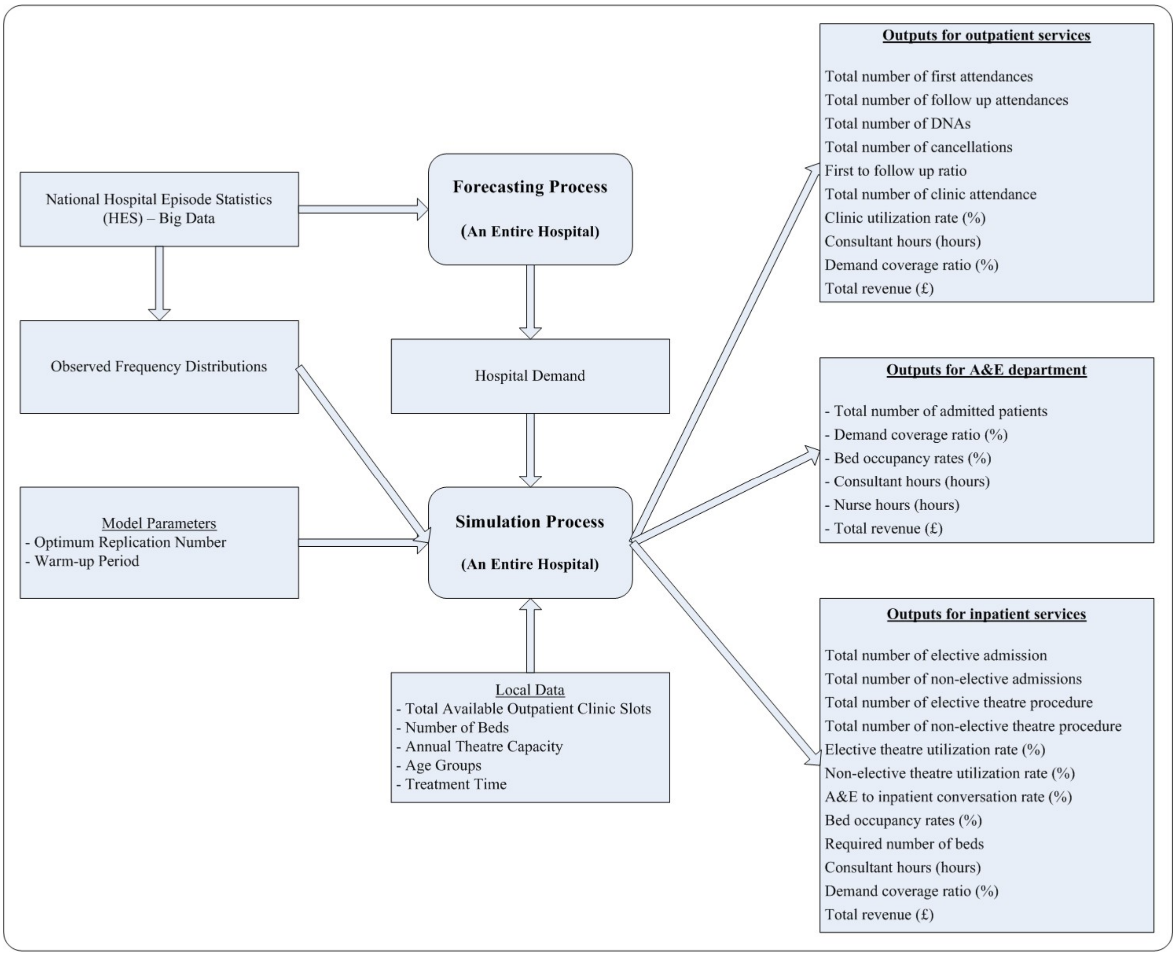

Figure 3.2: The structure of the decision support system combining generic hospital simulation model with comparative forecasting methods

3.8.3 Forecasting-simulation-optimization (FSO) approach

In this study, a decision support system (DSS) named as FSO approach is developed by combining comparative forecasting techniques, discrete event simulation and optimization techniques. The goal is to reallocate the available number of beds and optimize staffing levels in the inpatient services of the hospital. For this, the projected demands obtained from forecasting techniques are embedded as inputs in the simulation and optimization model. The structure of the DSS is presented as a flow diagram which shows how three distinct techniques are combined in Figure 3.3. Unlike the first two proposed methodologies, an integer linear programming is developed to optimize the level of resources of the inpatient services admitting patients in a ward. In this proposed methodology, a realistic behaviour of the hospital, which is expected to be in the projected year, is benefitted using the proposed second DSS to obtain a few inputs (i.e. average length of stay and average revenue) for the FSO approach.

The number of beds for each inpatient specialty is provided by the hospital. In addition, four types of inputs are from the literature, for example, target level of bed occupancy rate, average staffing costs of consultants and nurses, and finally nurse to patient ratio. The bed occupancy rate should not exceed the target level of 85% and nurse to patient ratio should be less than or equal to seven patients. The FSO approach then generates future level of key output metrics (i.e. the required number of beds, consultants and nurses working with full time equivalent). Theoretical concept of integer linear programming is explained in Chapter 6 and the results of the proposed methodology are presented in Chapter 9 in greater detail.

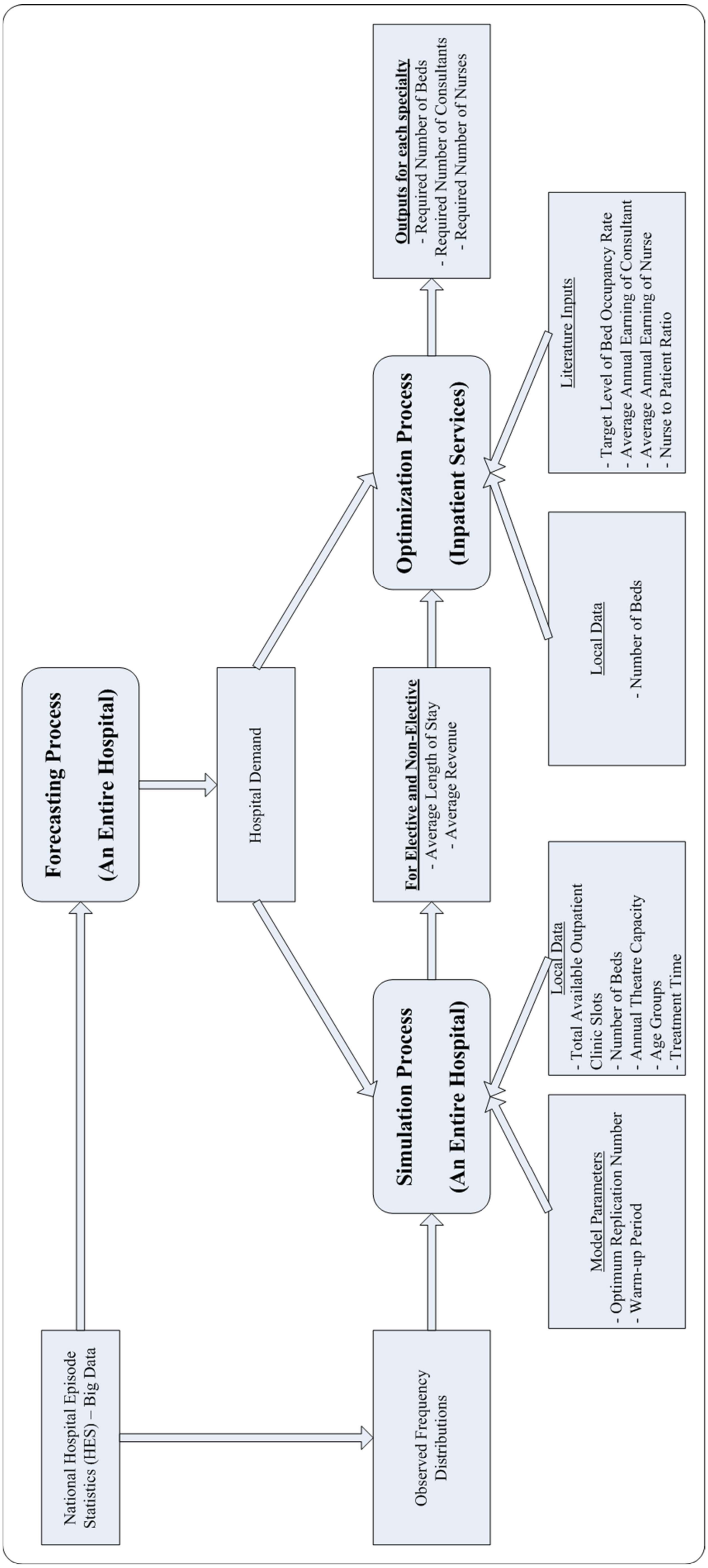

Figure 3.3: The structure of the decision support system

3.9 Summary

In this chapter, the research problem was identified, and the methodological approaches were proposed. The structure of the developed decision support system was clarified. In addition, study design was explained, study settings and population were described. This chapter also provided assumptions of the study and introduced the data sources, namely the National Hospital Episode Statistics (HES) dataset and local data provided by the hospital.

CHAPTER 4

Forecasting time series

4.1 Introduction

In this chapter, the theoretical concepts of forecasting time series are presented. In Section 4.2, the steps of the forecasting process are explained and methodologies of four forecasting techniques are described. Section 4.2.1 introduces the autoregressive integrated moving averages (ARIMA) method. Section 4.2.2 describes the exponential smoothing (ES) method. Section 4.2.3 and 4.2.4 demonstrate the seasonal and trend decomposition using loess forecasting model (STLF) and the stepwise linear regression (SLR) methods, respectively. Section 4.3 and 4.4 describe the goodness of fit and forecast accuracy measures, and how best the forecasting method is chosen, respectively.

4.2 Study method

Time Series Forecasting is a widely used approach to predict a future event or trend to better manage systems and processes. Forecasted estimates must therefore be robust and reliable predictions for projection purposes (DeLurgio, 1998). Many advantages are gained as a result of using these estimates towards managing a hospital. For example, the hospital managers are able to cope with varying demands by adjusting their capacities. In this context, they are able to plan ahead in terms of their revenue and costs, how many human resources (i.e. doctors and nurses) are required, which equipment are needed, etc. Forecasting is a crucial component of strategic planning of the hospital as well as other industries.

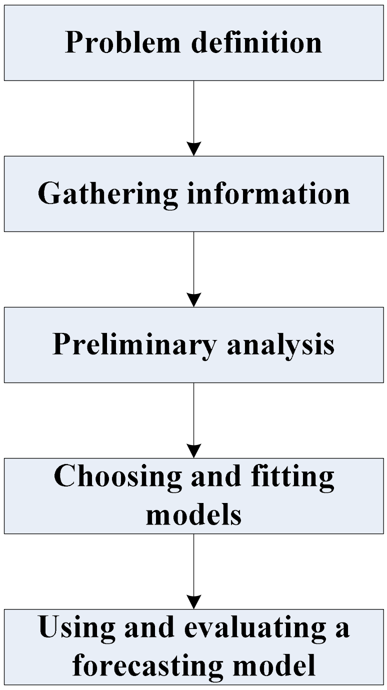

Figure 4.1: Flow Chart of Forecasting Process (*Adapted from Makridakis et al., 1998)

As illustrated in Figure 4.1 (Makridakis et al., 1998), forecasting process is explained step by step as follows:

1. Problem Definition

Problem is defined, and the definition describes what the problem is, what the time series is, who uses the estimates and why the estimates are used.

2. *Gathering Information*

Statistical data (a time series data) must be collected at regular intervals, e.g. daily or monthly, before building a forecasting model.

3. *Preliminary Analysis*

The data are examined in terms of exploring some features, e.g. trend, seasonality or cyclical pattern in the data. Preliminary analysis is carried out by using descriptive statistics and visual inspection of data (e.g. graphical representation).

Preliminary analysis is a crucial part in specifying the elements of a forecasting method or understanding which forecasting model is useful. For example, a stationarity analysis must be carried out in order to determine the value of *d* if an ARIMA (p, d, q) model where *d* denotes the stationarity of data is used in forecasting. The stationarity of the data can be analysed by using descriptive analysis. Another example is that if an exponential smoothing method is applied to construct a forecasting model, *single exponential smoothing method* for data excluding trend and seasonality, *Holt's linear method* for data having a trend or *Holt-Winters' method* for data including trend and seasonality must be selected. As a result, in order to understand whether a data includes a trend and/or seasonality pattern, preliminary analysis using descriptive analysis is required.

4. *Choosing and Fitting Models*

After preliminary analysis, a forecasting method (such as ARIMA and ES) firstly must be selected and fitted according to data. Secondly, parameters of the selected forecasting method must be found (e.g. p, d and q for ARIMA, α and/or β for ES). Thirdly, the data must be divided into two groups: training set and validation set. A forecasting model is built by using the training set (in-sample). After building a model, the goodness-of-fit of the model is calculated by assessment criteria such as MAE (mean absolute error), MAPE (mean absolute percentage error) or MASE (mean absolute scaled error).

5. *Using and Evaluating a Forecasting Model*

In this step, a validation process is carried out and the model is validated according to an assessment criterion. If two or more forecasting methods are compared, the best method is chosen using the assessment criteria.

4.2.1 Autoregressive integrated moving average (ARIMA) method

The autoregressive integrated moving average (ARIMA) method is a forecasting technique which has been widely used and generates forecasts by means of autocorrelations in the time series (Hyndman & Athanasopoulos, 2014). The ARIMA method has three parameters (p, d and q) where *p* denotes the order of autoregression, *d* is the order of differencing and *q* is the order of the moving average (DeLurgio, 1998).

Step 1:

Step 1 involves data preparation and model selection. Firstly, non-stationarity patterns in the time series cause the positive autocorrelations. Hence, the non-stationary data must be converted using the method of differencing.

$$Y_t' = Y_t - Y_{t-1} \tag{4.1}$$

How to take the first difference is described in Equation (4.1) where Y_t denotes the observation at time t and Y_{t-1} denotes the observation at time *(t-1)*.

Secondly, model selection in Figure 4.2 enables the values of AR (p) and MA (q) in an ARIMA method to be chosen. The AR (p) is the autoregression which implies that Y_t depends on previous observations in the data. Equation (4.2) presents an autoregressive model of order one and Equation (4.3) gives higher-order autoregressive models where c is a constant term, ϕ_j is *j*th autoregressive parameter and e_t is the error term at time *t*.

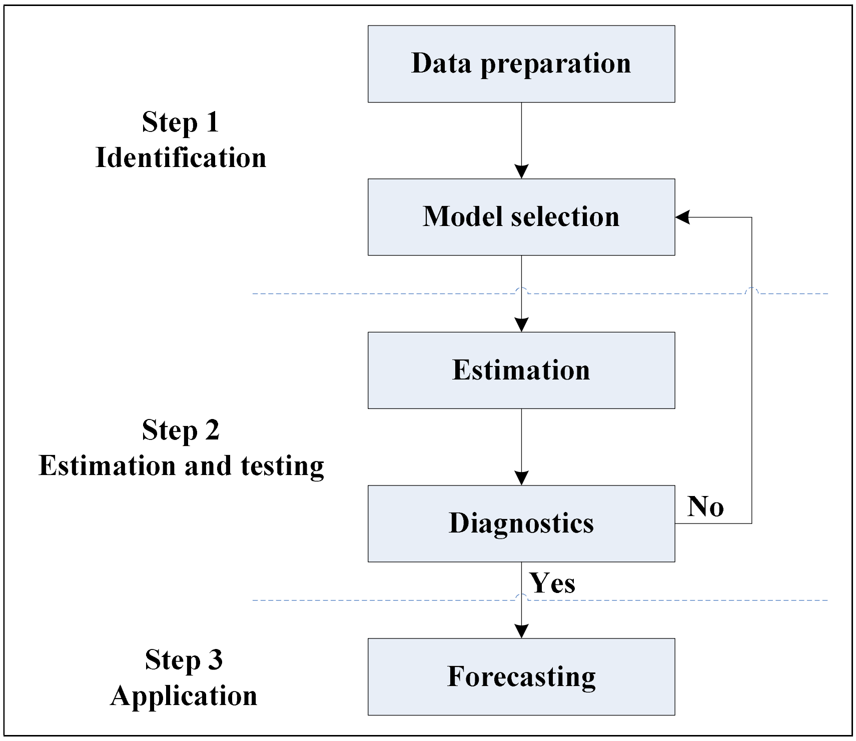

Figure 4.2: Forecasting process of ARIMA method (adapted from Makridakis et al., 1998)

$$Y_t = c + \phi_1 Y_{t-1} + e_t \tag{4.2}$$

$$Y_t = c + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \ldots + \phi_p Y_{t-p} + e_t \tag{4.3}$$

The MA (q) is the moving average, which relates Y_t to errors for previous terms in the data. Equation (4.4) presents a moving average of order one and Equation (4.5) gives higher-order moving average models where c is a constant term, θ_j is *j*th moving average parameter and e_{t-k} is the error term at time *(t-k)*.

$$Y_t = c + e_t - \theta_1 e_{t-1} \tag{4.4}$$

$$Y_t = c + e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \ldots - \theta_q e_{t-q} \tag{4.5}$$

Step 2:

In the estimation section, computer programs automatically compute the best parameters of ARIMA models. To do this, it generates the initial values of the parameters and the best model is found iteratively. The method of least squares or maximum likelihood estimation is used in order to determine an ARIMA model.

In this study, the auto.arima ()package in R developed by Hyndman and Khandakar (2008) is applied in order to select the best ARIMA models. This function uses the Akaike's Information Criterion (AIC) (see Equation (4.6) for the formula of the AIC) as a criterion in order to find the orders of AR (p) and MA (q) in ARIMA models. This function runs iteratively until the lowest AIC is found.

$$AIC = -2\log(L) + 2(p + q + P + Q + k) \tag{4.6}$$

where L is the maximum likelihood, if $c \neq 0$, $k=1$ and otherwise, $k=0$ (Hyndman and Khandakar, 2008).

The diagnostics section shows whether the ARIMA model selected in the estimation section is an appropriate model or not by using the portmanteau test which examines whether the residuals of the model is white noise or not. If the model is not adequate, a new model should be selected as shown in Figure 4.2 (Makridakis et al., 1998).

Step 3

The estimated values are produced by the selected and verified ARIMA model in this step.

4.2.2 Exponential smoothing method

Exponential smoothing (ES) is one of the most widely used forecasting methods. A feature is that "the ES implies exponentially decreasing weights as the observations get older" (Makridakis et al., 1998). In addition, the forecasting process of ES is shown in Figure 4.3.

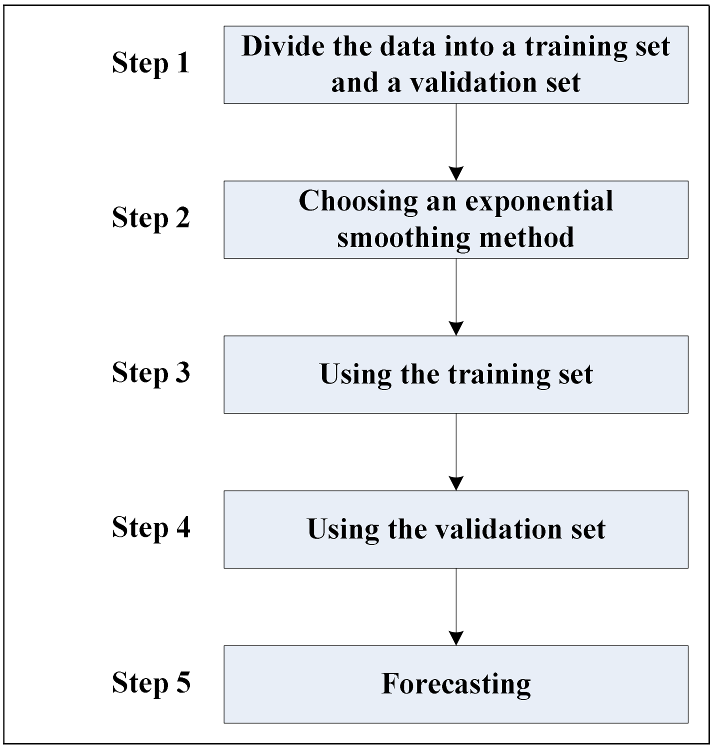

Figure 4.3: Forecasting process of exponential smoothing method (adapted from (Makridakis et al., 1998)

Step 1

Data are divided into two sets: training set (in-sample) and validation set (out of sample).

Step 2

There are 15 types of ES model if the error terms are not taken into account as shown in Table 4.1. There are in total 30 ES models with the additive error and the multiplicative error for each model in Table 4.1 (See Appendix 2, 3 and 4 for all formulas of these 30 ES models). The (N,N) model is the single exponential smoothing (SES), the (A,N) model is the Holt's linear model and the (A,A) model is the Holt-Winters' additive model, whereas the (A,M) model is the Holt-Winters' multiplicative model. (Hyndman et al., 2008).

Table 4.1: Types of exponential smoothing methods (Hyndman et al., 2008)

Trend component	**Seasonal component**		
	N (None)	**A (Additive)**	**M (Multiplicative)**
$\boldsymbol{N}$ (None)	N, N	N, A	N, M
$\boldsymbol{A}$ (Additive)	A, N	A, A	A, M
$\boldsymbol{A_d}$ (Additive damped)	A_d, N	A_d, A	A_d, M
$\boldsymbol{M}$ (Multiplicative)	M, N	M, A	M, M
$\boldsymbol{M_d}$ (Multiplicative damped)	M_d, N	M_d, A	M_d, M

A damped method is used to decrease the effect of the trend at the end of a time series during the period used in estimating. The damped method is frequently a successful approach (Hyndman et al., 2008). Table 4.2 shows the trend types and their formulas, where T_h is the forecast trend, b is a growth term, l is the level term, ϕ is the damping parameter ($0< \phi <1$) and h is the number of periods (Hyndman et al., 2008).

Table 4.2: Formulas of trend types (taken from Hyndman et al., 2008)

Trend types	**Formulas**
None	$T_h = l$
Additive	$T_h = l + bh$
Additive damped	$T_h = l + (\phi + \phi^2 + \cdots . + \phi^h)b$
Multiplicative	$T_h = l + b^h$
Multiplicative damped	$T_h = l + b^{(\phi + \phi^2 + \cdots . + \phi^h)}$

4.3.2.1 Single exponential smoothing method

Single exponential smoothing (SES) method (N,N) adds the previous observation value and the previous forecast error multiplied by α which is a constant between 0 and 1 as shown in Equation (4.7). Thus, if the previous forecast was too low, the next forecast will be higher, and if the previous forecast was too high, the next forecast will be lower.

$$F_{t+1} = F_t + \alpha(Y_t - F_t) \tag{4.7}$$

where F_{t+1} denotes the next forecast at time *(t+1)*, Y_t is the observation at time *t* (Hyndman et al., 2008).

4.3.2.2 Holt's linear method

Holt's Linear Method (A,N) goes beyond SES by taking a trend into account. It has two adjustable parameter terms (α and β) which are between 0 and 1. Equation (4.8) gives the level of the data and Equation (4.9) is the formula of the trend in the model and finally, Equation (4.10) is the point forecast of the Holt's linear model (Hyndman et al., 2008).

$$\text{Level} \quad : l_t = \alpha Y_t + (1-\alpha)(l_{t-1} - b_{t-1}) \tag{4.8}$$

$$\text{Growth} \quad : b_t = \beta^*(l_t - l_{t-1}) + (1-\beta^*)b_{t-1} \tag{4.9}$$

$$\text{Forecast} \quad : F_t = l_t + b_t h \tag{4.10}$$

where l_t is the forecasted value of the level at time *(t)*, b_t represents the forecasted value of the trend at time *(t)*, F_t denotes the forecast at time *(t)*, Y_t is the observation at time *t*, α denotes the smoothing parameter in the formula of the level, β^* denotes the smoothing parameter in the formula of the growth (Hyndman et al., 2008).

4.3.2.3 Damped trend method

Damped trend model (A_d, A) is developed after a damped trend is incorporated into the Holt's linear model. Equation (4.11) gives the level of the data and Equation (4.12) is the formula of the trend in the model and finally, Equation (4.13) is the point forecast of the damped trend model (Hyndman et al., 2008).

$$\text{Level} \quad : l_t = \alpha Y_t + (1-\alpha)(l_{t-1} + \phi b_{t-1}) \tag{4.11}$$

$$\text{Growth} \quad : b_t = \beta^*(l_t - l_{t-1}) + (1-\beta^*)\phi b_{t-1} \tag{4.12}$$

$$\text{Forecast} \quad : F_t = l_t + (\phi + \phi^2 + \ldots + \phi^h) b_t \tag{4.13}$$

where l_t is the forecasted value of the level at time *(t)*, b_t represents the forecasted value of the trend at time *(t)*, F_t denotes the forecast at time *(t)*, Y_t is the observation at time *t*, $\emptyset$ denotes the parameter of the trend to be damped, α denotes the smoothing parameter in the formula of the level, β^* denotes the smoothing parameter in the formula of the growth (Hyndman et al., 2008).

4.3.2.4 Holt-Winters' trend and seasonality method

Holt-Winters Method allows forecasting of the data when there are both trend and seasonal components. These two components can be combined additively or multiplicatively as shown in Equation (4.14) to Equation (4.21) (Hyndman et al., 2008).

The formula for the multiplicative seasonality (A, M):

Level : $$l_t = \alpha \frac{Y_t}{s_{t-m}} + (1-\alpha)(l_{t-1} - b_{t-1}) \quad (4.14)$$

Growth : $$b_t = \beta^*(l_t - l_{t-1}) + (1-\beta^*)b_{t-1} \quad (4.15)$$

Seasonal : $$s_t = \gamma Y_t / (l_{t-1} - b_{t-1}) + (1-\gamma)s_{t-m} \quad (4.16)$$

Forecast : $$F_t = (l_t + b_t h)s_{t-m+h_m^+} \quad (4.17)$$

The formula for the additive seasonality (A, A):

Level : $$l_t = \alpha(Y_t - s_{t-m}) + (1-\alpha)(l_{t-1} - b_{t-1}) \quad (4.18)$$

Growth : $$b_t = \beta^*(l_t - l_{t-1}) + (1-\beta^*)b_{t-1} \quad (4.19)$$

Seasonal : $$s_t = \gamma(Y_t - l_{t-1} - b_{t-1}) + (1-\gamma)s_{t-m} \quad (4.20)$$

Forecast : $$F_t = l_t + b_t h + s_{t-m+h_m^+} \quad (4.21)$$

where l_t is the forecasted value of the level at time *(t)*, b_t represents the forecasted value of the trend at time *(t)*, s_t is the forecasted value of the season at time *(t)*, F_t denotes the forecast at time *(t)*, Y_t is the observation at time t, γ denotes the smoothing parameter in the formula of the seasonal component , α denotes the smoothing parameter in the formula of the level, β^* denotes the smoothing parameter in the formula of the growth (Hyndman et al., 2008).

Step 3

A forecasting model is built using a training set. In this study, the ets() function in R developed by Hyndman and Khandakar (2008) is applied in order to select the best ES models. This function automatically finds the best ES model for the data by using the AIC values (Hyndman and Khandakar, 2008).

Step 4

After building a model, the forecast accuracy for the validation set is calculated by assessment criteria such as MAE (mean absolute error), MAPE (mean absolute percentage error) or MASE (mean absolute scaled error).

Step 5

The estimated values are produced by the selected and verified ES model in this step.

4.2.3 The seasonal and trend decomposition using loess (STLF) method

STL method is reliable decomposition method and uses the loess (i.e. locally estimated scatterplot smoothing) to decompose the time series (Hyndman and Athanasopoulos, 2014).

STLF method is a forecasting technique which uses a non-seasonal forecasting method after decomposition of time series using STL method. Firstly, the time series data are converted to seasonal time series data using STL decomposition (Hyndman and Athanasopoulos, 2014). To decompose the time series, Eq. (4.22) is used for an additive decomposition or Eq. (4.23) is used for a multiplicative decomposition.

$$y_t = \hat{S}_t + \hat{A}_t \tag{4.22}$$

where $\hat{A}_t = \hat{T}_t + \hat{E}_t$, $\hat{A}_t$ is the seasonally adjusted component at period *t*, $\hat{T}_t$ is trend-cycle component at period *t*, and $\hat{E}_t$ is error component at period *t* (Hyndman and Athanasopoulos, 2014).

$$y_t = \hat{S}_t \hat{A}_t \tag{4.23}$$

where $\hat{A}_t = \hat{T}_t \hat{E}_t$, $\hat{A}_t$ is the seasonally adjusted component at period t, $\hat{T}_t$ is trend-cycle component at period t, and $\hat{E}_t$ is error component at period t (Hyndman and Athanasopoulos, 2014).

After that, a non-seasonal forecasting technique (e.g. non-seasonal ARIMA method or Holt's method) is used to estimate time series. The estimated values are then re-seasonalized by using "the last year of the seasonal component" (Hyndman, 2016).

In this study, the stlf () package in R developed by Hyndman and Khandakar (2008) is applied in order to select the best STLF models.

After estimating, the validation process is completed and then, a forecast accuracy measure is calculated for the validation set.

4.2.4 Stepwise linear regression method

Multiple linear regression seeks a relationship between independent (explanatory) variables and a dependent variable. In other words, one variable is forecasted using two or more independent variables in the multiple linear regression as can be seen in Equation (4.24) (Makridakis et al., 1998).

$$Y = b_0 + b_1 X_1 + b_2 X_2 + \ldots + b_k X_k + e \tag{4.24}$$

where Y is dependent variable, X_k are explanatory variables, b_0 is a constant term, b_k is the coefficient of the explanatory variable and e is the error term.

A multiple linear regression is solved by using the least squares method in order to obtain minimum sum of squares of the residuals. (Makridakis et al., 1998). After finding the coefficients of the model, p-value, R^2 and adjusted R^2 are calculated in order to understand whether the regression model is significant or not.

The p-value is obtained from the ANOVA analysis of the regression model. If the p-value is less than 0.05, the explanatory variables offer a significant contribution to the regression model. (Makridakis et al., 1998).

The R^2 is determined by Equation (4.25). It is the percentage of the variation in the dependent variable that is explained by the model. If the R^2 is close to 1, the regression model fits the data well. (Makridakis et al., 1998).

$$R^2 = \frac{\sum (\hat{Y}_i - \overline{Y})^2}{\sum (Y_i - \overline{Y})^2} \tag{4.25}$$

The R^2 goes up when each explanatory variable is added to the regression model. The problematic issue is that degrees of freedom are not considered when calculating the R^2. For this reason, the R^2 is adjusted by using the degrees of freedom as shown in Equation (4.26) (Makridakis et al., 1998).

$$\overline{R}^2 = 1 - (1 - R^2)\frac{n-1}{n-k-1} \tag{4.26}$$

where n is the number of observations and k is the number of independent variables (Makridakis et al., 1998).

Stepwise linear regression (SLR) method is a kind of multiple linear regression. SLR method selects the explanatory variables relevant to the dependent variable starting from the initial model which includes all explanatory variables.

In this study, the stepwise linear regression is used to determine the best regression model for the time series. The stepAIC () function in R is applied. As mentioned by Ripley et al. (2016), it takes into account the AIC (as goodness of fit) when choosing the best model and it determines the best model which has the lowest AIC.

In the literature, the existing studies applying a multiple linear regression method have used dummy variables (e.g. days of week, months of year) for independent (explanatory) variables. For example, the stepwise linear regression model for the daily estimation includes days of week, months of year, variables related to holidays (H: a holiday, BH: a day before a holiday and AF: a day after a holiday).

4.3 Goodness of fit and forecast accuracy measures

Goodness of fit (GoF) measures how well a forecasting model estimates the in-sample data whereas forecast accuracy (FA) calculates it for the out of sample data. (Makridakis et al., 1998). According to Table 2.7, the information criterion such as AIC is generally used as goodness of fit and the best forecasting method is selected by comparing the AIC values. However, Hyndman and Athanasopoulos (2014) explain that the AIC cannot be used when comparing models which do not have the same number of observations. For example, an ARIMA model having a differencing does not use the same quantity of data with an ES model or an ARIMA model excluding a differencing, since taking a difference cause a decrease in the number of observations. Another reason is that an ARIMA and an ES model have different methods for estimating the parameters. Therefore, finding an ES model is based on the entire dataset while an ARIMA model takes fewer data into account. Thus, AIC values of the models are computed differently.

4.4 Choosing the best forecasting methods and periods

Forecast Accuracy (FA) refers to the goodness of fit of the developed forecasting model for the out of sample data. The important issue is to select the 'best' forecasting method. A number of metrics are available for this purpose. Gneiting (2011) reviewed the surveys on this matter and found that the measure most widely used in organizations is MAPE – the mean absolute percentage error. Unfortunately, it is not widely known that MAPE is a biased measure: it does not treat positive and negative errors symmetrically and consequently selects methods whose forecasts tend to be too low. The mechanism by which this occurs is explained in (Tofallis, 2015). We have chosen to use the mean absolute scaled error (MASE) method (See Eq. (4.27) and (4.28)) which also has the advantage that if zero occurs in the observations, MASE avoids the infinities which occur with mean absolute percentage error (MAPE) (Hyndman and Koehler, 2006). MASE is based on a simple quantity that managers can comprehend, namely the average prediction error (irrespective of sign). MASE is a ratio which compares this with the corresponding value from using the naïve forecasting method as a benchmark. In the MASE, the numerator is the mean absolute error of the forecasting method and the denominator is the mean absolute error of the naïve method, i.e. when the forecast is the previous observation. The denominator is therefore the same for all methods studied. Hence, the MASE compares the errors with those from the naïve method.

$$q_t = \frac{e_t}{\frac{1}{n-1}\sum_{i=1}^{n}\left|Y_i - Y_{i-1}\right|} \tag{4.27}$$

$$MASE = mean(|q_t|) \tag{4.28}$$

where q_t represents a scaled error, e_t is the error term and Y_i denotes the observation at time i (Hyndman and Koehler, 2006).

4.5 Summary

In this chapter, typical forecasting processes and the most widely used forecasting methods are described in greater detail. It explained how the parameters (p, d, q) of ARIMA method are determined and presented the exponential smoothing methods (i.e. single exponential smoothing method, Holt's linear method, damped trend method and Holt-Winters' trend and seasonality method). It illustrates each formula related to all types of ES with additive and multiplicative errors. This chapter also described the STLF method and summarised the stepwise linear regression model. In Section 4.3, we explained why AIC is not chosen as a goodness of fit measure. Section 4.4 justified why the mean absolute scaled error (MASE) is used as a forecast accuracy as opposed to other methods (e.g. the mean absolute percentage error).

CHAPTER 5

Discrete event simulation modelling

5.1 Introduction

In this chapter, theoretical concepts regarding discrete event simulation modelling are presented. In Section 5.2, theoretical concepts of simulation are explained. Section 5.2.1 presents steps for building a simulation model. Section 5.3 clarifies why discrete event simulation (DES) is preferred to model the hospital in this study. Section 5.4 describes how a system is conceptualized. Section 5.5 explains how the conceptualization stage is verified. Section 5.6 introduces how a simulation model is generated. Section 5.7 and 5.8 describes how a simulation model is verified and the determination of the required replication number and warm up period, respectively. Section 5.9 explains how a simulation model is validated. Section 5.10 presents experimental design and what-if scenarios.

5.2 Simulation

Simulation is an approach which allows that characteristic features of any system is built in a computer environment and several experiments are conducted (Pidd, 2004). On the other hand, as noted by Kelton, P. Sadowski and A. Sadowski (2001), simulation is an imitator of systems on computers by means of useful software. Simulation gives useful results to users. Some of these advantages according to Banks et al. (2005) are as follows: firstly, operations of the system can be better understood. Secondly, what-if analyses can be tested without interrupting the system. Finally, blockages can be determined by analysing the system. In addition, Pidd (2004) states that simulation is cheaper than real experiment and simulation methods can simulate systems for long periods, such as months, or years in a short time and simulation is replicable, therefore an average value can be obtained by rerunning simulation models so many times.

Simulation has been implemented in many industries, such as manufacturing, healthcare, business, transportation, logistics, supply chain and defence (Pidd 2004 and Banks et al. 2005). As can be understood from the literature review section, health care services are systems where simulation techniques have been carried out extensively. This situation is confirmed by Pidd (2004) by mentioning that simulation is an appropriate implementation which allows restricted resources of hospitals to be effectively used in healthcare services.

5.2.1 Steps for building a simulation model

Simulation projects must be carried out according to project phases. Banks et al. (2005) explains that simulation project consists of 12 phases described below.

1st phase: **Problem identification.** The problem should be clearly identified and should be understandable for the stakeholders of the project (i.e. key decision makers and analysts). The stakeholders agree with the clear definition of the problem.

2nd phase: **Objectives and planning of the projects.** The objectives should be determined, and the project should be planned. It is needed to make sure whether simulation is a solution method for the problem and objectives.

3rd phase: **Conceptualization.** The logical structure of a real life system is mapped out.

4th phase: **Data collection.** The required data are collected based on the complexity of the model.

5th phases: **Model translation.** The real-life system is modelled in a computer environment using a simulation software.

6th phase: **Verification.** The structure of a simulation model is properly established in a computer environment.

7th phase: **Validation.** Validation process is carried out by calibrating a simulation model until the simulation model behaves as if the actual system.

8th phase: **Experimental design.** The scenarios (i.e. alternatives to be assessed for the system analysis) are determined.

9th phase: **Model run and analysis.** The simulation model is run to measure the performance of the systems, and the key performance metrics (i.e. outputs) are analysed.

10th phase: **Decision of additional runs.** Additional runs are conducted based on further analysis and the requirements determined by the analysts.

11th phase: **Documentation and reporting.**

12th phase: **Model implementation.**

5.3 Why discrete event simulation (DES)?

A number of simulation techniques are available in simulating hospitals. These methods are discrete event simulation (DES), system dynamics (SD) and agent based simulation (ABS) (Gunal, 2012). DES method is a modelling approach which imitates events taking place discontinuously in time (Banks et al., 2005). In addition, Gunal (2012) specify that DES successfully models systems which involve queues and provides flexibility to users, that is, the users can create more detailed models. Moreover, the users can observe patients in hospital models through DES methods. Important components of treatment processes such as length of stay, and patient arrivals are taken into account in DES methods. On the other hand, Gunal (2012) states that "SD is a popular method for modelling continuous systems". SD method is two-step simulation technique. The first step is called "qualitative step" which specifies elements of systems and interactions between them are conceptualized in the model. The second step is known as "quantitative step" which stocks and flows of the system are determined in the model (Brailsford et al., 2004). Finally, another simulation method is agent based simulation which uses "autonomous agent" that has relationships with other agents and environments. Agents are individually modelled with respect to their behaviours and can make decisions autonomously (Macal and North, 2010).

Gunal (2012) compares these simulation techniques. Accordingly, there are some important differences between them. For example, firstly, DES has work centres to represent activities while rates are important in SD and ABS does not identify any work centre. Secondly, events are crucial in DES, in other words, DES method is based on event. On the other hand, SD simulations are directed by rates and ABS simulations are directed by agents and environments. Thirdly, DES is frequently *'stochastic'* whereas SD and ABS is typically *'deterministic'*. Moreover, Gunal (2012) states that DES is a successful technique in modelling systems which have queuing processes. Furthermore, ABS is a newer simulation approach, whereas DES has appeared extensively in the literature and is widely accepted and utilised for decision making purposes by healthcare organisations in the UK, including the NHS and 'The National Institute for Health and Care Excellence' (NICE), which has recognised DES as a valid technique for simulating complex patient pathways (Davis et al. 2014).

Amongst many modelling methods and approaches, Discrete Event Simulation (DES) is chosen as it enables us to capture the whole hospital at a sufficient level of detail, with the flexibility of further developing a user-friendly interface to get hospital managers to engage with the model. Furthermore, unlike other methods, DES is able to simulate random behaviours of systems (i.e. length of stay, waiting time and number of follow ups) and is able to track individual patient's footsteps in a hospital. DES can also model events occurring at any discrete point in time and takes into account different features of patients (i.e. age, gender, disease, etc.) (Demir and Southern, 2017).

5.4 Conceptualization stage

Conceptualization is a process which a prepare a plan of the simulation model (Gunal, 2012). To build a discrete event simulation model, it is required that elements of the system are specified and their relationships among each other are mapped out (Pidd, 2004). It means that firstly, a hospital should be conceptualized and after that, a simulation model should be built. The conceptualization stage is required to better understand the hospital system and establish a simulation model correctly. To build simulation model of an entire hospital, all departments (A&E, inpatient and outpatient departments) and the interactions among the departments must be taken into account. The conceptualized pathway of the PAH as a whole hospital is explained in Chapter 8 (Section 8.2).

5.5 Generating simulation models

Since the conceptualization stage provides better understanding of the system, it makes building of simulation model easier. Therefore, the simulation model of a system has been built after the conceptualization stage. Simulation models can be developed using a software (e.g. Simul8 and Arena).

Gunal (2012) determines that a discrete event simulation model involves four elements such as *'entities & attributes, resources, process network and variables such as inputs and outputs'*.

1) *Entities* are things which follow the network of processes in the system. For example, entities might be patients in hospital simulation model. *Attributes* are features of the entities in simulation models. For example, attributes of patients might be time which allow us to track the time of process (i.e. admission, treatment and discharge).
2) *Resources* might be objects used in the models, e.g. a consultant, a nurse, a CT scan, and a consultation room.
3) *Process networks* represents the interaction between resources and entities. For example, to clarify, the interactions between a doctor and a patient might be that patients wait for a doctor to be assigned accordingly. After that, patient is treated and discharged by the doctor. Another example, the interactions between patients and beds might be related to length of stay.
4) *Variables* are typically inputs and outputs. For example, inputs for hospital simulation model are basically human resources (i.e. doctors and nurses), demand (i.e. patient volume), physical inputs (i.e. beds, clinic rooms, triage rooms and theatre rooms), financial inputs (i.e. tariffs and costs), other inputs (i.e. shifts, distributions) and so on. In addition, input parameters and key output metrics used in the generic hospital simulation model developed in this study are shown in Section 8.3 and 8.6 (Chapter 8). The developed generic hospital simulation model of the PAH as a whole hospital is explained in Section 8.4.

5.6 Verification of conceptualization pathway and simulation models

Verification and validation steps are crucial for simulation projects. Banks et al. (2005) state that verification is related to whether processes of a system are certainly represented in a simulation model or not. In other words, *verification* is carried out to ensure whether the conceptual models are represented in the simulation model. Once simulation models are built in the computer logically and the inputs are correctly determined, verification stage is finalised.

During the development of patient pathway, we closely worked with specialists (consultants, service managers and directors). The pathway was verified by these specialists after several meetings. The verification of the conceptualized patient pathway and simulation model is explained in Section 8.7.

5.7 Determination of the required replication number and warm-up period

A simulation model is analysed by using random samples generated from distributions (i.e. observed frequency distributions and theoretical distributions) over time. Therefore, these estimates from the simulation model are a result of randomness which might include large variances. These estimates from a single run might be exceedingly different than the actual behaviour of the model (Law and Kelton, 2000). Generating better estimates from the simulation model is to have multiple replication and average the results of these replications (Robinson, 2004).

On the other hand, the period of simulation model is between starting time and end time. In addition, the simulation model starts with an empty condition in the beginning of the simulation period. This is called as initialization bias in simulation modelling. A warm up period is determined for removing this initialization bias. Therefore, simulation models can reach steady-state conditions (Robinson, 2004). The following subheadings explain in greater detail how a required replication number and warm up period are determined.

5.7.1. Required replication number

Using Fixed-Sample-Size Procedure, the required replication number is calculated for simulation models. Eq. (5.1) presents the formula for the fixed-sample-size procedure.

$$n_{\gamma}^{*}(\gamma) = \min\left\{ i \geq n : \frac{t_{i-1,1-\alpha/2}\sqrt{S^2(n)/i}}{\left|\bar{X}(n)\right|} \right\} \leq \gamma' \qquad (5.1)$$

$$\gamma' = \gamma/(1+\gamma) \qquad (5.2)$$

where n is initial replication number, i is required replication number, S is standard deviation, γ' is “adjusted” relative error (see Eq. (5.2)) and $\bar{X}$ is average estimates of key parameter (Law and Kelton, 2000).

It is recommended that γ ≤0.15 and at $n_0 \leq 10$ (Law and Kelton, 2000). Minimum value of replication number is chosen as required replication number if $n_\gamma^*(\gamma)$ is less than or equal to γ'(Law and Kelton, 2000). The required replication number for the PAH is determined in Section 8.5.

5.7.2. Warm-up period

There exist a number of methods (i.e. Welch's method) in the determination of a warm-up period. However, it is clear that any method determining warm up period is not superior than others (Robinson, 2007). Welch's Method is a widely-used technique for determining the length of the warm-up period. This method determines warm-up period through 4 steps: (1) Simulation is run *n* replication times. (2) For each observation, all replication values ($\overline{Y_\iota}$) of a key performance metric (i.e. waiting time) is averaged. (3) Moving averages of $\overline{Y_\iota}(w)$ by using formula in Eq. (5.3). (4) Graphs of moving averages of $\overline{Y_\iota}(w)$ are obtained for each key performance metric. Then, the point where moving averages are smoothed is selected (Law and Kelton, 2000).

$$\overline{Y}_i(w) = \begin{cases} \dfrac{\sum_{s=-w}^{w} \overline{Y}_{i+s}}{2w+1} & if\ i = w+1,\ldots,m - w \\ \dfrac{\sum_{s=-(i-1)}^{i-1} \overline{Y}_{i+s}}{2i-1} & if\ i = 1,\ldots,w \end{cases} \tag{5.3}$$

Welch's method separates the simulation run length by two periods: warm-up period and data collection period. However, in this study, a hospital is intended to be projected by the proposed methodologies for one-year period as data collection period. Therefore, an approach shown in Figure 5.1 is developed to determine the appropriate warm-up period for simulation models having a fixed data collection period. To clarify the approach, the data collection period of our model is fixed (i.e. m = 12 months). The initial warm-up period is 1 month (i.e. n = 1). Thus, the simulation model run length is 13 months. According to the results, the simulation is run through 13-month run length. The warm-up period is selected as 1 month if the moving average is smoothed at the point of the initial warm-up period (i.e. 1 month). Otherwise, repeat the second step and the initial warm-up period is increased. This loop is iteratively carried out until the points for the smoothed moving average equalizes to the initial warm-up period. The warm-up period for the PAH is determined in Section 8.5.

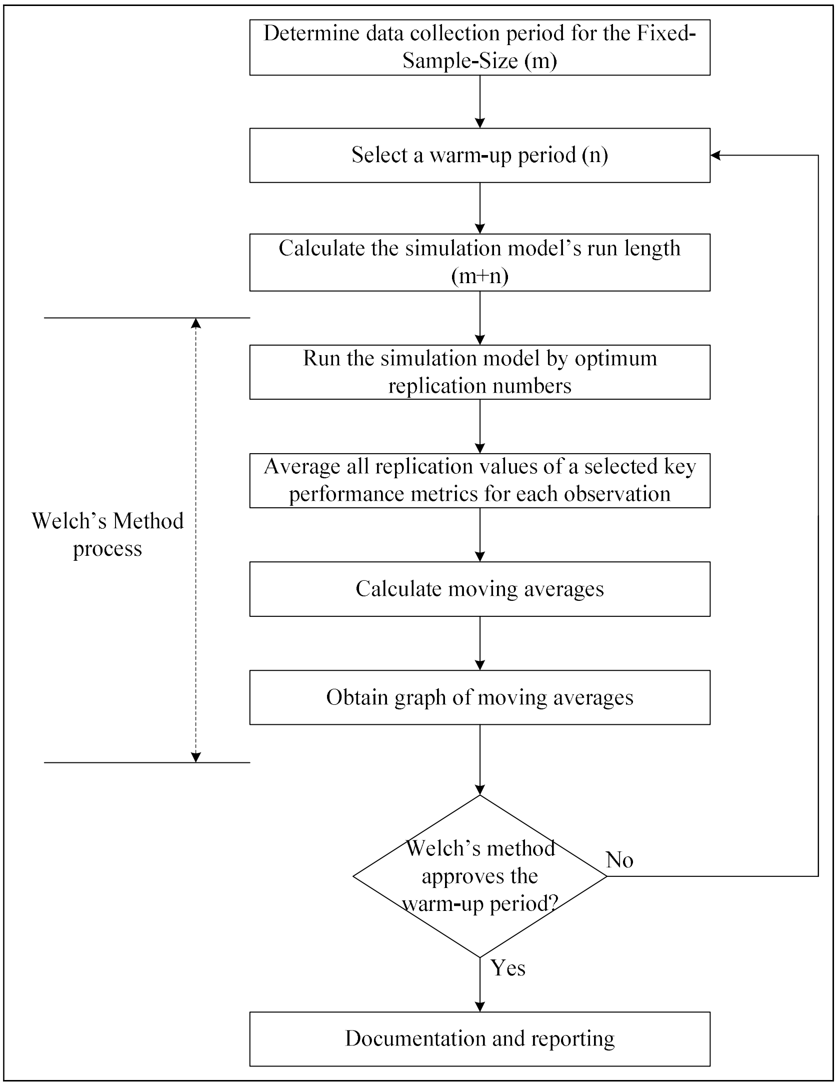

Figure 5.1: An approach combined Welch's Method for simulation models having a fixed data collection period

5.8 Validation of simulation models

Validation is a process which is carried out to test the accuracy of a developed simulation model. Banks et al. (2005) explain that validation is implemented by comparing the differences between the actual system (i.e. data) and the simulated outputs. There exists a variety of validation processes: Conceptual model validation process, white-box validation process and black-box validation process. *Conceptual model validation* is used to verify the conceptual model against the real world (problem). *White-box validation* is conducted to check whether the simulation model is logically accurate according to the real world (problem). *Black-box validation* focuses on the behaviour of the simulation model in terms of the relation of input-output (Robinson, 2004).

During the model development, we closely work with key stakeholders in the hospital and their feedback is received. The model is continually improved accordingly, and each model unit is tested for extreme conditions and logical consequences. It is decided that the model should pass the white-box validation tests. In the final demonstration of the model, which is face validation, project owners were convinced that the model is appropriate for the next usage.

In this study, black-box validation is also carried out by testing that our hospital simulation model behaves like the real system under the same input settings. As shown in Table 5.1, the validation process is conducted comparing actual outputs and simulated outputs within the confidence interval range of 95%. This method measures accuracies of models statistically. In addition, a number of current studies has used this comparison of actual and simulation outputs, for example, Demir et al. (2014), Lebcir et al. (2017), Glasgow et al. (2018) and so on. The validation of the hospital simulation model is explained in Section 8.7.

Table 5.1: Comparison of actual data and simulation results

Output parameters	Simulation	Actual	Differences	Percentage (%)
X_1	S_1	A_1	$S_1 - A_1$	$100 \times \frac{S_1 - A_1}{A_1}$
X_2	S_2	A_2	$S_2 - A_2$	$100 \times \frac{S_2 - A_2}{A_2}$
. . .	. . .	. . .	. . .	. . .
X_n	S_n	A_n	$S_n - A_n$	$100 \times \frac{S_n - A_n}{A_n}$

5.9 Experimental design and what-if scenarios

A number of alternatives (or scenarios) related to the system, which a simulation model is developed, should be specified to test the system for a variety of the purposes determined by the key decision makers (i.e. performance analysis, development of process, etc.) (Banks et al. 2005). Experimental design plays an effective role in the determination of the significant factors and levels which should affect the targets desired by the key decision makers. Therefore, experimental design is an important process to specify the scenarios to be simulated. For this, 2^k full factorial design or fractional factorial design can be applied. 2^k full factorial design, where k is number of factors, includes all combination of experiments based on maximum and minimum values of the levels. On the other hand, fractional factorial design is the reduction of the number of full factorial experiments with a certain ratio (i.e. 1/2) when the number of experiments in a full factorial design is too much (Robinson, 2004). Thus, a number of scenarios can be taken into account to investigate the effects of possible changes on performances of hospitals. For example, possible increases on hospital demands (arrivals in A&Es, admissions in inpatient services and attendances in outpatient services) can be considered, or different numbers of doctors, nurses or physicians can be tested. Therefore, changes can be tackled on the key output metrics of a hospital simulation model, for example, bed occupancy rate, utilization rates of human resources or total revenue. The experimental design and what-if analysis of this study is explained in Section 8.8.

5.10 Summary

In this chapter, typical discrete event simulation processes and steps for building a simulation model are described in greater detail. It explained why discrete event simulation (DES) is preferred to model the hospital in this study. It described the conceptualization of a system and developmental stages of a simulation model. This chapter also explained how the verification and validation of a simulation model is carried out. In addition, the determination of the required replication number and warm up period is also explained. Experimental design and what-if scenarios in simulation modelling are also explained. The next chapter gives further details related to theoretical concepts of integer linear programming.

CHAPTER 6

Integer Linear Programming

6.1 Introduction

In this chapter, theoretical concept regarding integer linear programming is presented. In Section 6.2, mathematical programming is explained. Section 6.3 introduces integer linear programming and explains why integer linear programming is selected. Section 6.4 clarifies what sensitivity analysis is and why it is important.

6.2 Mathematical programming

In developed countries, performance and capacity problems of hospitals increase as the population ages. Consequently, these problems have been significant points to take into consideration in healthcare services (Rais and Viana, 2010). Solutions have been investigated for capacity problems by using many operational research techniques. One of them is mathematical programming which has been widely used in solving capacity problems of hospitals as well as other industries. Mathematical programming is also a method used for resource allocation problems for the purposes of achieving the optimal solution (McLaughlin and Hays, 2008). In addition, it can be seen in the literature that optimization methods have been combined with simulation techniques to find better solutions.

6.3 Integer linear programming

Firstly, linear function and linear inequalities must be explained to better understand what linear programming is. **Linear function** (see Eq. 6.1) is a function of decision variables ($x_1, x_2, \ldots, x_n$) with a number of constraints ($c_1, c_2, \ldots, c_n$) (Winston, 2004).

$$f(x_1, x_2, \ldots, x_n) = c_1x_1 + c_2x_2 + \ldots + c_nx_n \quad (6.1)$$

Linear inequality (see Eq. 6.2 and 6.3) is the inequality of a linear function and y is a number (Winston, 2004).

$$f(x_1, x_2, \ldots, x_n) \le y \quad (6.2)$$

$$f(x_1, x_2, \ldots, x_n) \ge y \quad (6.3)$$

Linear programming is an optimization modelling which consists of objective function and constraints. This modelling approach involves three key points as clarified below:

- The objective function is a linear function which consists of coefficients and decision variables. The objective functions are aimed to be maximized or minimized.
- Each constraint must be stated with a linear function or a linear inequality.
- A sign restriction must be assigned to each decision variable, for example, equal to or bigger than zero (e.g. positive) (Winston, 2004).

Feasible region is defined as the region where the optimal solution is searched. The feasible region is determined by taking into account constraints and sign restrictions (Winston, 2004).

A maximization problem is solved by obtaining the optimal solution which is a point with the highest value of objective function in the feasible region. In the same way, the smallest value of objective function is searched in feasible region to solve a minimization problem (Winston, 2004).

Integer programming is a kind of linear programming on condition that all or some of decision variables must be integer and be equal to or bigger than zero. The following integer programming models are related to decision variables: **pure integer programming** (i.e. all variables are integer) and **mixed integer programming** (i.e. some of variables are integer) (Winston, 2004).

Integer linear programming covers the features of both linear and integer programming models as explained above. Eq. 6.4 gives an example for integer linear programming. This model is a maximization model so that the objective function is to maximize a linear function. In addition, all variables are an example of linear equality, and the decision variables are associated with a sign restriction (i.e. nonnegative integer) (Winston, 2004).

$$
\begin{aligned}
&\max\ z = c_1x_1 + c_2x_2 + \ldots + c_nx_n \\
&\textit{Subject to} \\
&a_{11}x_1 + a_{12}x_2 + \ldots + a_{1n}x_n = b_1 \\
&a_{21}x_1 + a_{22}x_2 + \ldots + a_{2n}x_n = b_2 \\
&. \qquad . \qquad . \qquad . \\
&. \qquad . \qquad . \qquad . \\
&. \qquad . \qquad . \qquad . \\
&a_{m1}x_1 + a_{m2}x_2 + \ldots + a_{mn}x_n = b_m \\
&x_i \geq 0\ (i=1,2,\ldots,n)
\end{aligned}
\tag{6.4}
$$

In healthcare resource allocation problems, typical decision variables (i.e. number of resources such as bed, consultant and nurse) must be nonnegative integer. In this respect, for this study, an integer linear programming has been decided to be developed to reallocate beds and optimize staffing levels.

6.3.1 Objective functions and constraints

Mathematical programming consists of three elements: Objective functions, decision variables and constraints (Winston, 2004). Objective functions provide getting desired solutions in models. In optimization models, the objective is typically either maximization or minimization. When the literature is reviewed, the objective is to maximize revenue or patients admitted to hospitals, on the other hand, it is to minimize cost, waiting times or length of stay. Furthermore, Bretthauer and Cote (1998) state hospitals have two opposite objective function types: ‘low capacity level (LCL)’ and ‘high service level (HSL)’. Getting LCL causes worse performance such as more waiting times while providing HSL means more capacity costs.

Depending upon the objective function described in the previous paragraph, a number of constraints need to be generated. In literature (see Section 2.5), mathematical models have been developed to solve capacity problems or measure the performance of hospital departments. In the context of these studies, constraints have been developed considering some factors affecting the current situations of the hospital departments (i.e. number of available beds, budget, staffing level, staffing cost and etc.). For example, the sum of the allocated beds is not able to exceed the number of available beds for a resource allocation problem. In this study the developed integer linear model for the hospital is explained in Chapter 9. Mathematical programming models can be solved using software such as LINGO, CPLEX and so on.

6.4 Sensitivity analysis

Sensitivity analysis is carried out to better understand and observe the changes on the optimal solution based on parameters of integer linear programming. Sensitivity analysis is conducted changing the values of parameters or coefficients. It is important in the optimization techniques because the parameters might change or be uncertain (Winston, 2004).

In healthcare systems, parameters may change. For example, hospital demand is based on many things. The demand increases if a nearby hospital is closed down, or in case of natural disasters in the region where the hospital serves, and so on. The hospital managements can better understand whether the hospital is able to cope with the unexpected demand increases through a sensitivity analysis (Winston, 2004).

6.5 Summary

In this chapter, fundamental concepts of integer linear programming are explained. It clarifies what objective functions and constraints are in mathematical programming. This chapter also described sensitivity analysis and its importance. The next chapter gives further detail related to a comparative analysis of demand forecasting for each specialty in a UK hospital.

CHAPTER 7

Forecasting hospital demand: The best forecasting model and period selection for each specialty

7.1 Introduction

In this chapter, the selection of the best forecasting model and period for each specialty are presented. In Section 7.2, the reasons for forecasting hospital demand are explained. Section 7.3 described the methods, and Section 7.4 illustrates the forecasting results. Section 7.4.1 gives demand estimation for the accident and emergency (A&E) department and validation of the A&E demand estimates. Section 7.4.2 and 7.4.3 shows demand estimation for outpatient and inpatient services along with validation results, respectively. Section 7.5 discusses general results.

7.2 Forecasting hospital demand

According to the National Health Services (NHS) in England, accident and emergency (A&E) departments have experienced considerably increased demand, approximately 26% from 2006/07 to 2017/18 financial year as shown in Figure 1.1 (National Health Services England, 2014 and 2018a). Severe demand causes A&E departments to run under intense pressure which results in shortage of beds, nurses, clinicians and equipment. Over the last decade, increasing waiting times and length of stay experienced by A&E departments in the UK has negatively affected daily functioning of A&E services. It is observed that waiting times and length of stay have been increasing and the 4-hour target (the percentage of patients spending 4 hours or more in hospital should be less than 5%) determined by the government has not been achieved since the financial year 2014-15 (National Health Services England, 2014 and 2018a).

In addition, over the past decade, the number of attendances and admissions to outpatient and inpatient specialties has increased by around 27% and 32%, respectively (National Health Services England, 2018b) as shown in Figure 1.2 and 1.3. The level of difficulties experienced by the hospital management around demand and capacity issues has been at an unprecedented level.

Demand for A&E beds is much greater during winter, and coupled with staff shortages, further disruptions are not just in A&E but other parts of hospital services as well (Blunt et al., 2015). For instance, NHS England has advised hospitals to postpone appointments to outpatient services during the winter of 2018 and in addition, non-urgent surgeries are also recommended to be delayed in order to reduce the pressure during the winter crisis (Iacobucci, 2018a). Furthermore, the high levels of demand have forced UK General Practitioners (GP) to reduce the number of patients referred to A&E due to inadequate capacity (Iacobucci, 2018b).

The increasing demand for hospital makes it even more difficult to manage the limited number of beds, not to mention the burden and additional workload on staff. Doctors and nurses are expected to treat more patients, thus putting patient safety at risk, which may further lead to inadequate discharges of patients. The key decision makers for each department will need to better understand the future demands to plan ahead for the needs of their local population. This may include planning for human resources, department expansion (or reduction), bed capacity requirements, and medical instrument needs.

7.3 Study methods

Hospital demand is predicted by using quantitative forecasting methods since patient admissions are used as an input to the simulation model and the optimization model. This study has been carried out in the Princess Alexandra Hospital serving in England. In this study, 36-months of data were used for the period 1 February, 2010 – 31 January, 2013. The data were trained for the forecasting methods used in this study by taking into account the period between 1 February, 2010 and 31 January, 2012. The period (1 February, 2012 – 31 January, 2013) was used to validate the forecast accuracies of out-of-samples of the models. The training set for the A&E department is shown in Figure 7.1 in three different period patterns (i.e. daily, weekly and monthly).

Many forecasting methods have been compared in hospital demand forecasting in the literature. As seen in Table 2.7 and 2.8, the autoregressive integrated moving average (ARIMA) method, exponential smoothing (ES) method and multiple linear regression method have been widely used. On the other hand, Hyndman & Athanasopoulos (2014) mention that the seasonal and trend decomposition using loess (STL) method is a reliable decomposition technique to separate the time series datasets into seasons and trends. Therefore, the STL function (STLF) method may be effective at forecasting. The STLF method has been compared with three other methods.

In the literature, the studies applying a multiple linear regression method have used dummy variables (e.g. days of week, months of year) for independent (explanatory) variables. In this study, stepwise linear regression methods involve the use of dummy variables. For example, the regression models include days-of-week (if daily is estimated), order of weeks (if weekly is estimated), months-of-year and variables related to holidays for all periods (a day before a holiday, a day after holiday, and the holiday itself).

In this dataset, values of independent variables for each day in the period examined are specified. For example, 1st April 2010 is a Thursday and the value of the independent variable (Thursday) is coded as 1 and 0 otherwise (i.e. the remaining days are coded as 0). In addition, UK public holidays (i.e. bank holidays, New Year's Day and so on) are taken into account as a "holiday" independent variable.

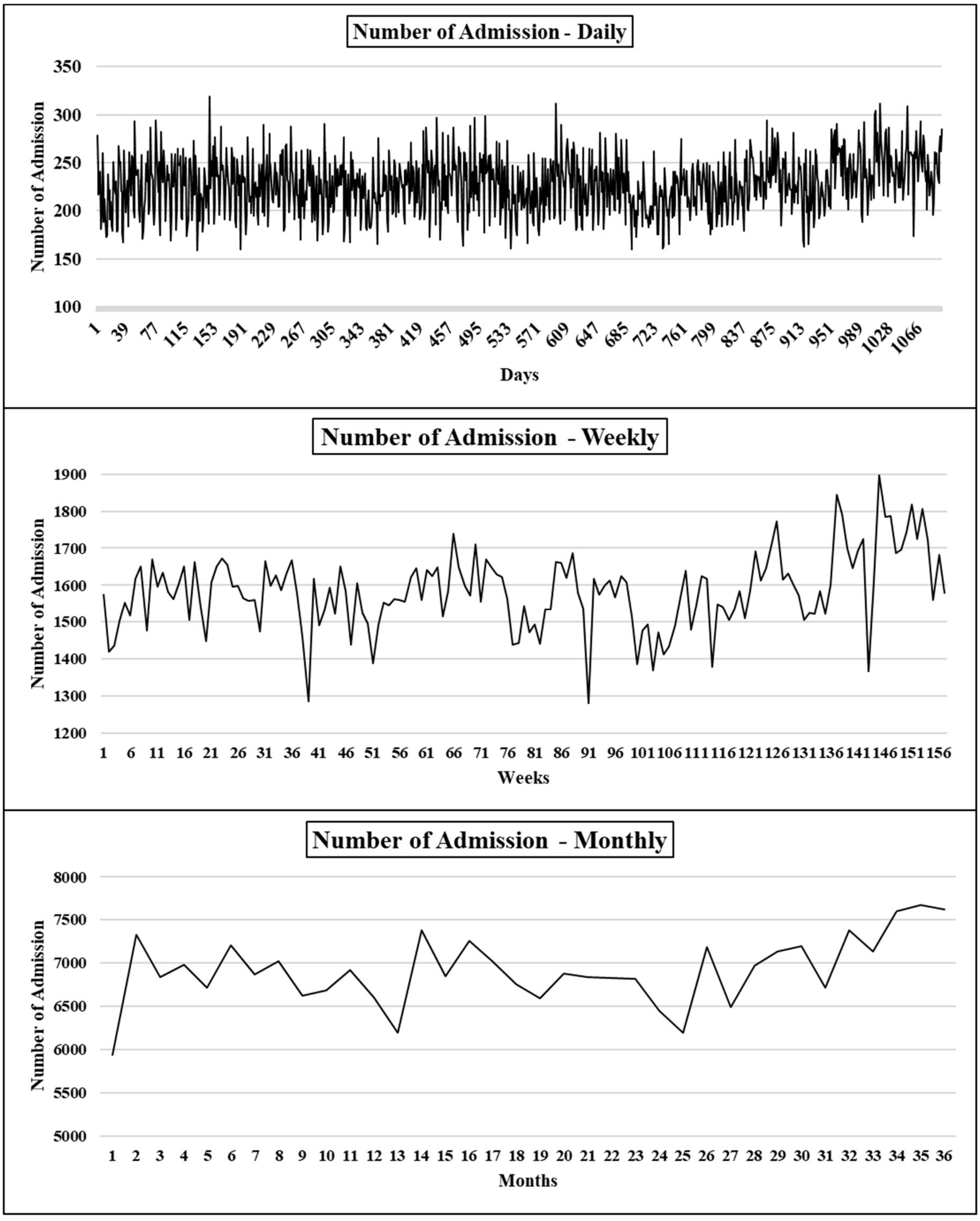

Figure 7.1: Graphs of the A&E demand under different periods

7.4 Forecasting results

This section provides greater details regarding the forecasting results for the A&E department, all outpatient and inpatient services, respectively. Comparative forecasting results for all outpatient first and follow up specialties are given in Appendix 5 and 6 whereas the results for all inpatient elective and non-elective specialties are given in Appendix 7 and 8.

7.4.1 Accident and emergency (A&E) department

This study was carried out using the data from the Princess Alexandra Hospital located in Harlow, England. The average number of A&E admissions per year is 82,535 patients over the study period. The A&E department operates 7 days a week and 24 hours a day. In addition, the A&E is a 22-bed department and treats on average of 227 patients per day (standard deviation [SD] ± 28.71), which equates to 1580 patients per week (standard deviation [SD] ± 108.85) and 6914 patients per month (standard deviation [SD] ± 392.17). Figure 7.2 shows the percentage of changes on the number of admissions to Princess Alexandra Hospital A&E department when the same month is compared against the previous year. According to Figure 7.2, admissions showed increases in 3-year data (i.e. 2010 to 2013), despite observing a decrease in January, March and July. For example, the demand increased by 3.26%, 4.27% and 6.59% in October 2010 to 2011, 2011 to 2012 and 2012 to 2013, respectively. Figure 7.2 also showed year on year increase in A&E admissions, for example, the demand increased significantly from September to March in almost every year (e.g. the demand increased by 2.08%, 11.39% and 1.09% in November 2010 to 2011, 2011 to 2012 and 2012 to 2013 respectively, and by 14.91% in the same month 2010 to 2013). This figure illustrates some evidence of the winter demand pressures experienced by Princess Alexandra Hospital A&E services (particularly in October, November, December and February). This situation means that the hospital management needs to better understand the most accurate forecasted future demand well in advance.

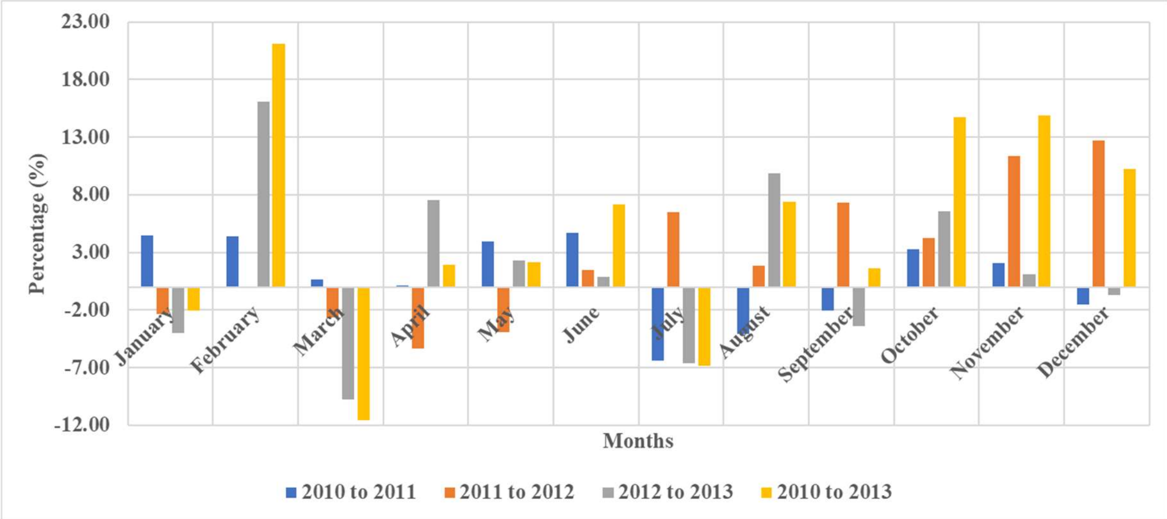

Figure 7.2: The percentages of increases/decreases on demand

As explained in Chapter 4, mean absolute scaled error (MASE) is used to calculate goodness of fit and forecast accuracies of forecasting methods. For the A&E department, the MASE values for goodness of fit (in sample) and forecast accuracy (out-of-sample) values are shown in Table 7.1.

Table 7.1: Forecast accuracy values for the A&E department

Periods	Forecasting Models	Daily		Weekly		Monthly	
		Parameters	MASE	Parameters	MASE	Parameters	MASE
Training Sets	SLR	SLR	0.62	SLR	0.76	SLR	0.44
	ARIMA	(2,1,1)	0.76	(0,1,3)	0.84	(0,1,1)	0.79
	ES	(A,N,N)	0.79	(M,N,N)	0.87	(A,N,N)	0.83
	STLF	(A,N,N)	0.81	(A,N,N)	0.78	(A,N,N)	0.49
Validation Sets	SLR	SLR	0.78	SLR	0.94	**SLR**	**0.53**
	ARIMA	(2,1,1)	1.01	(0,1,3)	1.05	(0,1,1)	1.08
	ES	(A,N,N)	1.01	(M,N,N)	1.40	(A,N,N)	1.04
	STLF	(A,N,N)	1.02	(A,N,N)	1.34	(A,N,N)	1.52

ARIMA: Autoregressive integrated moving average, ES: Exponential smoothing, SLR: Stepwise Linear Regression, MASE: Mean Absolute Scaled Error, STLF: The function of the seasonal and trend decomposition method

7.4.1.1 Model evaluation for A&E department

7.4.1.1.1 ARIMA

Taking into account autocorrelation and partial autocorrelation functions, ARIMA method determined the best fitting models with the parameter values (2,1,1), (0,1,3) and (0,1,1) for daily, weekly and monthly estimations, respectively. The results indicate that there were non-stationarity patterns in all time series data. Only first differences of time series were taken and the parameter d in all ARIMA models is 1. In addition, the observation Y_t was regressed on the observations Y_{t-1} and Y_{t-2} in only ARIMA model (i.e. p equals 2) for daily estimation, whereas there were uncorrelated data for others (i.e. p is 0). This means that to predict demand the model only requires the previous two activity related items of data, e.g., if we wanted to predict for Wednesday we only use the number of admissions on Tuesday and Monday. However, the MASE estimates in the validation set for daily, weekly and monthly were very poor, thus we would not endorse the use of ARIMA for this particular hospital.

7.4.1.1.2 Exponential Smoothing (ES)

The RStudio forecast package uses an automatic function proposed by Hyndman and Khandakar (2008) to find the best exponential smoothing method amongst all types of ES methods. Applying this function, the best exponential smoothing methods along with additive error, no trend and no seasonality were determined for daily and monthly estimations. On the other hand, weekly estimation was carried out by the parameter with multiplicative error, no trend and no seasonality. The exponential smoothing method for weekly and monthly periods was the worst method in terms of in-sample goodness of fit amongst all forecasting methods used in this study. The ES method for daily estimation outperformed only the STLF method. Again, we will not endorse the use of ES to forecast demand at Princess Alexandra Hospital.

7.4.1.1.3 STLF

The STLF models converted the time series data to deseasonalised data applying STL decomposition method. According to the results, an exponential smoothing method (with additive error, no trend and no seasonality) as non-seasonal forecasting method was used to forecast the A&E demand for three periods. The STLF method achieved the worst MASE value in daily estimation, whereas it presented a good result with 0.4885 MASE value in forecasting the demand monthly. The STLF method applied similar parameters (but their values are different) with the ES model in monthly estimation. However, decomposing the data before demand forecasting played an effective role for decreasing the MASE value (i.e. 0.8250 to 0.4885) significantly. The results from the SLTF show that the A&E activity at Princess Alexandra Hospital has no trend or seasonality according to the MASE values, thus the STLF in the validation sample produced poor MASE value.

7.4.1.1.4 Stepwise Linear Regression Model

The stepwise linear regression found the best regression model including the explanatory variables relevant to the dependent variable from the initial model including all explanatory variables. Performance indicators of all regression models were calculated such as R^2, adjusted R^2, AIC and p-value as given in Table 7.2.

In the dataset, values of independent variables for each day in the period examined are specified. For example, 1st February 2010 is a Monday and the value of the independent variable (Monday) is coded as 1 and 0 otherwise (i.e. the remaining days are coded as 0). In addition, UK public holidays (i.e. bank holidays, New Year's Day and so on) are taken into account as a "holiday" independent variable.

A&E demand was also estimated by stepwise linear regression models including dummy variables under different periods. The model was trained for the period 1 February, 2010 – 31 January, 2012 and validated using period 1 February, 2012 – 31 January, 2013. In order to solve the model, the statistical software RStudio *(library package MASS)* was used. The StepAIC () function in R was applied and the function selects the best model with the lowest AIC for each period taking into account the Akaike's Information Criterion as goodness of fit. All results are shown with the performance indicators in Table 7.2.

According to the adjusted R^2 measure, monthly SLR produced the best goodness of fit, meaning that approximately 60% of the variation in demand estimates are explained using the 7 independent variables (all significant at 5% level). Table 7.2 also shows that the adjusted R^2s were very low for the linear regression models in both daily and weekly estimation periods. The stepwise linear regression model in monthly estimation generated the lowest MASE values for both the training and the validation sets according to the goodness of fit and forecast accuracy. Considering the results of the stepwise linear regression model in monthly estimation, it is apparent that 7 independent variables affect the model. The remaining 8 independent variables do not contribute to the model significantly.

Table 7.2: Independent variables, their coefficients of the linear regression models for the A&E department

Variables	Stepwise Linear Regression		
	Daily	Weekly	Monthly
Intercept	242.65(***)	1622.36(***)	6991.00(***)
Monday	10.14(***)	-	-
Tuesday	NA	-	-
Wednesday	-6.18(*)	-	-
Thursday	-4.02	-	-
Friday	-26.29(***)	-	-
Saturday	-32.03(***)	-	-
Sunday	NA	-	-
January	-11.73(***)	-98.50(**)	-581.64(**)
February	-18.77(***)	-102.19(***)	-883.33(***)
March	-7.68(*)	NA	308.33(.)
April	-7.08(*)	NA	-382.81(*)
May	-4.87	NA	NA
June	NA	58.49(*)	NA
July	-6.46(*)	NA	NA
August	-16.68(***)	-42.64	-379.81(*)
September	NA	83.26(**)	NA
October	-12.87(***)	NA	NA
November	NA	63.37(.)	NA
December	NA	98.47(**)	NA
Order of Week	-	-1.58(.)	-
Day before a holiday	-34.73(***)	-43.15	-1101.50(**)
Holiday	NA	NA	1219.64(***)
Day after a holiday	NA	NA	NA
Performance indicators			
AIC	10347.35	1894.10	509.14
R-squared	0.2553	0.2545	0.6797
Adjusted R-squared	0.2456	0.2088	0.5997
p-value	<2.2e-16	<2.2e-16	<2.2e-16

Significance codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

NA: Not Available. AIC: Akaike’s Information Criterion

The estimated coefficient for January (-581.64) decreases A&E activity, whereas the holiday variable increases the estimated patient demand (1519.50). This may seem like a surprise, but according to Figure 7.2 year on year A&E admissions at Princess Alexandra Hospital in January is decreasing, thus our findings are in agreement with the dataset. As expected the holiday variables are significant, meaning closure of primary care services (e.g. general practitioners) during holiday season has a negative impact on A&E services.

The proposed forecasting approach will provide many benefits to the management of A&E departments. It will enable them to foresee patient demands for their hospitals in future and test whether these demands are met with their available resources. Twelve forecasting methods were developed to forecast A&E demand under different periods. A comparison of the forecast accuracy revealed that taking the validation set into account, the stepwise linear regression models were the most accurate forecasting models with a MASE of 0.7828, 0.9354 and 0.5259 for daily, weekly and monthly, respectively. According to the results, The Princess Alexandra Hospital A&E department should forecast demand on a monthly basis using the stepwise linear model, because it provides more accurate estimates compared to others.

7.4.1.3 Validation of the predicted A&E demand

We compared the best forecasting result and actual value by using a paired t test which is determined as a formula in Eq. (7.1).

$$t_0 = \frac{\bar{d} - \mu_d}{S_d / \sqrt{K}} \tag{7.1}$$

where $\bar{d}$ denotes average observed differences between actual values and simulation result, μ_d is mean difference, S_d denotes the standard deviation and K is the number of input data set (Banks et al. 2005). As a result, t test value is 1.56 and t critical value is 2.20. Therefore, the forecasted demand is validated since t test values ($|t_0|$) are less than or equal to t critical values ($t_{\alpha/2,K-1}$) at 5% significance level. In addition, average monthly number of admissions is 6990 and, lower and upper confidence intervals are 6698 and 7282, respectively. The validation graph for the best forecasting period against actual data under the best forecasting method is shown in Figure 7.3.

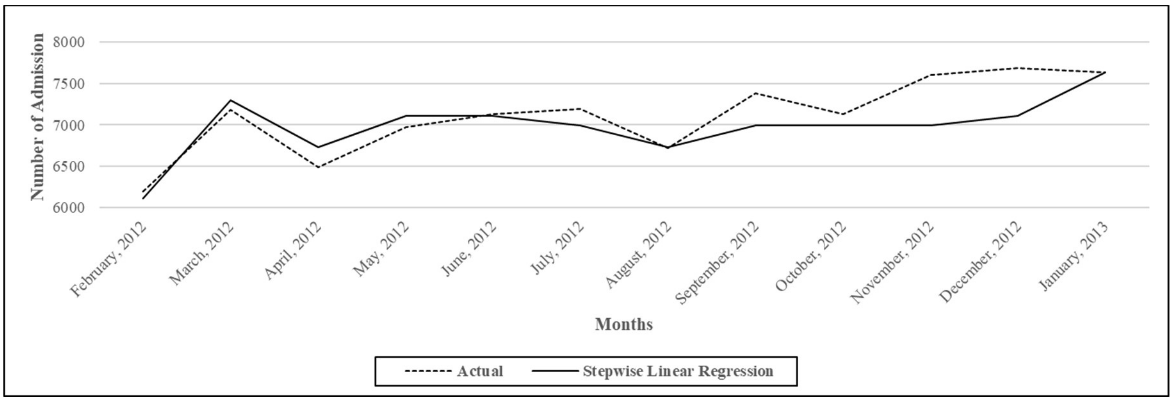

Figure 7.3: Validation graph of the A&E demand for the best period (i.e. monthly)

7.4.2 Outpatient services

This study was conducted using the data belonging to all outpatient specialties of the Princess Alexandra Hospital located in Harlow, England. The average number of first and follow up attendances per year is respectively 69528 and 155952 patients over the study period. Table 7.3 gives basic statistics for the first referrals of all outpatient specialties. For example, the trauma & orthopaedics outpatient service operates 5 days a week and 8 hours a day. In addition, the trauma & orthopaedics outpatient service have average 42 patient activities per day (standard deviation [SD] ± 19.31), which equates to 213 patient activities per week (standard deviation [SD] ± 48.45) and 928 patient activities per month (standard deviation [SD] ± 117.23) for the first referrals. General surgery outpatient specialty has the highest second patient volume whereas the lowest number of patients (i.e. first referral) are in the clinical oncology outpatient specialty. Table 7.4 gives basic statistics for the follow up referrals of all outpatient specialties. For example, for the follow up referrals, the trauma & orthopaedics outpatient service have average 87 patient activities per day (standard deviation [SD] ± 27.72), which equates to 430 patient activities per week (standard deviation [SD] ± 71.62) and 1874 patient activities per month (standard deviation [SD] ± 217.79). There exists the highest number of patients (i.e. follow up referral) in the obstetrics outpatient specialty whereas the neurology outpatient specialty has the lowest number of patients with follow up treatments.

Table 7.3: The basic statistics for the first referrals of all outpatient specialties over the study period

Specialties	Daily		Weekly		Monthly	
	A	SD	A	SD	A	SD
General Surgery	29	12.07	140	29.87	611	70.83
Urology	14	8.14	56	14.64	244	30.96
Trauma & Orthopaedics	42	19.31	213	48.45	928	117.23
Ear, Nose and Throat (ENT)	19	8.41	94	23.90	411	64.89
Ophthalmology	22	9.97	106	32.71	460	109.52
Oral Surgery	13	9.45	49	17.59	215	35.73
Anaesthetics	4	4.04	17	9.01	73	23.92
General Medicine	15	9.59	78	20.19	341	64.79
Gastroenterology	9	5.23	22	12.41	96	37.13
Clinical Haematology	7	3.27	33	8.77	142	29.71
Cardiology	16	7.10	77	18.93	335	48.79
Dermatology	16	9.50	69	18.82	302	62.82
Neurology	8	4.89	31	9.67	136	25.83
Rheumatology	6	3.08	25	7.05	110	17.94
Paediatrics	13	7.91	73	16.38	317	44.09
Obstetrics	11	7.04	57	36.80	248	149.86
Gynaecology	27	9.78	132	26.27	575	91.76
Clinical Oncology	4	2.58	16	5.50	71	11.33
Others	8	5.42	41	11.65	179	33.97

A: Average number of patients; SD: Standard Deviation

Table 7.4: The basic statistics for the follow up referrals of all outpatient specialties over the study period

Specialties	Daily		Weekly		Monthly	
	A	SD	A	SD	A	SD
General Surgery	28	14.71	133	35.12	580	81.24
Urology	27	14.83	131	30.19	570	94.61
Trauma & Orthopaedics	87	27.72	430	71.62	1874	217.79
Ear, Nose and Throat (ENT)	20	9.51	99	24.62	432	61.23
Ophthalmology	68	22.54	329	67.39	1434	196.98
Oral Surgery	15	10.26	70	20.09	306	63.10
Anaesthetics	51	20.19	250	82.89	1089	334.03
General Medicine	31	20.47	162	48.60	706	166.53
Gastroenterology	12	7.64	29	16.41	127	56.36
Clinical Haematology	26	13.46	96	24.62	418	83.84
Cardiology	17	8.88	80	22.53	351	57.88
Dermatology	19	12.43	90	27.04	392	91.09
Neurology	9	6.30	31	10.15	137	27.88
Rheumatology	17	6.29	81	19.63	354	46.20
Paediatrics	15	10.35	87	21.10	377	51.30
Obstetrics	73	58.68	507	326.85	2207	1407.90
Gynaecology	37	17.10	198	31.87	862	83.19
Clinical Oncology	22	13.43	104	21.69	454	53.35
Others	16	10.33	75	20.83	326	61.06

A: Average number of patients; SD: Standard Deviation

Comparative forecasting results for all outpatient first and follow up specialties are given in Appendix 5 and 6 whereas Table 7.5 summarizes only the best forecasting models and periods for both first and follow up referrals of all outpatient specialties.

In conclusion, as seen in Table 7.5, the best forecasting methods for all outpatient specialties are summarized below.

- 11 SLR methods for first referrals and 7 SLR methods for follow up referrals
- 1 ARIMA method for first referrals and 6 ARIMA methods for follow up referrals
- 3 ES methods for first referrals and 4 ES methods for follow up referrals
- 4 STLF methods for first referrals and 2 STLF methods for follow up referrals

The best forecasting periods (see Table 7.5) for all outpatient specialties are summarized below.

- 14 daily estimations for first referrals and 12 daily estimations for follow up referrals
- 1 weekly estimation for first referrals and 3 weekly estimations for follow up referrals
- 4 monthly estimations for first referrals and 4 monthly estimations for follow up referrals

Table 7.5: Forecasting results for all outpatient specialties

Outpatient specialties	First referrals		Follow up referrals	
	Forecasting model	Forecasting period	Forecasting model	Forecasting period
General Surgery	SLR	Daily	SLR	Daily
Urology	SLR	Daily	SLR	Daily
Trauma & Orthopaedics	SLR	Daily	STL+ETS(A,N,N)	Daily
Ear, Nose and Throat (ENT)	SLR	Daily	ARIMA (1,1,3)	Daily
Ophthalmology	ETS(A,N,N)	Daily	ETS(A,N,N)	Daily
Oral Surgery	ETS(M,N,N)	Monthly	STL+ETS(A,N,N)	Monthly
Anaesthetics	SLR	Daily	SLR	Daily
General Medicine	SLR	Daily	ARIMA (0,1,1)	Weekly
Gastroenterology	STL+ETS(A,N,N)	Daily	ETS(A,N,N)	Daily
Clinical Haematology	SLR	Daily	SLR	Daily
Cardiology	SLR	Daily	SLR	Monthly
Dermatology	STL+ETS(A,N,N)	Daily	ETS(M,N,N)	Weekly
Neurology	STL+ETS(M,N,N)	Monthly	ARIMA (5,1,0)	Daily
Rheumatology	SLR	Daily	SLR	Daily
Paediatrics	SLR	Daily	ARIMA (5,1,3)	Daily
Obstetrics	STL+ETS(A,N,N)	Monthly	ETS(M,A,N)	Monthly
Gynaecology	SLR	Daily	SLR	Daily
Clinical Oncology	ARIMA (4,0,0)	Weekly	ARIMA (0,1,1)	Weekly
Others	ETS(M,A_d,N)	Monthly	ARIMA (0,1,1)	Monthly

ARIMA: Autoregressive integrated moving average, ES: Exponential smoothing, SLR: Stepwise linear regression, STLF: The function of the seasonal and trend decomposition method

7.4.2.2 Validation of the predicted demand of an outpatient service

We compared the best forecasting result and actual value by using a paired t test which is determined as a formula in Eq. (7.1). In the case of the trauma & orthopaedics outpatient specialties, *t* test value is 0.66 for first referrals and 1.25 for follow up referrals, and *t* critical value is 2.20. Therefore, the forecasted demand is validated since t test values ($|t_0|$) are less than or equal to t critical values ($t_{\alpha/2,K-1}$) at 5% significance level. In addition, average monthly number of attendances for the first referrals is 1191 and, lower and upper confidence intervals are 1063 and 1320, respectively. Average monthly number of attendances for the follow up referrals is 639 and, lower and upper confidence intervals are 606 and 672, respectively. All forecasted demands of all outpatient specialties for first and follow up attendances are validated by using paired *t* test.

7.4.3 Inpatient services

This study was carried out using the data belonging to all inpatient specialties of the Princess Alexandra Hospital located in Harlow, England. The average number of elective and non-elective admissions per year is respectively 30588 and 33132 patients over the study period. Table 7.6 gives basic statistics for the elective admissions of all inpatient specialties. For example, the trauma & orthopaedics inpatient service operates 5 days a week and 8 hours a day. In addition, the trauma & orthopaedics inpatient service have average 13 patient activities per day (standard deviation [SD] ± 5.88), which equates to 71 patient activities per week (standard deviation [SD] ± 18.52) and 308 patient activities per month (standard deviation [SD] ± 64.81) for the elective admissions. General surgery inpatient specialty has the highest elective patient volume whereas the paediatrics inpatient specialty is visited by the lowest number of patients. Table 7.7 gives basic statistics for the non-elective admissions of all inpatient specialties. For example, for the non-elective admissions, the trauma & orthopaedics inpatient service have average 4 patient activities per day (standard deviation [SD] ± 2.21), which equates to 30 patient activities per week (standard deviation [SD] ± 7.59) and 132 patient activities per month (standard deviation [SD] ± 21.07). Two inpatient specialties (i.e. cardiology and gynaecology) have the highest number of non-elective patients whereas the lowest number of non-elective patients visits the trauma & orthopaedics inpatient specialty.

Table 7.6: The basic statistics for the elective admissions of all inpatient specialties over the study period

Specialties	Daily		Weekly		Monthly	
	A	SD	A	SD	A	SD
General Surgery	13	6.01	70	17.58	304	54.60
Urology	14	7.67	69	24.20	303	90.61
Trauma & Orthopaedics	13	5.88	71	18.52	308	64.81
Ear, Nose and Throat (ENT)	5	2.04	18	5.99	78	15.27
Ophthalmology	8	5.21	33	13.41	145	44.42
Oral Surgery	7	3.63	30	12.99	133	49.42
General Medicine	9	5.16	48	20.44	209	82.20
Gastroenterology	5	3.38	25	13.28	109	54.46
Clinical Haematology	11	3.42	53	9.30	231	30.64
Cardiology	6	2.77	20	8.98	88	19.58
Medical Oncology	4	2.34	16	4.89	70	17.21
Paediatrics	2	2.35	9	3.60	40	13.25
Gynaecology	6	2.88	31	7.30	137	19.08
Clinical Oncology	9	3.89	45	8.53	194	25.21
Radiology	7	4.19	32	10.00	141	32.24
Others	4	3.62	14	8.78	59	28.82

A: Average number of patients; SD: Standard Deviation

Table 7.7: The basic statistics for the non-elective admissions of all inpatient specialties over the study period

Specialties	Daily		Weekly		Monthly	
	A	SD	A	SD	A	SD
General Surgery	9	3.53	66	11.86	287	34.50
Trauma & Orthopaedics	4	2.21	30	7.59	132	21.07
General Medicine	18	6.55	124	20.65	539	60.53
Cardiology	3	1.71	20	5.82	86	17.17
Paediatrics	7	2.87	46	10.99	200	36.76
Geriatric Medicine	19	6.67	136	22.74	591	59.88
Obstetrics	22	6.82	155	25.17	673	80.77
Gynaecology	6	2.92	41	10.48	179	34.09
Others	3	2.56	17	13.27	74	53.75

A: Average number of patients; SD: Standard Deviation

Comparative forecasting results for all inpatient elective and non-elective specialties are given in Appendix 7 and 8 whereas Table 7.8 summarizes only the best forecasting models and periods for both elective and non-elective admissions of all inpatient specialties.

In conclusion, as seen in Table 7.8, the best forecasting methods for all inpatient specialties are summarized below.

- 8 SLR methods for elective admissions and 1 SLR method for non-elective admissions
- 5 ARIMA methods for elective admissions and 6 ARIMA methods for non-elective admissions
- 3 ES methods for elective admissions and 1 ES method for non-elective admissions
- 0 STLF method for elective admissions and 1 STLF method for non-elective admissions

The best forecasting periods (see Table 7.8) for all inpatient specialties are summarized below.

- 8 daily estimations for elective admissions and 5 daily estimations for non-elective admissions
- 5 weekly estimations for elective admissions and 1 weekly estimation for non-elective admissions
- 3 monthly estimations for elective admissions and 4 monthly estimations for non-elective admissions

Table 7.8: Forecasting results for all inpatient specialties

Inpatient specialties	Elective		Non-elective	
	Forecasting Model	Forecasting Period	Forecasting Model	Forecasting Period
General Surgery	SLR	Daily	ARIMA (0,1,1)	Daily
Urology	ETS(M,A_d,N)	Weekly	-	-
Trauma & Orthopaedics	ARIMA (2,1,3)	Daily	ARIMA (0,1,1)	Weekly
Ear, Nose and Throat (ENT)	SLR	Daily	-	-
Ophthalmology	ARIMA (0,1,0)	Monthly	-	-
Oral Surgery	SLR	Daily	-	-
General Medicine	ETS(M,A,N)	Monthly	STL+ETS(A,N,N)	Monthly
Gastroenterology	SLR	Daily	-	-
Clinical Haematology	SLR	Weekly	-	-
Cardiology	SLR	Daily	ETS(A,N,N)	Monthly
Medical Oncology	SLR	Daily	-	-
Paediatrics	ARIMA (0,1,3)	Weekly	ARIMA (1,1,1)	Daily
Geriatric Medicine	-	-	ARIMA (0,1,2)	Daily
Obstetrics	-	-	ARIMA (0,1,1)	Daily
Gynaecology	ARIMA (1,0,0)	Monthly	SLR	Monthly
Clinical Oncology	SLR	Daily	-	-
Radiology	ARIMA (0,1,1)	Weekly	-	-
Others	ETS(M,A_d,N)	Weekly	ARIMA (0,1,1)	Daily

ARIMA: Autoregressive integrated moving average, ES: Exponential smoothing, SLR: Stepwise linear regression, STLF: The function of the seasonal and trend decomposition method

7.4.3.2 Validation of the predicted demand of an inpatient service

We compared the best forecasting result and actual value by using a paired t test which is determined as a formula in Eq. (7.1). In the case of the trauma & orthopaedics inpatient specialties, t test value is 1.49 for elective admissions and 0.61 for non-elective admissions, and t critical value is 2.20. Therefore, the forecasted demand is validated since t test values ($|t_0|$) are less than or equal to t critical values ($t_{\alpha/2,K-1}$) at 5% significance level. In addition, average monthly number of the elective admissions is 273 and, lower and upper confidence intervals are 268 and 278, respectively. Average monthly number of the non-elective admissions is 128 and, lower and upper confidence intervals are 112 and 144, respectively. All forecasted demands of all inpatient specialties for elective and non-elective admissions are validated using paired t test.

7.5 General results and discussion

Hospital demand is predicted by using quantitative forecasting methods since patient inpatient admissions, outpatient attendances and A&E admissions are used as an input into the simulation and optimization model. The data were divided into two sets: the training set (i.e. the first two years of data) and the validation set (i.e. the last year of data).
The autoregressive integrated moving average (ARIMA) method, exponential smoothing (ES) method, stepwise linear regression method and the seasonal and trend decomposition using loess function (STLF) method were applied for the comparative analysis. In total 768 forecasting models were developed, made up of the following:

- 19 outpatient specialties x 2 (first and follow up referrals separately) x 3 periods (daily, weekly and monthly) x 4 forecasting methods, which is 456 models for outpatients.
- 16 inpatient specialties (for elective admissions) x 3 periods (daily, weekly and monthly) x 4 forecasting methods, which is 192 models for inpatients.
- 9 inpatient specialties (for non-elective admissions) x 3 periods (daily, weekly and monthly) x 4 forecasting methods, which is 108 models for inpatients.
- 1 A&E department x 3 periods (daily, weekly and monthly) x 4 forecasting methods, which is 12 models for A&E.

Using MASE, 64 best forecasting models and periods as shown are selected out of 768 models, i.e., 38 forecasted demand for outpatient specialties, 25 for inpatient specialties, and 1 for A&E.

This study indicates that forecasting hospital demand under different periods might generate more accurate result even if the past studies have preferred daily period to estimate hospital demand. This study shows that the best demand estimates are based on different forecasting methods and forecasting periods. Unlike the current and past studies conducted in the literature, our study filled a major gap by comparing different forecasting periods (i.e. daily, weekly and monthly). In addition, we also tested with a forecasting methodology that has never been considered within a healthcare setting before (i.e. the STLF method). It proves that the STLF method outperformed traditional time series forecasting methods (i.e. ARIMA, exponential smoothing) for a number of specialties, despite the method being applied for the first time. For instance, according to MASE, the STLF method was superior for the non-elective admissions in the general medicine specialty as seen in Table 7.8. In addition, this study highlights that hospital managements will need to take into consideration different forecasting periods to better estimate hospital demands.

As the complexity of healthcare services increases in an environment of constrained resources and increasing demand, so too does the need for evidence-based decision making. Reliable and accurate forecasting models are well positioned to provide that evidence and allow hospital service managers face upcoming challenges with greater confidence.

Hospital managers are very well aware that hospitals are at breaking point in most parts of the country, with patients sitting for hours in departments waiting for a bed. As such, accurate and reliable long term hospital forecasting models are required to assess and respond to the needs of local populations, both currently and in the future. This study will therefore enable key decision makers to better understand the demand for A&E, outpatient and inpatient services, thus the opportunity to effectively plan ahead for resource requirements (e.g. doctors and nurses).

7.6 Summary

In this chapter, the best forecasting models and periods for each specialty are selected. The reasons of forecasting hospital demand are explained. In addition, the study methods are described, and the forecasting results are analysed. Demand estimations for the A&E department, outpatient and inpatient services, and validation of the demand estimates are highlighted. Next chapter explains the generic hospital simulation modelling in greater detail. The next chapter gives further detail related to the development of a generic hospital simulation model integrated with comparative forecasting to better understand and balance current and future demand and capacity of a UK hospital.

CHAPTER 8

Modelling demand and capacity of the Princess Alexandra Hospital: A generic hospital simulation model combined with forecasting techniques

8.1 Introduction

In this chapter, the developed generic hospital simulation model integrated with forecasting techniques is presented. In Section 8.2, the verified conceptualized pathway is explained. Section 8.3 gives inputs used in this study. Section 8.3.1 clarifies the inputs for the accident and emergency (A&E) department; Section 8.3.2 explains the inputs for the outpatient services and Section 8.3.3 describes the inputs for the inpatient services. Section 8.4 introduces the developed simulation models. Section 8.5 illustrates how the optimum replication number and the warm up period are calculated. Section 8.6 gives the outputs generated from this study. Section 8.7 explains how the developed simulation model is validated. Section 8.8 describes the experimental design and scenario analysis. Section 8.9 discusses the general results.

8.2 Verified the conceptualized pathway

The first stage of the pathway mapping was to research the current practices within the hospital. This included utilising publications from the literature, which allowed to draft a baseline patient pathway within a hospital setting, including a high-level mapping of A&E, inpatient and outpatient pathway. Once the initial pathway is established, the second phase consisted of structured interviews with hospital consultants, nurses, clinical and financial directors.

The interviews were conducted face to face sharing the initial diagrammatic representation of the pathway. Each stage of the pathway was discussed with the panel taking account of their opinions and adjusting the pathway in 'real-time' as comments were made. The objective of this process is to explore the entire hospital pathway in the eyes of the experts and identify the important areas of development. It is also crucial to establish a pathway that is generic enough so that it is applicable to all NHS providers in England.

According to the interviews the typical care system in place in England, within inpatient, outpatient and A&E services, comprises a complex set of services offered in and out of hospital. In this context, the pathway consists of three parts: A&E department, outpatient and inpatient specialties (Figure 8.1). Also, the interactions among the departments were taken into account.

In this pathway, there are four different patient arrival types in the A&E department: patients can be referred from GPs, self-admission, emergency, or others (i.e. referral from educational establishments and general dental practitioner). Upon arriving to A&E, patients are registered by the receptionist and pre-assessment process (e.g. blood pressure) is carried out by a nurse. Patients then wait to be seen by a doctor. Doctors may request further investigations, such as X-ray, urinalysis, biochemistry, etc. Depending on patient's condition, they can either be admitted to inpatient care, discharged back to primary care; discharged to an outpatient department, discharged by death, or discharged home with no further action.

Patients can be referred to outpatient specialties either from GPs, self-attendance, from A&E department of the same hospital, and others (i.e. referral from optometrist and general dental practitioner). Patients may be booked for outpatient attendance after referral. At this point, some patients may cancel their appointments in advance or not attend the clinic without prior notice (some of these patients may rebook an appointment for a later date). Once a patient comes into an outpatient specialty, they check in at the reception and wait for treatment. If needed, a diagnostic procedure can be carried out before assessment and in some cases a treatment procedure could also be carried out by a consultant. After consultation, patients can either be discharged home, or can be admitted to an inpatient department if further treatment is necessary, or referred to the outpatient specialty for follow up treatments.

Patients in a typical inpatient specialty are referred in the following ways: patients can be referred from GPs, from an A&E department or outpatient specialty of the same hospital and others (i.e. dental casualty department). Admission is also divided by two types: elective and non-elective. Elective admission consists of an appointment made prior to admission, whereas non-elective admission comprises patients who are mostly referred from A&E department and in some cases GPs. Elective patient waits to be admitted to inpatient specialty, anything from a few days to 18 weeks. After patient arrival and booking process, pre-assessment is performed, and it is decided whether patient is admitted to a specialty ward for care or not. If patient is not admitted to a ward, a day case procedure is carried out. Otherwise, patient is admitted, and a theatre process is carried out if needed. Then, the patient can either be discharged home or discharged due to death.

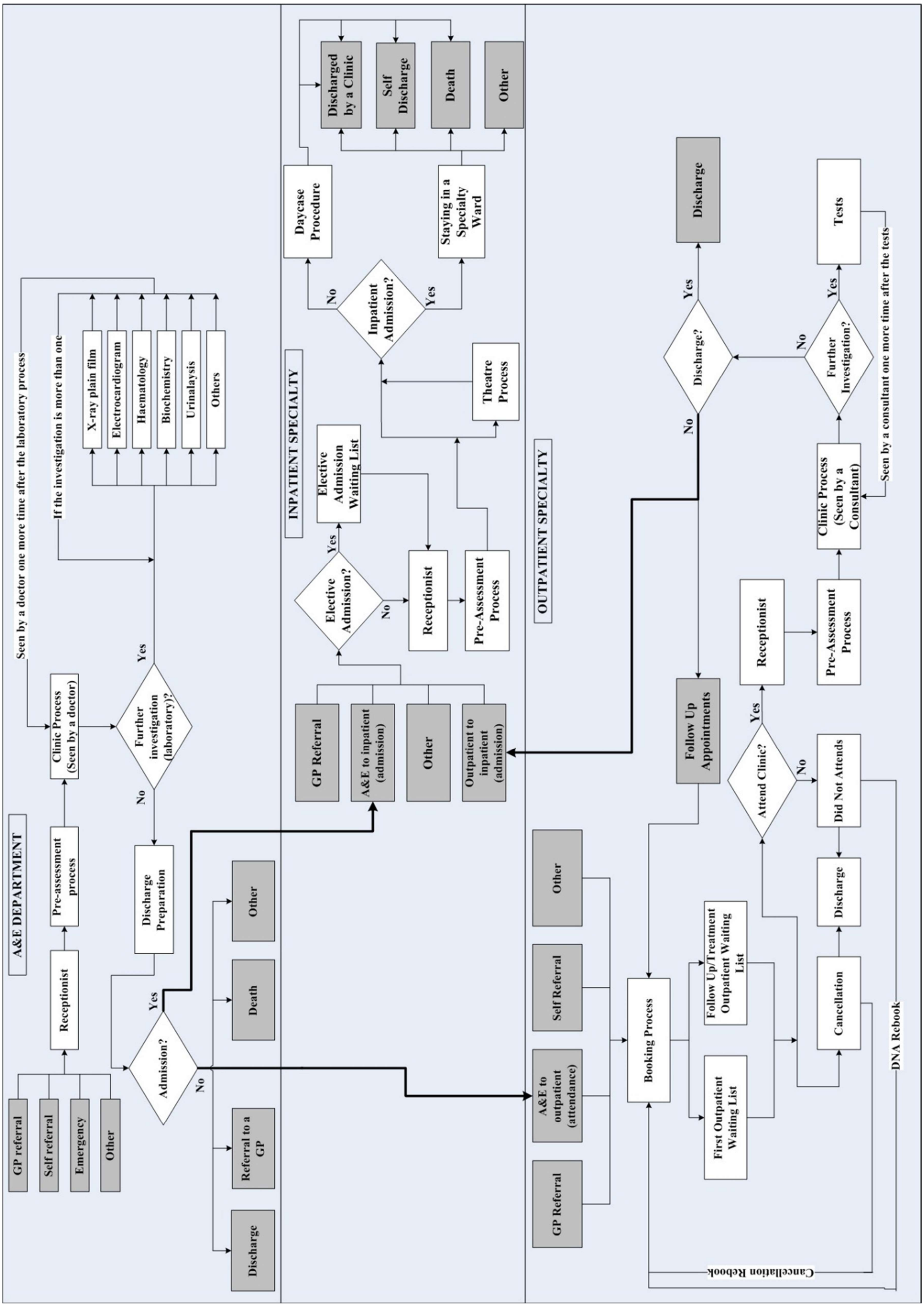

Figure 8.1: High-level conceptualization of the hospital

8.3 Input parameters

As the model aims at the whole hospital scale, there are a significant number of input parameters. Inputs to the model are related to patient demand provided by forecasts, treatment (pathways, percentage of patients falling into each specialty, discharges, length of stay), staffing (staffing levels, staff availability), and cost (staff salary, costing of each service), a full list of parameters for the A&E and the outpatient and inpatient specialties of the trauma & orthopaedics are given in Table 8.1, 8.2 and 8.3, respectively. The vast majority of input parameters are pre-determined through exhaustive analysis of HES and local hospital data. On a small number of occasions, experts were consulted during meetings. Note that all input parameters are prepopulated and can be changed by the service provider if the users deem this to be necessary to fit their geographical area.

Input parameters for all specialties were obtained as well as the trauma & orthopaedics outpatient and inpatient specialties given in Appendix 9 to 43. A&E, inpatient and outpatient demands were prepared as daily inputs into the simulation model. The referrals from A&E to inpatient specialties (for non-elective admissions) and to outpatient specialties were estimated accordingly.

Distributions are a crucial part of simulation modelling, we therefore used a number of distributions, for example, preparation time for treatment, treatment time, time for discharge *for the A&E department*; time for first appointment, number of follow-ups, length between follow-up treatments *for outpatient specialties;* time for first admission, and length of stay *for inpatient specialties*. All distributions were estimated for each age group separately (i.e. 0-15, 16-35, 36-50, 51-65, 65+), resulting in 600 distributions as follows.

- 19 outpatient specialties for first attendances x 2 observed frequency distributions (i.e. time for first appointment, number of follow-ups) x 5 age groups, which is 190 distributions for outpatients (for first attendances),
- 19 outpatient specialties for follow up attendances x 2 observed frequency distributions (i.e. number of follow-ups, length between follow-up treatments) x 5 age groups, which is 190 distributions for outpatients (for follow up attendances),
- 16 inpatient specialties for elective admissions x 2 observed frequency distributions (i.e. time for first admission, length of stay for elective) x 5 age groups, which is 160 distributions for inpatients (for electives).

- 9 inpatient specialties for non-elective admissions x 1 observed frequency distribution (i.e. length of stay) x 5 age groups, which is 45 distributions for inpatients (for non-electives).
- 1 A&E department x 3 observed frequency distributions (i.e. time for treatment, treatment time, time for discharge) x 5 age groups, which is 15 distributions for the A&E.

Observed frequency distributions were established using the Freedman-Diaconis Rule (Freedman and Diaconis, 1981) to specify the optimum width of observed frequency distributions.

We estimated the distributions (number of follow ups) related to how many times in a year a patient attends in an outpatient clinic for follow up treatments. Table 8.4 shows the observed frequency distributions which determine whether first attendances will attend in the clinic for the follow up treatment based on age group. For example, 63.83% of the first attendances in age group 1 do not need further treatment for the same health conditions, whereas the remaining 36.17% of patients do requires follow up treatments. Table 8.4 illustrates how many times in a year a patient with follow up treatment attends in a clinic after their first attendance. For example, 42.01% of the patients in age group 1 need one more treatment after the first follow up attendance. Therefore, these patients would attend the clinic three times (once first attendance and twice follow up attendance) in a year.

In addition, length of period for follow up treatment for a patient in an outpatient clinic was determined by considering the time between consecutive treatments of a patient, which are related to the same health condition. The time from follow up appointment to next follow up appointment of each patient in each specialty was used to establish the distribution for the length of period for follow up treatment. Length of stay in an inpatient specialty was the time from admission in a ward to discharge time.

The observed frequency distributions are established for various group patient depending on the severity of their injuries (investigation for treatment) such as waiting time to be seen by a doctor, waiting time for discharge, treatment time and cost of treatment. According to the HES dataset, there are eight HRG codes for the A&E department of the PAH (i.e. from “VB01Z” to “VB08Z”). These are used for classifying the investigation for treatment. These observed frequency distributions are established to assign individual patients according to the severity of their injuries (investigation for treatment). The reference costs are therefore based on severity of injuries for A&E patients. To give an example, different tariffs are applied based on HRG code (i.e. £237 for VB01Z whereas £110 for VB08Z) as shown in Table 8.1. In conclusion, HRG code is independent from age groups, where all patients are assigned the same HRG code depending on the severity of their condition. This risk adjustments enable us to better capture detailed treatment processes within A&E, financial implications, impact on resources, etc.

Financial inputs were taken from the publication by the Department of Health (2014) and Department of Health and Social Care (2013). Healthcare Research Groups (HRGs) is an indicator which classifies similar clinical “conditions” or “treatments” in terms of level of resources used in healthcare systems (NHS England, 2017). An HRG Code identified for the diagnostic of each patient was taken into account in calculating total revenue for A&E department (see Table 8.1 for the HRG codes in the A&E department), outpatient (first and follow up attendances) and inpatient (elective and non-elective admissions).

Inputs related to resources (i.e. bed, triage room, staff), outpatient clinic slots and inpatient annual theatre capacity were provided in collaboration with the hospital. For example, 36,700 outpatient clinic slots were available for the trauma & orthopaedics outpatient specialty. In addition, total number of annual theatre capacity for elective and non-elective admissions were 8,024 and 3,011 procedures, respectively.

Table 8.1: Input parameters of the simulation model for the accident and emergency (A&E) department

Input parameters	Estimates	Distributions	References
Patient inputs			
- Available demand (2012/13)	- Daily number of referrals for the available period	N/A	HES dataset
- Forecasted year (2013/14)	- Number of admissions from the forecasting method	N/A	N/A
Physical inputs			
- Number of beds	22	Fixed	Local data
- Number of triage rooms	5	Fixed	Local data
- Number of clinic rooms	4	Fixed	Local data
Staff inputs			
- Number of doctors	12	Fixed	Local data
- Number of nurses	21	Fixed	Local data
Financial inputs			
Revenues in the A&E (HRG Codes for severity of injuries):	2012/13 – 2013/14		
- VB01Z	£235 - £237	Fixed	DoH (2013 and 2014)
- VB02Z	£235 - £210	Fixed	DoH (2013 and 2014)
- VB03Z	£151 - £164	Fixed	DoH (2013 and 2014)
- VB04Z	£151 - £139	Fixed	DoH (2013 and 2014)
- VB05Z	£151 - £130	Fixed	DoH (2013 and 2014)
- VB06Z	£81 - £102	Fixed	DoH (2013 and 2014)
- VB07Z	£112 - £119	Fixed	DoH (2013 and 2014)
- VB08Z	£112 - £110	Fixed	DoH (2013 and 2014)
Other inputs			
Demographic features:			
- Gender			
1.Male	47%	Multinomial	HES dataset
2.Female	53%	Multinomial	HES dataset
- Age groups			
1. Age group 1 (0 - 15)	23%	Multinomial	HES dataset
2. Age group 2 (16 - 35)	28%	Multinomial	HES dataset
3. Age group 3 (36 - 50)	16%	Multinomial	HES dataset
4. Age group 4 (51 - 65)	12%	Multinomial	HES dataset
5. Age group 5 (65+)	21%	Multinomial	HES dataset
Laboratory process:			
- Laboratory service			
1. What percentage of patients are referred to the laboratory?	76%	Multinomial	HES dataset
2. What percentage of patients are not referred to the laboratory?	24%	Multinomial	HES dataset
- Percentage of tests			
First tests - Second tests - Third tests			
X-Ray	42% - 8% - 12%	Multinomial	HES dataset
Electrocardiogram	13% - 22% - 10%	Multinomial	HES dataset
Haematology	31% - 26% - 26%	Multinomial	HES dataset
Biochemistry	1% - 32% - 27%	Multinomial	HES dataset
Urinalysis	8% - 7% - 16%	Multinomial	HES dataset
Others	5% - 5% - 9%	Multinomial	HES dataset
Shifts	3	Fixed	Local data
Distributions			
- Severity of injuries	Frequency distribution	Frequency distribution	HES dataset
- Pre-assessment process	10 minutes	Multinomial	Expert opinion
- Treatment time	Frequency distribution	Frequency distribution	HES dataset
- Discharge time	Frequency distribution	Frequency distribution	HES dataset

DoH: Department of Health, HES: Hospital episodes statistics, N/A: Not available, NHS: National Health Service

Table 8.2: Input parameters of the simulation model for the trauma & orthopaedics outpatient specialty

Input parameters	Estimates	Distributions	References
Patient inputs			
1. First referral	- Daily number of referrals for the available period (2012/13)	N/A	HES dataset
2. Follow up referral	- Number of referrals from the forecasting method for the projected period (2013/14)	N/A	N/A
Financial inputs			
Revenue:	(2012/13 – 2013/14)		Department of Health and Social Care (2013)
1. First attendance tariff	Frequency distribution	Frequency distribution	
2. Follow up attendance tariff	Frequency distribution	Frequency distribution	
Other inputs			
Demographic features:			
- Age groups	(First referral – Follow up referral)		
1. Age group 1 (0 - 15)	19.00% – 11.44%	Multinomial	HES dataset
2. Age group 2 (16 - 35)	17.84% – 13.73%	Multinomial	HES dataset
3. Age group 3 (36 - 50)	19.37% – 19.42%	Multinomial	HES dataset
4. Age group 4 (51 - 65)	20.65% – 24.36%	Multinomial	HES dataset
5. Age group 5 (65+)	23.14% – 31.06%	Multinomial	HES dataset
Distributions:			
- Waiting time for first appointment	Frequency distribution	Frequency distribution	HES dataset
- Follow up number	Frequency distribution	Frequency distribution	HES dataset
- Length of period for follow up treatment	Frequency distribution	Frequency distribution	HES dataset
Total available outpatient clinic slots (per year):	36700	Fixed	Local data

HES: Hospital episodes statistics, N/A: Not available, NHS: National Health Service

Table 8.3: Input parameters of the simulation model for the trauma & orthopaedics inpatient specialty

Input parameters	Estimates	Distributions	References
Patient inputs			
1. Elective	- Daily number of admissions for the available period (2012/13)	N/A	HES dataset
2. Non-elective	- Number of admissions from the forecasting method for the projected period (2013/14)	N/A	N/A
Financial inputs			
Revenue:	(2012/13 – 2013/14)		Department of Health and Social Care (2013)
1. Elective tariff	Frequency distribution	Frequency distribution	
2. Non-elective tariff	Frequency distribution	Frequency distribution	
Physical inputs			
Number of beds	59	Fixed	Local data
Other inputs			
Demographic features:			
- Age groups	(Elective – Non-elective)		
1. Age group 1 (0 - 15)	2.94% – 12.21%	Multinomial	HES dataset
2. Age group 2 (16 - 35)	11.69% – 15.37%	Multinomial	HES dataset
3. Age group 3 (36 - 50)	21.00% – 15.73%	Multinomial	HES dataset
4. Age group 4 (51 - 65)	29.65% – 15.77%	Multinomial	HES dataset
5. Age group 5 (65+)	34.72% – 40.92%	Multinomial	HES dataset
Distributions:			
- Waiting time for first admission	Frequency distribution	Frequency distribution	HES dataset
- Length of stay	Frequency distribution	Frequency distribution	HES dataset
Theatre inputs			
- Total number of theatre procedure annual capacity			
1. Elective	8024	Fixed	Local data
2. Non-elective	3011	Fixed	Local data
- What percentage of inpatient admissions end up having a surgery?			
1. Elective	93%	Multinomial	Local data
2. Non-elective	90%	Multinomial	Local data

HES: Hospital episodes statistics, N/A: Not available, NHS: National Health Service

Table 8.4: Number of follow ups and percentages (%) for first patients in the trauma & orthopaedics outpatient specialty

Number of follow ups and percentages (%)					
First patients					
Number of follow up	**AG 1**	**AG 2**	**AG 3**	**AG 4**	**AG 5**
0	63.83	60.34	61.31	63.04	67.57
1	36.17	39.66	38.69	36.96	32.43
Follow up patients					
Number of follow up	**AG 1**	**AG 2**	**AG 3**	**AG 4**	**AG 5**
0	10.52	11.64	11.48	12.83	13.42
1	42.01	41.52	38.01	39.22	41.90
2	21.69	22.13	23.16	22.11	21.55
3	13.19	12.03	13.28	12.13	11.13
4	6.17	5.88	6.76	6.47	6.02
5	3.45	3.33	3.32	3.37	2.93
6	1.58	1.70	1.74	1.87	1.26
7	0.70	0.81	1.00	0.83	0.84
8	0.47	0.52	0.46	0.52	0.43
9	0.03	0.21	0.32	0.22	0.17
10	0.13	0.10	0.22	0.16	0.15
11	0.05	0.04	0.13	0.09	0.06
12	-	0.04	0.04	0.08	0.04
13	-	-	0.03	0.05	0.06
14	-	0.02	-	0.01	-
15	0.03	-	0.01	-	0.02
16	-	0.02	0.01	-	0.02
19	-	-	-	0.01	0.01
21	-	-	0.01	-	-
22	-	-	-	-	-
23	-	-	-	0.01	-

8.4 Developed simulation models

It is difficult to develop a generic simulation model imitating everything belonging to an entire hospital (Pidd, 2003). In the literature, there are very few studies that have developed simulation models for an entire hospital where all the relevant data are collected and analysed for each specialty within an inpatient and outpatient setting. As defined in the conceptual model, and visualised in Figure 8.1, a DES model was developed using Simul8 simulation software. A top-level iconic representation is given in Figure 8.2. The simulation model consists of all departments (A&E, outpatient and inpatient specialties) and all specialties (i.e. general surgery, urology and orthopaedics), along with the interactions between A&E, outpatient and inpatient specialties. Moreover, the feedback mechanism, (appointment rebooking typically faced in outpatient specialties) and system inefficiencies (cancellations and did not attends) are embedded into the simulation model.

The “AandE Arrival” entry point is made up of four arrival modes (i.e. GP referral, self-referral, emergency, and other) as shown in Figure 8.2. Patients are labelled in terms of age group according to their statistical distributions. Patients wait for pre-assessment which is normally carried out by a nurse. Patients are then asked to further wait to be seen by an A&E doctor. In the ‘AandE Clinic Process’, if a doctor wants a further investigation, patients are referred to the laboratory area such as X-Ray and electrocardiogram. An investigation bundle is assigned to each patient according to the distribution obtained from data. For example, if a patient has first investigation (X-Ray) and second investigation (Electrocardiogram), the patient visits firstly X-Ray area and then takes an electrocardiogram test. Patients are then further assessed by the A&E doctor and relevant treatment is decided. After that, patients are prepared to be discharged by “AandE Discharge Preparation” and a decision is made among five discharge modes as shown in Figure 8.1 (i.e. they can either be admitted to inpatient care, discharged back to primary care; discharged to an outpatient department, discharged by death, or discharged home with no further action). In this model, there are four distinct types in relation to process times: 1) pre-assessment time (triage), 2) treatment time (by clinician), 3) discharge time (post treatment), 4) total time in A&E, i.e. from arrival to discharge. Relevant distributions have been established for (1), (2) and (3) whereas (4) is an output.

A percentage of patients from the A&E department are referred to outpatient clinics of the hospital. This is where the interconnectedness in hospitals occurs, since output of one department is the input of a different department. Furthermore, complicated synchronisation rules are applied such as an A&E patient requiring outpatient clinic appointment. Along with the referral from the A&E, patients from other referral sources wait for their appointment date according to observed frequency distributions based on age groups and type of specialty. Some patients might cancel their appointments in advance by “First Cancellation” work centre or do not attend the clinic by “First DNA” work centre. First and follow up patients are referred to the waiting area, “FUP Cancellation” or “FUP DNA” work centres by using “Referral Control” work centre. At this point, some follow up patients may cancel their appointments in advance (“FUP Cancellation” work centre) or do not attend the clinic (“FUP DNA” work centre) whereas all first patients and some follow up patients, who request to attend the clinic, are directed to the waiting area for pre-assessment. A diagnostic procedure and/or treatment procedure is conducted by a consultant in the outpatient clinic (by “Outpatient Clinic Process” work centre). If a patient needs a follow up appointment or not is decided by a consultant after treatment. If the patient does not require a follow up treatment, a discharge procedure is carried out. Otherwise, each patient, who needs a follow up appointment, is assigned a number of follow up according to observed frequency distributions estimated by taking into account age groups and type of specialty. Patients then wait at home for their follow up treatment or check-up. The assigned number of follow up decreases by one as they attend the clinic. Patient repeats this cyclical process until the assigned number of follow-ups is zero. Using labels in our simulation model, a rebooked appointment is carried out if patient cancels the appointment or does not attend the clinic.

Patients can be referred from the A&E and outpatient to inpatient specialties according to the pathway shown in Figure 8.1. Elective patients are referred to inpatient specialties of the hospital and wait for their admissions according to observed frequency distributions based on age groups and type of specialty. Non-elective patients are admitted to the inpatient specialties in two main routes: mostly via the A&E department and others (i.e. GP and consultant clinic referrals). After a pre-assessment is carried out, theatre process is performed, if required. Patients, who need to be admitted to a ward, stay in a bed in accordance with the observed frequency distributions regarding length of stay until discharged. On the other hand, day-case patients are discharged as they do not require a bed.

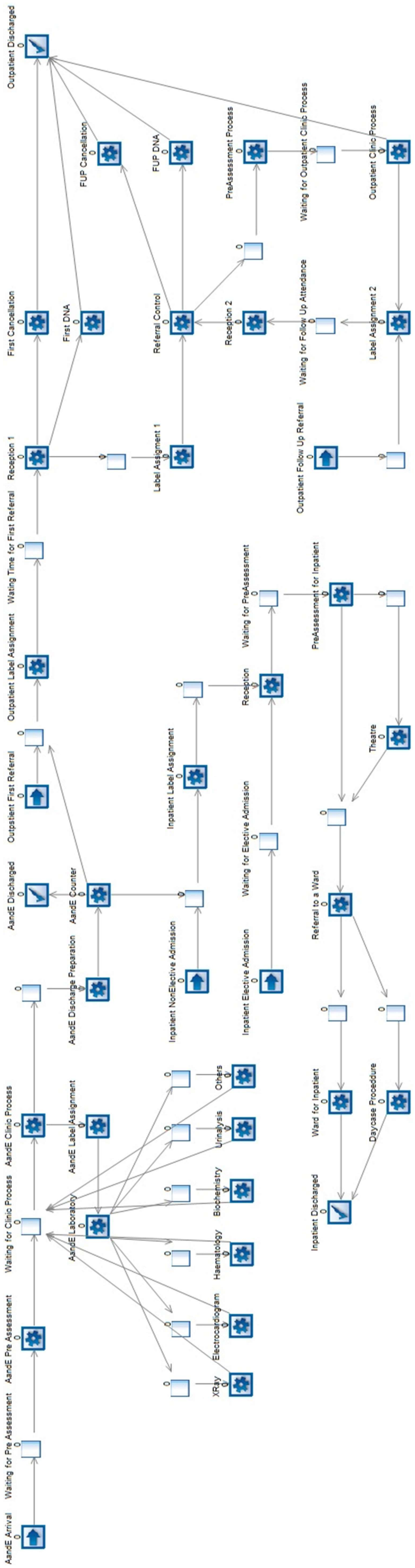

Figure 8.2: High-level simulation model of the hospital

8.5 Required replication number and warm up period

As clarified in Chapter 5, a Fixed-Sample-Size procedure was used to determine the required replication number for the simulation model. All analyses were carried out for key performance metrics for the A&E, and all outpatient and inpatient specialties. Average waiting time and length of stay were determined as key performance metrics for the A&E department. On the other hand, time to first appointment and time to follow up appointment were selected as key performance metrics for outpatient specialties whereas time to elective admission and length of stay were chosen for inpatient specialties. Table 8.5 shows the values of the parameters of the Fixed-Sample-Size procedure. The required replication numbers were iteratively found for each performance metrics. According to the results based on key performance metrics for the A&E, and all outpatient and inpatient specialties, 10 replications was specified as the required replication number since $n_r^*(\gamma)$ is less than or equal to γ'.

Table 8.5: The results for the required replication numbers according to key performance metrics of the A&E department

Parameters	Average waiting time	Average length of stay
Average	63.98	153.96
Standard deviation	0.2212	0.2870
Relative error (γ)	0.15	0.15
Adjusted relative error (γ')	0.13	0.13
i	10	10
$t_{i-1,1-\alpha/2}$ ($t_{9,0.025}$)	2.26	2.26
n	10	10
$n_r^*(0.10)$	0.001661425	0.00078644
Results	$n_r^*(\gamma) \leq \gamma'$	$n_r^*(\gamma) \leq \gamma'$

i: required replication number, n: initial replication number

In this study, the warm-up period is investigated for key performance metrics, such as waiting time for treatment and overall waiting time for the A&E department. In the simulation model, the warm up period was determined as two months for the key performance metrics of the A&E department as shown in Figure 8.3 and 8.4. According to the results based on key performance metrics of A&E, all outpatient and inpatient specialties, the warm up period is determined as 5 months for the simulation model. Therefore, the run length of the simulation model consists of two periods: warm up periods (5 months) and data collection periods (12 months). The run length is then 17 months.

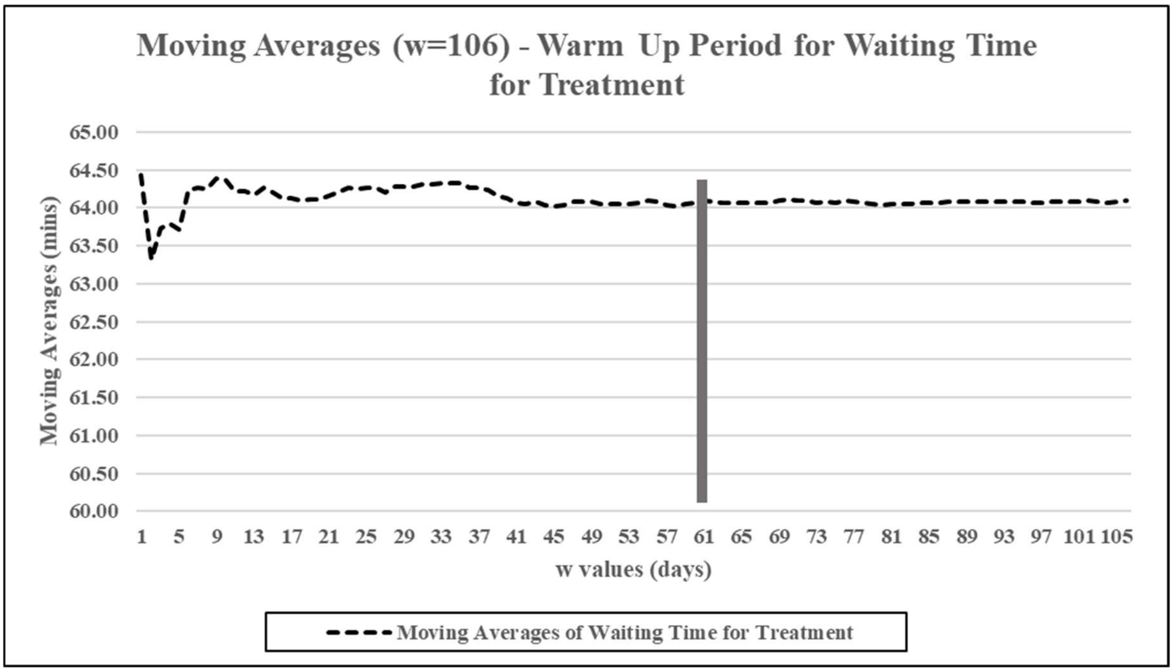

Figure 8.3: Graph for determining the warm-up period for average waiting time for treatment in the A&E department

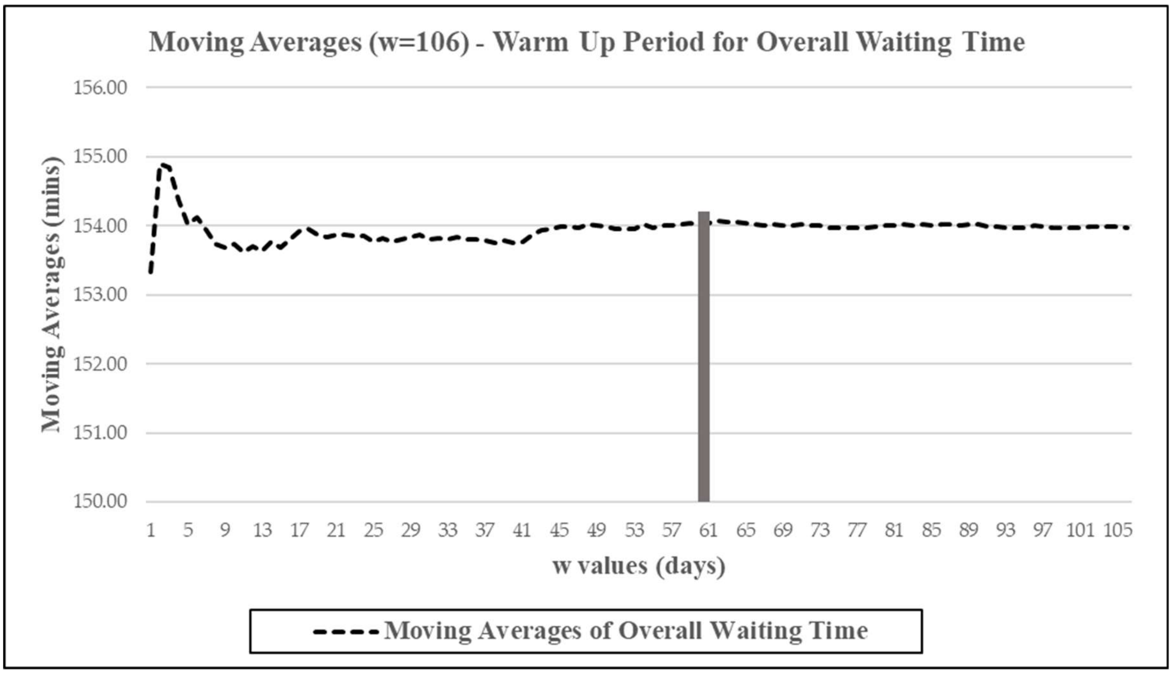

Figure 8.4: Graph for determining the warm-up period for average overall waiting time in the A&E department

8.6 Outputs

A simulation model of this scale generates many outputs, and the simulation model's output metrics are shown in Table 8.6.

Table 8.6: Outputs of the generic simulation model

Outputs	
A&E department	
• Total number of capacity • Bed occupancy rates (%) • Consultant Hours (hours) • Nurse Hours (hours) • Demand Coverage Ratio (%) • Total Revenue (£)	
Outpatient services	**Inpatient services**
• Total number of first attendances • Total number of follow up attendances • Total number of DNAs • Total number of cancellations • First to follow up ratio • Total number of clinic attendance • Clinic utilization rate (%) • Consultant Hours (hours) • Demand Coverage Ratio (%) • Total Revenue (£)	• Total number of elective admission • Total number of non-elective admissions • Total number of elective theatre procedure • Total number of non-elective theatre procedure • Elective theatre utilization rate (%) • Non-elective theatre utilization rate (%) • A&E to inpatient conversation rate (%) • Bed occupancy rates (%) • Required number of beds • Consultant Hours (hours) • Demand Coverage Ratio (%) • Total Revenue (£)

DNA: Did not attend

8.6.1 Outputs for the entire hospital

Among the set of outputs, three metrics were focussed on as agreed with hospital management. The performance was measured using the following output metrics at hospital level: Demand Coverage Ratio (DCR), Bed Occupancy Rate (BOR) and Total Revenue (TR).

Demand Coverage Ratio (%): DCR is a novel metric developed to measure the percentage of patients admitted to the hospital and discharged using the available resources of each specialty. Its generic formula is shown in Eq. (8.1). This output shows a hospital's ability to meet demand. For example, 100% DCR means that all patient demands are met with the available resources. Using this output metric, hospitals are able to better understand their performance, e.g. if DCR is below 100% (say 90%) this means that the specialty was unable to cope with the demand, thus require additional resources to treat the remaining 10%. The DCR of the hospital is computed by the formula in Eq. (8.2) and used in the simulation model.

$$\textit{Demand Coverage Ratio (\%)} = 100 \times \frac{\textit{Number of patients who are discharged}}{\textit{Number of patients who are admitted}} \tag{8.1}$$

$$\textit{Demand Coverage Ratio (\%)} = 100 \times \left(\frac{AEP + \sum_{j=1}^{s_o} NPDO_j + \sum_{j=1}^{s_i} NPDI_i}{AEA + \sum_{j=1}^{s_o} NPAO_j + \sum_{j=1}^{s_i} NPAI_i} \right) \tag{8.2}$$

where AEP is the number of patients who are discharged using available resources from the A&E department; $NPDO_j$ is the number of patients who are discharged using available resources from the outpatient specialty j; $NPDI_j$ is the number of patients who are discharged using available resources from the inpatient specialty j; AEA is the number of patients who are admitted to the A&E department; $NPAO_j$ is number of patients who are admitted to the outpatient specialty j; $NPAI_j$ is the number of patients who are admitted to inpatient specialty j; s_o is the total number of outpatient specialty; s_i is the total number of inpatient specialty.

There are a number of practical implications of DCR, particularly around the better understanding of bottlenecks of the system at the individual specialty (departmental and hospital) level. A DCR of less than 100% is a sign of a capacity issue, such as lack of beds, consultants, and outpatient clinic slots.

This will then enable the hospital management (i.e. service managers, consultants, and directors) to take necessary precautionary measures to ensure patient needs are met and that the service functions smoothly.

In addition, the DCR can help better understand outpatient performance in terms of demand and capacity planning. For example, let's assume that the DCR of an outpatient specialty is 95%. The available resources belonging to the related outpatient specialty is not sufficient to cope with the remaining demand (5%). The outpatient specialty needs to increase the available outpatient clinic slots.

If the DCR of an inpatient specialty is less than 100%, then the management can detect the problem by examining capacity oriented metrics (i.e. the bed occupancy rate, theatre utilization rate or consultation hours), and increase these resources to ensure all patients are treated and discharged timely. To the best of our knowledge DCR is a new metric that has never been utilised within healthcare context.

Xu et al. (2016) used a metric called "Saturation" in their research which investigated the relation between capacity and demand under uncertain demand conditions. They developed a simulation-based algorithm to examine capacity-oriented passenger flow control in a subway station in Beijing. Saturation calculates a ratio dividing the total demand by capacity whereas the DCR provides a percentage of capacity within the demand. Both measures are comparing demand with capacity in some way, but one is the reciprocal of the other. For example, the Saturation is 1.10 whereas the DCR of 90.91% if total demand is 110 and capacity is 100. In addition, after an exhaustive and systematic literature review, it is clear that there is no other measure in healthcare like the DCR presented in this study.

Bed occupancy rates (%): NHS Trusts in the UK measure bed occupancy rate of the hospitals on a regular basis as a key output metric of their inpatient services. NHS Trusts measure the BOR using Eq. (8.3) which is a rate calculating the number of hospital beds occupied in the total number of available hospital beds in a period (Harper and Shahani, 2002).

$$\textit{Bed occupancy rate (\%)} = 100 \times \frac{\textit{The number of occupied bed days}}{\textit{Total number of beds} \times \textit{Number of days in the period}} \tag{8.3}$$

Total Revenue (£): Financial output is one of the most important key metrics for strategic planning purposes. Total revenue is measured in the simulation study as one of the outputs using the formula shown in Eq. (8.4). This output consists of the following sources of revenue: A&E department, outpatient and inpatient specialties. At this point, the Market Forces Factor (MFF) is used as a multiplier in calculation of the revenue. The MFF indicates a reflection of service cost which might depend on the location of each hospital in the country (Department of Health and Social Care, 2013). Firstly, the portion of revenue coming from the A&E department is calculated by taking into account the HRG Codes identified for the severity of injuries (i.e. investigation of treatment) given in Table 8.1. For example, the hospital reimburses £237 if an HRG Code "VB01Z - Any investigation with category 5 treatment" is assigned to a patient, who attends in the A&E department. Secondly, an HRG Code is identified for each patient to determine the diagnostic procedures in outpatient and inpatient specialties. These codes were taken into account in calculating total revenue for outpatient (first and follow up treatment) and inpatient (for the elective and non-elective treatments). For example, the hospital reimburses £80 (£92 with the MFF) if an HRG Code "FZ57Z - Diagnostic or Therapeutic Rigid Sigmoidoscopy 19 years and over" is assigned to a patient, who attends in a general surgery outpatient clinic as a first referral.

The revenue for an inpatient specialty is calculated differently compared to A&E and outpatient specialties. The revenue depends on the patients' length of stay in a bed. A long stay payment for days exceeding the trim point is applied by considering the trim point determined by the NHS. Trimpoint is a threshold for the length of stay for patients (NHS Digital, 2018). For example, the non-elective long stay trimpoint is 5 days for a HRG Code EB01Z (Non-Interventional Acquired Cardiac Conditions) in the general surgery inpatient specialty and £211 (£243 with the MFF) per day for exceeding the trimpoint is charged, whereas the non-elective spell tariff is £585 (£675 with the MFF). The hospital reimburses £1161 (MFF × £585 + MFF × 2 days × £211) if a non-elective patient with the HRG code "EB01Z" stays in a bed for 7 days.

$$\begin{aligned} \textit{Total Revenue (£)} &= \left(\sum_{i=1}^{s_a} AE_i \times RAE_i \times MFF \right) + \left(\sum_{i=1}^{s_o} \sum_{j=1}^{f_j} RF_{ji} \times MFF + \sum_{i=1}^{s_o} \sum_{j=1}^{fup_j} RFUP_{ji} \times MFF \right) \\ &+ \left(\sum_{i=1}^{s_e} \sum_{j=1}^{e_j} (TE_{ji} + TAE_{ji}) \times MFF + \sum_{i=1}^{s_{ne}} \sum_{j=1}^{ne_j} (TNE_{ji} + TANE_{ji}) \times MFF \right) \end{aligned} \tag{8.4}$$

where AE_i: Total number of A&E arrivals who have severity of injury i; RAE_i: Unit tariff for i. severity of injury in the A&E department; s_a: Total number of types of severity of injuries in the A&E department; f_j: Total number of first attendance and DNAs at outpatient specialty j; RF_{ji}: i. tariff for first attendance and DNAs at outpatient specialty j; fup_j: Total number of follow up attendance and DNAs at outpatient specialty j; $RFUP_{ji}$: i. tariff for follow up attendance and DNAs at outpatient specialty j; s_o: Total number of outpatient specialty; s_e: Total number of inpatient elective specialty; s_{ne}: Total number of inpatient non-elective specialty; e_j: Total number of admission at inpatient elective specialty j; ne_j: Total number of admissions at inpatient non-elective specialty j; TE_{ji}: i. tariff at inpatient elective specialty j; TAE_{ji}: i. tariff adjustment at inpatient elective specialty j; TNE_{ji}: i. tariff at inpatient non-elective specialty j; $TANE_{ji}$: i. tariff adjustment at inpatient non-elective specialty j; MFF: Market forces factor.

8.6.2 Outputs for departments

Outputs for each department (i.e. accident and emergency department, outpatient and inpatient services) are explained as follows.

8.6.2.1 Accident and emergency (A&E) department

Outputs for the accident and emergency department are described below.

Total number of admitted patients: Total number of patients (i.e. capacity) are admitted and discharged in the A&E department.
Demand Coverage Ratio (%): A ratio representing the percentage of patients admitted to an A&E department and discharged using the available resources of the A&E department.
Bed occupancy rates (%): A rate representing the percentage of the A&E beds occupied in the total number of available beds in the A&E.
Consultant Hours (hours): Total consultation time served by total number of consultants working in the A&E department.
Nurse Hours (hours): Total nursing time served by total number of nurses in the A&E department.
Total Revenue (£): Total revenue from the patient care in the A&E department.

8.6.2.2 Outpatient Services

Outputs for the outpatient services are described below.

Total number of first attendances: Total number of patients who is seen by a healthcare provider at the first attendances in an outpatient specialty.

Total number of follow up attendances: Total number of patients who are seen by a healthcare provider at follow up attendances in an outpatient specialty.

Total number of DNAs: Total number of patients who did not attend in a clinic at the first or follow up attendances in an outpatient specialty.

Total number of cancellations: Total number of patients who cancels their appointments for the first or follow up attendances in an outpatient specialty.

First to follow up ratio: This ratio indicates number of follow up attendances for every first attendances. It is calculated by dividing the number of follow up attendances by the number of first attendances.

Total number of clinic attendance: Total number of first and follow up attendances.

Clinic utilization rate (%): A rate representing the percentage of the available outpatient clinic slots used in the total number of available outpatient clinic slots in an outpatient specialty.

Consultant Hours (hours): Total consultation time served by total number of consultants working in an outpatient specialty.

Demand Coverage Ratio (%): A ratio representing the percentage of patients admitted to an outpatient specialty and discharged using the available resources of the outpatient specialty.

Total Revenue (£): Total revenue from the patient care in an outpatient specialty.

8.6.2.3 Inpatient Services

Outputs for the inpatient services are described below.

Total number of elective admissions: Total number of elective admissions in an inpatient specialty.

Total number of non-elective admissions: Total number of non-elective admissions in an inpatient specialty.

Total number of elective theatre procedure: Total number of theatre procedures carried out for elective admissions in an inpatient specialty.

Total number of non-elective theatre procedure: Total number of theatre procedures carried out for non-elective admissions in an inpatient specialty.

Elective theatre utilization rate (%): A rate representing the percentage of theatre utilization for elective admissions in an inpatient specialty.
Non-elective theatre utilization rate (%): A rate representing the percentage of theatre utilization for non-elective admissions in an inpatient specialty.
A&E to inpatient conversation rate (%): A rate representing the percentage of the patient admitted to an inpatient specialty from the A&E department.
Bed occupancy rates (%): A rate representing the percentage of the beds occupied in an inpatient specialty.
Required number of beds: A number representing the required number of beds based on the target level in an inpatient specialty.
Consultant Hours (hours): Total consultation time in hours within the inpatient specialty.
Demand Coverage Ratio (%): A ratio representing the percentage of patients admitted to an inpatient specialty and discharged using the available resources of the inpatient specialty.
Total Revenue (£): Total revenue from the patient care in an inpatient specialty.

8.7 Verification and validation of the simulation models

To validate our simulation model, black-box and white-box validations were carried out and it was checked for face validity. During the model development, we closely worked with key personnel in the hospital and their feedback was received. The model was continually improved accordingly, and each model unit was tested for extreme conditions and logical consequences. It is decided that the model has passed white-box validation tests. In the final demonstration of the model, which was for face validation, project owners were convinced that the model is appropriate for further usage.

Black-box validation assumes that a simulation model will behave like the real system under the same input settings. The output variables that were collected in simulation and observed in the real system are DCR, bed occupancy rates, and total revenue. In Table 8.7, it was seen that the real system's output in the data column, and simulation results in the next column. Since the simulation model is a stochastic model, its output is a random variable and therefore it has confidence intervals. From these figures, it can be concluded that the simulation model is behaving like the real system.

In addition, the simulation model was validated by taking into account all key output metrics for all specialties. For example, the validation results for the output metrics of the trauma & orthopaedics outpatient specialty (see Table 8.8) and inpatient specialty (see Table 8.9).

Table 8.7: Validation of the simulation model

Output parameters	Data	Simulation results (95% LCI, UCI)	Deviation	Percentage (%)
Demand coverage ratio (%)	99.71%	99.68% (99.38%, 99.98%)	-0.03% (-0.33, 0.27)	-0.03% (-0.33%, 0.27%)
Bed occupancy rate (%)	71.96%	73.15% (70.91%, 75.43%)	1.19% (-1.05, 3.47)	1.65% (1.46%, 4.82%)
Total revenue (£)	£162.80m	£161.19m (£159.40m, £162.98m)	-1.61m (-3.40m, 0.18m)	-0.99% (-2.09%, 0.11%)

LCI: Lower value of confidence interval, UCI: Upper value of confidence interval

Table 8.8: The validation results for the output parameters of the trauma & orthopaedics outpatient specialty

Output parameters	Simulation	Actual	Differences	Percentages (%)
Total first attendance	10643 (10568, 10717)	10601	42 (-33, 116)	0.40 (-0.31, 1.09)
Total follow up attendance	21025 (20710, 21340)	20758	267 (-48, 582)	1.29 (-0.23, 2.80)
Total DNAs	2990 (2861, 3118)	3088	-98 (-227, 30)	-3.17 (-7.35, 0.97)
Total cancellation	9103 (8896, 9310)	8916	187 (-20, 394)	2.10 (-0.22, 4.42)
First to follow up ratio	1.98 (1.95, 2.00)	1.96	0.02 (-0.01, 0.04)	1.02 (-0.51, 2.04)
Total number of clinic attendance	31668 (31317, 32018)	31359	309 (-42, 659)	0.99 (-0.13, 2.10)
Clinic utilization (%)	86.29 (85.33, 87.24)	85.45	0.84 (-0.12, 1.79)	0.98 (-0.14, 2.09)
Consultant hours (hours)	16389 (16169, 16608)	16268	121 (-99, 340)	0.74 (-0.61, 2.09)
Total revenue (£)	4.028m (3.991m, 4.066m)	4.014m	0.014m (-0.023m, 0.052m)	0.35 (-0.57, 1.30)

DNA: Did not attend

Table 8.9: The validation results for the output parameters of the trauma & orthopaedics inpatient specialty

Output parameters	Simulation	Actual	Differences	Percentages (%)
Total elective admission	3246 (3159, 3332)	3179	67 (-20, 153)	2.11 (-0.63, 4.81)
Total non-elective admission	1515 (1486, 1544)	1526	-11 (-40, 18)	-0.72 (-2.62, 1.18)
Total elective theatre procedure	3018 (2935, 3102)	2956	62 (-21, 146)	2.10 (-0.71, 4.94)
Total non-elective theatre procedure	1364 (1337, 1390)	1373	-9 (-36, 17)	-0.66 (-2.62, 1.24)
Elective theatre utilization rate (%)	37.62 (36.59, 38.65)	36.84	0.78 (-0.25, 1.81)	2.12 (-0.68, 4.91)
Non-elective theatre utilization rate (%)	45.28 (44.41, 46.14)	45.59	-0.31 (-1.18, 0.55)	-0.68 (-2.59, 1.21)
Bed occupancy rate (%)	73.96 (72.77, 75.13)	73.91	0.05 (-1.14, 1.22)	0.07 (-1.54, 1.65)
Required number of bed	52 (51, 53)	52	0 (1, 2)	0.00 (-1.92, 3.85)
Consultant time (hour)	4786 (4455, 5117)	5065	-279 (-610, 52)	-5.51 (-12.04, 1.03)
A&E to inpatient conversation rate (%)	1.69 (1.56, 1.82)	1.79	-0.10 (-0.23, 0.03)	-5.03 (-12.85, 1.68)
Total revenue (£)	18.229m (18.051m, 18.408m)	18.081m	0.148m (-0.030m, 0.327m)	1.12 (-0.17, 0.18)

DNA: Did not attend

8.8 Experimental design and scenario analysis

The whole hospital simulation model has many inputs and outputs and therefore it was difficult to design the experiments. Discussions with the hospital management made it clear that the hospital is expecting the number of patients to increase in the upcoming years, and in return the management wants to know its effects. Therefore, it was decided to investigate the effects of increase in patient demand on revenue and level of service provision. Level of service provision is measured by two metrics, DCR and BOR. The two metrics are interrelated however: the first shows how successful the hospital is in providing healthcare to its surrounding population, and the second shows the success of hospital management in managing its bed capacity. The revenue, on the other hand, is a function of patient mix and number of patients. The increase in numbers does not necessarily mean an increase in revenue since different tariffs are applied to patients.

As a reply to the hospital management's concerns on increase in demand, 16 scenarios were built to investigate the effects of increase in arrivals at three levels. Four factors were taken into account; A&E arrivals (A), elective inpatient arrivals (B), non-elective inpatient arrivals (C), and outpatient clinic arrivals (D). For each factor, 5% and 10% increases, which created 2^4=16 experiments, are applied. The two-factor experiment is essential to understand the interaction effects between the factors and convenient for exploration purposes. In addition to the two-factor analysis, 2 additional scenarios were tested to better understand the effects of 15% and 20% increase in inpatient demand when there is 10% increase in the A&E department and outpatients. The simulation model was run for 10 replications with 5-months warm up period and the results are shown in Table 8.10.

Table 8.10: The all outputs of the A&E department and a single specialty along with outpatient and inpatient services

Output Results	
A&E department	
Output parameters	**Simulation results**
Total number of admitted patients	82340 (81926, 82754)
Demand Coverage Ratio (%)	99.95 (99.43, 100.00)
Bed occupancy rates (%)	70.34 (70.02, 70.67)
Consultant Hours (hours)	87880 (86907, 88843)
Nurse Hours (hours)	165380 (162133, 168664)
Total Revenue (£)	10.21m (10.05m, 10.37m)
Outpatient service	
Output parameters	**Simulation results**
Total first attendance	10404 (10360, 10448)
Total follow up attendance	23721 (23526, 23915)
Total DNAs	3256 (3226, 3285)
Total cancellation	9782 (9724, 9841)
First to follow up ratio	2.28 (2.26, 2.29)
Total number of clinic attendance	34125 (33904, 34345)
Clinic utilization (%)	92.98 (92.38, 93.58)
Consultant hours (hours)	17200 (17187, 17211)
Total revenue (£)	3.706m (3.685m, 3.727m)
Inpatient service	
Output parameters	**Simulation results**
Total elective admission	3762 (3730, 3794)
Total non-elective admission	1421 (1369, 1447)
Total elective theatre procedure	3499 (3469, 3529)
Total non-elective theatre procedure	1279 (1254, 1304)
Elective theatre utilization rate (%)	43.61 (43.23, 43.98)
Non-elective theatre utilization rate (%)	42.48 (41.63, 43.31)
Bed occupancy rate (%)	76.60 (75.06, 78.14)
Required number of bed	54 (53, 55)
Consultant time (hour)	5500 (5423, 5566)
A&E to inpatient conversation rate (%)	1.59 (1.56, 1.62)
Total revenue (£)	18.781m (18.636m, 18.925m)

8.9 Results and Discussion

As the management of a typical hospital is interested in investigating the effects of an increase in patient demand on DCR, BOR, and revenue, the experiments were designed accordingly. Although, the DSS proposed in this study is able to answer many other questions, such as the number of beds configuration, increases in patient demand scenarios were focused on. The structure of the scenarios, experimental design and responses for key output metrics (total revenue, DCR and BOR) are given in Table 8.11 and in Figure 8.5. The Baseline model is established using predicted hospital demands as input into the simulation model. According to the baseline model, approximately £164 million revenue is expected from patient care with 97.20% DCR and around 75% BOR in next year. The model predicts that the hospital will not be able to meet 3% of all demand. The reasons for not meeting the 3% demand will be clearly understood when the DCR's of each specialty are examined, and the lack of resources here will be comprehended. At this point, available clinic slots in some outpatient specialties will be insufficient and then the clinic utilization of those outpatient specialties will be at maximum level (100%). In addition, the number of beds in some inpatient specialties will be inadequate even if the bed occupancy rate of the hospital is less than 100% so that further investigation reveals that there exists a bed reallocation problem as seen in Table 8.12.

Table 8.11: Experimental design and results of the analysis at 95% confidence interval

Experiments		Factors				Outputs		
		A&E	IE	INE	O	Total revenue (million £)	Demand coverage ratio (%)	Bed occupancy rates (%)
Baseline model (forecasting)		0	0	0	0	164.37m (162.55m, 166.19m)	97.20 (96.83, 97.57)	74.97 (72.72, 77.22)
Levels	E1	5	5	5	5	171.30m (169.40m, 173.20m)	96.11 (95.75, 96.47)	78.07 (75.73, 80.41)
	E2	5	5	5	10	172.39m (170.48m, 174.30m)	95.17 (94.81, 95.53)	78.05 (75.71, 80.39)
	E3	5	5	10	5	172.77m (170.85m, 174.69m)	95.97 (95.62, 96.31)	79.29 (76.91, 81.67)
	E4	5	5	10	10	173.95m (172.02m, 175.88m)	95.17 (94.85, 95.49)	79.30 (76.92, 81.70)
	E5	5	10	5	5	173.25m (171.33m, 175.17m)	96.18 (95.84, 96.52)	78.37 (76.41, 80.33)
	E6	5	10	5	10	174.52m (172.58m, 176.46m)	95.22 (94.88, 95.56)	78.36 (75.85, 80.87)
	E7	5	10	10	5	174.73m (172.79m, 176.67m)	96.05 (95.69, 96.41)	79.54 (77.15, 81.93)
	E8	5	10	10	10	175.92m (173.97m, 177.87m)	95.14 (94.80, 95.48)	79.60 (77.21, 81.99)
	E9	10	5	5	5	173.67m (171.74m, 175.60m)	95.96 (95.60, 96.32)	80.02 (77.62, 82.42)
	E10	10	5	5	10	174.75m (172.81m, 176.69m)	95.06 (94.72, 95.40)	80.04 (77.64, 82.44)
	E11	10	5	10	5	175.13m (173.19m, 177.07m)	95.81 (95.44, 96.18)	81.36 (78.92, 83.80)
	E12	10	5	10	10	176.27m (174.31m, 178.23m)	94.91 (94.59, 95.23)	81.20 (78.76, 83.64)
	E13	10	10	5	5	175.55m (173.60m, 177.50m)	95.98 (95.64, 96.32)	80.20 (77.79, 82.61)
	E14	10	10	5	10	176.79m (174.83m, 178.75m)	95.17 (94.82, 95.52)	80.25 (77.84, 82.66)
	E15	10	10	10	5	177.03m (175.06m, 179.00m)	95.98 (95.67, 96.29)	81.41 (78.97, 83.85)
	E16	10	10	10	10	178.25m (176.21m, 180.23m)	95.04 (94.72, 95.36)	81.43 (78.99, 83.87)
E17		10	15	15	10	181.75m (179.73m, 183.77m)	94.83 (94.48, 95.18)	83.26 (80.76, 85.76)
E18		10	20	20	10	185.15m (183.09m, 187.21m)	94.73 (94.44, 95.02)	84.83 (82.29, 87.37)

A&E: Accident and emergency department, E: Experiment, IE: Inpatient elective, INE: Inpatient non-elective and O: Outpatient

The study revealed a reallocation problem/opportunity regarding the available number of beds in the hospital. It was considered as a further study; thus, we integrated the optimization modelling with the generic hospital simulation model and forecasting. The objective is to optimally reallocate the available number of beds by taking into account a number of constraints related to the hospital.

Table 8.12: Number of beds and bed occupancy rates for the projected year (i.e. baseline model)

Specialty	Number of beds	Bed occupancy rate (%)
General surgery	88	56.07 (54.48, 57.65)
Trauma & orthopaedics	59	76.60 (75.06, 78.14)
General medicine	85	106.75 (105.71, 107.78)
Cardiology	25	97.23 (94.63, 99.82)
Paediatrics	16	116.55 (111.49, 121.60)
Geriatric medicine	111	126.90 (125.33, 128.46)
Obstetrics	41	78.28 (77.67, 78.87)
Gynaecology	41	31.54 (30.88, 32.19)
Others	91	16.70 (16.17, 17.23)

The hospital solves the overcapacity problems experienced in a few inpatient specialties by transferring patients of fully occupied inpatient specialties to beds of an unoccupied one. In the case of a 10% demand increase, the bed occupancy rate will be under the target level of 85%. Experiments 17 and 18 clearly showed that the hospital has the capacity to admit 10% more patients to beds and thus, it could increase revenue. One would expect the DCR to increase (due to availability of beds), however a decrease in this instance means that the beds are not allocated efficiently (as it is occupied less than 85% of the time).

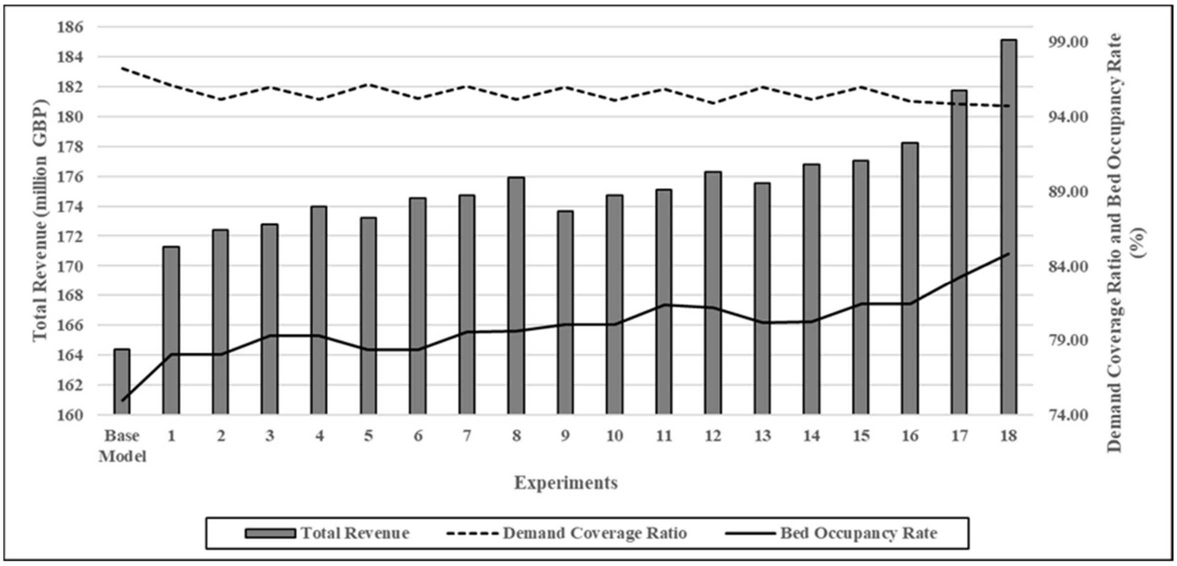

Figure 8.5: Graph of the experimental analysis based on key output metrics

8.9.1 Demand Coverage Ratio

Normal plots of the effects for key output metrics are shown in Figure 8.6 as experimental analysis results. In a normal plot of the effects, the further that a factor is away from the line, the greater its effect. The effects, which are located along the line are insignificant (Montgomery, 2013).

Factors which affect the demand coverage ratio are the main effects of outpatient (*D)*, A&E (*A)* and non-elective admissions (*C)* (in order of the effects). Outpatient arrivals are the most important hospital demand affecting the DCR. It is understood that the available capacity of outpatient specialties will not be able to meet the possible unexpected demand increase so that the DCR decreases as the outpatient attendances increase. This result also shows that DCR is significantly affected by the first point of patient contact with hospitals, which is outpatient clinics.

8.9.2 Bed Occupancy Rate

Factors which affect the bed occupancy rate are the main effects of *A*, *C* and *B* (in order of the effects). The effect of outpatient attendances is negligible on the bed occupancy rate. BOR is most affected from patients admitted via the A&E department. Non-elective admissions are more important than elective admissions in the increase of BOR when we investigated the types of inpatient arrivals. In conclusion, BOR is most influenced by the changes in number of emergency patient arrivals (A&E and non-elective).

8.9.3 Total Revenue

Factors which affect the total revenue are the main effects of *A*, *B*, *C* and *D*, and the *B-D* interaction (in order of the effects). The fluctuations on total revenue are most affected by the number of patients admitted in the A&E and indirectly non-elective admissions (via A&E department). The effects of inpatient admissions (i.e. elective and non-elective) are larger than the effect of outpatient attendances on total revenue although the number of inpatient admissions is not as high as the number of outpatient attendances. That is why revenue items on inpatient admissions (particularly non-elective) are high.

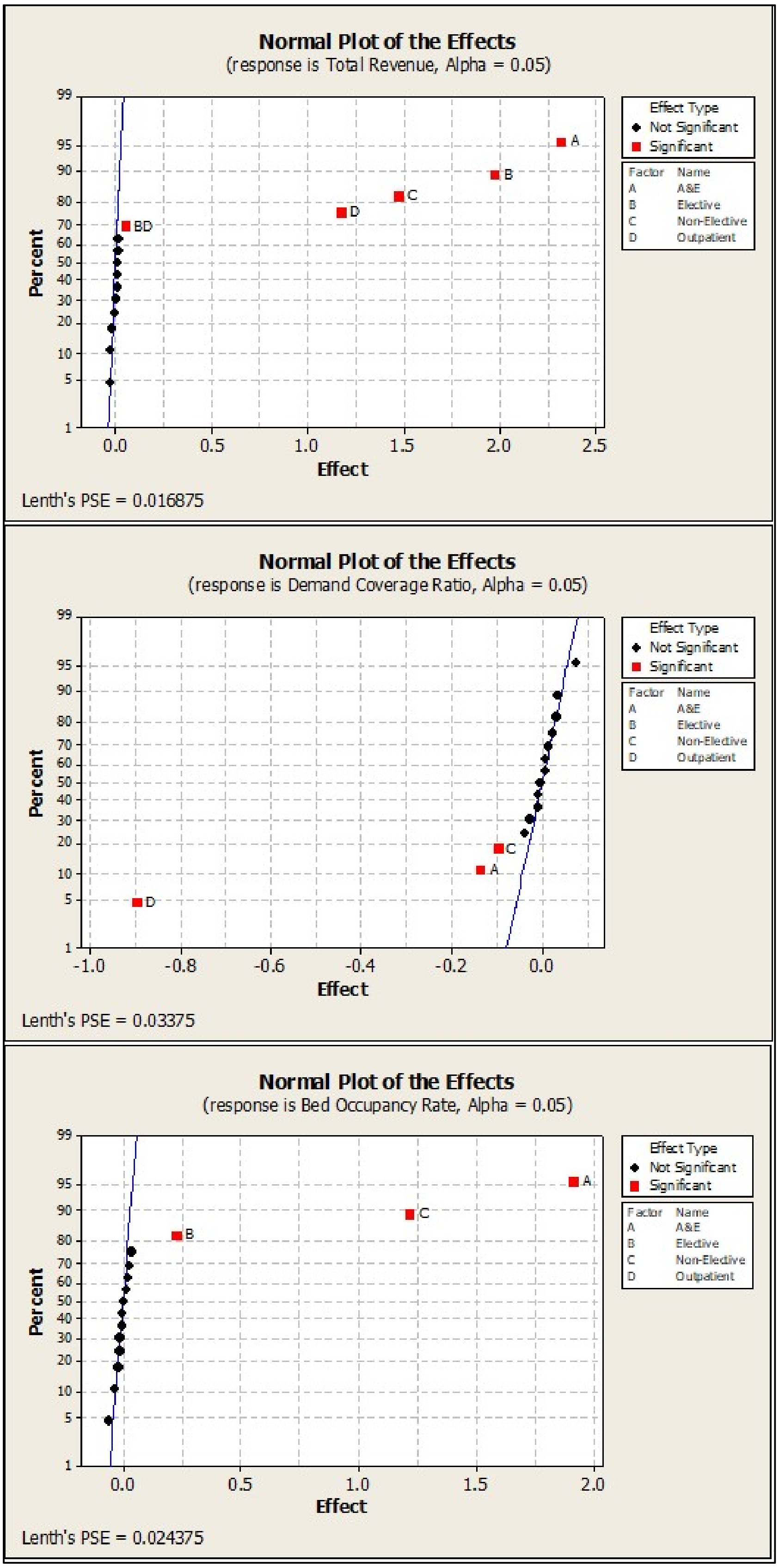

Figure 8.6: Normal plots of the effects in the experimental analysis for each output metric

8.10 Summary

In this chapter, the verified conceptualized pathway of the hospital is explained. The input parameters derived from the HES dataset, local data and literature are described as follows: patient inputs (e.g. forecasted demand), physical inputs (e.g. triage room, clinic room and number of beds), financial inputs (e.g. HRG tariff codes), other inputs (e.g. distributions) and theatre inputs (annual theatre capacity). This chapter also described the entire hospital simulation model along with all the model parameters entered into the Simul8 model (including replication number and warm up period). All key output metrics are listed and explained in detail. The structure of the experimental design (i.e. what-if analysis) is explained and the results for each key output metric are clarified. This chapter clearly show that inpatient beds were not optimally allocated for each specialty. In addition, the key findings also revealed the important factors that affects key output metrics (i.e. total revenue, demand coverage ratio and bed occupancy rate). The next chapter develops a hybrid framework integrating three distinct methodologies (i.e. forecasting, simulation and optimization) to reallocate beds and optimize staffing levels in the inpatient services of the hospital.

CHAPTER 9

Reallocating beds and optimizing staffing levels for balancing demand and capacity: A hybrid framework for forecasting-simulation-optimization (FSO approach)

9.1 Introduction

In this chapter, a hybrid framework for forecasting-simulation-optimization (FSO approach) to reallocate the available beds and optimize the staffing levels for balancing demand and capacity of the Princess Alexandra Hospital is presented. In Section 9.2, the proposed forecasting-simulation-optimization (FSO) approach is explained. Section 9.2.1 presents the parameters and decision variables. Section 9.2.2 states the objective function and constraints. Section 9.2.3 gives all inputs. Section 9.2.4 discusses the results and describes the sensitivity analysis based on the unexpected demand increases.

9.2 Forecasting-Simulation-Optimization (FSO) approach

In this study, a decision support system (DSS) named as FSO approach is developed by combining comparative forecasting techniques, discrete event simulation and optimization (i.e. integer linear programming). The goal is to reallocate the available beds and optimize staffing levels of inpatient services at The Princess Alexandra Hospital. The structure of the DSS is presented as a flow diagram which shows how three distinct techniques are combined in Figure 3.3 (see Chapter 3 for details).

The first component of the proposed methodology establishes the best forecasting method to capture demand for inpatient specialties (see Chapter 7 for details). The second component of the DSS develops the entire hospital simulation model taking into account all the specialties (i.e. A&E, outpatient and inpatient services) and interactions to capture the stochastic behaviour of the hospital (see Chapter 8 for details). Finally, the third component develops an integer linear programming (combining the first two components) to reallocate the available number of beds and optimize the staffing levels. The outputs from the forecasting and simulation are used as inputs in the optimization model. The desired values of the decision variables are obtained by maximizing the number of admitted patients (throughput) under a number of constraints.

The literature around developing models for healthcare providers is rich and vast. Many simulation-optimisation methods have been developed with the aim of determining optimal solutions for their decision variables (e.g. number of operating rooms and beds or staffing cost). The past and current models in the literature typically maximized number of admissions and financial outputs, or minimized length of stay, waiting time and costs in healthcare settings. In the majority of instances these models have focused on modelling a service, department or a specialty, however no models have tackled current and future bed occupancy (and other key metrics of interest) at the entire hospital level. A model for a single service (or few) would not be inadequate to determine the required capacity for all specialties within a hospital.

A comprehensive entire hospital modelling framework is necessary that combines all the specialties and services within a single decision support system (DSS). No model so far has ever been developed at this scale, such that it is able to, 1) forecast demand for all specialties within inpatient, outpatient and A&E, 2) capture the entire hospital patient pathway at a sufficient level of detail, and 3) optimise the required bed capacity and the required number of consultants and nurses.

Such a DSS is able to answer many key questions beyond capacity requirements. For example, a hospital may experience a sharp increase in activity, possibly due to severe weather conditions, or a general trend. The forecasts will generate the expected activity to be integrated into the simulation model, whereas the simulation will capture all the uncertainties around the dynamics of the hospital, ranging from time related activities (e.g. length of stay, waiting times, and treatment duration) to hospital finances (revenue, cost and surplus), with the aim of testing wide range of scenarios around impact of change. The simulation has limitations around establishing the optimal capacity requirements. This is where the optimisation becomes a great tool to estimate the exact bed requirements (along with consultant and nurse hours) subject to constraints (e.g. targeted bed occupancy rate).

In conclusion, the main contribution of this study is the development of a hybrid modelling framework integrating three distinct methodologies as explained above. The study therefore fills a huge gap in the literature in the field of healthcare modelling for better planning of hospital resources. The details of the proposed methodology are explained below.

9.2.1 Parameters and decision variables

The set of inpatient specialties that serve wards for patients consists of general surgery, trauma & orthopaedics, general medicine, cardiology, paediatrics, geriatric medicine, obstetrics, gynaecology, and others which includes all specialties with less than 1% total patient activity in the hospital. The parameters of the integer linear programming are explained as follows.

9.2.1.1. Parameters

***NDP_s*:** Number of discharged patients at specialty *s*,
BOR: Bed occupancy rate (assumed to be annual bed occupancy rate of the hospital)
TARGET: Target level of bed occupancy rate (assumed to be 85% according to the literature),
***NB_s*:** The number of available beds at specialty *s*,
BEDS: The total number of available beds,
***$NDEP_s$*:** Number of discharged elective patients at specialty *s*,
***$NAEP_s$*:** Number of forecasted admitted elective patients at specialty *s* (assumed to be forecasted bed demand of the hospital),
***NE_s*:** Number of non-elective patients at specialty *s*,

$NONELECTIVE_s$: Number of forecasted non-elective patients at specialty s (assumed to be forecasted bed demand of the hospital for non-elective patients),

INCOME: Total income from patient care,

COST: Total staffing costs,

NPR_s: Nurse to patient ratio at specialty s,

CH_s: Consultant hours at specialty s (assumed to be the consultation time served by total number of consultants),

CT_s: Consultation times at specialty s (assumed to be the consultation time required by patients).

The bed occupancy rate of the hospitals is measured by the NHS Trusts in the UK on a regular basis as a key output metric of their inpatient services. For this, NHS Trusts use Eq. (9.1), a ratio that divides the number of hospital beds occupied by the total number of available hospital beds in a period (Harper and Shahani, 2002).

$$Bed\ Occupancy\ Rate\ (\%) = 100 \times \left(\frac{The\ number\ of\ occupied\ bed\ days}{Total\ number\ of\ beds\ \times\ Number\ of\ days\ in\ the\ period} \right) \tag{9.1}$$

In the UK a full time equivalent (FTE) is 37.5 hours per week, which equates to 1950 hours in a year (NHS improvement, 2017). Consultant hours are calculated by multiplying annual working time based on 1.0 FTE with the total number of consultants at the related specialty. According to experts, a consultant on average spends around 20 minutes per day per patient. Consultation times are calculated by multiplying the time for care (i.e. 20 minutes) with total length of stay (as specified in Eq. (9.2)).

$$Consultation\ Time_j = T \times \left(\sum_{i=1}^{e_j} (NAEP_{ij} \times EALoS_{ij}) + \sum_{i=1}^{ne_j} (NANEP_{ij} \times NEALoS_{ij}) \right) \tag{9.2}$$

where e_j: Total number of admissions at inpatient elective specialty j; $EALoS_{ij}$: Length of stay of elective patient i at specialty j; $NAEP_{ij}$: Number of admitted elective patient i at specialty j; $NANEP_{ij}$: Number of non-elective patient i at specialty j; ne_j: Total number of admissions at inpatient non-elective specialty j; $NEALoS_{ij}$: Length of stay of non-elective patient i at specialty j; T: Average time for patient care by consultant.

According to the report published by the National Institute for Health and Care Excellence (2014), a nurse should not be liable to more than 8 patients, otherwise, the risk of harm is increased for nurses (NICE, 2014). The quality of service significantly decreases when a nurse is responsible for more than 8 patients (Griffiths et al., 2017). Therefore, nurse to patient ratio is considered as a nurse care with a maximum of 8 patients per shift in a day.

Total revenue from an inpatient specialty is calculated by multiplying the number of patients with the average revenue per patient (an output from the simulation model). The formula is shown in Eq. (9.3).

$$Total\ \text{Re}venue\ (£) = \sum_{j=1}^{s_e}\left(EAR_j \times ENP_j\right) + \sum_{j=1}^{s_{ne}}\left(NEAR_j \times NENP_j\right) \quad (9.3)$$

where EAR_j: average revenue at elective specialty j; ENP_j: Number of patients at elective specialty j; $NEAR_j$: average revenue at non-elective specialty j; $NENP_j$: number of patients at non-elective specialty j; s_e: Total number of inpatient elective specialty; s_{ne}: Total number of inpatient non-elective specialty.

Total costs are from the staffing costs of all related inpatient specialties as shown in Eq. (9.4). The average annual earnings of consultants and nurses are taken into account in the calculation of staffing costs.

$$Total\ Cost\ (£) = AEC \times \sum_{j=1}^{s} NC_j + AEN \times \sum_{j=1}^{s} NN_j \quad (9.4)$$

where AEC: Annual average earnings of consultants; AEN: Annual average earnings of nurses; NC_j: number of consultant at specialty j; NN_j: Number of nurses at specialty j; s: Total number of inpatient specialty.

9.2.1.2. Decision variables

The decision variables of the integer linear programming are explained as follows.

***DE_s*:** Number of discharged elective patients at specialty s,

***DNE_s*:** Number of discharged non-elective patients at specialty s,

***NB_s*:** Required number of beds at specialty s,

***NN_s*:** Required number of nurses at specialty s,

***NC_s*:** Required number of consultants at specialty s.

9.2.2 Objective function and constraints

The objective function and constraints are explained as follows.

$$Max \sum_{i=1}^{s} NDP_s, \qquad \forall s \in S \tag{9.5}$$

Subject to :

$$BOR_s \leq TARGET, \qquad \forall s \in S \tag{9.6}$$

$$\sum_{s \in S} NB_s \leq BEDS \tag{9.7}$$

$$NDEP_s \leq NAEP_s, \qquad \forall s \in S \tag{9.8}$$

$$NE_s = NONELECTIVE_s, \qquad \forall s \in S \tag{9.9}$$

$$\sum INCOME \geq \sum COST \tag{9.10}$$

$$NPR_s \leq 8, \qquad \forall s \in S \tag{9.11}$$

$$CH_s \geq CT_s, \qquad \forall s \in S \tag{9.12}$$

$$DE_s,\ DNE_s,\ NB_s,\ N_s,\ C_s \in Z^+, \qquad \forall s \in S \tag{9.13}$$

The objective function (9.5) maximizes the number of discharged patients (throughput). Constraint (9.6) ensures that bed occupancy rate of each specialty does not exceed the target level of 85%. Constraint (9.7) allocates the bed capacity (total number of available beds). Constraint (9.8) denotes that the number of discharged elective patients does not exceed the number of admitted elective patients. Constraint (9.9) ensures that each non-elective patient is admitted to the hospital and stays in a bed. Constraint (9.10) ensures that the total income from patient care must be more than or equal to the total costs. Constraint (9.11) indicates that each nurse must not care for no more than a maximum of eight patients. Constraint (9.12) ensures that the total consultation time served by total number of consultants must be more than the total consultation time needed by patients. Constraint (9.13) denotes that all decision variables must be positive integer. An extensive version of the integer linear model adapted for the LINGO software is given in Appendix 44.

The optimization model we developed is generally a model that has been adapted from the literature. However, we take into account some new constraints (i.e. 9.6, 9.11, 9.12). On the other hand, the objective function is a used objective function in literature before. Also, we can see similar constraints with 9.7, 9.8, 9.9, 9.10, 9.13 in literature.

9.2.3 Inputs

The inputs for the FSO approach are provided by four types of resources: Local data, forecasting, simulation and literature (see Table 9.1). At present there are 557 beds at PAH (see Table 9.2 for a breakdown of beds by specialty). Financial inputs, target level of bed occupancy rate and nurse to patient ratio are obtained from the literature. The bed occupancy rate in the UK hospitals must not exceed the target level of 85% (Royal College of Psychiatrists, 2015). In addition, the financial inputs (e.g. the average annual earnings of consultants and nurses) are obtained from the NHS Digital (2014). Another important input from the literature is the nurse to patient ratio. Therefore, nurse to patient ratio of eight is included in the model as a constraint.

Table 9.1: Inputs of FSO approach

Inputs	LD	F	S	L
Target level of bed occupancy rate				X
Total number of beds	X			
Average length of stay for elective patients at s. specialty			X	
Average length of stay for non-elective patients at s. specialty			X	
Number of admitted elective patients at s. specialty		X		
Number of admitted non-elective patients at s. specialty		X		
Average annual earning of consultant				X
Average annual earning of nurse				X
Average income for elective patients at s. specialty			X	
Average income for non-elective patients at s. specialty			X	
Nurse to patient ratio				X

F: Forecasting, L: Literature, LD: Local data, S: Simulation

The demand for each specialty is estimated using the comparative forecasting methods. Average length of stay and average revenue are inputs generated by the generic hospital simulation model. In the simulation model, a diagnostics code is assigned to each patient, derived from the HES dataset using the observed frequency distributions. According to the diagnostic codes based on type of specialty and age groups, we took into account different HRG tariffs depending on length of stay of patients. Thus, the simulation model calculates the average revenue for each specialty. The integer linear model is then embedded by using these stochastic inputs (i.e. average length of stay and revenue) to reflect reality of the hospital. Values of all input parameters are given in Table 9.2.

Table 9.2: Input values of the FSO approach

Specialty			Elective			Non-elective		
Code	**Name**	**ENB**	**ALoS (day)**	**NAP**	**AI (£)**	**ALoS (day)**	**NAP**	**AI (£)**
1	General surgery	85	1.04	3468	1282	4.09	3660	2080
2	Trauma & Orthopaedics	59	1.67	3276	3034	5.90	1536	3459
3	General Medicine	88	0.33	1469	1486	3.90	9004	2110
4	Cardiology	25	0.73	972	2117	7.15	1224	2383
5	Paediatrics	16	0.96	264	1568	1.42	2196	1038
6	Gynaecology	41	0.60	1553	1224	1.64	2147	1386
7	Others	91	0.77	372	784	3.99	732	1629
8	Geriatric Medicine	111	-	-	-	6.03	7692	2280
9	Obstetrics	41	-	-	-	1.94	7320	1636

AI: Average income, ALoS: Average length of stay, ENB: Existing number of beds, NAP: Number of admitted patients

9.2.4 Results and discussion

We developed a hybrid framework integrating three distinct methodologies to determine the required level of resources of a mid-size hospital inpatient services in England. Demand is forecasted for each specialty as inputs for both the simulation and optimization models. A generic hospital simulation model is developed to capture the key performance metrics (i.e. average length of stay and revenue) by tackling stochastic behaviour of the hospital (including patients, human resources, beds, treatment procedures, etc.). An integer linear model is integrated with forecasting and discrete event simulation to reallocate the existing number of beds and optimize the staffing levels. The developed integer linear model is solved using LINGO 17.0 software.

9.2.4.1 Reallocated number of beds

Table 9.3 illustrates the number of discharged elective and non-elective patients, bed occupancy rate (%), the reallocated number of beds and the number of human resources required to meet all demands for each specialty. Bed occupancy rates of all the inpatient specialties are less than the target level of 85%. A total of 486 beds is adequate for the hospital to ensure the hospital is within the recommended BOR.

Table 9.3: The results of the FSO approach for the base model

Code	Name	NDEP	NDNEP	BOR	NB	NC	NN
1	General surgery	3468	3660	84.82	60	4	20
2	Trauma & Orthopaedics	3276	1536	84.72	47	3	15
3	General Medicine	1469	9004	84.81	115	7	37
4	Cardiology	972	1224	83.62	31	2	10
5	Paediatrics	264	2196	83.98	11	1	4
6	Gynaecology	1553	2147	81.33	15	1	5
7	Others	372	732	79.88	11	1	4
8	Geriatric Medicine	-	7692	84.72	150	8	48
9	Obstetrics	-	7320	84.58	46	3	15
Total		11374	35511	-	486	30	158

BOR: Bed occupancy rate, NB: Number of beds, NC: Number of Consultants, NDEP: Number of discharged elective patients, NDNEP: Number of discharged non-elective patients, NN: Number of nurses

Figure 9.1 illustrates a comparison of FSO results with the current situations. According to the results, there are significant differences between the proposed number of beds and current number of beds in a few specialties. Unfortunately, many beds in a number of specialties are idle while some specialties run in overcapacity. For example, the general surgery inpatient specialty requires only 60 beds, however it currently has 88 beds. Incredible number of idle beds are determined to be available in other specialties. On the other hand, the geriatric medicine inpatient specialty works under severe demand pressure in terms of available beds, and the bed occupancy rate decreases from 127% to 85% when the required number of beds is increased by 39 beds. In conclusion, the following specialties have idle beds: general surgery (with 28 beds), trauma & orthopaedics (12 beds), paediatrics (5 beds), gynaecology (26 beds) and others (80 beds). The remaining specialties require additional beds to cope with the overcapacity, for example, general medicine (by 30 beds), cardiology (6 beds), geriatric medicine (39 beds) and obstetrics (5 beds).

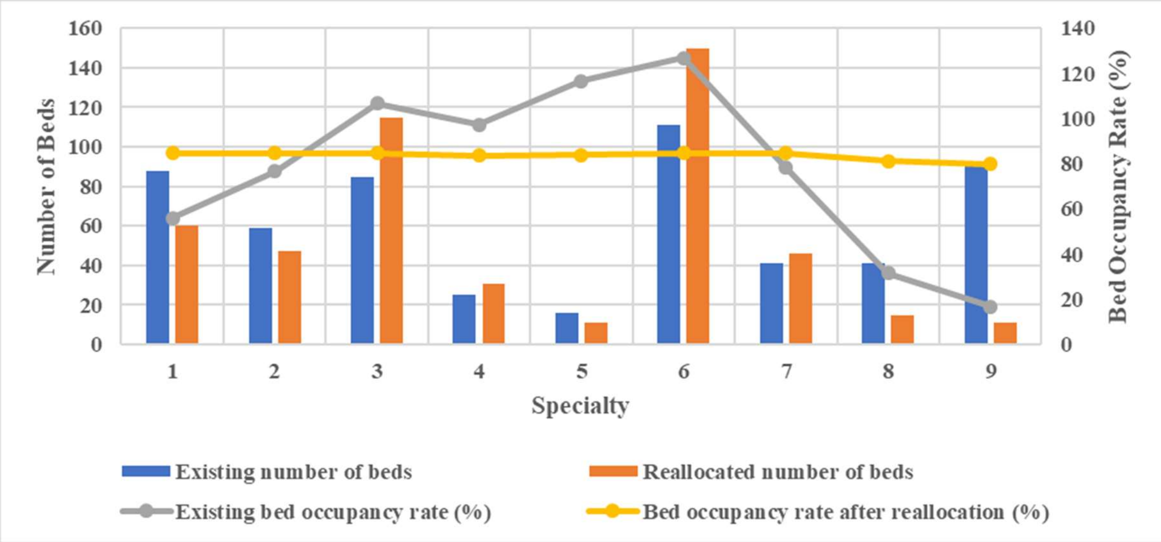

Figure 9.1: Comparison of results with the current situation. Specialties are 1) General surgery, 2) Trauma & orthopaedics, 3) General medicine, 4) Cardiology, 5) Paediatrics, 6) Geriatric medicine, 7) Obstetrics, 8) Gynaecology and 9) Others

9.2.4.2 Sensitivity analysis

A sensitivity analysis is carried out increasing the forecasted demand (i.e. above the base model). The sensitivity analysis consists of 20 experiments where demand is cumulatively increased by 1%, for example, the demand increased by 1% based on forecasted demand in the first experiment, and 2%-increase on demand is used as input in the second experiment etc. (see Table 9.4). We tested the sensitivity of the developed model against the unexpected demand increases. We also calculated DCRs of the inpatient service for each experiment to better understand the performance of the hospital wards. The results show that the hospital wards will be able to cope up to 14% demand increase at most within the forecasted year (see Table 9.4 and Figure 9.2). That is why DCR rates (i.e. Experiments 1 to 14) are 100%, meaning that the related inpatient specialties are able to discharge all patient demands with their available resources. In addition, BOR is less than 85% meaning the wards are able to operate within the recommended level. More than 14% demand increase will force the hospital to reject or transfer patients to other hospitals, whereas the bed occupancy rate will remain around the desired level. The demand coverage ratio reduces according to the increasing demand. For example, in Experiment 20, DCR is below 100% (i.e. approximately 91%). This means that the inpatient specialties were unable to cope with all demand, thus need additional resources to treat the remaining 9%. All results of the experiments for the sensitivity analysis are given in Appendix 45 to 64.

Table 9.4: The results of the sensitivity analysis

Experiments	DCR	BOR	Number of Beds	Number of Consultants	Number of Nurses
Base Model	100.00	73.68	486	30	158
Experiment 1	100.00	74.42	491	31	160
Experiment 2	100.00	75.16	498	31	161
Experiment 3	100.00	75.90	502	31	164
Experiment 4	100.00	76.63	506	31	165
Experiment 5	100.00	77.37	512	31	167
Experiment 6	100.00	78.11	516	31	167
Experiment 7	100.00	78.84	521	31	168
Experiment 8	100.00	79.58	525	31	170
Experiment 9	100.00	80.32	531	31	170
Experiment 10	100.00	81.05	535	31	174
Experiment 11	100.00	81.79	540	31	175
Experiment 12	100.00	82.53	547	32	176
Experiment 13	100.00	83.26	549	32	177
Experiment 14	100.00	84.00	555	33	180
Experiment 15	99.33	84.60	557	33	180
Experiment 16	97.77	84.66	557	33	183
Experiment 17	96.56	84.69	557	33	184
Experiment 18	94.72	84.76	557	33	185
Experiment 19	93.42	84.83	557	33	186
Experiment 20	91.35	84.85	557	33	187

DCR: Demand coverage ratio, BOR: Bed occupancy rate

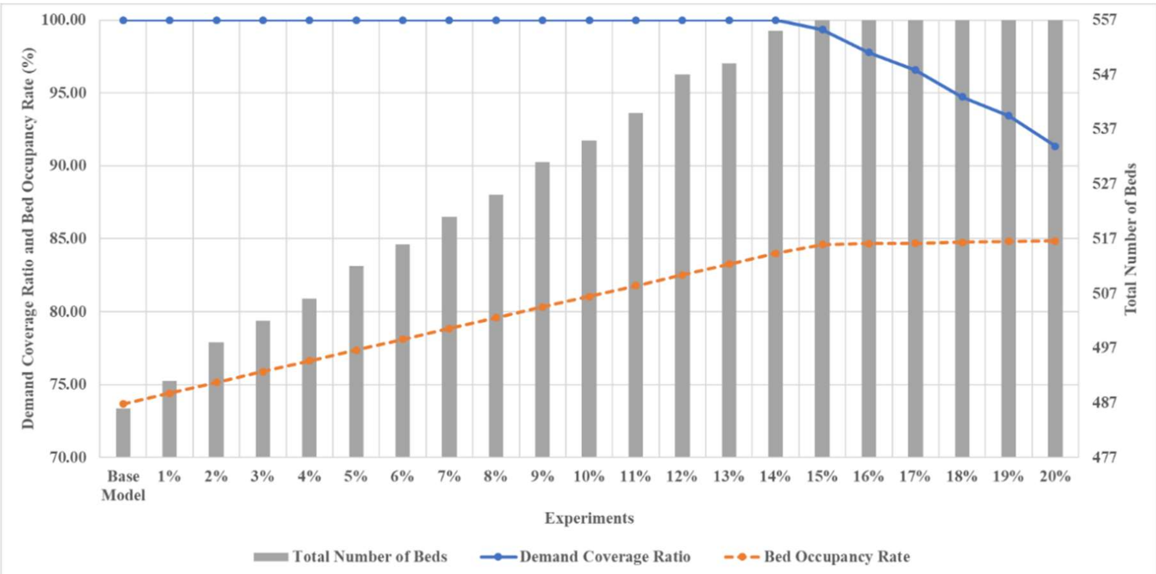

Figure 9.2: Graph of the analysis results with DCR, BOR and total number of beds

9.2.4.3 A comparison of three approaches for reallocation of bed capacity

We compared the results from the FSO approach with the results of forecasting-simulation and forecasting optimization models. Forecasting-simulation model is developed integrating generic hospital simulation model with the comparative forecasting. Forecasting-optimization model includes the forecasted demands and the integer linear programming, which uses the average length of stay and revenue derived from historical data instead of using outputs from the hospital simulation model. Table 9.5 shows the existing number of beds and the reallocated number of beds based on three methodological approaches. “Decisions” column is intended to help key decision makers in the hospital to determine the ideal number of beds in each specialty. The hospital management can decide on the required number of beds depending on budgeting constraints. For example, they can select the minimum number of beds if they prefer to decrease costs (i.e. holding cost) or do not have the available spaces in the wards. They can choose the maximum number of beds if they want to avoid the risk of operating under intense pressure due to increasing demand (particularly during the winter period).

Table 9.5: A comparison of three approaches (i.e. FS, FO and FSO) for the base model

Code	Name	ENB	Methods			Decisions		
			FS	FO	FSO	Minimum	Maximum	Average
1	General surgery	85	59	60	60	59	60	60
2	Trauma & Orthopaedics	59	50	50	47	47	50	49
3	General Medicine	88	114	111	115	111	115	113
4	Cardiology	25	31	30	31	30	31	31
5	Paediatrics	16	11	27	11	11	27	16
6	Gynaecology	41	14	17	15	14	17	15
7	Others	91	19	11	11	11	19	14
8	Geriatric Medicine	111	146	154	150	146	154	150
9	Obstetrics	41	51	43	46	43	51	47
Total		557	495	503	486	486	503	495

ENB: Existing number of beds, FS: Forecasting-simulation, FO: Forecasting-optimization, FSO: Forecasting-simulation-optimization

We notice that the findings in all three methods are in line with each other, with the exception of FO for “Paediatrics” and FS for “Other” specialties. FO model is not able to capture the stochastic nature of the hospital. The FS model is not able to benefit from the advantages of a mathematical model (i.e. focusing on any specific objective, searching for optimal solution of decision variables under constraints). In this context, FSO model is able to include all of these advantages. Table 9.6 gives the average number of beds which is calculated dividing total required number of beds determined by three methods (i.e. FS, FO and FSO) by the number of methods (i.e. 3). In Table 9.6, the mean absolute errors (MAE) between the models and average number of beds are also presented. The lowest MAE based on the average number of beds are generated by the proposed method (i.e. FSO approach), again supporting the fact that the FSO is superior compared to FS and FO.

Table 9.6: The mean absolute errors between the models and average number of beds for the base model

Code	Name	FS	FO	FSO	Average	FS&A	FO&A	FSO&A
1	General surgery	59	60	60	60	1	0	0
2	Trauma & Orthopaedics	50	50	47	49	1	1	2
3	General Medicine	114	111	115	113	1	2	2
4	Cardiology	31	30	31	31	0	1	0
5	Paediatrics	11	27	11	16	5	11	5
6	Gynaecology	14	17	15	15	1	2	0
7	Others	19	11	11	14	5	3	3
8	Geriatric Medicine	146	154	150	150	4	4	0
9	Obstetrics	51	43	46	47	4	4	1
Mean Absolute Errors						2.44	3.11	1.44

FS: Forecasting-simulation, FO: Forecasting-optimization, FSO: Forecasting-simulation-optimization, A: Average number of beds

9.2.4.4 Optimized number of staff

Figures 9.3 and 9.4 show the relationship between bed occupancy rate and total number of consultants, and bed occupancy rate and total number of nurses, respectively. According to the graphs, a minimum of 30 consultants and 158 nurses are needed to be able to operate effectively. These estimates are based on the assumption that a consultant or a nurse spends the entire workload treating patients (typically 1950 hours per year). This is a strong assumption and not realistic.

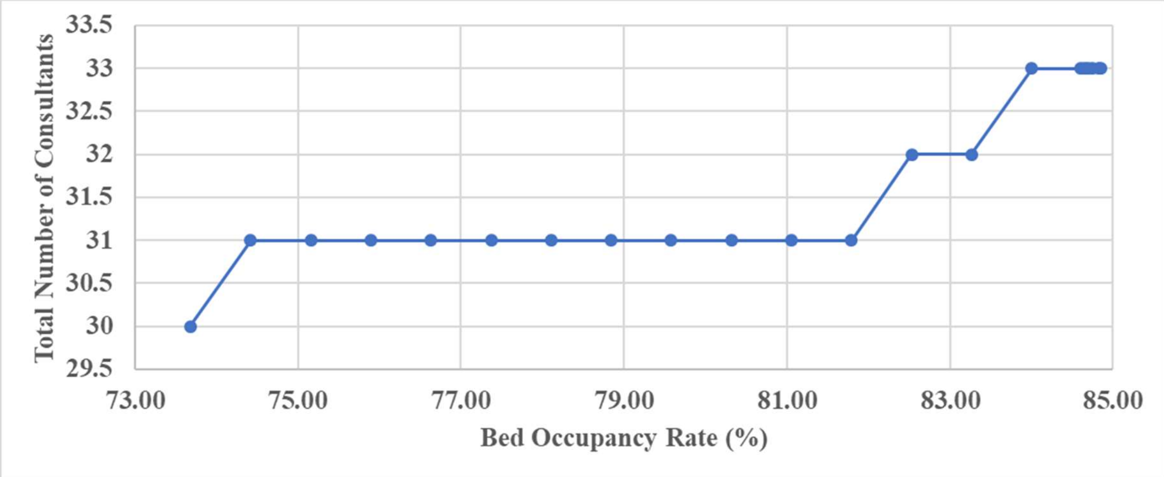

Figure 9.3: Graph of the analysis results with BOR and total number of consultants

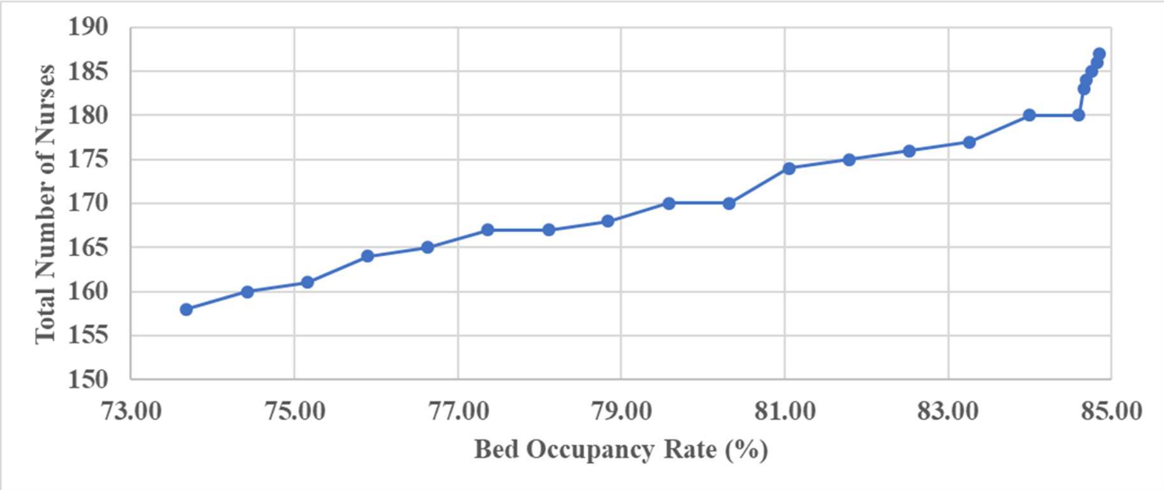

Figure 9.4: Graph of the analysis results with BOR and total number of nurses

In the NHS, a full-time equivalent (FTE) is 37.5 hours per week (around 1950 hours per year) (NHS improvement, 2017). As seen in Table 9.3, the required number of consultants and nurses in all inpatient services, are determined by assuming that all staff are in full time employment (i.e. 1 FTE). However, consultants or nurses may choose to have a lower FTE rate instead of full time contracts, or the hospital management may employ on a different FTE rate. More importantly, staff do not spend all of 1950 hours per year treating patients.

Therefore, the estimates in Table 9.3 (number of consultants and nurses) needs to be adjusted, 1) according to the percentage of their time spent on treating patients, and 2) various FTE employment contracts (for example, a hospital may have a combination of consultants, some working full time, some 0.5 FTE, etc.). In addition, consultants are typically employed in an inpatient service for a certain rate of their working hours and the remaining part is consumed by consulting in an outpatient clinic, or vice versa. Considering these reasons, the inpatient specialties will require more than the number of consultants or nurses stated in Table 9.3. Therefore, we specified the number of staff working with different FTE rates (i.e. 1.0, 0.8, 0.5, and a case mix). A case mix includes 50% of consultants work with 1.0 FTE, 30% with 0.8 FTE, and the remaining with 0.5 FTE. We also considered the percentage of time a typical consultant or a nurse treats patients within their contractual hours, i.e. 20%, 40% and 60%. For example, 20% means that a consultant on average spends 20% of his/her time treating patients, and the remaining time is allocated for other activities (i.e. writing reports, meetings, training, etc.). Let's assume that consultants at PAH works with a case mix of FTE's, and on average they spend 40% of their time treating patients. The inpatient services will need 109 consultants for the 8 specialties plus a group of "Other" specialties (see Table 9.7). Similar interpretations can be made for nurses in Table 9.8.

Table 9.7: Number of consultants depending on different FTE ratios for the base model

Specialty	1.0 FTE			0.8 FTE			0.5 FTE			Case Mix		
	20%	40%	60%	20%	40%	60%	20%	40%	60%	20%	40%	60%
General surgery	20	10	7	25	13	8	40	20	13	30	15	10
Trauma & Orthopaedics	15	8	5	20	10	7	30	15	10	20	10	7
General Medicine	35	18	12	45	23	15	70	35	23	45	23	15
Cardiology	10	5	3	15	8	5	20	10	7	15	8	5
Paediatrics	5	3	2	10	5	3	10	5	3	10	5	3
Gynaecology	5	3	2	10	5	3	10	5	3	10	5	3
Others	5	3	2	10	5	3	10	5	3	10	5	3
Geriatric Medicine	40	20	13	50	25	17	80	40	27	55	28	18
Obstetrics	15	8	5	20	10	7	30	15	10	20	10	7
Total	150	78	51	205	104	68	300	150	99	215	109	71

FTE: Full time equivalence, Case Mix is 50% with 1.0 FTE, 30% with 0.8 FTE, 20% with 0.5 FTE

Table 9.8: Number of nurses depending on different FTE ratios for the base model

Specialty	1.0 FTE			0.8 FTE			0.5 FTE			Case Mix		
	20%	**40%**	**60%**	**20%**	**40%**	**60%**	**20%**	**40%**	**60%**	**20%**	**40%**	**60%**
General surgery	100	50	33	125	63	42	200	100	67	130	65	43
Trauma & Orthopaedics	75	38	25	95	48	32	150	75	50	100	50	33
General Medicine	185	93	62	235	118	78	370	185	123	240	120	80
Cardiology	50	25	17	65	33	22	100	50	33	65	33	22
Paediatrics	20	10	7	25	13	8	40	20	13	30	15	10
Gynaecology	25	13	8	35	18	12	50	25	17	35	18	12
Others	20	10	7	25	13	8	40	20	13	30	15	10
Geriatric Medicine	240	120	80	300	150	100	480	240	160	310	155	103
Obstetrics	75	38	25	95	48	32	150	75	50	100	50	33
Total	790	397	264	1000	504	334	1580	790	526	1040	521	346

FTE: Full time equivalence, Case Mix is 50% with 1.0 FTE, 30% with 0.8 FTE, 20% with 0.5 FTE

9.3 Summary

This chapter explained how the proposed FSO approach is developed by integrating three distinct methodologies. Parameters and decision variables of the developed integer linear model are described in greater detail. Relevant sources of the inputs are clarified: local data (i.e. existing number of beds), forecasting (i.e. demand), simulation (i.e. average length of stay and revenue) and literature (i.e. target level of bed occupancy rate, average annual earnings of consultants and nurses, nurse to patient ratio). All results are discussed including the sensitivity analysis based on various demand increases. The hospital is able to cope with a maximum of 14% demand increase, where BOR and DCR is around 85% and 100%, respectively.

In addition, the required number of resources (number of beds, consultants and nurses) the hospital should have at its disposable are specified. The next chapter concludes the thesis and highlights future work.

CHAPTER 10

Conclusion and Further Work

10.1 Conclusion

A day hardly ever passes in the UK without the NHS hitting the tabloids, with headlines such as “our NHS is dying”, “NHS in crisis”, “A&E patients hit by winter crisis”, “NHS cuts 15000 beds in 6 years”, and “worst nurse shortage ever”. With ever increasing demand (mainly due to an ageing population), lack of resources and beds (due to severe financial cuts), coupled with the likely impact of Brexit on staffing within the NHS, means that we will continue seeing such headlines now and in the future.

The increasing pressures on the healthcare system in the UK and other parts of the world are well documented. Widespread coverage from the media backed with findings from healthcare professionals and academics (using real life data) provides evidence of such cracks (the NHS is no different). Problems surrounding these pressures include budgeting constraints, increasing demand, disjointed care and lack of workforce. These pressures will not be resolved anytime soon, in fact it’s here to stay with us. Austerity in the UK will continue beyond 2020, and the impact of Brexit (with a no deal with the European Union) is likely to cause further disruptions to the UK economy, thus a knock-on effect on all public services (including healthcare).

Key decision makers are very well aware that hospital bed occupancy is near 100%. Mental health bed occupancies are no different, with patients sitting for hours in emergency departments waiting for a bed. Primary care is struggling, some patients are unable to get appointments to be seen by a General Practitioner. Social care is near breaking point with limited community places available and no budget for care packages. So, it's time to do things differently, because the current status quo is not an option.

In these circumstances business as usual in the NHS is not an option. This may mean a major shift in the decision-making process in relation to capacity (resource) requirements. We are very well aware that key decision makers in the NHS heavily rely on basic statistical analysis (e.g. average number of admissions, average length of stay, average bed occupancy rates). A simple analysis of activity around averages (or any other statistical measures) within a specialty or a service will not be adequate for an effective solution of the problem. A holistic approach that integrates the entire hospitals specialties are needed, as all the services are interconnected, which cannot be assumed to be independent from each other. There is an increasing demand and capacity shortages across all the services in the NHS, thus modelling at this level of detail is an absolute necessity.

10.1.1 Comparative forecasting to estimate hospital demand

This study indicates that forecasting hospital demand under different periods might generate more accurate result even if the past studies have preferred daily period to estimate hospital demand. This study shows that the best demand estimates are based on different forecasting methods and forecasting periods. Unlike the current and past studies conducted in the literature, our study filled a major gap by comparing different forecasting periods (i.e. daily, weekly and monthly). In addition, we also tested with a forecasting methodology that has never been considered within a healthcare setting before (i.e. the STLF method). The STLF method outperformed traditional time series forecasting methods (i.e. ARIMA, exponential smoothing) for a number of specialties, despite the method has been applied for the first time. For instance, based on MASE, the STLF method was superior for the non-elective admissions in the general medicine specialty. In addition, this study highlights that hospital managements will need to take into consideration different forecasting periods to better estimate hospital demands.

As the complexity of healthcare services increases in an environment of constrained resources and increasing demand, so too does the need for evidence-based decision making.

Reliable and accurate forecasting models are well positioned to provide that evidence and allow hospital service managers face upcoming challenges with greater confidence.

Hospital managers are very well aware that hospitals are at breaking point in most parts of the country, with patients sitting for hours in departments waiting for a bed. As such, accurate and reliable long term hospital forecasting models are required to assess and respond to the needs of local populations, both currently and in the future. This study will therefore enable key decision makers to better understand the demand for A&E, outpatient and inpatient services, thus the opportunity to effectively plan ahead for resource requirements (e.g. doctors and nurses).

10.1.2 Generic hospital simulation modelling integrated with comparative forecasting

Clear and robust, long term hospital level models are required to assess and respond to the needs of local populations, both currently and in the future. We genuinely need models that integrate every component of a hospital to find efficient and effective use of scarce resources. Each and every department, ward, specialties and services are interconnected. An individual service cannot be assumed to be independent.

After an extensive review of the literature we noticed that there is a gap waiting to be filled in research and academic terms, and an urgent need for a generic hospital level simulation model for the management of hospitals. We therefore developed a model in a way that has never been tackled before, linking each and every service and specialty within A&E, outpatient and inpatient services.

A vast amount of data analysis was carried out using local data and the Hospital Episodes Statistics dataset. In total, 768 forecasting models were developed for the 31 outpatient and inpatient specialties broken down by age group. We further established approximately 600 observed frequency distributions for the simulation model.

This study shows that the hospital can cope with the increasing demand (as forecasted) with its current level of resources. Results of the simulation scenarios revealed that when the demand in A&E and outpatients increase by 10%, and elective and non-elective inpatients increase by 20%, the DCR will remain almost the same, and the BOR will increase by 10% reaching almost to the national bed occupancy target of 85%. Furthermore, with the increase in patient volumes, the revenue generated will increase by almost 13%. This study shows the gradual increase in BOR and revenue by the stepwise percentage of increments in demands. The results help hospital managements see the effects of demand changes on key performance metrics.

Furthermore, interrelationships between emergency, inpatient, and outpatients are investigated with the DSS. Simulation output analysis revealed that DCR is significantly affected by number of outpatients, and the main driver of BOR is emergency, and hence, unplanned admissions. This result suggests that hospitals must concentrate on emergency patients to better utilise their bed resources. Efficient use of beds is only possible when emergency patients are managed better.

The DSS in this study also demonstrates that generic and nation-wide data sources are sufficient for analysis and modelling at hospitals. As in the UK, data repositories, like HES, should be maintained and made available to do routine analysis and create generic models for analysis. Artificial Intelligence (AI) algorithms can help human decisions in such automated evaluations.

The proposed DSS will provide many benefits to the management of hospitals. It will enable them to foresee patient demands for their hospitals in future years and test whether these demands are met with their available resources (using the key outputs generated from the model). In addition, the management will be able to observe how possible changes in resources (e.g. staffs, beds, rooms) affect the performance of hospitals in the safety of a simulation environment. Note that the management could easily test the system not just for one part of the hospital but to all services. For instance, at the time of developing this model, a nearby hospital's services were closing. The model was tested for scenarios where the hospital would incur an increase of 5-10% in outpatient attendance and inpatient admissions across all 31 specialties and examined whether the hospital was able to cope with this level of demand. These results will bring a different perspective to the management of the NHS for short and long term strategic planning, which will enable them to make rational and realistic plans.

The DSS further enables the management to assess the needs of the hospital in terms of human resources, department expansion or reduction, and medical equipment/bed requirements. Effective personnel planning prevents overemployment in hospitals, and department expansion (or reduction) readjusts bed capacity according to demands periodically and thus idle capacity (or lack of capacity) is avoided.

The whole hospital level simulation model can become a crucial instrument for key decision makers towards becoming an efficient and cost-effective service for NHS Trusts across the UK. Savings as a result of using the DSS may enable the hospital to allocate additional funds for scientific research, training of staff, and sponsorships of research students. The NHS will be able to extend their vision and maintain a sustainable service for now and into the future.

This study has produced a crucial and a practical decision support tool to help patients, taxpayers, managements of hospitals, the NHS and beyond. The tool has been utilised by senior management of a mid-size NHS Trust in England.

10.1.3 FSO approach

After an exhaustive review of the literature we notice that an entire hospital model has never been developed that combines forecasting, simulation and optimization techniques. We therefore developed a model that linked each and every service and specialty within A&E, outpatient and inpatient services, with the aim of, 1) forecasting demand for all the specialties (including first/follow up outpatient attendances, elective/non-elective inpatient admissions, and A&E admissions), 2) capturing all the uncertainties of patient pathway within a hospital setting to facilitate the testing of wide range of scenarios in the safety of a validated simulation model, 3) provide a precise estimate of the required bed capacity (and staff) needs.

Based on simulation findings, estimates and the confidence intervals (CI) were obtained. The key decision makers would like to better understand exactly how many beds the specialties should have in each service. Therefore, the optimization enables the analyst (developer) to provide a precise estimate. The entire hospital modelling framework will therefore facilitate the service planning and decision making and more importantly speed up the pace of change in the specialty or service of interest.

In addition, due to severe budget cuts in the NHS, hospitals do not have the necessary funding to increase capacity, either in the form of beds or staff. Therefore, hospital management needs to find efficient and effective ways of utilising existing resources. This may mean the management doing things differently, a shift from conventional decision-making process to a more evidence-based approach (a behavioural change). Optimization methods help the decision makers to plan their resources efficiently. Taking into account objective functions, optimization methods seek an optimal solution under a number of constraints restricting the hospital systems. Linear optimization is such a method which is able to be used for reallocating beds and optimizing staffing levels of a hospital.

A total of 85 constraints along with objective functions were developed for the optimization model. Possible risks of harm for nurses related to work overload in hospitals were taken into consideration in the model. At each stage, the decision support tool was designed, verified and validated with specialists (consultants, service managers and directors).

According to our findings a total of 486 beds is adequate for the hospital to maintain the 85% bed occupancy target. We also noticed that the beds were inappropriately distributed. For instance, at present general medicine has 88 beds, whereas the FSO results indicate that it should have around 115 beds in order to cope with existing demand. On the other hand, other specialties have 91 beds, but it only needs around 11. Inappropriate bed allocation is a major concern amongst many healthcare providers. Goulding et al. (2015) explored patient's perspectives of the quality and safety of the care received during their inpatient stay on a clinically inappropriate hospital ward and found that patients have reported dissatisfaction in terms of preference and belonging.

The FSO model also established the required number of consultants and nurses within inpatient services. In the majority of instances, the NHS has varying FTE contractual agreements, particularly amongst consultants, where they may have multiple roles, e.g. as a researcher, academic roles, private clinics, etc. The assumption that they work full time is wrong. Based on a mix of FTE contractual agreements, if a consultant spends 20% of their workload physically treating patients, then the inpatient services will require 215 consultants.

The level of complexity of FSO approach is extremely challenging. All components of FSO include enormous amount of modelling as explained in Chapter 7 to 9. For instance, forecasting section consists of 768 developed forecasting models. The generic simulation model includes every single specialty in a hospital. As a result of this level of difficulty, complexity (and lack of time), previous researchers have not considered the FSO approach.

These results can be immensely useful for the management in a number of key areas, 1) capture demand for the entire hospital for each specialty, 2) observe the impact of change (such as change in resources) on key performance metrics before it is implemented in practice, and 3) determine the optimal resource requirements with confidence (namely staff and beds) in order to meet demand now and into the future. These results will bring a different perspective to key decision makers with a DSS for short and long term strategic planning to make rational and realistic plans.

10.2 Opportunities for further work

This study has a number of limitations for forecasting, simulation and FSO techniques. Forecasting studies should also focus on estimating hospital demand based on age groups and patient activity, for example, severity of injury for A&E arrivals, diagnostic procedures for elective and non-elective inpatient specialties and first and follow up outpatient specialties.

Generic hospital simulation model might include more operational level modelling of some specialties. These specialties are needed to be modelled deeply in terms of improving performance metrics, for example, majority of A&E services over the world have highest patient volume than other specialties. In the PAH, the A&E department are visited by an average of 227 patients per day and this department has a limited number of consultants and nurses. In this situation, additional data might be required to be collected in addition to available data.

The FSO technique has a number of limitations. Outpatient services play a crucial role within a hospital, where a typical NHS Trust could deal with over 300,000 attendances per year. The forecasting techniques are able to capture outpatient demand for each specialty, broken down by age and first/follow up referrals; the simulation model captures the entire outpatient services pathway with the flexibility of testing wide range of scenarios, but the optimization model does not determine the required resources, such as consultation room requirements, clinic slot requirements, outpatient staff needs, etc. Likewise, the optimization should also focus on A&E departments and determine the required number of emergency beds in order to minimize patient waiting times (i.e. less than the four-hour target from admission to discharge set by the Department of Health in England). Future research can be directed towards integrating these issues into the optimisation model.

10.3 Summary

In this chapter, the importance of the study is highlighted. This chapter explains how this study approaches the current and future needs of NHS and how NHS could benefit from it. In addition, the emphasis is placed on the practical implication of this study and its contributions to knowledge. This chapter addresses the opportunities of future work that can address the development of the optimization models through integration of inpatient services with the A&E department and outpatient services.

References

1. Abdelaziz, F. B. & Masmoudi, M. (2012) 'A multiobjective stochastic program for hospital bed planning'. *Journal of the Operational Research Society*. 63 (4) pp.530 – 538. https://doi.org/10.1057/jors.2011.39

2. Aboagye-Sarfo, P., Mai, Q., Sanfilippo, F. M., Preen, D. B., Stewart, L. M., & Fatovich, D. M. (2015) 'A comparison of multivariate and univariate time series approaches to modelling and forecasting emergency department demand in Western Australia'. *Journal of Biomedical Informatics*. 57 pp.62-73. https://doi.org/10.1016/j.jbi.2015.06.022

3. Adan, I., Bekkers, J., Dellaert, N., Vissers, J. & Yu, X. (2009) 'Patient mix optimisation and stochastic resource requirements: a case study in cardiothoracic surgery planning'. *Health Care Management Science*. 12 (2) pp.129–141. DOI 10.1007/s10729-008-9080-9

4. Ahmad, N., Ghani, N. A., Kamil, A. A., Tahar, R. M. & Teo, A. H. (2012) 'Evaluating emergency department resource capacity using simulation'. *Modern Applied Science*. 6 pp.9-19. http://dx.doi.org/10.5539/mas.v6n11p9

5. Ahmed, A., & Alkhamis, T. M. (2009) 'Simulation optimization for an emergency department healthcare unit in Kuwait'. *European Journal of Operational Research*. 198, pp.936–942. https://doi.org/10.1016/j.ejor.2008.10.025

6. Akcali, E., Cote, M. J. & Lin, C. (2006) 'A network flow approach to optimizing hospital bed capacity decisions'. *Health Care Management Science*. 9 (4) pp.391–404. DOI 10.1007/s10729-006-0002-4

7. Aksarayli, M., Kidak, L. B. & Gunes, M. (2009) 'Optimization of the bed utilization by simulation in healthcare services: An application in an education & research

hospital'. *Journal of the Faculty of Economics and Administrative Sciences of Gazi University*. 11 (1) pp.1–22 (in Turkish).

8. Antmen, Z. F. & Ogulata, S. N. (2012) 'Simulation modelling of capacity planning problem for third level intensive care units and case study'. *Çukurova Üniversitesi Fen ve Mühendislik Bilimleri Dergisi*. 28 pp.42–47 (in Turkish).

9. Babashov, V., Aivas, I., Begen, M. A., Cao, J. Q., Rodrigues, G., D'Souza, D., Lock, M., & Zaric, G. S. (2017) 'Reducing Patient Waiting Times for Radiation Therapy and Improving the Treatment Planning Process: a Discrete-event Simulation Model (Radiation Treatment Planning)'. *Clinical Oncology*. 29 pp.385–391. https://doi.org/10.1016/j.clon.2017.01.039

10. Bachouch, R. B., Guinet, A. & Hajri-Gabouj, S. (2012) 'An integer linear model for hospital bed planning'. *International Journal Production Economics*. 140 (2) pp.833–843. https://doi.org/10.1016/j.ijpe.2012.07.023

11. Ballard, S. M. & Kuhl, M. E. (2006) The use of simulation to determine maximum capacity in the surgical suite operating room. In: L. F. Perrone, F. P. Wieland, J. Liu, B. G. Lawson, D. M. Nicol, and R. M. Fujimoto (eds.) *Winter Simulation Conference 2006, 3–6 December 2006, Monterey, USA*. New York, Institute of Electrical and Electronics Engineers. pp. 433-438.

12. Banks, J., Carson II, J.S., Nelson, B.L. & Nicol, D.M. 2005. *Discrete-Event System Simulation*. New Jersey, USA: Pearson.

13. Barnes, S., Hamrock, E., Toerper, M., Siddique, S., & Levin, S. (2016) 'Real-time prediction of inpatient length of stay for discharge prioritization'. *Journal of the American Medical Informatics Association*. 23 pp.e2–e10. doi:10.1093/jamia/ocv106

14. Batal H., Tench J., McMillan S., Adams J., Mehler P. S. (2001) 'Predicting patient visits to an urgent care clinic using calendar variables'. *Academic Emergency Medicine*. 8 pp.48-53. https://doi.org/10.1111/j.1553-2712.2001.tb00550.x

15. Bergs, J., Heerinckx, P., & Verelst, S. (2013) 'Knowing what to expect, forecasting monthly emergency department visits: A time-series analysis'. *International Emergency Nursing*. 22 pp.112–115. http://dx.doi.org/10.1016/j.ienj.2013.08.001

16. Blaisdell, C. J., Weiss, S. R., Kimes, D. S., Levine, E. R., Myers, M., Timmins, S., & Bollinger, M. E. (2002) 'Using seasonal variations in asthma hospitalizations in

children to predict hospitalization frequency'. *The Journal of Asthma: Official Journal of the Association for the Care of Asthma*. 39 (7) pp.567-575. http://doi.org/10.1081/JAS 120014921.

17. Blunt, I. (2014) *Focus on: A&E attendances: why are patients waiting longer?* Available at: http://www.qualitywatch.org.uk/sites/files/qualitywatch/field/field_document/QW%2 Focus%20on%20A%26E%20attendances%20%28for%20web%29.pdf. [Accessed 21st June 2017].
18. Blunt, I., Edwards, N. & Merry, L. (2015) *What's behind the A&E 'Crisis'?* Policy Briefing #3.
19. Bowers, J. & Mould, G. (2004) 'Managing uncertainty in orthopaedic trauma theatres'. *European Journal of Operation Research*. 154 (3) pp.599–608. https://doi.org/10.1016/S0377-2217(02)00816-0
20. Bowers, J. & Mould, G. (2005) 'Ambulatory and orthopaedic capacity planning'. *Health Care Management Science*. 8 (1) pp.41–47. https://doi.org/10.1007/s10729-005-5215-4
21. Brailsford, S. C., Lattimer, V. A., Tarnaras, P. & Turnbull, J. C. (2004) 'Emergency and on-demand health care: modelling a large complex system'. *Journal of the Operational Research Society*. 55 (1) pp.34–42. https://doi.org/10.1057/palgrave.jors.2601667
22. Boyle, J., Jessup, M., Crilly, J., Green, D., Lind, J., Wallis, M., Miller, P., & Fitzgerald, G. (2012) 'Predicting emergency department admissions'. *Emergency Medicine Journal*. 29 pp.358-365. http://dx.doi.org/10.1136/emj.2010.103531
23. Boutsioli, Z. (2010) 'Forecasting the stochastic demand for inpatient care: the case of Greek national health system'. *Health Services Management Research*. 23 pp.116-120. https://doi.org/10.1258/hsmr.2009.009025
24. Boutsioli, Z. (2013) 'Estimation of unpredictable hospital demand variations in two Piraeus public hospitals, Greece'. *Journal of Hospital Administration*. 2 pp.126-137. https://doi.org/10.5430/jha.v2n4p126
25. Brenner, S., Zeng, Z., Liu, Y., Wang, J., Li, J. & Howard, P. K. (2010) 'Modeling and analysis of the emergency department at University of Kentucky Chandler

Hospital using simulation'. *Journal of Emergency Nursing*. 36 (4) pp.303–310. https://doi.org/10.1016/j.jen.2009.07.018

26. Bretthauer, K. M., & Cote, M. J. (1998) 'A model for planning resource requirements in health care organizations'. *Decision Sciences*. 29 (1) pp.243-270. https://doi.org/10.1111/j.1540-5915.1998.tb01351.x

27. BMA. (2017) *State of the health system – Beds in the UK*. Available at: https://www.bma.org.uk/collective-voice/policy-and-research/nhs-structure-and delivery/monitoring-quality-in-the-nhs/beds-in-the-nhs. [Accessed on 1st November 2018].

28. Cabrera, E., Taboada, M., Iglesias, M. L., Epelde, F., & Luque, E. (2011) 'Optimization of Healthcare Emergency Departments by Agent-Based Simulation'. *Procedia Computer Science*. 4 pp.1880–1889. https://doi.org/10.1016/j.procs.2011.04.204

29. Cabrera, E., Taboada, M., Iglesias, M. L., Epelde, F., & Luque, E. (2012) 'Simulation Optimization for Healthcare Emergency Departments'. *Procedia Computer Science*. 9 pp.1464–1473. doi: 10.1016/j.procs.2012.04.161

30. Cappanera, P., Visintin, F., & Banditori, C. (2014) 'Comparing resource balancing criteria in master surgical scheduling: A combined optimisation-simulation approach'. *International journal of production economics*. 158 pp.179–196. https://doi.org/10.1016/j.ijpe.2014.08.002

31. Champion, R., Kinsman, L. D., Lee, G. A., Masman, K. A., May, E. A., Mills, T. M., Taylor, M. D., Thomas, P. R., & Williams, R. J. (2007) 'Forecasting emergency department presentations'. *Australian Health Review*. 31 pp.83-90. https://doi.org/10.1071/AH070083

32. Cochran, J. K., & Bharti, A. (2006) 'A multi-stage stochastic methodology for whole hospital bed planning under peak loading'. *International Journal of Industrial and Systems Engineering*. 1 pp.8–36. https://doi.org/10.1504/IJISE.2006.009048

33. Coelli, F. C., Ferreira, R. B., Almeida, R. M. V. R. & Pereira, W. C. A. (2007) 'Computer simulation and discrete-event models in the analysis of a mammography clinic patient flow'. *Computer Methods and Programs in Biomedicine*. 87 (3) pp.201–207. https://doi.org/10.1016/j.cmpb.2007.05.006

34. Combes, C., Kadri, F., & Chaabane, S. (2014) Predicting hospital length of stay using regression models: Application to emergency department. *10th International Conference on Modeling, Optimization & Simulation, MOSIM'14, 5-7 November 2014, Nancy, France.*

35. Connelly, L. G. & Bair, A. E. (2004) 'Discrete event simulation of emergency department activity: a platform for system-level operations'. *Academic Emergency Medicine*. 11 pp.1177-1185. https://doi.org/10.1197/j.aem.2004.08.021

36. Costa, A. X., Ridley, S. A., Shahani, A. K., Harper, P. R. & Senna V. De, (2003) 'Mathematical modelling and simulation for planning critical care capacity'. *Anaesthesia*. 58 (4) pp.320–327. https://doi.org/10.1046/j.1365-2044.2003.03042.x

37. Cote, M. J. (1999) 'Patient flow and resource utilization in an outpatient clinic'. *Socio Economic Planning Sciences*. 33 (3) pp.231–245. https://doi.org/10.1016/S0038-0121(99)00007-5

38. Cote, M. J. & Smith, M. A. (2018) 'Forecasting the demand for radiology services'. *Health Systems*. 7 pp.79-88. https://doi.org/10.1080/20476965.2017.1390056

39. Cracknell, R. (2010) *The ageing population*. Key issues for the new parliament 2010.

40. Davis, S., Stevenson, M., Tappenden, P. & Wailoo, A. J. (2014) *NICE DSU technical support document 15: Cost-effectiveness modelling using patient-level simulation*. Available at: http://www.nicedsu.org.uk. [Accessed 4th July 2017].

41. Demir, E. (2014) 'A decision support tool for predicting patients at risk of readmission: A comparison of classification trees, logistic regression, generalized additive models, and multivariate adaptive regression splines'. *Decision Science*. 45 (5) pp.849-880. https://doi.org/10.1111/deci.12094

42. Demir, E., & Chaussalet, T. (2009) A systematic approach in defining readmission. *22nd IEEE International Symposium on Computer-Based Medical Systems, 3-4 August 2009, New Mexico, USA.*

43. Demir, E., & Southern, D. (2017) 'Enabling better management of patients: Discrete event simulation combined with the STAR approach'. *Journal of the Operational Research Society*. 68 pp.577–590. https://doi.org/10.1057/s41274-016-0029-y

44. Demir, E., Lebcir, R., & Adeyemi, S. (2014) 'Modelling length of stay and patient flows: methodological case studies from the UK neonatal care services'. *Journal of*

the Operational Research Society. 65 pp.532–545. https://doi.org/10.1057/jors.2013.51

45. Demir, E., Gunal, M. & Southern, D. (2017) 'Demand and capacity modelling for acute services using discrete event simulation'. *Health Systems*. 6 pp.33-40. https://doi.org/10.1057/hs.2016.1

46. Demir, E., Southern, D., Verner, A., & Amoaku, W. (2018) 'A simulation tool for better management of retinal services'. *BMC Health Services Research*. 18. https://doi.org/10.1186/s12913-018-3560-5

47. DeLurgio, S.A. 1998. *Forecasting Principles and Applications*. McGraw – Hill.

48. Department of Health. (2013) *Reference costs 2012–13*. Available at: https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/261154/nhs_reference_costs_2012-13_acc.pdf. [Accessed 26th May 2017].

49. Department of Health. (2014) *Reference costs 2013–14*. Available at: https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/380322/01_Final_2013-14_Reference_Costs_publication_v2.pdf. [Accessed 26th May 2017].

50. Department of Health and Social Care. (2013) *Payment by results in the NHS: tariff for 2013 to 2014*. Available at: https://www.gov.uk/government/publications/payment-by-results-pbr-operational-guidance-and-tariffs. [Accessed 25th March 2018].

51. Duguay, C. & Chetouane, F. (2007) 'Modeling and improving emergency department systems using discrete event simulation'. *Simulation*. 83 pp.311-320. https://doi.org/10.1177/0037549707083111

52. Elkhuizen, S. G., Das, S. F., Bakker, P. J. M. & Hontelez, J. A. M. (2007) 'Using computer simulation to reduce access time for outpatient departments'. *Quality & Safety in Health Care*. 16 (5) pp.382–386. http://dx.doi.org/10.1136/qshc.2006.021568

53. Everett, J. E. (2002) 'A decision support simulation model for the management of an elective surgery waiting system'. *Health Care Management Science*. 5 (2) pp.89–95. https://doi.org/10.1023/A:1014468613635

54. Exadaktylos, A. K., Evangelopoulos, D. S., Wullschleger, M., Bürki, L. & Zimmermann, H. (2008) 'Strategic emergency department design: an approach to capacity planning in healthcare provision in overcrowded emergency rooms'. *Journal of Trauma Management & Outcomes*. 2 (1) pp.1–8. https://doi.org/10.1186/1752-2897-2-11

55. Frank, T., Augusto, V., Xie, X., Gonthier, R., & Achour, E. (2015) Performance evaluation of an integrated care for geriatric departments using discrete event simulation. In: L. Yilmaz, W. K. V. Chan, I. Moon, T. M. K. Roeder, C. Macal, and M. D. Rossetti (eds.) *Winter Simulation Conference 2015, 6-9 December 2015, California, USA*. New York, Institute of Electrical and Electronics Engineers. pp. 1331-1342.

56. Freedman, D., & Diaconis, P. (1981) 'On the histogram as a density estimator: L_2 theory'. *Zeit. Wahr. ver. Geb.*. 57 pp.453–476. https://doi.org/10.1007/BF01025868

57. Garg, B., Sufyan Beg, M. M., Ansari, A. Q., & Imran, B. M. (2011) Soft computing model to predict length of stay of patient. In: S. Dua, S. Sahni, & D. P. Goyal (eds.). *5th International Conference on Information Intelligence, Systems, Technology and Management, 10-12 March 2011, Gurgaon, India.* pp. 221-232.

58. German, J. D., Mina, J. K. P., Yang, K. H. (2018) A Study on Shortage of Hospital Beds in the Philippines Using System Dynamics. *5th International Conference on Industrial Engineering and Applications, 26-28 April 2018, Singapore.* pp. 72–78.

59. Ghanes, K., Wargon, M., Jouini, O., Jemai, Z., Diakogiannis, A., Hellmann, R., Thomas, V., & Koole, G. (2015) 'Simulation-based optimization of staffing levels in an emergency department'. *Simulation*. 91 pp.942-953. https://doi.org/10.1177/0037549715606808

60. Glasgow, S. M., Perkins, Z. B., Tai, N. R. M., Brohi, K., & Vasilakis, C. (2018) 'Development of a discrete event simulation model for evaluating strategies of red blood cell provision following mass casualty events'. *European Journal of Operational Research*. 270 pp.362–374. https://doi.org/10.1016/j.ejor.2018.03.008

61. Gneiting, T. (2011) 'Making and evaluating point forecasts'. *Journal of the American Statistical Association.* 494 pp.746-762. https://doi.org/10.1198/jasa.2011.r10138

62. Goulding, L., Adamson, J., Watt, I., & Wright, J. (2015) ‘Lost in hospital: a qualitative interview study that explores the perception of NHS inpatients who spent time on clinically inappropriate hospital wards’. *Health Expectations.* 18 pp.982-994. https://doi.org/10.1111/hex.12071

63. Griffiths, P., Dall’Ora, C., & Ball, J. (2017) *How many nurses: what does the evidence say? Evidence Brief*, University of Southampton.

64. Gul, M., Celik, E., Guneri, A. F. & Taskin Gumus, A. (2012) ‘Simulation with integrated multi criteria decision making: An application of scenario selection for a hospital emergency department’. *Istanbul Commerce University Journal of Science*. 22 pp.1-18 (in Turkish).

65. Gul, M., & Guneri, A. F. (2015) ‘Forecasting patient length of stay in emergency department by artificial neural networks’. *Journal of Aeronautics and Space Technologies*. 8 (2) pp.43–48.

66. Gunal, M. M. (2012) ‘A guide for building hospital simulation models’. *Heath Systems*. 1 (1) pp.17–25. https://doi.org/10.1057/hs.2012.8

67. Gunal, M., & Pidd, M. (2006) Understanding accident and emergency department performance using simulation. In L. F. Perrone, F. P. Wieland, J. Liu, B. G. Lawson, D. M. Nicol, & R. M. Fujimoto (eds.) *Winter Simulation Conference, 3-6 December 2006, Monterey, USA*. New York, Institute of Electrical and Electronics Engineers. pp. 446-452.

68. Gunal, M. M. & Pidd, M. (2007) Interconnected DES Models of emergency, Outpatient, and Inpatient Departments of a Hospital. In: S. G. Henderson, B. Biller, M.-H. Hsieh, J. Shortle, J. D. Tew, and R. R. Barton (eds.) *Winter Simulation Conference 2007, 9 – 12 December 2007, Washington, USA.* New York, Institute of Electrical and Electronics Engineers. pp. 1461-1466.

69. Gunal, M. M., & Pidd, M. (2010) ‘Discrete Event Simulation for Performance Modelling in Health Care: A Review of the Literature’. *Journal of Simulation*. 4 pp.42-51. https://doi.org/10.1057/jos.2009.25

70. Gunal, M. M., & Pidd, M. (2011) ‘DGHPSIM: Generic Simulation of Hospital Performance’. *ACM Transactions on Modeling and Computer Simulation (TOMACS).* 21 (4). https://doi.org/10.1145/2000494.2000496

71. Gupta, D., Natarajan, M. K., Gafni, A., Wang, L., Shilton, D., Holder, D. & Yusuf, S. (2007) ‘Capacity planning for cardiac catheterization: a case study’. *Health Policy*. 82 (1) pp.1–11. https://doi.org/10.1016/j.healthpol.2006.07.010

72. Hachesu, P. R., Ahmadi, M., Alizadeh, S., & Sadoughi, F. (2013) ‘Use of Data Mining Techniques to Determine and Predict Length of Stay of Cardiac Patients’. *Healthcare Informatics Research*. 19 (2) pp.121–129. http://dx.doi.org/10.4258/hir.2013.19.2.121

73. Hamm, C. (2010) ‘The coalition government’s plans for the NHS in England’. *British Medical Journal*. 341 pp.3790. DOI:10.1136/bmj.c3790

74. Harper, P. R. (2002) ‘A Framework for operational modelling of hospital resources’. *Health Care Management Science*. 5 pp.165–173. https://doi.org/10.1023/A:1019767900627

75. Harper, P. R. & Gamlin, H. M. (2003) ‘Reduced outpatient waiting times with improved appointment scheduling: a simulation modelling approach’. *OR Spectrum*. 25 (2) pp.207–222. https://doi.org/10.1007/s00291-003-0122-x

76. Harper, P. R., & Shahani, A. K. (2002) ‘Modelling for the planning and management of bed capacities in hospitals’. *Journal of the Operational Research Society*. 53 (1) pp.11–18. https://doi.org/10.1057/palgrave.jors.2601278

77. Harper, A., Mustafee, N., & Feeney, M. (2017) A hybrid approach using forecasting and discrete-event simulation for endoscopy services. In: W. K. V. Chan, A. D'Ambrogio, G. Zacharewicz, N. Mustafee, G. Wainer, and E. Page (eds.) *Winter Simulation Conference 2017, 3-6 December 2017, Las Vegas, USA*. New York, Institute of Electrical and Electronics Engineers. pp. 1583–1594.

78. Holm, L. B., Luras H., & Dahl, F. A. (2013) ‘Improving hospital bed utilisation through simulation and optimisation with application to a 40% increase in patient volume in a Norwegian general hospital’. *International journal of medicine informatics*. 82 pp.80–89. https://doi.org/10.1016/j.ijmedinf.2012.05.006

79. Hussey, D. L., & Guo, S. (2005) ‘Forecasting length of stay in child residential treatment’. *Child Psychiatry and Human Development*. 36 (1) pp.95–111. https://doi.org/10.1007/s10578-004-3490-9

80. Hussein, N. A., Abdelmaguid, T. F., Tawfik, B. S., & Ahmed, N. G. S. (2017) ‘Mitigating overcrowding in emergency departments using Six Sigma and simulation: A case study in Egypt’. *Operations Research for Health Care*. 15 pp.1–12. http://dx.doi.org/10.1016/j.orhc.2017.06.003

81. Hyndman, R. J. (2016) *Package ‘forecast’*. Available at: https://cran.r-project.org/web/packages/forecast/forecast.pdf. [Accessed 26th May 2017].

82. Hyndman, R.J. & Athanasopoulos, G. 2014. *Forecasting Principles and Practice*. Otexts.

83. Hyndman, R. J. & Khandakar, Y. (2008) ‘Automatic Time Series Forecasting: The forecast Package for R’. *Journal of Statistical Software*. 27.

84. Hyndman, R. J., & Koehler, A. B. (2006) ‘Another look at measures of forecast accuracy’. *International Journal of Forecasting*. (22) pp.679-688. https://doi.org/10.1016/j.ijforecast.2006.03.001

85. Hyndman, R.J., Koehler, A.B., Ord, J.K. & Snyder, R.D. 2008. *Forecasting with Exponential Smoothing: The State Space Approach*. Berlin, Germany: Springer.

86. Iacobucci, G. (2018a) ‘NHS cancels planned surgery and outpatient appointments in response to winter crisis’. *BMJ*. 360:k19. https://doi.org/10.1136/bmj.k19

87. Iacobucci, G. (2018b) ‘GPs forced to turn away patients because of winter pressures’. *BMJ*. 360:k81. https://doi.org/10.1136/bmj.k81

88. Jones, S. S. and Evans, R. S. (2008) An agent based simulation tool for scheduling emergency department physicians. *AMIA Annual Symposium, 8 – 12 November 2008, Washington.* American Medical Informatics Association.

89. Jones, S. S., Thomas, A., Evans, R. S., Welch, S. J., Haug, P. J., & Snow, G. L. (2008) ‘Forecasting daily patient volumes in the emergency department’. *Academic Emergency Medicine*. 15 pp.159-170. https://doi.org/10.1111/j.1553-2712.2007.00032.x

90. Joy, M. P., & Jones, S. (2005) Predicting bed demand in a hospital using neural networks and ARIMA models: A hybrid approach. *European Symposium on Artificial Neural Networks, ESANN:’2005, 27-29 April 2005, Bruges, Belgium.* pp. 127-132.

91. Kaier, K., Mutters, N.T., & Frank, U. (2012) 'Bed occupancy rates and hospital-acquired infections - should beds be kept empty?'. *Clinical Microbiology and Infection*. 18 pp.941-945. https://doi.org/10.1111/j.1469-0691.2012.03956.x

92. Kam, H. J., Sung, J. O. & Park, R. W. (2010) 'Prediction of daily patient numbers for a regional emergency medical center using time series analysis'. *Healthcare Informatics Research*. 16 pp.158-165. https://doi.org/10.4258/hir.2010.16.3.158

93. Kaushal, A., Zhao, Y., Peng, Q., Strome, T., Weldon, E., Zhang, M., & Chochinov, A. (2015) 'Evaluation of fast track strategies using agent-based simulation modeling to reduce waiting time in a hospital emergency department'. *Socio-Economic Planning Sciences*. 50 pp.18–31. https://doi.org/10.1016/j.seps.2015.02.002

94. Kelton, D., Sadowski, R.P. & Sadowski, D.A. 2001. *Simulation with Arena*. New York: McGraw Hill.

95. Khadem, M., Bashir, H. A., Al-Lawati & Al-Azri, F. (2008) Evaluating the layout of the emergency department of a hospital using computer simulation modeling: a case study. *Industrial Engineering and Engineering Management, 8 – 11 December 2008, Singapore.* IEEE Engineering Management Society.

96. Kim, K., Lee, C., O'Leary, K. J., Rosenauer, S. & Mehrotra, S. (2014) *Predicting patient volumes in hospital medicine: A comparative study of different time series forecasting methods*. Technical Report. Northwestern University.

97. Kokangul, A. (2008) 'A combination of deterministic and stochastic approaches to optimize bed capacity in a hospital unit'. *Computer Methods and Programs in Biomedicine*. 9 pp.56–65. https://doi.org/10.1016/j.cmpb.2008.01.001

98. Komashie, A., & Mousavi, A. (2005) Modelling emergency departments using discrete event simulation techniques. In: M. E. Kuhl, N. M. Steiger, F. B. Armstrong, & J. A., Joines (eds.) *Winter Simulation Conference 4-7 December 2005, Orlando, USA.* New York, Institute of Electrical and Electronics Engineers. pp. 2681-2685.

99. Komashie, A., Mousavi, A. and Gore, J. (2008) Using Discrete Event Simulation (DES) to Manage Theatre Operations in Healthcare: An Audit-Based Case Study. *International Conference on Computer Modeling and Simulation, 1 – 3 April 2008, Cambridge, UK.* IEEE Computer Society.

100. Kumar, S. (2011) 'Modeling hospital surgical delivery process design using system simulation: optimizing patient flow and bed capacity as an illustration'. *Technology and Health Care*. 19 (1) pp.1–20.

101. Landa, P., Sonnessa, M., Tanfani, E., & Testi, A. (2014) A Discrete Event Simulation Model to Support Bed Management. In: Mohammad S. Obaidat, Janusz Kacprzyk and Tuncer Ören (eds.) *4th International Conference on Simulation And Modeling Methodologies, Technologies And Applications, SIMULTECH. 28-30 August 2014, Vienna, Austria*.

102. Lamiri, M., Grimaud, F., & Xie, X. (2009) 'Optimization methods for a stochastic surgery planning problem'. *International Journal of Production Economics*. 120 pp.400–410. https://doi.org/10.1016/j.ijpe.2008.11.021

103. Lane, D. C., Monefeldt, C. & Rosenhead, J. V. (2000) 'Looking in the wrong place for healthcare improvements: a system dynamics study of an accident and emergency department'. *The Journal of the Operational Research Society*. 51 (5) pp.518–531. https://doi.org/10.1057/palgrave.jors.2600892

104. Lane, D. C., Monefeldt C. & Rosenhead J.V. (2016) 'Looking in the Wrong Place for Healthcare Improvements: A System Dynamics Study of an Accident and Emergency Department'. In: Mustafee N. (eds), *Operational Research for Emergency Planning in Healthcare*. London: Palgrave Macmillan.

105. Law, A.M. & Kelton, W.D. 2000. *Simulation Modeling and Analysis*. McGraw – Hill.

106. Lebcir, R., Demir, E., & Ahmad, R., Vasilakis, C., & Southern, D. (2017) 'A discrete event simulation model to evaluate the use of community services in the treatment of patients with Parkinson's disease in the United Kingdom'. *BMC Health Services Research*. 17. https://doi.org/10.1186/s12913-017-1994-9

107. Levin, S. R., Dittus, R., Aronsky, D., Weinger, M. B., Han, J., Boord, J. & France, D. (2008) 'Optimizing cardiology capacity to reduce emergency department boarding: a system engineering approach'. *American Heart Journal*. 156 pp.1202-1209. https://doi.org/10.1016/j.ahj.2008.07.007

108. Levin, S. R., Harley, E. T., Fackler, J. C., Lehmann, C. U., Custer, J. W., France, D., & Zeger, S. L. (2012) 'Real-time forecasting of pediatric intensive care unit length of

stay using computerized provider orders'. *Critical Care Medicine*. 40 (11) pp.3058–3064. DOI: 10.1097/CCM.0b013e31825bc399

109.Li, J. S., Tian, Y., Liu, Y. F., Shu, T., & Liang, M. H. (2013) Applying a BP neural network model to predict the length of hospital stay. In: G. Huang, X. Liu, J. He, F. Klawonn, & G. Yao (eds.). *2nd International Conference on Health Information Science, 25-27 arch 2017, London, UK*. pp. 18–29.

110.Ma, G., & Demeulemeester, E. (2013) 'A multilevel integrative approach to hospital case mix and capacity planning'. *Computers & Operations Research*. 40 pp.2198–2207. https://doi.org/10.1016/j.cor.2012.01.013

111.Macal, C. M. & North, M. J. (2010) 'Tutorial on agent-based modelling and simulation'. *Journal of Simulation*. 4 (3) pp.151–162. https://doi.org/10.1057/jos.2010.3

112.Makridakis, S., Wheelwright, S.C. & Hyndman, R.J. 1998. *Forecasting Methods and Applications*. New York, USA: John Wiley & Sons.

113.Marcilio, I., Hajat, S., & Gouveia, N. (2013) 'Forecasting daily emergency department visits using calendar variables and ambient temperature readings'. *Academic Emergency Medicine*. 20 pp.769-777. https://doi.org/10.1111/acem.12182

114.Martin, E., Gronhaug, R. & Haugene, K. (2003) Proposal to reduce over-crowding, length of stays and improve patient care: study of the geriatric department in norway's largest hospital. In: S. Chick, P. J. Sánchez, D. Ferrin, and D. J. Morrice (eds.) *Winter Simulation Conference 2003. 7–10 December 2003, New Orleans*. New York: Institute of Electrical and Electronics Engineers.

115.Mathews, K. S., & Long, E. F. (2015) 'A Conceptual Framework for Improving Critical Care Patient Flow and Bed Use'. *Annals of the American Thoracic Society*. 12 (6) pp.886–894. DOI: 10.1513/AnnalsATS.201409-419OC

116. Mazier, A., Xie, X. & Sarazin, M. (2010) Real-Time Patient Assignment: A Method for Improving Emergency Department Flow. *IEEE Workshop on Health Care Management, WHCM, 18-20 February 2010, Venice, Italy. pp.1–6.*

117.McCarthy, M. L., Zeger, S. L., Ding, R., Aronsky, D., Hoot, N. R., & Kelen, G. D. (2008). 'The challenge of predicting demand for emergency department services'.

Academic Emergency Medicine. 15 pp.337-346. https://doi.org/10.1111/j.1553-2712.2008.00083.x

118.McLaughlin, D.B. & Hays, J.M. 2008. *Healthcare Operations Management*. Washington: AUPHA Press.

119.Medeiros, D. J., Swenson, E., & DeFlitch, C. (2008). Improving patient flow in a hospital emergency department. In: J. S. Mason, R. R. Hill, L. Monch, O. Rose, T. Jefferson, & J. W. Fowler (eds.) *Winter Simulation Conference, 7-10 December 2008, Miami, USA*. New York, Institute of Electrical and Electronics Engineers. pp. 1526-1531.

120.Meng, L. Y. & Spedding, T. (2008) Modelling patient arrivals when simulating an accident and emergency unit. In: J. S. Mason, R. R. Hill, L. Monch, O. Rose, T. Jefferson, & J. W. Fowler (eds.) *Winter Simulation Conference, 7-10 December 2008, Miami, USA*. New York: Institute of Electrical and Electronics Engineers.

121.Montgomery, D.C. 2013. *Design and Analysis of Experiments*. Wiley.

122.Moustris, K. P., Douros, K., Nastos, P. T., Larissi, I. K., Anthracopoulos, M. B., Paliatsos, A. G., & Priftis, K. N. (2011) 'Seven-days-ahead forecasting of childhood asthma admissions using artificial neural networks in Athens, Greece'. *International Journal of Environmental Health Research*. 22 (2) pp.93-104. https://doi.org/10.1080/09603123.2011.605876

123.Mulholland, M. W., Abrahamse, P. & Bahl, V. (2005) 'Linear Programming to Optimize Performance in a Department of Surgery'. *Journal of the American College Surgeons*. 200 (6) pp.861–868. https://doi.org/10.1016/j.jamcollsurg.2005.01.001

124.National Health Services England. (2014) *A&E Attendances and Emergency Admissions and Bed Availability and Occupancy*. Available at: https://www.england.nhs.uk/statistics/statistical-work-areas/ae-waiting-times-and activity/. [Accessed 2nd June 2014].

125.National Health Services England. (2018a) *A&E Attendances and Emergency Admissions and Bed Availability and Occupancy*. Available at: https://www.england.nhs.uk/statistics/statistical-work-areas/ae-waiting-times-and-activity/. [Accessed 20th June 2018].

126.National Health Services England. (2018b) *NHS Inpatient Elective Admission Events and Outpatient Referrals and Attendances*. Available at: https://www.england.nhs.uk/statistics/statistical-work-areas/hospital-activity/quarterly-hospital-activity/qar-data/. [Accessed 20th June 2018].

127.National Health Services England. (2018c) *Bed Availability and Occupancy*. Available at: https://www.england.nhs.uk/statistics/statistical-work-areas/bed-availability-and-occupancy/. [Accessed 20th June 2018].

128.NHS Digital. (2014) *NHS staff earnings estimates to June 2013 – provisional, experimental statistics*. https://digital.nhs.uk/data-and-information/publications/statistical/nhs-staff-earnings-estimates/nhs-staff-earnings-estimates-to-february-2014-provisional-statistics. [Accessed 26th May 2017].

129.NHS Digital. (2018) *Trimpoint methodology HRG4+ 2017/18 Reference Costs Grouper*. Available at: https://digital.nhs.uk/binaries/content/assets/legacy/pdf/o/7/hrg4__201718_reference_costs_grouper_trimpoint_methodologyv1.0.pdf. [Accessed 26th May 2018].

130.NHS England. (2017) *NHS national tariff payment system 2016/17*. Available at: https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/509697/2016-17_National_Tariff_Payment_System.pdf. [Accessed 26th May 2017].

131.NHS improvement. (2017) *Equality for all: Delivering safe care – seven days a week*. Available at: https://www.england.nhs.uk/improvement-hub/wp-content/uploads/sites/44/2017/11/Equality-for-all-Delivering-safe-care-seven-days-a-week.pdf. [Accessed 6th June 2018].

132.NICE (National Institute for Health and Care Excellence). (2014) *Safe staffing for nursing in adult inpatient wards in acute hospitals*. Available at: nice.org.uk/guidance/sg1. [Accessed 28th August 2018].

133.Nuffield Trust. (2016) *Understanding patient flow in hospitals*. Available at: https://www.nuffieldtrust.org.uk/resource/understanding-patient-flow-in-hospitals. [Accessed 1st November 2018].

134.Oddoye, J. P., Jones, D. F., Tamiz, M., & Schmidt, P. (2009) 'Combining simulation and goal programming for healthcare planning in a medical assessment unit'.

European Journal of Operational Research. 193 pp.250–261. https://doi.org/10.1016/j.ejor.2007.10.029

135. Oh, C., Novotny, A. M., Carter, P. L., Ready, R. K., Campbell, D. D. & Leckie, M. C. (2016) ‘Use of a simulation – based decision support tool to improve emergency department throughput’. *Operations Research for Health Care*. 9 pp.29-39. https://doi.org/10.1016/j.orhc.2016.03.002

136. Ozdagoglu, A., Yalcinkaya, O. & Ozdagoglu, G. (2009) ‘A simulation based analysis of a research and application hospital emergency patient data in Aegean region’. *Istanbul Commerce University Journal of Science*. 16 pp.61-73 (in Turkish).

137. Papi, M., Pontecorvi, L., & Setola, R. (2016) ‘A new model for the length of stay of hospital patients’. *Health Care Management Science*. 19 (1) pp.58–65. https://doi.org/10.1007/s10729-014-9288-9

138. Pidd, M. 2003. *Tools for Thinking: Modelling in Management Science*. Chichester, UK: Wiley.

139. Pidd, M. 2004. *Computer Simulation in Management Science*. Chichester, England: John Wiley and Sons.

140. Rais, A. & Viana, A. (2010) ‘Operations research in healthcare: a survey’. *International Transactions in Operational Research*. 18 (1) pp.1–31. https://doi.org/10.1111/j.1475-3995.2010.00767.x

141. Rashwan, W., Abo-Hamad, W., & Arisha, A. (2015) ‘A system dynamics view of the acute bed blockage problem in the Irish healthcare system’. *European Journal of Operational Research*. 247 pp.276–293. http://dx.doi.org/10.1016/j.ejor.2015.05.043

142. Ridge, J. C., Jones, S. K., Nielsen, M. S. & Shahani, A. K. (1998) ‘Capacity planning for intensive care units’. *European Journal of Operation Research*. 105 (2) pp.346–355. https://doi.org/10.1016/S0377-2217(97)00240-3

143. Ripley, B., Venables, B., Bates, D. M., Hornik, K., Gebhardt, A., & Firth, D. (2016) *Package ‘MASS’*. Available at: https://cran.r-project.org/web/packages/MASS/MASS.pdf. [Accessed 26th May 2017].

144. Reis, B. Y., & Mandl, K. D. (2003) ‘Time series modelling for syndromic surveillance’. *BMC Medical Informatics and Decision Making*. 3 (2). https://doi.org/10.1186/1472 6947-3-2

145.Robinson, S. 2004. *Simulation the practice of model development and use*. Chichester, England: John Wiley and Sons.

146.Robinson, S. (2007) 'A statistical process control approach to selecting a warm-up period for a discrete-event simulation'. *European Journal of Operational Research*. 176 pp.332–346. https://doi.org/10.1016/j.ejor.2005.07.014

147.Rohleder, T. R., Lewkonia, P., Bischak, D. P., Duffy, P. & Hendijani, R. (2011) 'Using simulation modelling to improve patient flow at an outpatient orthopaedic clinic'. *Health Care Management Science*. 14 pp.135-145. https://doi.org/10.1007/s10729-010-9145-4

148.Royal College of Physicians. (2015) *Work and wellbeing in the NHS: why staff health matters to patient care*. Available at: https://www.rcpsych.ac.uk/pdf/RCP-%20WorkWellbeingNHS.pdf. [Accessed 23rd August 2018].

149.Ruohonen, T., & Teittinen, J. (2006) Simulation model for improving the operational of the emergency department of special health care. In: L. F. Perrone, F. P. Wieland, J. Liu, B. G. Lawson, D. M. Nicol, & R. M. Fujimoto (eds.) *Winter Simulation Conference 2006, 3-6 December 2006, Monterey, USA*. New York, Institute of Electrical and Electronics Engineers. pp. 453-458.

150.Saadouli, H., Jerbi, B., Dammak, A., Masmoudi, L., & Bouaziz, A. (2015) 'A stochastic optimization and simulation approach for scheduling operating rooms and recovery beds in an orthopedic surgery department'. *Computers & Industrial Engineering*. 80 pp.72–79. https://doi.org/10.1016/j.cie.2014.11.021

151.Schweigler, L. M., Desmond, J. S., McCarthy, M. L., Bukowski, K. J., Ionides, E. L., & Younger, J. G. (2009) 'Forecasting models of emergency department crowding'. *Academic Emergency Medicine*. 16 (4) pp.301–308. https://doi.org/10.1111/j.1553-2712.2009.00356.x

152.Shapoval, A., & Lee, E. K. (2017) Optimizing Inpatient Bed Capacity to Improve Care Delivery. *IEEE International Conference on Bioinformatics and Biomedicine, BIBM, 13-16 November 2017, Kansas City, USA*. pp. 855–860.

153.Simul8. (2019) *Case Studies*. https://www.simul8healthcare.com/case-studies/. [Accessed 16th March 2019].

154.Sitepu, S., Mawengkang, H., & Husein, I. (2018) Optimization Model for Capacity Management and Bed Scheduling for Hospital. *IOP Conf. Series: Materials Science and Engineering*. 300 pp.1-7. doi:10.1088/1757-899X/300/1/012016

155.Sun, Y., Heng, B. H., Seow, Y. T., & Seow, E. (2009) 'Forecasting daily attendances at an emergency department to aid resource planning'. *BMC Emergency Medicine*. 9 (1). https://doi.org/10.1186/1471-227X-9-1

156.Swisher, J. R., Jacobson, S. H., Jun, J. B. & Balci, O. (2001) 'Modeling and analyzing a physician clinic environment using discrete-event (visual) simulation'. *Computers & Operations Research*. 28 (2) pp.105–125. https://doi.org/10.1016/S0305-0548(99)00093-3

157.The King's Fund. (2012) *Older people and emergency bed use*. Available at: https://www.kingsfund.org.uk/publications/older-people-and-emergency-bed-use. [Accessed 1st November 2018].

158.Toerper, M. F., Flanagan, E., Siddique, S., Appelbaum, J., Kasper, E. K., & Levin S. (2016) 'Cardiac catheterization laboratory inpatient forecast tool: a prospective evaluation'. *Journal of the American Medical Informatics Association*. 23 pp.e49–e57. doi:10.1093/jamia/ocv124

159.Tofallis, C. (2015) 'A better measure of relative prediction accuracy for model selection and model estimation'. *Journal of the Operational Research Society*. 66 pp.1352-1362. https://doi.org/10.1057/jors.2014.103

160.Uriarte, A. G., Zuniga E. R., Moris, M. U., & Ng A. H. C. (2017) 'How can decision makers be supported in the improvement of an emergency department? A simulation, optimization and data mining approach'. *Operations Research for Health Care*. 15 pp.102–122. https://doi.org/10.1016/j.orhc.2017.10.003

161.VanBerkel, P. T. & Blake, J. T. (2007) 'A comprehensive simulation for wait time reduction and capacity planning applied in general surgery'. *Health Care Management Science*. 10 pp.373-385. https://doi.org/10.1007/s10729-007-9035-6

162.Vasilakis, C. & El-Darzi, E. (2001) 'A simulation study of the winter bed crisis'. *Health Care Management Science.* 4 pp.31-36. https://doi.org/10.1023/A:1009649615548

163. Villamizar, J. R., Coelli, F. C., Pereira, W. C. A. & Almeida, R. M. V. R. (2011) 'Discrete event computer simulation methods in the optimisation of a physiotherapy clinic'. *Physiotherapy*. 97 (1) pp.71–77. https://doi.org/10.1016/j.physio.2010.02.009

164. Virtue, A., Kelly, J., & Chaussalet, T. (2011) Using simplified discrete-event simulation models for health care applications. In: S. Jain, R. R. Creasey, J. Himmelspach, K. P., & M. Fu (Eds.). *Winter Simulation Conference 2011, 11-14 December 2011, Phoenix, USA*. New York, Institute of Electrical and Electronics Engineers. pp. 1154-1165.

165. Vissers, J. M. H., Adan, I. J. B. F. & Bekkers, J. A. (2005) 'Patient mix optimization in tactical cardiothoracic surgery planning: a case study'. *IMA Journal of Management Mathematics*. 16 (3) pp.281–304. https://doi.org/10.1093/imaman/dpi023

166. Wang, L. (2009) An agent – based simulation for workflow in emergency department. *IEEE Systems and Information Engineering Design Symposium, 24 April 2009, Charlottesville.* New York: Institute of Electrical and Electronics Engineers.

167. Wang, T., Guinet A. & Besombes B. (2009) 'A Sizing Tool for Allocation Planning of Hospital Bed Resources'. In McClean S., Millard P., El-Darzi E., Nugent C. (eds.), *Intelligent Patient Management*. Berlin, Heidelberg: Springer.

168. Wang, J., Li, J., Tussey, K. & Ross, K. (2012) 'Reducing Length of Stay in Emergency Department: A Simulation Study at a Community Hospital'. *Systems, Man and Cybernetics, Part A: Systems and Humans, IEEE Transaction*. 42 pp.1314-1322. DOI: 10.1109/TSMCA.2012.2210204

169. Wargon, M., Casalino, E., & Guidet, B. (2010) 'From model to forecasting: A multicenter study in emergency departments'. *Academic Emergency Medicine*. 17 (9) pp.970-978. https://doi.org/10.1111/j.1553-2712.2010.00847.x

170. Werker, G., Saure, A., French, J. & Shechter, S. (2009) 'The use of discrete-event simulation modelling to improve radiation therapy planning times'. *Radiotherapy and Oncology*. 92 (1) pp.76–82. https://doi.org/10.1016/j.radonc.2009.03.012

171. Wijewickrama, A. K. A. (2006) 'Simulation analysis for reducing queues in mixed patients' outpatient department'. *International Journal of Simulation Modelling*. 5 (2) pp.56–68. DOI:10.2507/IJSIMM05(2)2.055

172. Winston, W.L. 2004. *Operations Research Applications and algorithms*. USA: Thomson.

173. Wrenn, J., Jones, I., Lanaghan, K., Congdon, C. B., & Aronsky, D. (2005) Estimating Patient's Length of Stay in the Emergency Department with an Artificial Neural Network. *AMIA Annual Symposium, Washington, USA*. pp. 1155.

174. Xu, X., Liu, J., Li, H. & Jiang, M. (2016). Capacity oriented passenger flow control under uncertain demand: Algorithm development and real-world case study. *Transportation Research Part E*. 87, 130-148. http://dx.doi.org/10.1016/j.tre.2016.01.004

175. Yeh, J. Y. & Lin, W. S. (2007) 'Using simulation technique and genetic algorithm to improve the quality care of a hospital emergency department'. *Expert System with Applications*. 32 (4) pp.1073–1083. https://doi.org/10.1016/j.eswa.2006.02.017

176. Zhang, B., Murali, P., Dessouky, M. M., & Belson, D. (2009) 'A mixed integer programming approach for allocating operating room capacity'. *Journal of the Operational Research Society*. 60 (5) pp.663–673. https://doi.org/10.1057/palgrave.jors.2602596

177. Zhang, Y., Puterman, M. L., Nelson, M., & Atkins, D., (2012) 'A Simulation Optimization Approach to Long-Term Care Capacity Planning'. *Operations Research*. 60 (2) pp.249-261. https://doi.org/10.1287/opre.1110.1026

178. Zhu, Z., Hen, B. H. & Teow, K. L. (2012) 'Estimating ICU bed capacity using discrete event simulation'. *International Journal of Health Care Quality Assurance*. 25 pp.134-144. https://doi.org/10.1108/09526861211198290

179. Zinouri, N., Taaffe, K. M. & Neyens, D. M. (2018) 'Modelling and forecasting daily surgical case volume using time series analysis'. *Health Systems*. 7 pp.111-119. https://doi.org/10.1080/20476965.2017.1390185

Publications during research

Journals

1. Ordu, M., Demir, E., & Tofallis, C. 'An entire hospital forecasting study: comparative analysis of periods and methods'. *In preparation for Health Care Management Review*.
2. Ordu, M., Demir, E. & Tofallis, C. 'A comparative analysis of forecasting periods to forecast demand for accident and emergency services'. *In preparation for Academic Emergency Medicine*.
3. Ordu, M., Demir, E., Tofallis, C. & Gunal M. M. 'A novel healthcare resource allocation decision support tool: a forecasting-simulation-optimization approach'. *The Journal of the Operational Research Society*, (Under Review).
4. Ordu, M., Demir, E., Tofallis, C. & Gunal M. M. 'An innovative entire hospital level decision support system for efficient and effective delivery of healthcare services'. *European Journal of Operational Research* (Under Review).
5. Ordu, M., Demir, E. & Tofallis, C. 'A decision support system for demand and capacity modelling of an accident and emergency department'. *Health Systems* (Accepted).
6. Ordu, M., Demir, E. & Tofallis, C. 'A projective approach for clinic utilization and management in trauma and orthopedics outpatient clinic through a simulation-based decision support system'. *Journal of the Faculty of Engineering and Architecture of Gazi University* (Under Review).
7. Ordu, M., Demir, E. & Tofallis, C. (2018) 'A discrete event simulation model to manage bed usage for non-elective admissions in a geriatric medicine speciality'.

World Academy of Science, Engineering and Technology International Journal of Industrial and Systems Engineering. 12 (3), pp.239–244 (Published).

Proceedings

1. Ordu, M., Demir, E. & Tofallis, C. (2018) Reallocation of bed capacity in a hospital combining discrete event simulation and integer linear programming. *20th International Conference on Healthcare Engineering and Healthcare Systems Optimization, ICHEHSO 2018, 3-4 December 2018, Amsterdam, the Netherlands.* pp. 284. <u>(The study has been awarded with 'Best Presentation Award')</u>.
2. Ordu, M., Demir, E., Tofallis, C. & Gunal M. M. (2018) A simulation model integrated with forecasting for demand and capacity modelling of a hospital to provide strategic decision supports. *Hertfordshire Business School Research Conference, 12 September 2018, Hatfield, United Kingdom*.
3. Ordu, M., Demir, E. & Tofallis, C. (2018) Better understanding of clinic utilization for projection in a trauma & orthopaedics outpatient clinic. *6th Student Conference on Operational Research, SCOR18, 6-8 April 2018, Nottingham, United Kingdom*.
4. Ordu, M., Demir, E., & Tofallis, C. (2018) A Discrete Event Simulation Model to Manage Bed Usage for Non-Elective Admissions in a Geriatric Medicine Speciality. *20th International Conference on Modeling and Simulation, ICMS 2018, 15-16 March 2018, Paris, France*. pp. 1369–1376.
5. Ordu, M., Demir, E. & Tofallis, C. (2017) A Discrete Event Simulation Modelling to Capture Demand and Capacity in an Accident and Emergency Department. *19th International Conference on Industrial Engineering and Operations Research, ICIEOR 2017, 20-21 April 2017, Zurich, Switzerland*. pp. 1434.

Conferences

1. Ordu, M., Demir, E. & Tofallis, C. (2018) Reallocation of bed capacity in a hospital combining discrete event simulation and integer linear programming. *20th*

International Conference on Healthcare Engineering and Healthcare Systems Optimization (ICHEHSO), 3-4 December 2018, Amsterdam, the Netherlands. (The study has been awarded with 'Best Presentation Award').

2. Ordu, M., Demir, E., Tofallis, C. & Gunal M. M. (2018) A simulation model integrated with forecasting for demand and capacity modelling of a hospital to provide strategic decision supports. *Hertfordshire Business School Research Conference, 12 September 2018, Hatfield, United Kingdom*.
3. Ordu, M., Demir, E. & Tofallis, C. (2018) Better understanding of clinic utilization for projection in a trauma & orthopaedics outpatient clinic. *6th Student Conference on Operational Research (SCOR18), 6-8 April 2018, Nottingham, United Kingdom*.
4. Ordu, M., Demir, E. & Tofallis, C. (2018) A Discrete Event Simulation Model to Manage Bed Usage for Non-Elective Admissions in a Geriatric Medicine Speciality. *20th International Conference on Modeling and Simulation (ICMS), 15-16 March 2018, Paris, France.*
5. Ordu, M., Demir, E. & Tofallis, C. (2017) A Discrete Event Simulation Modelling to Capture Demand and Capacity in an Accident and Emergency Department. *19th International Conference on Industrial Engineering and Operations Research (ICIEOR 2017), 20-21 April 2017, Zurich, Switzerland.*
6. Ordu, M., Demir, E. & Tofallis, C. (2015) Demand and Capacity Modelling of Acute Services Using Simulation and Optimization Techniques. *University of Hertfordshire PhD Student Workshop, 9 December 2015, United Kingdom, Hatfield.*

Appendices

Appendix 1

The Ethic Approval Notification given by the University of Hertfordshire Social Sciences, Arts and Humanities the Ethics Committees with Delegated Authority (ECDA)

University of Hertfordshire UH

SOCIAL SCIENCES, ARTS AND HUMANITIES ECDA

ETHICS APPROVAL NOTIFICATION

TO: Muhammed Ordu

CC: Dr Eren Demir

FROM Dr Tim Parke, Social Sciences,Arts and Humanities ECDA Chairman

DATE: 21/11/2016

Protocol number: **BUS/PGR/UH/02715**

Title of study: Demand and Capacity Modelling of Acute Services Using Simulation and Optimization Techniques.

Your application for ethics approval has been accepted and approved by the ECDA for your School.

This approval is valid:

From: 01/12/2016

To: 01/03/2017

Please note:

Approval applies specifically to the research study/methodology and timings as detailed in your Form EC1. Should you amend any aspect of your research, or wish to apply for an extension to your study, you will need your supervisor's approval and must complete and submit form EC2. In cases where the amendments to the original study are deemed to be substantial, a new Form EC1 may need to be completed prior to the study being undertaken.

Should adverse circumstances arise during this study such as physical reaction/harm, mental/emotional harm, intrusion of privacy or breach of confidentiality this must be reported to the approving Committee immediately. Failure to report adverse circumstance/s would be considered misconduct.

Ensure you quote the UH protocol number and the name of the approving Committee on all paperwork, including recruitment advertisements/online requests, for this study.

Students must include this Approval Notification with their submission.

Appendix 2

Point forecast formulas of exponential smoothing methods (Taken from (Hyndman, Koehler, Ord and Snyder, 2008, p. 18)

Trend	Seasonal: N	Seasonal: A	Seasonal: M
N	$\ell_t = \alpha y_t + (1-\alpha)\ell_{t-1}$ $\hat{y}_{t+h\|t} = \ell_t$	$\ell_t = \alpha(y_t - s_{t-m}) + (1-\alpha)\ell_{t-1}$ $s_t = \gamma(y_t - \ell_{t-1}) + (1-\gamma)s_{t-m}$ $\hat{y}_{t+h\|t} = \ell_t + s_{t-m+h_m^+}$	$\ell_t = \alpha(y_t / s_{t-m}) + (1-\alpha)\ell_{t-1}$ $s_t = \gamma(y_t / \ell_{t-1}) + (1-\gamma)s_{t-m}$ $\hat{y}_{t+h\|t} = \ell_t s_{t-m+h_m^+}$
A	$\ell_t = \alpha y_t + (1-\alpha)(\ell_{t-1} + b_{t-1})$ $b_t = \beta^*(\ell_t - \ell_{t-1}) + (1-\beta^*)b_{t-1}$ $\hat{y}_{t+h\|t} = \ell_t + hb_t$	$\ell_t = \alpha(y_t - s_{t-m}) + (1-\alpha)(\ell_{t-1} + b_{t-1})$ $b_t = \beta^*(\ell_t - \ell_{t-1}) + (1-\beta^*)b_{t-1}$ $s_t = \gamma(y_t - \ell_{t-1} - b_{t-1}) + (1-\gamma)s_{t-m}$ $\hat{y}_{t+h\|t} = \ell_t + hb_t + s_{t-m+h_m^+}$	$\ell_t = \alpha(y_t / s_{t-m}) + (1-\alpha)(\ell_{t-1} + b_{t-1})$ $b_t = \beta^*(\ell_t - \ell_{t-1}) + (1-\beta^*)b_{t-1}$ $s_t = \gamma(y_t / (\ell_{t-1} + b_{t-1})) + (1-\gamma)s_{t-m}$ $\hat{y}_{t+h\|t} = (\ell_t + hb_t)s_{t-m+h_m^+}$
A_d	$\ell_t = \alpha y_t + (1-\alpha)(\ell_{t-1} + \phi b_{t-1})$ $b_t = \beta^*(\ell_t - \ell_{t-1}) + (1-\beta^*)\phi b_{t-1}$ $\hat{y}_{t+h\|t} = \ell_t + \phi_h b_t$	$\ell_t = \alpha(y_t - s_{t-m}) + (1-\alpha)(\ell_{t-1} + \phi b_{t-1})$ $b_t = \beta^*(\ell_t - \ell_{t-1}) + (1-\beta^*)\phi b_{t-1}$ $s_t = \gamma(y_t - \ell_{t-1} - \phi b_{t-1}) + (1-\gamma)s_{t-m}$ $\hat{y}_{t+h\|t} = \ell_t + \phi_h b_t + s_{t-m+h_m^+}$	$\ell_t = \alpha(y_t / s_{t-m}) + (1-\alpha)(\ell_{t-1} + \phi b_{t-1})$ $b_t = \beta^*(\ell_t - \ell_{t-1}) + (1-\beta^*)\phi b_{t-1}$ $s_t = \gamma(y_t / (\ell_{t-1} + \phi b_{t-1})) + (1-\gamma)s_{t-m}$ $\hat{y}_{t+h\|t} = (\ell_t + \phi_h b_t)s_{t-m+h_m^+}$
M	$\ell_t = \alpha y_t + (1-\alpha)\ell_{t-1}b_{t-1}$ $b_t = \beta^*(\ell_t / \ell_{t-1}) + (1-\beta^*)b_{t-1}$ $\hat{y}_{t+h\|t} = \ell_t b_t^h$	$\ell_t = \alpha(y_t - s_{t-m}) + (1-\alpha)\ell_{t-1}b_{t-1}$ $b_t = \beta^*(\ell_t / \ell_{t-1}) + (1-\beta^*)b_{t-1}$ $s_t = \gamma(y_t - \ell_{t-1}b_{t-1}) + (1-\gamma)s_{t-m}$ $\hat{y}_{t+h\|t} = \ell_t b_t^h + s_{t-m+h_m^+}$	$\ell_t = \alpha(y_t / s_{t-m}) + (1-\alpha)\ell_{t-1}b_{t-1}$ $b_t = \beta^*(\ell_t / \ell_{t-1}) + (1-\beta^*)b_{t-1}$ $s_t = \gamma(y_t / (\ell_{t-1}b_{t-1})) + (1-\gamma)s_{t-m}$ $\hat{y}_{t+h\|t} = \ell_t b_t^h s_{t-m+h_m^+}$
M_d	$\ell_t = \alpha y_t + (1-\alpha)\ell_{t-1}b_{t-1}^{\phi}$ $b_t = \beta^*(\ell_t / \ell_{t-1}) + (1-\beta^*)b_{t-1}^{\phi}$ $\hat{y}_{t+h\|t} = \ell_t b_t^{\phi_h}$	$\ell_t = \alpha(y_t - s_{t-m}) + (1-\alpha)\ell_{t-1}b_{t-1}^{\phi}$ $b_t = \beta^*(\ell_t / \ell_{t-1}) + (1-\beta^*)b_{t-1}^{\phi}$ $s_t = \gamma(y_t - \ell_{t-1}b_{t-1}^{\phi}) + (1-\gamma)s_{t-m}$ $\hat{y}_{t+h\|t} = \ell_t b_t^{\phi_h} + s_{t-m+h_m^+}$	$\ell_t = \alpha(y_t / s_{t-m}) + (1-\alpha)\ell_{t-1}b_{t-1}^{\phi}$ $b_t = \beta^*(\ell_t / \ell_{t-1}) + (1-\beta^*)b_{t-1}^{\phi}$ $s_t = \gamma(y_t / (\ell_{t-1}b_{t-1}^{\phi})) + (1-\gamma)s_{t-m}$ $\hat{y}_{t+h\|t} = \ell_t b_t^{\phi_h} s_{t-m+h_m^+}$

In each case, ℓ_t denotes the series level at time t, b_t denotes the slope at time t, s_t denotes the seasonal component of the series at time t, and m denotes the number of seasons in a year; α, β^*, γ and ϕ are constants, $\phi_h = \phi + \phi^2 + \cdots + \phi^h$ and $h_m^+ = \lfloor (h-1) \bmod m \rfloor + 1$.

Appendix 3

Exponential smoothing models with the additive errors (Taken from (Hyndman, Koehler, Ord and Snyder, 2008, p. 21))

Trend	Seasonal		
	N	A	M
N	$\mu_t = \ell_{t-1}$ $\ell_t = \ell_{t-1} + \alpha\varepsilon_t$	$\mu_t = \ell_{t-1} + s_{t-m}$ $\ell_t = \ell_{t-1} + \alpha\varepsilon_t$ $s_t = s_{t-m} + \gamma\varepsilon_t$	$\mu_t = \ell_{t-1}s_{t-m}$ $\ell_t = \ell_{t-1} + \alpha\varepsilon_t / s_{t-m}$ $s_t = s_{t-m} + \gamma\varepsilon_t / \ell_{t-1}$
A	$\mu_t = \ell_{t-1} + b_{t-1}$ $\ell_t = \ell_{t-1} + b_{t-1} + \alpha\varepsilon_t$ $b_t = b_{t-1} + \beta\varepsilon_t$	$\mu_t = \ell_{t-1} + b_{t-1} + s_{t-m}$ $\ell_t = \ell_{t-1} + b_{t-1} + \alpha\varepsilon_t$ $b_t = b_{t-1} + \beta\varepsilon_t$ $s_t = s_{t-m} + \gamma\varepsilon_t$	$\mu_t = (\ell_{t-1} + b_{t-1})s_{t-m}$ $\ell_t = \ell_{t-1} + b_{t-1} + \alpha\varepsilon_t / s_{t-m}$ $b_t = b_{t-1} + \beta\varepsilon_t / s_{t-m}$ $s_t = s_{t-m} + \gamma\varepsilon_t / (\ell_{t-1} + b_{t-1})$
$\mathrm{A_d}$	$\mu_t = \ell_{t-1} + \phi b_{t-1}$ $\ell_t = \ell_{t-1} + \phi b_{t-1} + \alpha\varepsilon_t$ $b_t = \phi b_{t-1} + \beta\varepsilon_t$	$\mu_t = \ell_{t-1} + \phi b_{t-1} + s_{t-m}$ $\ell_t = \ell_{t-1} + \phi b_{t-1} + \alpha\varepsilon_t$ $b_t = \phi b_{t-1} + \beta\varepsilon_t$ $s_t = s_{t-m} + \gamma\varepsilon_t$	$\mu_t = (\ell_{t-1} + \phi b_{t-1})s_{t-m}$ $\ell_t = \ell_{t-1} + \phi b_{t-1} + \alpha\varepsilon_t / s_{t-m}$ $b_t = \phi b_{t-1} + \beta\varepsilon_t / s_{t-m}$ $s_t = s_{t-m} + \gamma\varepsilon_t / (\ell_{t-1} + \phi b_{t-1})$
M	$\mu_t = \ell_{t-1}b_{t-1}$ $\ell_t = \ell_{t-1}b_{t-1} + \alpha\varepsilon_t$ $b_t = b_{t-1} + \beta\varepsilon_t / \ell_{t-1}$	$\mu_t = \ell_{t-1}b_{t-1} + s_{t-m}$ $\ell_t = \ell_{t-1}b_{t-1} + \alpha\varepsilon_t$ $b_t = b_{t-1} + \beta\varepsilon_t / \ell_{t-1}$ $s_t = s_{t-m} + \gamma\varepsilon_t$	$\mu_t = \ell_{t-1}b_{t-1}s_{t-m}$ $\ell_t = \ell_{t-1}b_{t-1} + \alpha\varepsilon_t / s_{t-m}$ $b_t = b_{t-1} + \beta\varepsilon_t / (s_{t-m}\ell_{t-1})$ $s_t = s_{t-m} + \gamma\varepsilon_t / (\ell_{t-1}b_{t-1})$
$\mathrm{M_d}$	$\mu_t = \ell_{t-1}b_{t-1}^{\phi}$ $\ell_t = \ell_{t-1}b_{t-1}^{\phi} + \alpha\varepsilon_t$ $b_t = b_{t-1}^{\phi} + \beta\varepsilon_t / \ell_{t-1}$	$\mu_t = \ell_{t-1}b_{t-1}^{\phi} + s_{t-m}$ $\ell_t = \ell_{t-1}b_{t-1}^{\phi} + \alpha\varepsilon_t$ $b_t = b_{t-1}^{\phi} + \beta\varepsilon_t / \ell_{t-1}$ $s_t = s_{t-m} + \gamma\varepsilon_t$	$\mu_t = \ell_{t-1}b_{t-1}^{\phi}s_{t-m}$ $\ell_t = \ell_{t-1}b_{t-1}^{\phi} + \alpha\varepsilon_t / s_{t-m}$ $b_t = b_{t-1}^{\phi} + \beta\varepsilon_t / (s_{t-m}\ell_{t-1})$ $s_t = s_{t-m} + \gamma\varepsilon_t / (\ell_{t-1}b_{t-1}^{\phi})$

Appendix 4

Exponential smoothing models with the multiplicative errors (Taken from (Hyndman, Koehler, Ord and Snyder, 2008, p. 22)

Trend	Seasonal N	Seasonal A	Seasonal M
N	$\mu_t = \ell_{t-1}$ $\ell_t = \ell_{t-1}(1+\alpha\varepsilon_t)$	$\mu_t = \ell_{t-1} + s_{t-m}$ $\ell_t = \ell_{t-1} + \alpha(\ell_{t-1} + s_{t-m})\varepsilon_t$ $s_t = s_{t-m} + \gamma(\ell_{t-1} + s_{t-m})\varepsilon_t$	$\mu_t = \ell_{t-1}s_{t-m}$ $\ell_t = \ell_{t-1}(1+\alpha\varepsilon_t)$ $s_t = s_{t-m}(1+\gamma\varepsilon_t)$
A	$\mu_t = \ell_{t-1} + b_{t-1}$ $\ell_t = (\ell_{t-1} + b_{t-1})(1+\alpha\varepsilon_t)$ $b_t = b_{t-1} + \beta(\ell_{t-1} + b_{t-1})\varepsilon_t$	$\mu_t = \ell_{t-1} + b_{t-1} + s_{t-m}$ $\ell_t = \ell_{t-1} + b_{t-1} + \alpha(\ell_{t-1} + b_{t-1} + s_{t-m})\varepsilon_t$ $b_t = b_{t-1} + \beta(\ell_{t-1} + b_{t-1} + s_{t-m})\varepsilon_t$ $s_t = s_{t-m} + \gamma(\ell_{t-1} + b_{t-1} + s_{t-m})\varepsilon_t$	$\mu_t = (\ell_{t-1} + b_{t-1})s_{t-m}$ $\ell_t = (\ell_{t-1} + b_{t-1})(1+\alpha\varepsilon_t)$ $b_t = b_{t-1} + \beta(\ell_{t-1} + b_{t-1})\varepsilon_t$ $s_t = s_{t-m}(1+\gamma\varepsilon_t)$
A_d	$\mu_t = \ell_{t-1} + \phi b_{t-1}$ $\ell_t = (\ell_{t-1} + \phi b_{t-1})(1+\alpha\varepsilon_t)$ $b_t = \phi b_{t-1} + \beta(\ell_{t-1} + \phi b_{t-1})\varepsilon_t$	$\mu_t = \ell_{t-1} + \phi b_{t-1} + s_{t-m}$ $\ell_t = \ell_{t-1} + \phi b_{t-1} + \alpha(\ell_{t-1} + \phi b_{t-1} + s_{t-m})\varepsilon_t$ $b_t = \phi b_{t-1} + \beta(\ell_{t-1} + \phi b_{t-1} + s_{t-m})\varepsilon_t$ $s_t = s_{t-m} + \gamma(\ell_{t-1} + \phi b_{t-1} + s_{t-m})\varepsilon_t$	$\mu_t = (\ell_{t-1} + \phi b_{t-1})s_{t-m}$ $\ell_t = (\ell_{t-1} + \phi b_{t-1})(1+\alpha\varepsilon_t)$ $b_t = \phi b_{t-1} + \beta(\ell_{t-1} + \phi b_{t-1})\varepsilon_t$ $s_t = s_{t-m}(1+\gamma\varepsilon_t)$
M	$\mu_t = \ell_{t-1}b_{t-1}$ $\ell_t = \ell_{t-1}b_{t-1}(1+\alpha\varepsilon_t)$ $b_t = b_{t-1}(1+\beta\varepsilon_t)$	$\mu_t = \ell_{t-1}b_{t-1} + s_{t-m}$ $\ell_t = \ell_{t-1}b_{t-1} + \alpha(\ell_{t-1}b_{t-1} + s_{t-m})\varepsilon_t$ $b_t = b_{t-1} + \beta(\ell_{t-1}b_{t-1} + s_{t-m})\varepsilon_t/\ell_{t-1}$ $s_t = s_{t-m} + \gamma(\ell_{t-1}b_{t-1} + s_{t-m})\varepsilon_t$	$\mu_t = \ell_{t-1}b_{t-1}s_{t-m}$ $\ell_t = \ell_{t-1}b_{t-1}(1+\alpha\varepsilon_t)$ $b_t = b_{t-1}(1+\beta\varepsilon_t)$ $s_t = s_{t-m}(1+\gamma\varepsilon_t)$
M_d	$\mu_t = \ell_{t-1}b_{t-1}^{\phi}$ $\ell_t = \ell_{t-1}b_{t-1}^{\phi}(1+\alpha\varepsilon_t)$ $b_t = b_{t-1}^{\phi}(1+\beta\varepsilon_t)$	$\mu_t = \ell_{t-1}b_{t-1}^{\phi} + s_{t-m}$ $\ell_t = \ell_{t-1}b_{t-1}^{\phi} + \alpha(\ell_{t-1}b_{t-1}^{\phi} + s_{t-m})\varepsilon_t$ $b_t = b_{t-1}^{\phi} + \beta(\ell_{t-1}b_{t-1}^{\phi} + s_{t-m})\varepsilon_t/\ell_{t-1}$ $s_t = s_{t-m} + \gamma(\ell_{t-1}b_{t-1}^{\phi} + s_{t-m})\varepsilon_t$	$\mu_t = \ell_{t-1}b_{t-1}^{\phi}s_{t-m}$ $\ell_t = \ell_{t-1}b_{t-1}^{\phi}(1+\alpha\varepsilon_t)$ $b_t = b_{t-1}^{\phi}(1+\beta\varepsilon_t)$ $s_t = s_{t-m}(1+\gamma\varepsilon_t)$

Appendix 5

Forecast accuracy value for the first referrals of outpatient specialties

Specialty	Forecasting Models	Daily			Weekly			Monthly		
		Parameters	TS	VS	Parameters	TS	VS	Parameters	TS	VS
General Surgery	SLR	**SLR**	**0.41**	**0.58**	SLR	0.94	1.07	SLR	0.71	0.80
	ARIMA	(3,1,3)	0.82	0.94	(0,1,1)	0.95	0.79	(1,0,0)	0.98	0.76
	ES	(A,Ad,N)	1.01	0.95	(A,Ad,N)	0.91	0.68	(M,A,N)	1.04	0.98
	STLF	(A,N,N)	1.06	1.35	(A,N,N)	0.71	1.93	(M,N,N)	0.90	1.12
Urology	SLR	**SLR**	**0.86**	**0.60**	SLR	0.73	0.92	SLR	0.65	0.85
	ARIMA	(5,1,2)	0.65	0.80	(0,1,1)	0.82	0.78	(0,0,0)	0.82	0.71
	ES	(A,Ad,N)	0.90	0.83	(A,Ad,N)	0.77	0.77	(M,N,N)	0.82	0.71
	STLF	(A,N,N)	1.08	1.10	(A,Ad,N)	0.78	0.96	(M,N,N)	0.92	0.98
Ear, Nose and Throat (ENT)	SLR	**SLR**	**0.50**	**0.65**	SLR	0.90	0.82	SLR	0.79	0.92
	ARIMA	(2,0,2)	0.86	0.88	(2,0,1)	0.86	0.76	(0,0,1)	0.90	0.72
	ES	(A,Ad,N)	0.90	0.88	(A,Ad,N)	0.85	0.79	(M,N,N)	0.91	0.69
	STLF	(A,N,N)	0.98	1.02	(A,N,N)	0.70	1.20	(A,N,N)	1.01	1.24
Ophthalmology	SLR	SLR	1.15	1.17	SLR	0.80	1.45	SLR	1.21	2.26
	ARIMA	(2,1,3)	0.76	0.89	(0,0,0)	0.90	1.18	(0,1,1)	0.79	1.84
	ES	**(A,N,N)**	**0.80**	**0.86**	(A,N,N)	0.81	1.03	(M,N,N)	0.80	9.34
	STLF	(A,N,N)	0.91	1.12	(M,N,N)	0.78	0.95	(M,N,N)	0.71	1.73
Trauma & Orthopaedics	SLR	**SLR**	**0.47**	**0.65**	SLR	0.93	1.04	SLR	0.75	1.32
	ARIMA	(3,1,3)	0.79	0.87	(4,0,0)	0.78	0.91	(1,0,1)	1.00	0.86
	ES	(A,A_d,N)	0.85	0.87	(A,A_d,N)	0.80	1.11	(M,A,N)	1.14	4.66
	STLF	(A,N,N)	0.89	1.10	(A,N,N)	0.77	1.54	(M,N,N)	1.15	1.65
Oral Surgery	SLR	SLR	0.58	0.57	SLR	0.69	0.82	SLR	0.82	0.68
	ARIMA	(2,1,2)	0.76	0.80	(2,0,2)	0.74	0.71	(0,0,0)	0.87	0.56
	ES	(A,Ad,N)	0.80	0.77	(M,Ad,N)	0.73	0.71	**(M,N,N)**	**0.87**	**0.54**
	STLF	(A,N,N)	0.91	0.89	(A,N,N)	0.84	1.05	(M,N,N)	0.71	0.84
Anaesthetics	SLR	**SLR**	**0.62**	**0.61**	SLR	0.80	1.06	SLR	0.80	1.33
	ARIMA	(0,0,1)	0.84	0.80	(2,0,2)	0.78	1.10	(0,0,0)	0.79	1.35
	ES	(A,N,N)	0.85	0.80	(M,A,N)	0.88	0.92	(A,N,N)	0.79	1.35
	STLF	(A,Ad,N)	0.98	0.88	(A,N,N)	0.78	1.13	(M,N,N)	0.74	1.28
General Medicine	SLR	**SLR**	**0.46**	**0.67**	SLR	1.06	1.09	SLR	0.89	0.94
	ARIMA	(3,1,2)	0.80	0.90	(1,0,1)	0.89	0.80	(0,0,0)	1.03	0.73
	ES	(A,Ad,N)	0.89	0.86	(A,Ad,N)	0.83	0.75	(A,N,N)	1.03	0.71
	STLF	(A,N,N)	0.97	1.02	(A,N,N)	0.66	1.30	(A,N,N)	0.78	1.04
Gastroenterology	SLR	SLR	0.56	0.89	SLR	0.97	1.28	SLR	0.94	2.81
	ARIMA	(5,1,3)	0.70	0.81	(1,1,4)	0.82	1.10	(0,1,0)	0.96	2.51
	ES	(A,N,N)	0.82	0.82	(A,N,N)	0.94	1.13	(A,N,N)	0.88	2.28
	STLF	**(A,N,N)**	**0.92**	**0.75**	(A,N,N)	0.67	0.97	(A,N,N)	0.61	1.95
Clinical Haematology	SLR	**SLR**	**0.56**	**0.63**	SLR	0.67	0.85	SLR	0.40	1.31
	ARIMA	(1,0,2)	0.77	0.74	(1,0,1)	0.73	0.75	(0,0,0)	0.67	0.97
	ES	(A,N,N)	0.77	0.74	(M,Ad,N)	0.76	0.80	(A,N,N)	0.67	0.97
	STLF	(A,N,N)	0.96	0.89	(A,N,N)	1.07	1.25	(M,N,N)	1.08	1.35

ARIMA: Autoregressive integrated moving average, ES: Exponential smoothing, SLR: Stepwise Linear Regression, STLF: The function of the seasonal and trend decomposition method, TS: Training Set, VS: Validation Set

Appendix 5 (cont.)

Forecast accuracy value for the first referrals of outpatient specialties

Specialty	Forecasting Models	Daily			Weekly			Monthly		
		Parameters	TS	VS	Parameters	TS	VS	Parameters	TS	VS
Cardiology	SLR	**SLR**	**0.46**	**0.62**	SLR	0.72	1.01	SLR	0.62	1.37
	ARIMA	(2,0,4)	0.79	0.81	(2,0,0)	0.79	0.87	(0,0,0)	0.80	1.04
	ES	(A,Ad,N)	0.85	0.81	(M,Ad,N)	0.78	0.69	(M,N,N)	0.80	1.04
	STLF	(A,N,N)	0.98	0.96	(M,Ad,N)	0.78	1.14	(M,N,N)	0.91	1.27
Dermatology	SLR	SLR	0.49	0.62	SLR	0.88	0.93	SLR	0.84	1.05
	ARIMA	(5,1,3)	0.62	0.94	(0,1,1)	0.88	0.89	(1,0,0)	0.94	1.25
	ES	(A,Ad,N)	0.89	0.97	(A,Ad,N)	0.86	0.90	(A,N,N)	0.99	0.97
	STLF	**(A,N,N)**	**0.91**	**0.56**	(A,N,N)	0.77	0.97	(A,N,N)	0.88	1.25
Neurology	SLR	SLR	0.54	0.60	SLR	0.76	0.81	SLR	0.60	0.75
	ARIMA	(2,0,5)	0.76	0.75	(1,0,1)	0.80	0.76	(1,0,0)	0.65	0.58
	ES	(A,Ad,N)	0.81	0.75	(A,Ad,N)	0.75	0.76	(M,N,N)	0.71	0.59
	STLF	(A,N,N)	0.87	0.83	(M,Ad,N)	0.84	0.74	**(M,N,N)**	**0.80**	**0.56**
Rheumatology	SLR	**SLR**	**0.58**	**0.72**	SLR	0.68	0.90	SLR	0.45	1.05
	ARIMA	(3,0,3)	0.82	0.85	(1,0,1)	0.80	0.76	(0,0,0)	0.79	0.83
	ES	(A,Ad,N)	0.84	0.86	(A,Ad,N)	0.78	0.74	(A,N,N)	0.79	0.83
	STLF	(A,N,N)	0.88	1.04	(M,N,N)	0.86	1.16	(M,N,N)	1.10	1.26
Paediatrics	SLR	**SLR**	**0.49**	**0.79**	SLR	0.57	1.47	SLR	0.32	1.67
	ARIMA	(1,0,4)	0.76	0.88	(2,0,1)	0.72	1.29	(0,0,0)	0.69	1.62
	ES	(A,N,N)	0.81	0.88	(M,Ad,N)	0.74	1.35	(A,N,N)	0.69	1.62
	STLF	(A,N,N)	0.97	1.16	(M,N,N)	0.92	1.45	(A,N,N)	1.27	1.74
Obstetrics	SLR	SLR	1.03	1.82	SLR	1.53	7.32	SLR	0.68	1.13
	ARIMA	(0,0,0)	0.80	0.98	(0,0,0)	0.86	1.98	(0,0,0)	0.86	1.28
	ES	(A,N,N)	0.71	0.98	(M,A,N)	1.01	5.52	(M,A,N)	1.00	1.77
	STLF	(A,Ad,N)	1.28	2.22	(A,Ad,N)	1.26	5.08	**(A,N,N)**	**1.47**	**0.95**
Gynaecology	SLR	**SLR**	**0.46**	**0.53**	SLR	0.87	1.43	SLR	0.80	1.77
	ARIMA	(5,1,3)	0.63	0.88	(2,1,2)	0.90	0.71	(0,0,0)	0.81	1.77
	ES	(A,Ad,N)	0.90	0.92	(A,Ad,N)	0.94	0.76	(M,N,N)	0.81	1.77
	STLF	(A,Ad,N)	0.97	1.03	(A,N,N)	0.70	1.21	(A,N,N)	0.94	1.53
Clinical Oncology	SLR	SLR	0.63	0.75	SLR	0.67	0.65	SLR	0.80	1.06
	ARIMA	(1,1,1)	0.86	0.91	**(4,0,0)**	**0.72**	**0.64**	(0,0,1)	0.76	0.83
	ES	(A,Ad,N)	0.92	0.91	(A,Ad,N)	0.69	0.65	(M,N,N)	0.86	0.78
	STLF	(A,N,N)	1.02	1.03	(A,Ad,N)	0.87	0.80	(M,N,N)	0.77	1.18
Others	SLR	SLR	0.63	0.76	SLR	0.78	0.80	SLR	0.77	0.79
	ARIMA	(5,1,1)	0.78	0.83	(1,0,1)	0.77	0.77	(1,0,0)	0.81	0.72
	ES	(A,N,N)	0.85	0.79	(A,Ad,N)	0.73	0.73	**(M,Ad,N)**	**0.66**	**0.58**
	STLF	(A,N,N)	0.92	0.97	(A,Ad,N)	0.77	0.84	(A,N,N)	0.68	0.88

ARIMA: Autoregressive integrated moving average, ES: Exponential smoothing, SLR: Stepwise Linear Regression, STLF: The function of the seasonal and trend decomposition method, TS: Training Set, VS: Validation Set

Appendix 6

Forecast accuracy value for the follow up referrals of outpatient specialties

Specialty	Forecasting Models	Daily			Weekly			Monthly		
		Parameters	TS	VS	Parameters	TS	VS	Parameters	TS	VS
General Surgery	SLR	**SLR**	**0.41**	**0.72**	SLR	0.63	0.86	SLR	0.37	0.78
	ARIMA	(3,1,3)	0.81	0.90	(0,1,1)	0.74	0.78	(0,0,0)	0.64	0.74
	ES	(A,N,N)	0.93	0.90	(A,N,N)	0.74	0.78	(M,N,N)	0.64	0.74
	STLF	(A,N,N)	1.11	1.42	(A,N,N)	1.02	0.95	(M,N,N)	1.15	0.97
Urology	SLR	**SLR**	**0.50**	**0.60**	SLR	0.89	1.01	SLR	1.47	1.12
	ARIMA	(4,1,2)	0.74	0.93	(0,1,1)	0.75	0.94	(1,1,0)	0.77	1.16
	ES	(A,N,N)	0.85	0.93	(A,N,N)	0.75	0.94	(A,N,N)	0.80	1.23
	STLF	(A,N,N)	0.93	0.97	(M,A,N)	0.58	2.14	(A,N,N)	0.37	1.38
Ear, Nose and Throat (ENT)	SLR	SLR	0.70	1.29	SLR	0.89	2.53	SLR	1.06	2.25
	ARIMA	**(1,1,3)**	**0.93**	**1.13**	(2,1,2)	0.92	2.47	(1,0,0)	1.15	3.55
	ES	(A,N,N)	0.91	1.24	(M,A_d,N)	1.14	2.70	(M,N,N)	1.10	2.34
	STLF	(A,N,N)	1.15	2.39	(A,N,N)	0.97	3.06	(M,N,N)	0.92	1.33
Ophthalmology	SLR	SLR	1.07	1.14	SLR	0.76	1.20	SLR	0.92	1.33
	ARIMA	(2,1,3)	0.76	0.94	(0,0,0)	0.90	1.03	(0,1,1)	0.79	1.25
	ES	**(A,N,N)**	**0.80**	**0.91**	(A,N,N)	0.81	1.13	(M,N,N)	0.80	0.92
	STLF	(A,N,N)	0.99	1.14	(M,N,N)	0.78	1.23	(M,N,N)	0.71	0.98
Trauma & Orthopaedics	SLR	SLR	0.45	0.93	SLR	0.80	1.63	SLR	1.23	2.12
	ARIMA	(2,1,2)	0.78	0.92	(3,1,1)	0.80	0.91	(0,1,0)	0.96	0.96
	ES	(A,A_d,N)	0.83	0.85	(M,N,N)	0.82	0.89	(M,N,N)	0.93	0.98
	STLF	**(A,N,N)**	**0.95**	**0.53**	(M,N,N)	0.80	1.35	(M,N,N)	0.46	1.26
Oral Surgery	SLR	SLR	0.53	0.58	SLR	0.62	0.69	SLR	0.47	0.70
	ARIMA	(5,1,1)	0.72	0.80	(0,1,2)	0.68	0.67	(0,1,1)	0.72	0.65
	ES	(A,N,N)	0.82	0.80	(M,N,N)	0.69	0.65	(A,N,N)	0.74	0.65
	STLF	(A,N,N)	0.90	0.84	(A,N,N)	1.01	0.74	**(A,N,N)**	**0.75**	**0.47**
Anaesthetics	SLR	**SLR**	**0.44**	**0.82**	SLR	1.46	1.96	SLR	1.41	2.75
	ARIMA	(3,1,2)	0.82	0.88	(2,1,3)	0.85	0.98	(0,1,0)	0.96	1.06
	ES	(A,A_d,N)	0.97	0.89	(M,A_d,N)	0.88	0.88	(A,N,N)	0.96	1.06
	STLF	(A,N,N)	0.92	1.05	(A,N,N)	0.42	2.19	(A,N,N)	0.47	2.34
General Medicine	SLR	SLR	0.51	0.99	SLR	0.86	1.43	SLR	0.89	2.38
	ARIMA	(4,1,1)	0.82	0.90	**(0,1,1)**	**0.82**	**0.72**	(1,1,0)	0.85	0.73
	ES	(A,N,N)	0.85	0.90	(M,A,N)	1.20	0.80	(M,A,N)	1.08	0.81
	STLF	(A,N,N)	1.06	1.21	(A,N,N)	1.02	1.33	(M,N,N)	0.92	1.78
Gastroenterology	SLR	SLR	0.75	1.00	SLR	1.09	1.36	SLR	0.69	2.81
	ARIMA	(5,0,3)	0.91	0.87	(0,0,1)	0.95	0.96	(0,0,0)	0.82	2.60
	ES	**(A,N,N)**	**0.94**	**0.76**	(M,A_d,N)	1.05	0.86	(M,A,N)	1.07	6.36
	STLF	(A,N,N)	1.12	1.51	(A,N,N)	1.08	1.71	(A,N,N)	1.12	4.86
Clinical Haematology	SLR	**SLR**	**0.56**	**0.68**	SLR	0.60	0.85	SLR	0.33	1.50
	ARIMA	(0,0,3)	0.77	0.81	(0,0,0)	0.69	0.76	(0,0,0)	0.72	1.33
	ES	(A,N,N)	0.80	0.81	(A,N,N)	0.69	0.76	(A,N,N)	0.72	1.33
	STLF	(A,N,N)	0.97	0.96	(A,N,N)	1.06	1.16	(M,N,N)	1.16	1.79

ARIMA: Autoregressive integrated moving average, ES: Exponential smoothing, SLR: Stepwise Linear Regression, STLF: The function of the seasonal and trend decomposition method, TS: Training Set, VS: Validation Set

Appendix 6 (cont.)

Forecast accuracy value for the follow up referrals of outpatient specialties

Specialty	Forecasting Models	Daily			Weekly			Monthly		
		Parameters	TS	VS	Parameters	TS	VS	Parameters	TS	VS
Cardiology	SLR	SLR	0.51	0.92	SLR	0.80	0.97	**SLR**	**1.13**	**0.85**
	ARIMA	(5,1,3)	0.69	0.89	(0,1,1)	0.76	0.89	(1,0,2)	0.66	0.88
	ES	(A,N,N)	0.87	0.90	(A,N,N)	0.76	0.89	(A,N,N)	0.91	0.90
	STLF	(A,N,N)	1.00	1.06	(A,N,N)	0.67	0.97	(A,N,N)	0.49	0.97
Dermatology	SLR	SLR	0.56	0.74	SLR	0.87	0.96	SLR	0.71	0.96
	ARIMA	(1,1,2)	0.85	0.89	(4,0,0)	0.99	0.78	(0,0,1)	0.88	0.79
	ES	(A,A_d,N)	0.88	0.92	**(M,N,N)**	**1.12**	**0.72**	(M,N,N)	0.92	0.77
	STLF	(A,N,N)	1.01	1.15	(A,N,N)	1.11	1.26	(M,N,N)	0.90	1.36
Neurology	SLR	SLR	0.61	1.00	SLR	0.79	1.37	SLR	0.57	1.53
	ARIMA	**(5,1,0)**	**0.88**	**0.82**	(0,1,1)	0.80	0.98	(2,1,0)	0.60	1.03
	ES	(A,A,N)	0.78	0.84	(M,A_d,N)	1.10	1.06	(M,N,N)	0.92	1.04
	STLF	(A,N,N)	0.98	1.09	(A,N,N)	0.97	1.61	(M,N,N)	1.21	1.88
Rheumatology	SLR	**SLR**	**0.60**	**0.95**	SLR	0.64	1.12	SLR	0.27	1.20
	ARIMA	(1,0,1)	0.82	0.97	(0,0,1)	0.78	1.12	(0,0,0)	0.75	1.12
	ES	(A,N,N)	0.83	0.97	(A,N,N)	0.79	1.12	(A,N,N)	0.75	1.12
	STLF	(A,N,N)	0.91	1.12	(M,N,N)	1.00	1.43	(M,N,N)	1.15	1.30
Paediatrics	SLR	SLR	0.53	1.38	SLR	0.69	2.91	SLR	0.86	4.33
	ARIMA	**(5,1,3)**	**0.69**	**1.11**	(0,1,1)	0.75	1.68	(0,1,1)	0.85	2.29
	ES	(A,N,N)	0.83	1.12	(M,N,N)	0.75	1.68	(M,N,N)	0.90	2.29
	STLF	(A,N,N)	0.99	1.46	(M,N,N)	0.74	1.97	(A,A,N)	0.55	2.05
Obstetrics	SLR	SLR	1.08	1.93	SLR	1.35	6.44	SLR	1.23	0.99
	ARIMA	(0,1,1)	0.92	1.43	(0,1,1)	1.02	3.44	(0,1,0)	0.96	1.37
	ES	(A,N,N)	0.92	1.46	(M,A,N)	1.09	4.05	**(M,A,N)**	**1.09**	**0.93**
	STLF	(A,A_d,N)	0.85	1.82	(A,A_d,N)	0.75	7.82	(A,N,N)	0.54	1.95
Gynaecology	SLR	**SLR**	**0.41**	**0.68**	SLR	0.85	1.58	SLR	0.84	1.19
	ARIMA	(5,1,3)	0.58	1.07	(1,0,4)	0.80	1.23	(0,0,0)	0.90	1.03
	ES	(A,N,N)	0.94	0.97	(M,A_d,N)	0.85	1.41	(M,N,N)	0.90	1.03
	STLF	(A,N,N)	0.94	1.09	(A,N,N)	0.69	2.35	(M,N,N)	0.60	1.30
Clinical Oncology	SLR	SLR	0.58	0.73	SLR	0.59	0.76	SLR	0.43	1.07
	ARIMA	(0,0,5)	0.83	0.88	**(0,1,1)**	**0.63**	**0.69**	(0,0,0)	0.74	0.92
	ES	(A,N,N)	0.90	0.88	(M,A,N)	0.63	0.70	(A,N,N)	0.74	0.92
	STLF	(A,N,N)	1.05	1.08	(M,A_d,N)	0.93	0.91	(M,N,N)	0.81	1.04
Others	SLR	SLR	0.62	0.80	SLR	0.73	0.91	SLR	0.40	1.61
	ARIMA	(2,1,1)	0.86	0.81	(3,1,1)	0.77	0.77	**(0,1,1)**	**0.78**	**0.61**
	ES	(A,A_d,N)	0.84	0.81	(M,N,N)	1.00	0.77	(M,A,N)	0.75	2.33
	STLF	(A,N,N)	1.11	1.17	(A,N,N)	1.08	1.19	(A,N,N)	1.08	1.93

ARIMA: Autoregressive integrated moving average, ES: Exponential smoothing, SLR: Stepwise Linear Regression, STLF: The function of the seasonal and trend decomposition method, TS: Training Set, VS: Validation Set

Appendix 7

Forecast accuracy value for elective patients of inpatient specialties

Specialty	Forecasting Models	Daily			Weekly			Monthly		
		Parameters	TS	VS	Parameters	TS	VS	Parameters	TS	VS
General Surgery	SLR	**SLR**	**0.45**	**0.53**	SLR	0.83	1.10	SLR	0.68	1,43
	ARIMA	(2,1,5)	0.77	0.76	(0,1,1)	0.83	0.81	(1,0,0)	0.95	0.71
	ES	(A,N,N)	0.87	0.76	(M,A_d,N)	0.80	0.79	(M,A,N)	0.83	1.70
	STLF	(A,A_d,N)	0.94	0.86	(M,A,N)	0.74	6.99	(M,N,N)	0.87	1.41
Urology	SLR	SLR	0.41	1.03	SLR	1.24	2.19	SLR	1.54	4.77
	ARIMA	(4,1,3)	0.62	0.83	(0,1,2)	0.84	0.84	(1,0,0)	1.02	2.34
	ES	(A,A_d,N)	0.85	0.84	**(M,A_d,N)**	**0.81**	**0.80**	(M,A,N)	1.07	1.86
	STLF	(A,A_d,N)	1.00	1.25	(M,N,N)	0.46	1.10	(A,N,N)	0.51	2.84
Ear, Nose and Throat (ENT)	SLR	**SLR**	**0.52**	**0.61**	SLR	0.68	0.95	SLR	0.71	1.25
	ARIMA	(1,0,2)	0.81	0.80	(1,0,1)	0.79	0.82	(0,0,0)	0.77	1.00
	ES	(A,N,N)	0.83	0.81	(M,A_d,N)	0.77	0.81	(A,N,N)	0.77	1.00
	STLF	(A,N,N)	0.90	0.90	(M,N,N)	0.89	1.15	(A,N,N)	0.72	1.68
Ophthalmology	SLR	SLR	0.44	0.68	SLR	0.98	1.25	SLR	1.27	1.98
	ARIMA	(1,1,1)	0.79	0.73	(0,1,2)	0.80	0.70	**(0,1,0)**	**0.96**	**0.55**
	ES	(A,N,N)	0.79	0.73	(A,N,N)	0.81	0.67	(M,N,N)	0.93	0.69
	STLF	(A,N,N)	0.87	0.91	(A,N,N)	0.48	0.85	(A,N,N)	0.60	0.88
Trauma & Orthopaedics	SLR	SLR	0.46	0.89	SLR	1.28	1.63	SLR	1.09	2.50
	ARIMA	**(2,1,3)**	**0.74**	**0.87**	(0,1,1)	0.92	1.21	(1,0,0)	0.95	1.20
	ES	(A,A_d,N)	0.89	0.88	(A,N,N)	0.93	1.21	(A,N,N)	0.96	1.11
	STLF	(A,N,N)	0.84	1.00	(A,N,N)	0.42	1.32	(A,N,N)	0.55	1.84
Oral Surgery	SLR	**SLR**	**0.39**	**0.70**	SLR	0.78	1.04	SLR	0.89	1.79
	ARIMA	(0,1,1)	0.83	0.83	(0,1,1)	0.75	0.74	(0,1,0)	0.96	1.12
	ES	(A,A,N)	0.83	0.86	(M,A_d,N)	0.75	0.75	(A,N,N)	0.81	0.78
	STLF	(A,N,N)	0.96	0.95	(A,N,N)	0.81	0.89	(A,N,N)	0.59	0.91
General Medicine	SLR	SLR	0.55	1.28	SLR	1.04	2.93	SLR	1.66	2.64
	ARIMA	(2,1,2)	0.80	1.06	(0,1,1)	0.80	1.55	(0,1,0)	0.96	3.02
	ES	(A,A_d,N)	0.94	0.92	(M,A_d,N)	0.69	1.32	**(M,A,N)**	**0.89**	**0.62**
	STLF	(A,N,N)	0.94	2.40	(M,A_d,N)	0.52	1.84	(M,N,N)	0.53	1.92
Gastroenterology	SLR	**SLR**	**0.64**	**0.76**	SLR	1.28	1.68	SLR	1.11	1.72
	ARIMA	(4,1,2)	0.76	0.94	(1,1,1)	0.90	1.39	(0,1,0)	0.96	1.18
	ES	(A,N,N)	0.86	0.97	(A,N,N)	0.94	1.25	(A,N,N)	0.86	1.37
	STLF	(A,N,N)	0.93	1.03	(A,N,N)	0.50	1.65	(A,N,N)	0.55	1.60
Clinical Haematology	SLR	SLR	0.45	0.94	**SLR**	**1.16**	**0.61**	SLR	1.21	0.91
	ARIMA	(4,1,2)	0.73	1.01	(0,1,2)	0.90	0.73	(1,0,0)	1.10	0.93
	ES	(A,A_d,N)	1.03	0.95	(A,N,N)	0.91	0.76	(A,N,N)	0.96	0.91
	STLF	(A,N,N)	1.09	1.32	(A,N,N)	0.63	0.76	(A,N,N)	0.94	1.23

ARIMA: Autoregressive integrated moving average, ES: Exponential smoothing, SLR: Stepwise Linear Regression, STLF: The function of the seasonal and trend decomposition method, TS: Training Set, VS: Validation Set

Appendix 7 (cont.)

Forecast accuracy value for elective patients of inpatient specialties

Specialty	Forecasting Models	Daily			Weekly			Monthly		
		Parameters	TS	VS	Parameters	TS	VS	Parameters	TS	VS
Cardiology	SLR	**SLR**	**0.54**	**0.66**	SLR	0.67	0.97	SLR	0.47	1.04
	ARIMA	(2,0,5)	0.80	0.89	(3,0,0)	0.71	1.06	(0,0,0)	0.74	1.18
	ES	(A,A$_d$,N)	0.86	0.89	(A,A$_d$,N)	0.65	1.00	(M,N,N)	0.74	1.18
	STLF	(A,N,N)	0.94	0.98	(A,A$_d$,N)	0.78	1.03	(M,N,N)	1.05	1.19
Medical Oncology	SLR	**SLR**	**0.57**	**0.66**	SLR	0.86	0.93	SLR	1.05	1.04
	ARIMA	(4,1,3)	0.71	0.87	(1,1,1)	0.72	0.73	(0,1,0)	0.96	0.77
	ES	(A,N,N)	0.81	0.88	(A,A$_d$,N)	0.76	0.72	(A,N,N)	0.98	0.80
	STLF	(A,N,N)	0.98	0.89	(A,N,N)	0.72	1.06	(M,N,N)	0.69	1.27
Paediatrics	SLR	SLR	0.37	1.42	SLR	0.86	2.08	SLR	0.94	5.65
	ARIMA	(5,1,3)	0.61	0.83	**(0,1,3)**	**0.80**	**0.66**	(1,0,0)	0.94	3.26
	ES	(A,A$_d$,N)	0.81	1.52	(A,A$_d$,N)	0.80	1.59	(A,N,N)	0.92	1.45
	STLF	(A,N,N)	0.99	1.64	(A,N,N)	0.70	1.37	(A,N,N)	0.82	5.34
Gynaecology	SLR	SLR	0.54	0.74	SLR	0.76	0.79	SLR	0.92	1.32
	ARIMA	(0,1,5)	0.80	0.89	(1,0,1)	0.75	0.68	**(1,0,0)**	**0.86**	**0.67**
	ES	(A,A$_d$,N)	0.95	0.89	(A,A$_d$,N)	0.74	0.68	(M,A,N)	1.12	1.40
	STLF	(A,N,N)	1.25	1.27	(A,N,N)	0.67	0.80	(A,N,N)	0.69	1.27
Clinical Oncology	SLR	**SLR**	**0.58**	**0.61**	SLR	0.74	0.82	SLR	1.23	0.99
	ARIMA	(5,1,3)	0.70	1.01	(0,1,2)	0.66	0.65	(0,1,0)	0.96	4.73
	ES	(A,A$_d$,N)	0.86	0.94	(A,A$_d$,N)	0.68	0.65	(A,A$_d$,N)	0.79	0.63
	STLF	(A,N,N)	0.96	0.93	(M,A$_d$,N)	0.67	0.72	(A,N,N)	0.55	0.95
Radiology	SLR	SLR	0.56	0.76	SLR	0.84	1.28	SLR	0.79	1.70
	ARIMA	(4,1,2)	0.72	0.82	**(0,1,1)**	**0.82**	**0.75**	(0,1,0)	0.96	0.76
	ES	(A,N,N)	0.83	0.83	(M,A,N)	0.84	1.88	(M,A,N)	0.98	3.79
	STLF	(A,N,N)	0.98	1.01	(M,A,N)	0.63	7.41	(A,N,N)	0.68	1.89
Others	SLR	SLR	0.59	0.94	SLR	0.77	1.59	SLR	1.39	3.57
	ARIMA	(2,1,2)	0.82	0.81	(1,1,1)	0.72	0.70	(0,1,0)	0.96	0.99
	ES	(A,N,N)	0.91	0.81	**(M,A$_d$,N)**	**0.68**	**0.69**	(M,A,N)	0.97	3.73
	STLF	(A,N,N)	1.39	1.39	(A,N,N)	0.70	1.04	(M,A,N)	0.58	2.10

ARIMA: Autoregressive integrated moving average, ES: Exponential smoothing, SLR: Stepwise Linear Regression, STLF: The function of the seasonal and trend decomposition method, TS: Training Set, VS: Validation Set

Appendix 8

Forecast accuracy value for non-elective patients of inpatient specialties

Specialty	Forecasting Models	Daily			Weekly			Monthly		
		Parameters	TS	VS	Parameters	TS	VS	Parameters	TS	VS
General Surgery	SLR	SLR	0.83	0.88	SLR	1.17	1.32	SLR	0.88	1.71
	ARIMA	**(0,1,1)**	**0.75**	**0.73**	(0,1,1)	0.90	0.90	(1,0,0)	1.02	1.65
	ES	(A,N,N)	0.75	0.78	(A,A_d,N)	0.93	0.90	(A,N,N)	0.95	0.91
	STLF	(A,N,N)	0.67	0.98	(A,N,N)	0.64	1.45	(M,N,N)	0.96	2.05
Trauma & Orthopaedics	SLR	SLR	0.81	0.81	SLR	1.00	0.89	SLR	1.06	1.91
	ARIMA	(0,1,1)	0.75	0.74	**(0,1,1)**	**0.86**	**0.67**	(1,0,0)	0.96	2.83
	ES	(A,N,N)	0.75	0.74	(A,A_d,N)	0.86	0.68	(A,N,N)	0.96	1.12
	STLF	(A,N,N)	0.80	1.02	(A,N,N)	0.67	1.08	(A,N,N)	0.72	2.56
General Medicine	SLR	SLR	0.83	1.11	SLR	1.36	2.32	SLR	1.25	3.80
	ARIMA	(3,1,3)	0.74	0.80	(0,1,1)	0.94	0.84	(0,1,0)	0.96	1.57
	ES	(A,N,N)	0.75	0.80	(A,N,N)	0.94	0.84	(A,N,N)	0.99	1.58
	STLF	(A,N,N)	0.70	0.88	(A,N,N)	0.51	1.01	**(A,N,N)**	**0.69**	**0.74**
Cardiology	SLR	SLR	0.79	0.79	SLR	0.86	1.09	SLR	0.74	1.11
	ARIMA	(0,1,1)	0.77	0.75	(0,1,1)	0.83	0.75	(1,0,0)	0.95	1.01
	ES	(A,N,N)	0.77	0.75	(A,A_d,N)	0.78	0.75	**(A,N,N)**	**0.95**	**0.62**
	STLF	(A,N,N)	0.83	0.95	(M,A_d,N)	0.67	1.19	(M,N,N)	0.79	1.12
Paediatrics	SLR	SLR	0.88	0.85	SLR	1.61	1.23	SLR	1.70	2.16
	ARIMA	**(1,1,1)**	**0.70**	**0.75**	(1,0,1)	0.92	0.80	(1,0,0)	1.00	0.89
	ES	(A,N,N)	0.70	0.78	(A,N,N)	0.88	0.83	(A,N,N)	0.96	1.32
	STLF	(A,N,N)	0.62	1.00	(A,N,N)	0.37	1.25	(A,N,N)	0.31	1.91
Geriatric Medicine	SLR	SLR	0.86	0.82	SLR	1.02	1.03	SLR	0.86	1.74
	ARIMA	**(0,1,2)**	**0.83**	**0.77**	(0,1,2)	0.81	0.80	(1,0,0)	1.01	1.78
	ES	(A,N,N)	0.85	0.78	(A,A_d,N)	0.79	0.79	(A,N,N)	0.94	0.81
	STLF	(A,N,N)	0.70	1.02	(A,N,N)	0.54	1.15	(M,N,N)	0.79	2.40
Obstetrics	SLR	SLR	0.94	1.08	SLR	1.79	2.49	SLR	1.91	2.81
	ARIMA	**(0,1,1)**	**0.76**	**0.87**	(0,1,1)	0.90	1.54	(0,1,0)	0.96	1.16
	ES	(A,N,N)	0.76	0.89	(A,N,N)	0.90	1.50	(A,A_d,N)	1.13	1.07
	STLF	(A,N,N)	0.62	1.05	(A,N,N)	0.35	1.34	(A,A_d,N)	0.43	1.33
Gynaecology	SLR	SLR	0.82	0.98	SLR	1.12	1.89	**SLR**	**1.02**	**0.94**
	ARIMA	(0,1,1)	0.75	1.55	(0,1,1)	0.92	3.63	(0,1,0)	0.96	4.79
	ES	(A,N,N)	0.75	1.55	(A,N,N)	0.92	3.63	(A,N,N)	0.97	1.12
	STLF	(A,N,N)	0.76	1.58	(A,N,N)	0.62	3.63	(A,N,N)	0.76	5.13
Others	SLR	SLR	0.87	1.28	SLR	0.99	1.96	SLR	2.06	2.07
	ARIMA	**(0,1,1)**	**0.84**	**1.15**	(0,1,1)	0.82	1.54	(0,1,0)	0.96	1.67
	ES	(A,N,N)	0.84	1.25	(A,A_d,N)	0.80	1.67	(A,N,N)	0.96	1.67
	STLF	(A,N,N)	0.78	1.28	(A,N,N)	0.62	1.69	(A,N,N)	0.36	1.64

ARIMA: Autoregressive integrated moving average, ES: Exponential smoothing, SLR: Stepwise Linear Regression, STLF: The function of the seasonal and trend decomposition method, TS: Training Set, VS: Validation Set

Appendix 9

Input parameters of the simulation model for the general surgery outpatient specialty

Input parameters	Estimates	Distributions	References
Patient inputs	- Daily number of referrals for the available period (2012/13)	N/A	HES dataset
1. First referral			
2. Follow up referral	- Number of referrals from the forecasting method for the projected period (2013/14)	N/A	N/A
Financial inputs			Department of Health and Social Care (2013)
Revenue:	(2012/13 – 2013/14)		
1. First attendance tariff	Frequency distribution	Frequency distribution	
2. Follow up attendance tariff	Frequency distribution	Frequency distribution	
Other inputs			
Demographic features:			
- Age groups	(First referral – Follow up referral)		
1. Age group 1 (0 - 15)	1.08% – 0.41%	Multinomial	HES dataset
2. Age group 2 (16 - 35)	16.71% – 7.92%	Multinomial	HES dataset
3. Age group 3 (36 - 50)	25.37% – 23.09%	Multinomial	HES dataset
4. Age group 4 (51 - 65)	23.96% – 27.22%	Multinomial	HES dataset
5. Age group 5 (65+)	32.88% – 41.37%	Multinomial	HES dataset
Distributions:			
- Waiting time for first appointment	Frequency distribution	Frequency distribution	HES dataset
- Follow up number	Frequency distribution	Frequency distribution	HES dataset
- Length of period for follow up treatment	Frequency distribution	Frequency distribution	HES dataset
Total available outpatient clinic slots (per year):	17416	Fixed	Local data

HES: Hospital episodes statistics, N/A: Not available, NHS: National Health Service

Appendix 10

Input parameters of the simulation model for the urology outpatient specialty

Input parameters	Estimates	Distributions	References
Patient inputs	- Daily number of referrals for the available period (2012/13)	N/A	HES dataset
1. First referral			
2. Follow up referral	- Number of referrals from the forecasting method for the projected period (2013/14)	N/A	N/A
Financial inputs			Department of Health and Social Care (2013)
Revenue:	(2012/13 – 2013/14)		
1. First attendance tariff	Frequency distribution	Frequency distribution	
2. Follow up attendance tariff	Frequency distribution	Frequency distribution	
Other inputs			
Demographic features:			
- Age groups	(First referral – Follow up referral)		
1. Age group 1 (0 - 15)	14.09% – 6.28%	Multinomial	HES dataset
2. Age group 2 (16 - 35)	10.58% – 5.60%	Multinomial	HES dataset
3. Age group 3 (36 - 50)	13.62% – 10.79%	Multinomial	HES dataset
4. Age group 4 (51 - 65)	21.79% – 26.14%	Multinomial	HES dataset
5. Age group 5 (65+)	39.92% – 51.19%	Multinomial	HES dataset
Distributions:			
- Waiting time for first appointment	Frequency distribution	Frequency distribution	HES dataset
- Follow up number	Frequency distribution	Frequency distribution	HES dataset
- Length of period for follow up treatment	Frequency distribution	Frequency distribution	HES dataset
Total available outpatient clinic slots (per year):	16077	Fixed	Local data

HES: Hospital episodes statistics, N/A: Not available, NHS: National Health Service

Appendix 11

Input parameters of the simulation model for the ear, nose and throat outpatient specialty

Input parameters	Estimates	Distributions	References
Patient inputs	- Daily number of referrals for the available period (2012/13)	N/A	HES dataset
1. First referral			
2. Follow up referral	- Number of referrals from the forecasting method for the projected period (2013/14)	N/A	N/A
Financial inputs			Department of Health and Social Care (2013)
Revenue:	(2012/13 – 2013/14)		
1. First attendance tariff	Frequency distribution	Frequency distribution	
2. Follow up attendance tariff	Frequency distribution	Frequency distribution	
Other inputs			
Demographic features:			
- Age groups	(First referral – Follow up referral)		
1. Age group 1 (0 - 15)	26.61% – 30.06%	Multinomial	HES dataset
2. Age group 2 (16 - 35)	15.37% – 12.77%	Multinomial	HES dataset
3. Age group 3 (36 - 50)	17.45% – 17.42%	Multinomial	HES dataset
4. Age group 4 (51 - 65)	19.04% – 18.51%	Multinomial	HES dataset
5. Age group 5 (65+)	21.53% – 21.24%	Multinomial	HES dataset
Distributions:			
- Waiting time for first appointment	Frequency distribution	Frequency distribution	HES dataset
- Follow up number	Frequency distribution	Frequency distribution	HES dataset
- Length of period for follow up treatment	Frequency distribution	Frequency distribution	HES dataset
Total available outpatient clinic slots (per year):	13777	Fixed	Local data

HES: Hospital episodes statistics, N/A: Not available, NHS: National Health Service

Appendix 12

Input parameters of the simulation model for the ophthalmology outpatient specialty

Input parameters	Estimates	Distributions	References
Patient inputs	- Daily number of referrals for the available period (2012/13)	N/A	HES dataset
1. First referral			
2. Follow up referral	- Number of referrals from the forecasting method for the projected period (2013/14)	N/A	N/A
Financial inputs			Department of Health and Social Care (2013)
Revenue:	(2012/13 – 2013/14)		
1. First attendance tariff	Frequency distribution	Frequency distribution	
2. Follow up attendance tariff	Frequency distribution	Frequency distribution	
Other inputs			
Demographic features:			
- Age groups	(First referral – Follow up referral)		
1. Age group 1 (0 - 15)	17.04% – 15.06%	Multinomial	HES dataset
2. Age group 2 (16 - 35)	7.83% – 3.94%	Multinomial	HES dataset
3. Age group 3 (36 - 50)	12.86% – 10.59%	Multinomial	HES dataset
4. Age group 4 (51 - 65)	19.96% – 27.22%	Multinomial	HES dataset
5. Age group 5 (65+)	42.31% – 43.19%	Multinomial	HES dataset
Distributions:			
- Waiting time for first appointment	Frequency distribution	Frequency distribution	HES dataset
- Follow up number	Frequency distribution	Frequency distribution	HES dataset
- Length of period for follow up treatment	Frequency distribution	Frequency distribution	HES dataset
Total available outpatient clinic slots (per year):	32659	Fixed	Local data

HES: Hospital episodes statistics, N/A: Not available, NHS: National Health Service

Appendix 13

Input parameters of the simulation model for the oral surgery outpatient specialty

Input parameters	Estimates	Distributions	References
Patient inputs 1. First referral 2. Follow up referral	- Daily number of referrals for the available period (2012/13) - Number of referrals from the forecasting method for the projected period (2013/14)	N/A N/A	HES dataset N/A
Financial inputs *Revenue:* 1. First attendance tariff 2. Follow up attendance tariff	 (2012/13 – 2013/14) Frequency distribution Frequency distribution	 Frequency distribution Frequency distribution	Department of Health and Social Care (2013)
Other inputs			
Demographic features:			
- Age groups	(First referral – Follow up referral)		
1. Age group 1 (0 - 15)	10.68% – 3.92%	Multinomial	HES dataset
2. Age group 2 (16 - 35)	28.23% – 17.34%	Multinomial	HES dataset
3. Age group 3 (36 - 50)	18.79% – 17.25%	Multinomial	HES dataset
4. Age group 4 (51 - 65)	18.18% – 22.35%	Multinomial	HES dataset
5. Age group 5 (65+)	24.12% – 39.14%	Multinomial	HES dataset
Distributions:			
- Waiting time for first appointment	Frequency distribution	Frequency distribution	HES dataset
- Follow up number	Frequency distribution	Frequency distribution	HES dataset
- Length of period for follow up treatment	Frequency distribution	Frequency distribution	HES dataset
Total available outpatient clinic slots (per year):	9127	Fixed	Local data

HES: Hospital episodes statistics, N/A: Not available, NHS: National Health Service

Appendix 14

Input parameters of the simulation model for the anaesthetics outpatient specialty

Input parameters	Estimates	Distributions	References
Patient inputs 1. First referral 2. Follow up referral	- Daily number of referrals for the available period (2012/13) - Number of referrals from the forecasting method for the projected period (2013/14)	N/A N/A	HES dataset N/A
Financial inputs *Revenue:* 1. First attendance tariff 2. Follow up attendance tariff	 (2012/13 – 2013/14) Frequency distribution Frequency distribution	 Frequency distribution Frequency distribution	Department of Health and Social Care (2013)
Other inputs			
Demographic features:			
- Age groups	(First referral – Follow up referral)		
1. Age group 1 (0 - 15)	5.95% – 5.84%	Multinomial	HES dataset
2. Age group 2 (16 - 35)	28.41% – 14.54%	Multinomial	HES dataset
3. Age group 3 (36 - 50)	16.38% – 20.63%	Multinomial	HES dataset
4. Age group 4 (51 - 65)	14.09% – 23.20%	Multinomial	HES dataset
5. Age group 5 (65+)	35.17% – 35.79%	Multinomial	HES dataset
Distributions:			
- Waiting time for first appointment	Frequency distribution	Frequency distribution	HES dataset
- Follow up number	Frequency distribution	Frequency distribution	HES dataset
- Length of period for follow up treatment	Frequency distribution	Frequency distribution	HES dataset
Total available outpatient clinic slots (per year):	12692	Fixed	Local data

HES: Hospital episodes statistics, N/A: Not available, NHS: National Health Service

Appendix 15

Input parameters of the simulation model for the general medicine outpatient specialty

Input parameters	Estimates	Distributions	References
Patient inputs 1. First referral 2. Follow up referral	- Daily number of referrals for the available period (2012/13) - Number of referrals from the forecasting method for the projected period (2013/14)	N/A N/A	HES dataset N/A
Financial inputs			Department of Health and Social Care (2013)
Revenue:	(2012/13 – 2013/14)		
1. First attendance tariff	Frequency distribution	Frequency distribution	
2. Follow up attendance tariff	Frequency distribution	Frequency distribution	
Other inputs			
Demographic features:			
- Age groups	(First referral – Follow up referral)		
1. Age group 1 (0 - 15)	0.63% – 0.28%	Multinomial	HES dataset
2. Age group 2 (16 - 35)	16.57% – 16.55%	Multinomial	HES dataset
3. Age group 3 (36 - 50)	19.52% – 20.57%	Multinomial	HES dataset
4. Age group 4 (51 - 65)	23.89% – 25.38%	Multinomial	HES dataset
5. Age group 5 (65+)	39.39% – 37.21%	Multinomial	HES dataset
Distributions:			
- Waiting time for first appointment	Frequency distribution	Frequency distribution	HES dataset
- Follow up number	Frequency distribution	Frequency distribution	HES dataset
- Length of period for follow up treatment	Frequency distribution	Frequency distribution	HES dataset
Total available outpatient clinic slots (per year):	14519	Fixed	Local data

HES: Hospital episodes statistics, N/A: Not available, NHS: National Health Service

Appendix 16

Input parameters of the simulation model for the gastroenterology outpatient specialty

Input parameters	Estimates	Distributions	References
Patient inputs 1. First referral 2. Follow up referral	- Daily number of referrals for the available period (2012/13) - Number of referrals from the forecasting method for the projected period (2013/14)	N/A N/A	HES dataset N/A
Financial inputs			Department of Health and Social Care (2013)
Revenue:	(2012/13 – 2013/14)		
1. First attendance tariff	Frequency distribution	Frequency distribution	
2. Follow up attendance tariff	Frequency distribution	Frequency distribution	
Other inputs			
Demographic features:			
- Age groups	(First referral – Follow up referral)		
1. Age group 1 (0 - 15)	0.39% – 0.09%	Multinomial	HES dataset
2. Age group 2 (16 - 35)	18.38% – 19.05%	Multinomial	HES dataset
3. Age group 3 (36 - 50)	22.04% – 23.25%	Multinomial	HES dataset
4. Age group 4 (51 - 65)	25.58% – 27.16%	Multinomial	HES dataset
5. Age group 5 (65+)	33.61% – 30.45%	Multinomial	HES dataset
Distributions:			
- Waiting time for first appointment	Frequency distribution	Frequency distribution	HES dataset
- Follow up number	Frequency distribution	Frequency distribution	HES dataset
- Length of period for follow up treatment	Frequency distribution	Frequency distribution	HES dataset
Total available outpatient clinic slots (per year):	8195	Fixed	Local data

HES: Hospital episodes statistics, N/A: Not available, NHS: National Health Service

Appendix 17

Input parameters of the simulation model for the clinical haematology outpatient specialty

Input parameters	Estimates	Distributions	References
Patient inputs	- Daily number of referrals for the available period (2012/13)	N/A	HES dataset
1. First referral			
2. Follow up referral	- Number of referrals from the forecasting method for the projected period (2013/14)	N/A	N/A
Financial inputs			Department of Health and Social Care (2013)
Revenue:	(2012/13 – 2013/14)		
1. First attendance tariff	Frequency distribution	Frequency distribution	
2. Follow up attendance tariff	Frequency distribution	Frequency distribution	
Other inputs			
Demographic features:			
- Age groups	(First referral – Follow up referral)		
1. Age group 1 (0 - 15)	0.18% – 0.10%	Multinomial	HES dataset
2. Age group 2 (16 - 35)	8.23% – 7.94%	Multinomial	HES dataset
3. Age group 3 (36 - 50)	12.36% – 14.79%	Multinomial	HES dataset
4. Age group 4 (51 - 65)	21.33% – 23.54%	Multinomial	HES dataset
5. Age group 5 (65+)	57.90% – 53.63%	Multinomial	HES dataset
Distributions:			
- Waiting time for first appointment	Frequency distribution	Frequency distribution	HES dataset
- Follow up number	Frequency distribution	Frequency distribution	HES dataset
- Length of period for follow up treatment	Frequency distribution	Frequency distribution	HES dataset
Total available outpatient clinic slots (per year):	10515	Fixed	Local data

HES: Hospital episodes statistics, N/A: Not available, NHS: National Health Service

Appendix 18

Input parameters of the simulation model for the cardiology outpatient specialty

Input parameters	Estimates	Distributions	References
Patient inputs	- Daily number of referrals for the available period (2012/13)	N/A	HES dataset
1. First referral			
2. Follow up referral	- Number of referrals from the forecasting method for the projected period (2013/14)	N/A	N/A
Financial inputs			Department of Health and Social Care (2013)
Revenue:	(2012/13 – 2013/14)		
1. First attendance tariff	Frequency distribution	Frequency distribution	
2. Follow up attendance tariff	Frequency distribution	Frequency distribution	
Other inputs			
Demographic features:			
- Age groups	(First referral – Follow up referral)		
1. Age group 1 (0 - 15)	0.10% – 0.01%	Multinomial	HES dataset
2. Age group 2 (16 - 35)	8.60% – 4.30%	Multinomial	HES dataset
3. Age group 3 (36 - 50)	16.77% – 10.05%	Multinomial	HES dataset
4. Age group 4 (51 - 65)	26.85% – 25.14%	Multinomial	HES dataset
5. Age group 5 (65+)	47.68% – 60.50%	Multinomial	HES dataset
Distributions:			
- Waiting time for first appointment	Frequency distribution	Frequency distribution	HES dataset
- Follow up number	Frequency distribution	Frequency distribution	HES dataset
- Length of period for follow up treatment	Frequency distribution	Frequency distribution	HES dataset
Total available outpatient clinic slots (per year):	11078	Fixed	Local data

HES: Hospital episodes statistics, N/A: Not available, NHS: National Health Service

Appendix 19

Input parameters of the simulation model for the dermatology outpatient specialty

Input parameters	Estimates	Distributions	References
Patient inputs 1. First referral 2. Follow up referral	- Daily number of referrals for the available period (2012/13) - Number of referrals from the forecasting method for the projected period (2013/14)	N/A N/A	HES dataset N/A
Financial inputs *Revenue:* 1. First attendance tariff 2. Follow up attendance tariff	 (2012/13 – 2013/14) Frequency distribution Frequency distribution	 Frequency distribution Frequency distribution	Department of Health and Social Care (2013)
Other inputs			
Demographic features:			
- Age groups	(First referral – Follow up referral)		
1. Age group 1 (0 - 15)	10.02% – 6.27%	Multinomial	HES dataset
2. Age group 2 (16 - 35)	19.31% – 17.40%	Multinomial	HES dataset
3. Age group 3 (36 - 50)	16.97% – 18.33%	Multinomial	HES dataset
4. Age group 4 (51 - 65)	19.80% – 20.38%	Multinomial	HES dataset
5. Age group 5 (65+)	33.90% – 37.62%	Multinomial	HES dataset
Distributions:			
- Waiting time for first appointment	Frequency distribution	Frequency distribution	HES dataset
- Follow up number	Frequency distribution	Frequency distribution	HES dataset
- Length of period for follow up treatment	Frequency distribution	Frequency distribution	HES dataset
Total available outpatient clinic slots (per year):	12689	Fixed	Local data

HES: Hospital episodes statistics, N/A: Not available, NHS: National Health Service

Appendix 20

Input parameters of the simulation model for the neurology outpatient specialty

Input parameters	Estimates	Distributions	References
Patient inputs 1. First referral 2. Follow up referral	- Daily number of referrals for the available period (2012/13) - Number of referrals from the forecasting method for the projected period (2013/14)	N/A N/A	HES dataset N/A
Financial inputs *Revenue:* 1. First attendance tariff 2. Follow up attendance tariff	 (2012/13 – 2013/14) Frequency distribution Frequency distribution	 Frequency distribution Frequency distribution	Department of Health and Social Care (2013)
Other inputs			
Demographic features:			
- Age groups	(First referral – Follow up referral)		
1. Age group 1 (0 - 15)	0.16% – 0.09%	Multinomial	HES dataset
2. Age group 2 (16 - 35)	23.44% – 19.76%	Multinomial	HES dataset
3. Age group 3 (36 - 50)	25.09% – 22.91%	Multinomial	HES dataset
4. Age group 4 (51 - 65)	23.92% – 24.93%	Multinomial	HES dataset
5. Age group 5 (65+)	27.39% – 32.31%	Multinomial	HES dataset
Distributions:			
- Waiting time for first appointment	Frequency distribution	Frequency distribution	HES dataset
- Follow up number	Frequency distribution	Frequency distribution	HES dataset
- Length of period for follow up treatment	Frequency distribution	Frequency distribution	HES dataset
Total available outpatient clinic slots (per year):	4885	Fixed	Local data

HES: Hospital episodes statistics, N/A: Not available, NHS: National Health Service

Appendix 21

Input parameters of the simulation model for the rheumatology outpatient specialty

Input parameters	Estimates	Distributions	References
Patient inputs 1. First referral 2. Follow up referral	- Daily number of referrals for the available period (2012/13) - Number of referrals from the forecasting method for the projected period (2013/14)	N/A N/A	HES dataset N/A
Financial inputs *Revenue:* 1. First attendance tariff 2. Follow up attendance tariff	 (2012/13 – 2013/14) Frequency distribution Frequency distribution	 Frequency distribution Frequency distribution	Department of Health and Social Care (2013)
Other inputs			
Demographic features:			
- Age groups	(First referral – Follow up referral)		
1. Age group 1 (0 - 15)	0.26% – 0.04%	Multinomial	HES dataset
2. Age group 2 (16 - 35)	15.02% – 9.47%	Multinomial	HES dataset
3. Age group 3 (36 - 50)	27.13% – 21.69%	Multinomial	HES dataset
4. Age group 4 (51 - 65)	31.50% – 34.14%	Multinomial	HES dataset
5. Age group 5 (65+)	26.09% – 34.66%	Multinomial	HES dataset
Distributions:			
- Waiting time for first appointment	Frequency distribution	Frequency distribution	HES dataset
- Follow up number	Frequency distribution	Frequency distribution	HES dataset
- Length of period for follow up treatment	Frequency distribution	Frequency distribution	HES dataset
Total available outpatient clinic slots (per year):	7097	Fixed	Local data

HES: Hospital episodes statistics, N/A: Not available, NHS: National Health Service

Appendix 22

Input parameters of the simulation model for the paediatrics outpatient specialty

Input parameters	Estimates	Distributions	References
Patient inputs 1. First referral 2. Follow up referral	- Daily number of referrals for the available period (2012/13) - Number of referrals from the forecasting method for the projected period (2013/14)	N/A N/A	HES dataset N/A
Financial inputs *Revenue:* 1. First attendance tariff 2. Follow up attendance tariff	 (2012/13 – 2013/14) Frequency distribution Frequency distribution	 Frequency distribution Frequency distribution	Department of Health and Social Care (2013)
Other inputs			
Demographic features:			
- Age groups	(First referral – Follow up referral)		
1. Age group 1 (0 - 15)	98.55% – 94.11%	Multinomial	HES dataset
2. Age group 2 (16 - 35)	1.45% – 5.89%	Multinomial	HES dataset
3. Age group 3 (36 - 50)	0.00% – 0.00%	Multinomial	HES dataset
4. Age group 4 (51 - 65)	0.00% – 0.00%	Multinomial	HES dataset
5. Age group 5 (65+)	0.00% – 0.00%	Multinomial	HES dataset
Distributions:			
- Waiting time for first appointment	Frequency distribution	Frequency distribution	HES dataset
- Follow up number	Frequency distribution	Frequency distribution	HES dataset
- Length of period for follow up treatment	Frequency distribution	Frequency distribution	HES dataset
Total available outpatient clinic slots (per year):	10673	Fixed	Local data

HES: Hospital episodes statistics, N/A: Not available, NHS: National Health Service

Appendix 23

Input parameters of the simulation model for the obstetrics outpatient specialty

Input parameters	Estimates	Distributions	References
Patient inputs	- Daily number of referrals for the	N/A	HES dataset
1. First referral	available period (2012/13)		
2. Follow up referral	- Number of referrals from the forecasting method for the projected period (2013/14)	N/A	N/A
Financial inputs			Department of Health and Social Care (2013)
Revenue:	(2012/13 – 2013/14)		
1. First attendance tariff	Frequency distribution	Frequency distribution	
2. Follow up attendance tariff	Frequency distribution	Frequency distribution	
Other inputs			
Demographic features:			
- Age groups	(First referral – Follow up referral)		
1. Age group 1 (0 - 15)	0.25% – 0.10%	Multinomial	HES dataset
2. Age group 2 (16 - 35)	76.27% – 82.61%	Multinomial	HES dataset
3. Age group 3 (36 - 50)	21.25% – 16.98%	Multinomial	HES dataset
4. Age group 4 (51 - 65)	1.13% – 0.17%	Multinomial	HES dataset
5. Age group 5 (65+)	1.10% – 0.14%	Multinomial	HES dataset
Distributions:			
- Waiting time for first appointment	Frequency distribution	Frequency distribution	HES dataset
- Follow up number	Frequency distribution	Frequency distribution	HES dataset
- Length of period for follow up treatment	Frequency distribution	Frequency distribution	HES dataset
Total available outpatient clinic slots (per year):	52839	Fixed	Local data

HES: Hospital episodes statistics, N/A: Not available, NHS: National Health Service

Appendix 24

Input parameters of the simulation model for the gynaecology outpatient specialty

Input parameters	Estimates	Distributions	References
Patient inputs	- Daily number of referrals for the	N/A	HES dataset
1. First referral	available period (2012/13)		
2. Follow up referral	- Number of referrals from the forecasting method for the projected period (2013/14)	N/A	N/A
Financial inputs			Department of Health and Social Care (2013)
Revenue:	(2012/13 – 2013/14)		
1. First attendance tariff	Frequency distribution	Frequency distribution	
2. Follow up attendance tariff	Frequency distribution	Frequency distribution	
Other inputs			
Demographic features:			
- Age groups	(First referral – Follow up referral)		
1. Age group 1 (0 - 15)	0.49% – 0.30%	Multinomial	HES dataset
2. Age group 2 (16 - 35)	51.09% – 59.18%	Multinomial	HES dataset
3. Age group 3 (36 - 50)	30.04% – 26.78%	Multinomial	HES dataset
4. Age group 4 (51 - 65)	11.15% – 6.88%	Multinomial	HES dataset
5. Age group 5 (65+)	7.23% – 6.85%	Multinomial	HES dataset
Distributions:			
- Waiting time for first appointment	Frequency distribution	Frequency distribution	HES dataset
- Follow up number	Frequency distribution	Frequency distribution	HES dataset
- Length of period for follow up treatment	Frequency distribution	Frequency distribution	HES dataset
Total available outpatient clinic slots (per year):	20702	Fixed	Local data

HES: Hospital episodes statistics, N/A: Not available, NHS: National Health Service

Appendix 25

Input parameters of the simulation model for clinical oncology outpatient specialty

Input parameters	Estimates	Distributions	References
Patient inputs	- Daily number of referrals for the available period (2012/13)	N/A	HES dataset
1. First referral			
2. Follow up referral	- Number of referrals from the forecasting method for the projected period (2013/14)	N/A	N/A
Financial inputs			Department of Health and Social Care (2013)
Revenue:	(2012/13 – 2013/14)		
1. First attendance tariff	Frequency distribution	Frequency distribution	
2. Follow up attendance tariff	Frequency distribution	Frequency distribution	
Other inputs			
Demographic features:			
- Age groups	(First referral – Follow up referral)		
1. Age group 1 (0 - 15)	0.12% – 0.01%	Multinomial	HES dataset
2. Age group 2 (16 - 35)	0.99% – 0.69%	Multinomial	HES dataset
3. Age group 3 (36 - 50)	9.28% – 13.64%	Multinomial	HES dataset
4. Age group 4 (51 - 65)	30.17% – 32.40%	Multinomial	HES dataset
5. Age group 5 (65+)	59.44% – 53.26%	Multinomial	HES dataset
Distributions:			
- Waiting time for first appointment	Frequency distribution	Frequency distribution	HES dataset
- Follow up number	Frequency distribution	Frequency distribution	HES dataset
- Length of period for follow up treatment	Frequency distribution	Frequency distribution	HES dataset
Total available outpatient clinic slots (per year):	8008	Fixed	Local data

HES: Hospital episodes statistics, N/A: Not available, NHS: National Health Service

Appendix 26

Input parameters of the simulation model for the others outpatient specialty

Input parameters	Estimates	Distributions	References
Patient inputs	- Daily number of referrals for the available period (2012/13)	N/A	HES dataset
1. First referral			
2. Follow up referral	- Number of referrals from the forecasting method for the projected period (2013/14)	N/A	N/A
Financial inputs			Department of Health and Social Care (2013)
Revenue:	(2012/13 – 2013/14)		
1. First attendance tariff	Frequency distribution	Frequency distribution	
2. Follow up attendance tariff	Frequency distribution	Frequency distribution	
Other inputs			
Demographic features:			
- Age groups	(First referral – Follow up referral)		
1. Age group 1 (0 - 15)	9.24% – 4.25%	Multinomial	HES dataset
2. Age group 2 (16 - 35)	6.37% – 7.20%	Multinomial	HES dataset
3. Age group 3 (36 - 50)	10.84% – 4.56%	Multinomial	HES dataset
4. Age group 4 (51 - 65)	17.90% – 8.91%	Multinomial	HES dataset
5. Age group 5 (65+)	55.65% – 75.07%	Multinomial	HES dataset
Distributions:			
- Waiting time for first appointment	Frequency distribution	Frequency distribution	HES dataset
- Follow up number	Frequency distribution	Frequency distribution	HES dataset
- Length of period for follow up treatment	Frequency distribution	Frequency distribution	HES dataset
Total available outpatient clinic slots (per year):	7406	Fixed	Local data

HES: Hospital episodes statistics, N/A: Not available, NHS: National Health Service

Appendix 27

Input parameters of the simulation model for the general surgery inpatient specialty

Input parameters	Estimates	Distributions	References
Patient inputs 1. Elective 2. Non-elective	- Daily number of admissions for the available period (2012/13) - Number of admissions from the forecasting method for the projected period (2013/14)	N/A N/A	HES dataset N/A
Financial inputs *Revenue:* 1. Elective tariff 2. Non-elective tariff	 (2012/13 – 2013/14) Frequency distribution Frequency distribution	 Frequency distribution Frequency distribution	 Department of Health and Social Care (2013)
Physical inputs Number of beds	 88	 Fixed	 Local data
Other inputs *Demographic features:* - Age groups 1. Age group 1 (0 - 15) 2. Age group 2 (16 - 35) 3. Age group 3 (36 - 50) 4. Age group 4 (51 - 65) 5. Age group 5 (65+) *Distributions:* - Waiting time for first admission - Length of stay	 (Elective – Non-elective) 0.53% – 5.41% 9.23% – 24.51% 18.48% – 19.44% 29.11% – 18.42% 42.65% – 32.22% Frequency distribution Frequency distribution	 Multinomial Multinomial Multinomial Multinomial Multinomial Frequency distribution Frequency distribution	 HES dataset HES dataset HES dataset HES dataset HES dataset HES dataset HES dataset
Theatre inputs - Total number of theatre procedure annual capacity 1. Elective 2. Non-elective - What percentage of inpatient admissions end up having a surgery? 1. Elective 2. Non-elective	 1704 2813 44% 34%	 Fixed Fixed Multinomial Multinomial	 Local data Local data Local data Local data

HES: Hospital episodes statistics, N/A: Not available, NHS: National Health Service

Appendix 28

Input parameters of the simulation model for the urology inpatient specialty

Input parameters	Estimates	Distributions	References
Patient inputs 1. Elective	- Daily number of admissions for the available period (2012/13) - Number of admissions from the forecasting method for the projected period (2013/14)	N/A N/A	HES dataset N/A
Financial inputs *Revenue:* 1. Elective tariff	(2012/13 – 2013/14) Frequency distribution	Frequency distribution	Department of Health and Social Care (2013)
Other inputs *Demographic features:* - Age groups	(Elective)		
1. Age group 1 (0 - 15)	5.80%	Multinomial	HES dataset
2. Age group 2 (16 - 35)	4.86%	Multinomial	HES dataset
3. Age group 3 (36 - 50)	10.21%	Multinomial	HES dataset
4. Age group 4 (51 - 65)	23.17%	Multinomial	HES dataset
5. Age group 5 (65+)	55.96%	Multinomial	HES dataset
Distributions: - Waiting time for first admission	Frequency distribution	Frequency distribution	HES dataset
Theatre inputs - Total number of theatre procedure annual capacity 1. Elective	1867	Fixed	Local data
- What percentage of inpatient admissions end up having a surgery? 1. Elective	45%	Multinomial	Local data

HES: Hospital episodes statistics, N/A: Not available, NHS: National Health Service

Appendix 29

Input parameters of the simulation model for the ear, nose and throat inpatient specialty

Input parameters	Estimates	Distributions	References
Patient inputs 1. Elective	- Daily number of admissions for the available period (2012/13) - Number of admissions from the forecasting method for the projected period (2013/14)	N/A N/A	HES dataset N/A
Financial inputs *Revenue:* 1. Elective tariff	(2012/13 – 2013/14) Frequency distribution	Frequency distribution	Department of Health and Social Care (2013)
Other inputs *Demographic features:* - Age groups	(Elective)		
1. Age group 1 (0 - 15)	50.76%	Multinomial	HES dataset
2. Age group 2 (16 - 35)	17.92%	Multinomial	HES dataset
3. Age group 3 (36 - 50)	13.43%	Multinomial	HES dataset
4. Age group 4 (51 - 65)	10.15%	Multinomial	HES dataset
5. Age group 5 (65+)	7.74%	Multinomial	HES dataset
Distributions: - Waiting time for first admission	Frequency distribution	Frequency distribution	HES dataset

HES: Hospital episodes statistics, N/A: Not available, NHS: National Health Service

Appendix 30

Input parameters of the simulation model for the ophthalmology inpatient specialty

Input parameters	Estimates	Distributions	References
Patient inputs 1. Elective	- Daily number of admissions for the available period (2012/13) - Number of admissions from the forecasting method for the projected period (2013/14)	N/A N/A	HES dataset N/A
Financial inputs *Revenue:* 1. Elective tariff	(2012/13 – 2013/14) Frequency distribution	Frequency distribution	Department of Health and Social Care (2013)
Other inputs *Demographic features:* - Age groups	(Elective)		
1. Age group 1 (0 - 15)	4.55%	Multinomial	HES dataset
2. Age group 2 (16 - 35)	2.62%	Multinomial	HES dataset
3. Age group 3 (36 - 50)	6.32%	Multinomial	HES dataset
4. Age group 4 (51 - 65)	17.85%	Multinomial	HES dataset
5. Age group 5 (65+)	68.66%	Multinomial	HES dataset
Distributions: - Waiting time for first admission	Frequency distribution	Frequency distribution	HES dataset
Theatre inputs - Total number of theatre procedure annual capacity 1. Elective	2314	Fixed	Local data
- What percentage of inpatient admissions end up having a surgery? 1. Elective	100%	Multinomial	Local data

HES: Hospital episodes statistics, N/A: Not available, NHS: National Health Service

Appendix 31

Input parameters of the simulation model for the oral surgery inpatient specialty

Input parameters	Estimates	Distributions	References
Patient inputs 1. Elective	- Daily number of admissions for the available period (2012/13) - Number of admissions from the forecasting method for the projected period (2013/14)	N/A N/A	HES dataset N/A
Financial inputs *Revenue:* 1. Elective tariff	(2012/13 – 2013/14) Frequency distribution	Frequency distribution	Department of Health and Social Care (2013)
Other inputs *Demographic features:* - Age groups	(Elective)		
1. Age group 1 (0 - 15)	10.00%	Multinomial	HES dataset
2. Age group 2 (16 - 35)	27.22%	Multinomial	HES dataset
3. Age group 3 (36 - 50)	17.68%	Multinomial	HES dataset
4. Age group 4 (51 - 65)	16.38%	Multinomial	HES dataset
5. Age group 5 (65+)	28.72%	Multinomial	HES dataset
Distributions: - Waiting time for first admission	Frequency distribution	Frequency distribution	HES dataset

HES: Hospital episodes statistics, N/A: Not available, NHS: National Health Service

Appendix 32

Input parameters of the simulation model for the general medicine inpatient specialty

Input parameters	Estimates	Distributions	References
Patient inputs 1. Elective 2. Non-elective	- Daily number of admissions for the available period (2012/13) - Number of admissions from the forecasting method for the projected period (2013/14)	N/A N/A	HES dataset N/A
Financial inputs			
Revenue:	(2012/13 – 2013/14)		Department of
1. Elective tariff	Frequency distribution	Frequency distribution	Health and Social
2. Non-elective tariff	Frequency distribution	Frequency distribution	Care (2013)
Physical inputs			
Number of beds	85	Fixed	Local data
Other inputs			
Demographic features:			
- Age groups	(Elective – Non-elective)		
1. Age group 1 (0 - 15)	0.16% – 0.01%	Multinomial	HES dataset
2. Age group 2 (16 - 35)	10.55% – 12.55%	Multinomial	HES dataset
3. Age group 3 (36 - 50)	19.19% – 15.40%	Multinomial	HES dataset
4. Age group 4 (51 - 65)	28.37% – 20.10%	Multinomial	HES dataset
5. Age group 5 (65+)	41.73% – 51.94%	Multinomial	HES dataset
Distributions:			
- Waiting time for first admission	Frequency distribution	Frequency distribution	HES dataset
- Length of stay	Frequency distribution	Frequency distribution	HES dataset

HES: Hospital episodes statistics, N/A: Not available, NHS: National Health Service

Appendix 33

Input parameters of the simulation model for the gastroenterology inpatient specialty

Input parameters	Estimates	Distributions	References
Patient inputs 1. Elective	- Daily number of admissions for the available period (2012/13) - Number of admissions from the forecasting method for the projected period (2013/14)	N/A N/A	HES dataset N/A
Financial inputs			Department of
Revenue:	(2012/13 – 2013/14)		Health and Social
1. Elective tariff	Frequency distribution	Frequency distribution	Care (2013)
Other inputs			
Demographic features:			
- Age groups	(Elective)		
1. Age group 1 (0 - 15)	0.10%	Multinomial	HES dataset
2. Age group 2 (16 - 35)	11.87%	Multinomial	HES dataset
3. Age group 3 (36 - 50)	19.19%	Multinomial	HES dataset
4. Age group 4 (51 - 65)	26.72%	Multinomial	HES dataset
5. Age group 5 (65+)	42.12%	Multinomial	HES dataset
Distributions:			
- Waiting time for first admission	Frequency distribution	Frequency distribution	HES dataset

HES: Hospital episodes statistics, N/A: Not available, NHS: National Health Service

Appendix 34

Input parameters of the simulation model for the clinical haematology inpatient specialty

Input parameters	Estimates	Distributions	References
Patient inputs 1. Elective	- Daily number of admissions for the available period (2012/13) - Number of admissions from the forecasting method for the projected period (2013/14)	N/A N/A	HES dataset N/A
Financial inputs *Revenue:* 1. Elective tariff	(2012/13 – 2013/14) Frequency distribution	Frequency distribution	Department of Health and Social Care (2013)
Other inputs			
Demographic features:			
- Age groups	(Elective)		
1. Age group 1 (0 - 15)	0.00%	Multinomial	HES dataset
2. Age group 2 (16 - 35)	4.37%	Multinomial	HES dataset
3. Age group 3 (36 - 50)	10.80%	Multinomial	HES dataset
4. Age group 4 (51 - 65)	30.25%	Multinomial	HES dataset
5. Age group 5 (65+)	54.58%	Multinomial	HES dataset
Distributions:			
- Waiting time for first admission	Frequency distribution	Frequency distribution	HES dataset

HES: Hospital episodes statistics, N/A: Not available, NHS: National Health Service

Appendix 35

Input parameters of the simulation model for the cardiology inpatient specialty

Input parameters	Estimates	Distributions	References
Patient inputs 1. Elective 2. Non-elective	- Daily number of admissions for the available period (2012/13) - Number of admissions from the forecasting method for the projected period (2013/14)	N/A N/A	HES dataset N/A
Financial inputs *Revenue:* 1. Elective tariff 2. Non-elective tariff	 (2012/13 – 2013/14) Frequency distribution Frequency distribution	 Frequency distribution Frequency distribution	 Department of Health and Social Care (2013)
Physical inputs Number of beds	 25	 Fixed	 Local data
Other inputs *Demographic features:* - Age groups 1. Age group 1 (0 - 15) 2. Age group 2 (16 - 35) 3. Age group 3 (36 - 50) 4. Age group 4 (51 - 65) 5. Age group 5 (65+) *Distributions:* - Waiting time for first admission - Length of stay	 (Elective – Non-elective) 0.00% – 0.00% 0.89% – 3.87% 8.19% – 10.05% 29.42% – 21.67% 61.50% – 64.41% Frequency distribution Frequency distribution	 Multinomial Multinomial Multinomial Multinomial Multinomial Frequency distribution Frequency distribution	 HES dataset HES dataset HES dataset HES dataset HES dataset HES dataset HES dataset
Theatre inputs - Total number of theatre procedure annual capacity 1. Non-elective - What percentage of inpatient admissions end up having a surgery? 1. Non-elective	 28 1.18%	 Fixed Multinomial	 Local data Local data

HES: Hospital episodes statistics, N/A: Not available, NHS: National Health Service

Appendix 36

Input parameters of the simulation model for the medical oncology inpatient specialty

Input parameters	Estimates	Distributions	References
Patient inputs 1. Elective	- Daily number of admissions for the available period (2012/13) - Number of admissions from the forecasting method for the projected period (2013/14)	N/A N/A	HES dataset N/A
Financial inputs *Revenue:* 1. Elective tariff	(2012/13 – 2013/14) Frequency distribution	Frequency distribution	Department of Health and Social Care (2013)
Other inputs *Demographic features:* - Age groups	(Elective)		
1. Age group 1 (0 - 15)	0.00%	Multinomial	HES dataset
2. Age group 2 (16 - 35)	1.82%	Multinomial	HES dataset
3. Age group 3 (36 - 50)	10.75%	Multinomial	HES dataset
4. Age group 4 (51 - 65)	33.72%	Multinomial	HES dataset
5. Age group 5 (65+)	53.71%	Multinomial	HES dataset
Distributions: - Waiting time for first admission	Frequency distribution	Frequency distribution	HES dataset

HES: Hospital episodes statistics, N/A: Not available, NHS: National Health Service

Appendix 37

Input parameters of the simulation model for the paediatrics inpatient specialty

Input parameters	Estimates	Distributions	References
Patient inputs 1. Elective 2. Non-elective	- Daily number of admissions for the available period (2012/13) - Number of admissions from the forecasting method for the projected period (2013/14)	N/A N/A	HES dataset N/A
Financial inputs *Revenue:* 1. Elective tariff 2. Non-elective tariff	(2012/13 – 2013/14) Frequency distribution Frequency distribution	Frequency distribution Frequency distribution	Department of Health and Social Care (2013)
Physical inputs Number of beds	16	Fixed	Local data
Other inputs *Demographic features:* - Age groups	(Elective – Non-elective)		
1. Age group 1 (0 - 15)	97.99% – 99.66%	Multinomial	HES dataset
2. Age group 2 (16 - 35)	2.01% – 0.34%	Multinomial	HES dataset
3. Age group 3 (36 - 50)	0.00% – 0.00%	Multinomial	HES dataset
4. Age group 4 (51 - 65)	0.00% – 0.00%	Multinomial	HES dataset
5. Age group 5 (65+)	0.00% – 0.00%	Multinomial	HES dataset
Distributions: - Waiting time for first admission	Frequency distribution	Frequency distribution	HES dataset
- Length of stay	Frequency distribution	Frequency distribution	HES dataset

HES: Hospital episodes statistics, N/A: Not available, NHS: National Health Service

Appendix 38

Input parameters of the simulation model for the geriatric medicine inpatient specialty

Input parameters	Estimates	Distributions	References
Patient inputs 1. Non-elective	- Daily number of admissions for the available period (2012/13) - Number of admissions from the forecasting method for the projected period (2013/14)	N/A N/A	HES dataset N/A
Financial inputs *Revenue:* 1. Non-elective tariff	(2012/13 – 2013/14) Frequency distribution	Frequency distribution	Department of Health and Social Care (2013)
Physical inputs Number of beds	111	Fixed	Local data
Other inputs			
Demographic features:			
- Age groups	(Non-elective)		
1. Age group 1 (0 - 15)	0.00%	Multinomial	HES dataset
2. Age group 2 (16 - 35)	6.71%	Multinomial	HES dataset
3. Age group 3 (36 - 50)	8.48%	Multinomial	HES dataset
4. Age group 4 (51 - 65)	11.91%	Multinomial	HES dataset
5. Age group 5 (65+)	72.90%	Multinomial	HES dataset
Distributions:			
- Waiting time for first admission	Frequency distribution	Frequency distribution	HES dataset
- Length of stay	Frequency distribution	Frequency distribution	HES dataset

HES: Hospital episodes statistics, N/A: Not available, NHS: National Health Service

Appendix 39

Input parameters of the simulation model for the obstetrics inpatient specialty

Input parameters	Estimates	Distributions	References
Patient inputs 1. Non-elective	- Daily number of admissions for the available period (2012/13) - Number of admissions from the forecasting method for the projected period (2013/14)	N/A N/A	HES dataset N/A
Financial inputs *Revenue:* 1. Non-elective tariff	(2012/13 – 2013/14) Frequency distribution	Frequency distribution	Department of Health and Social Care (2013)
Physical inputs Number of beds	41	Fixed	Local data
Other inputs			
Demographic features:			
- Age groups	(Non-elective)		
1. Age group 1 (0 - 15)	55.29%	Multinomial	HES dataset
2. Age group 2 (16 - 35)	37.34%	Multinomial	HES dataset
3. Age group 3 (36 - 50)	7.25%	Multinomial	HES dataset
4. Age group 4 (51 - 65)	0.07%	Multinomial	HES dataset
5. Age group 5 (65+)	0.05%	Multinomial	HES dataset
Distributions:			
- Waiting time for first admission	Frequency distribution	Frequency distribution	HES dataset
- Length of stay	Frequency distribution	Frequency distribution	HES dataset

HES: Hospital episodes statistics, N/A: Not available, NHS: National Health Service

Appendix 40

Input parameters of the simulation model for the gynaecology inpatient specialty

Input parameters	Estimates	Distributions	References
Patient inputs			
1. Elective	- Daily number of admissions for the available period (2012/13)	N/A	HES dataset
2. Non-elective	- Number of admissions from the forecasting method for the projected period (2013/14)	N/A	N/A
Financial inputs			
Revenue:	(2012/13 – 2013/14)		Department of Health and Social Care (2013)
1. Elective tariff	Frequency distribution	Frequency distribution	
2. Non-elective tariff	Frequency distribution	Frequency distribution	
Physical inputs			
Number of beds	41	Fixed	Local data
Other inputs			
Demographic features:			
- Age groups	(Elective – Non-elective)		
1. Age group 1 (0 - 15)	0.35 % – 0.60%	Multinomial	HES dataset
2. Age group 2 (16 - 35)	31.69% – 77.95%	Multinomial	HES dataset
3. Age group 3 (36 - 50)	38.12% – 18.85%	Multinomial	HES dataset
4. Age group 4 (51 - 65)	18.18% – 1.18%	Multinomial	HES dataset
5. Age group 5 (65+)	11.66% – 1.42%	Multinomial	HES dataset
Distributions:			
- Waiting time for first admission	Frequency distribution	Frequency distribution	HES dataset
- Length of stay	Frequency distribution	Frequency distribution	HES dataset
Theatre inputs			
- Total number of theatre procedure annual capacity			
1. Elective	1802	Fixed	Local data
2. Non-elective	913	Fixed	Local data
- What percentage of inpatient admissions end up having a surgery?			
1. Elective	100%	Multinomial	Local data
2. Non-elective	33%	Multinomial	Local data

HES: Hospital episodes statistics, N/A: Not available, NHS: National Health Service

Appendix 41

Input parameters of the simulation model for the clinical oncology inpatient specialty

Input parameters	Estimates	Distributions	References
Patient inputs 1. Elective	- Daily number of admissions for the available period (2012/13) - Number of admissions from the forecasting method for the projected period (2013/14)	N/A N/A	HES dataset N/A
Financial inputs *Revenue:* 1. Elective tariff	(2012/13 – 2013/14) Frequency distribution	Frequency distribution	Department of Health and Social Care (2013)
Other inputs *Demographic features:* - Age groups	(Elective)		
1. Age group 1 (0 - 15)	0.00%	Multinomial	HES dataset
2. Age group 2 (16 - 35)	1.36%	Multinomial	HES dataset
3. Age group 3 (36 - 50)	19.63%	Multinomial	HES dataset
4. Age group 4 (51 - 65)	37.87%	Multinomial	HES dataset
5. Age group 5 (65+)	41.14%	Multinomial	HES dataset
Distributions: - Waiting time for first admission	Frequency distribution	Frequency distribution	HES dataset

HES: Hospital episodes statistics, N/A: Not available, NHS: National Health Service

Appendix 42

Input parameters of the simulation model for the radiology inpatient specialty

Input parameters	Estimates	Distributions	References
Patient inputs 1. Elective	- Daily number of admissions for the available period (2012/13) - Number of admissions from the forecasting method for the projected period (2013/14)	N/A N/A	HES dataset N/A
Financial inputs *Revenue:* 1. Elective tariff	(2012/13 – 2013/14) Frequency distribution	Frequency distribution	Department of Health and Social Care (2013)
Other inputs *Demographic features:* - Age groups	(Elective)		
1. Age group 1 (0 - 15)	1.81%	Multinomial	HES dataset
2. Age group 2 (16 - 35)	14.11%	Multinomial	HES dataset
3. Age group 3 (36 - 50)	27.19%	Multinomial	HES dataset
4. Age group 4 (51 - 65)	25.83%	Multinomial	HES dataset
5. Age group 5 (65+)	31.06%	Multinomial	HES dataset
Distributions: - Waiting time for first admission	Frequency distribution	Frequency distribution	HES dataset

HES: Hospital episodes statistics, N/A: Not available, NHS: National Health Service

Appendix 43

Input parameters of the simulation model for the others inpatient specialty

Input parameters	Estimates	Distributions	References
Patient inputs 1. Elective 2. Non-elective	- Daily number of admissions for the available period (2012/13) - Number of admissions from the forecasting method for the projected period (2013/14)	N/A N/A	HES dataset N/A
Financial inputs *Revenue:* 1. Elective tariff 2. Non-elective tariff	 (2012/13 – 2013/14) Frequency distribution Frequency distribution	 Frequency distribution Frequency distribution	 Department of Health and Social Care (2013)
Physical inputs Number of beds	 91	 Fixed	 Local data
Other inputs *Demographic features:* - Age groups 1. Age group 1 (0 - 15) 2. Age group 2 (16 - 35) 3. Age group 3 (36 - 50) 4. Age group 4 (51 - 65) 5. Age group 5 (65+) *Distributions:* - Waiting time for first admission - Length of stay	 (Elective – Non-elective) 0.10% – 9.33% 10.55% – 17.73% 22.34% – 15.79% 29.41% – 16.74% 37.60% – 40.41% Frequency distribution Frequency distribution	 Multinomial Multinomial Multinomial Multinomial Multinomial Frequency distribution Frequency distribution	 HES dataset HES dataset HES dataset HES dataset HES dataset HES dataset HES dataset
Theatre inputs - Total number of theatre procedure annual capacity 1. Non-elective - What percentage of inpatient admissions end up having a surgery? 1. Non-elective	 35 0.40%	 Fixed Multinomial	 Local data Local data

HES: Hospital episodes statistics, N/A: Not available, NHS: National Health Service

Appendix 44

The integer linear programming for the forecasting-simulation-optimization approach

$$Max \sum DE1 + DE2 + DE3 + DE4 + DE5 + DE6 + DE7 + DNE1 + DNE2 + DNE3 + DNE4 + DNE5 + DNE6 + DNE7 + DNE8 + DNE9 \quad (A.1)$$

Subject to:

$$100x(DE1x1.04 + DNE1x4.09) \leq 85 \times NB1x365 \quad (A.2)$$

$$100x(DE2x1.67 + DNE2x5.90) \leq 85 \times NB2x365 \quad (A.3)$$

$$100x(DE3x0.33 + DNE3x3.90) \leq 85 \times NB3x365 \quad (A.4)$$

$$100x(DE4x0.73 + DNE4x7.15) \leq 85 \times NB4x365 \quad (A.5)$$

$$100x(DE5x0.96 + DNE5x1.42) \leq 85 \times NB5x365 \quad (A.6)$$

$$100x(DE6x0.60 + DNE6x1.64) \leq 85 \times NB6x365 \quad (A.7)$$

$$100x(DE7x0.77 + DNE7x3.99) \leq 85 \times NB7x365 \quad (A.8)$$

$$100x(DNE8x6.03) \leq 85 \times NB8x365 \quad (A.9)$$

$$100x(DNE9x1.94) \leq 85 \times NB9x365 \quad (A.10)$$

$$NB1 + NB2 + NB3 + NB4 + NB5 + NB6 + NB7 + NB8 + NB9 \leq 557 \quad (A.11)$$

$$DE1 \leq 3468 \quad (A.12)$$

$$DE2 \leq 3276 \quad (A.13)$$

$$DE3 \leq 1469 \quad (A.14)$$

$$DE4 \leq 972 \quad (A.15)$$

$$DE5 \leq 264 \quad (A.16)$$

$$DE6 \leq 1553 \quad (A.17)$$

$$DE7 \leq 372 \quad (A.18)$$

$$DNE1 = 3360 \quad (A.19)$$

$$DNE2 = 1536 \quad (A.20)$$

$$DNE3 = 9004 \quad (A.21)$$

$$DNE4 = 1224 \quad (A.22)$$

$$DNE5 = 2196 \quad (A.23)$$

$$DNE6 = 2147 \quad (A.24)$$

$$DNE7 = 732 \quad (A.25)$$

$$DNE8 = 7692 \quad (A.26)$$

$$DNE9 = 7320 \tag{A.27}$$

$$\begin{aligned}&(1282xDE1)+(3034xDE2)+(1486xDE3)+(2117xDE4)+(1568xDE5)+(1224xDE6)+(784xDE7)+\\&(2080xDNE1)+(3459xDNE2)+(2110xDNE3)+(2383xDNE4)+(1038xDNE5)+(1386xDNE6)+\\&(1629xDNE7)+(2280xDNE8)+(1636xDNE9)\geq 75063x(NC1+NC2+NC3+NC4+NC5+NC6+NC7+NC8+NC9)+\\&30752x(NN1+NN2+NN3+NN4+NN5+NN6+NN7+NN8+NN9)\end{aligned} \tag{A.28}$$

$$3x\left(DE1x1.04+DNE1x4.09\right)\leq 8\times NN1x365 \tag{A.29}$$

$$3x\left(DE2x1.67+DNE2x5.90\right)\leq 8\times NN2x365 \tag{A.30}$$

$$3x\left(DE3x0.33+DNE3x3.90\right)\leq 8\times NN3x365 \tag{A.31}$$

$$3x\left(DE4x0.73+DNE4x7.15\right)\leq 8\times NN4x365 \tag{A.32}$$

$$3x\left(DE5x0.96+DNE5x1.42\right)\leq 8\times NN5x365 \tag{A.33}$$

$$3x\left(DE6x0.60+DNE6x1.64\right)\leq 8\times NN6x365 \tag{A.34}$$

$$3x\left(DE7x0.77+DNE7x3.99\right)\leq 8\times NN7x365 \tag{A.35}$$

$$3x\left(DNE8x6.03\right)\leq 8\times NN8x365 \tag{A.36}$$

$$3x\left(DNE9x1.94\right)\leq 8\times NN9x365 \tag{A.37}$$

$$NC1\times 37.5x52\geq (20/60)x\left(DE1x1.04+DNE1x4.09\right) \tag{A.38}$$

$$NC2\times 37.5x52\geq (20/60)x\left(DE2x1.67+DNE2x5.90\right) \tag{A.39}$$

$$NC3\times 37.5x52\geq (20/60)x\left(DE3x0.33+DNE3x3.90\right) \tag{A.40}$$

$$NC4\times 37.5x52\geq (20/60)x\left(DE4x0.73+DNE4x7.15\right) \tag{A.41}$$

$$NC5\times 37.5x52\geq (20/60)x\left(DE5x0.96+DNE5x1.42\right) \tag{A.42}$$

$$NC6\times 37.5x52\geq (20/60)x\left(DE6x0.60+DNE6x1.64\right) \tag{A.43}$$

$$NC7\times 37.5x52\geq (20/60)x\left(DE7x0.77+DNE7x3.99\right) \tag{A.44}$$

$$NC8\times 37.5x52\geq (20/60)x\left(DNE8x6.03\right) \tag{A.45}$$

$$NC9\times 37.5x52\geq (20/60)x\left(DNE9x1.94\right) \tag{A.46}$$

$$\begin{aligned}
&DE1,\ DE2,\ DE3,\ DE4,\ DE5,\ DE6,\ DE7,\\
&DNE1,\ DNE2,\ DNE3,\ DNE4,\ DNE5,\ DNE6,\ DNE7,\ DNE8,\ DNE9,\\
&NB1,\ NB2,\ NB3,\ NB4,\ NB5,\ NB6,\ NB7,\ NB8,\ NB9,\\
&NC1,\ NC2,\ NC3,\ NC4,\ NC5,\ NC6,\ NC7,\ NC8,\ NC9,\\
&NN1,\ NN2,\ NN3,\ NN4,\ NN5,\ NN6,\ NN7,\ NN8,\ NN9 \in Z^{+}
\end{aligned} \tag{A.47}$$

Appendix 45

The results of the FSO approach for the Experiment 1

Code	Name	NDEP	NDNEP	BOR	NB	NC	NN
1	General surgery	3503	3697	84.28	61	20	20
2	Trauma & Orthopaedics	3309	1552	83.81	48	16	16
3	General Medicine	1484	9095	84.93	116	37	37
4	Cardiology	982	1237	84.50	31	10	10
5	Paediatrics	267	2218	84.83	11	4	4
6	Gynaecology	1569	2169	82.17	15	5	5
7	Others	376	740	80.75	11	4	4
8	Geriatric Medicine	-	7769	85.00	151	49	49
9	Obstetrics	-	7394	83.62	47	15	15
Total		11490	35871	-	491	31	160

BOR: Bed occupancy rate, NB: Number of beds, NC: Number of Consultants, NDEP: Number of discharged elective patients, NDNEP: Number of discharged non-elective patients, NN: Number of nurses

Appendix 46

The results of the FSO approach for the Experiment 2

Code	Name	NDEP	NDNEP	BOR	NB	NC	NN
1	General surgery	3538	3734	83.75	62	20	20
2	Trauma & Orthopaedics	3342	1567	84.63	48	16	16
3	General Medicine	1499	9185	84.32	118	38	38
4	Cardiology	992	1249	82.66	32	10	10
5	Paediatrics	270	2240	78.54	12	4	4
6	Gynaecology	1585	2190	82.97	15	5	5
7	Others	380	747	81.52	11	4	4
8	Geriatric Medicine	-	7846	84.72	153	49	49
9	Obstetrics	-	7467	84.44	47	15	15
Total		11606	36225	-	498	31	161

BOR: Bed occupancy rate, NB: Number of beds, NC: Number of Consultants, NDEP: Number of discharged elective patients, NDNEP: Number of discharged non-elective patients, NN: Number of nurses

Appendix 47

The results of the FSO approach for the Experiment 3

Code	Name	NDEP	NDNEP	BOR	NB	NC	NN
1	General surgery	3573	3770	84.56	62	4	20
2	Trauma & Orthopaedics	3375	1583	83.73	49	3	16
3	General Medicine	1514	9275	84.43	119	7	38
4	Cardiology	1002	1261	83.46	32	2	11
5	Paediatrics	272	2262	79.30	12	1	4
6	Gynaecology	1600	2212	83.79	15	1	5
7	Others	384	754	82.29	11	1	4
8	Geriatric Medicine	-	7923	85.00	154	9	50
9	Obstetrics	-	7540	83.49	48	3	16
	Total	11720	36580	-	502	31	164

BOR: Bed occupancy rate, NB: Number of beds, NC: Number of Consultants, NDEP: Number of discharged elective patients, NDNEP: Number of discharged non-elective patients, NN: Number of nurses

Appendix 48

The results of the FSO approach for the Experiment 4

Code	Name	NDEP	NDNEP	BOR	NB	NC	NN
1	General surgery	3607	3807	84.03	63	4	20
2	Trauma & Orthopaedics	3408	1598	84.54	49	3	16
3	General Medicine	1528	9365	84.54	120	7	39
4	Cardiology	1011	1273	84.25	32	2	11
5	Paediatrics	275	2284	80.07	12	1	4
6	Gynaecology	1616	2233	84.60	15	1	5
7	Others	387	762	83.15	11	1	4
8	Geriatric Medicine	-	8000	84.72	156	9	50
9	Obstetrics	-	7613	84.30	48	3	16
	Total	11832	36935	-	506	31	165

BOR: Bed occupancy rate, NB: Number of beds, NC: Number of Consultants, NDEP: Number of discharged elective patients, NDNEP: Number of discharged non-elective patients, NN: Number of nurses

Appendix 49

The results of the FSO approach for the Experiment 5

Code	Name	NDEP	NDNEP	BOR	NB	NC	NN
1	General surgery	3642	3843	84.83	63	21	21
2	Trauma & Orthopaedics	3440	1613	83.62	50	16	16
3	General Medicine	1543	9455	84.65	121	39	39
4	Cardiology	1021	1286	82.53	33	11	11
5	Paediatrics	278	2306	80.85	12	4	4
6	Gynaecology	1631	2255	80.08	16	5	5
7	Others	391	769	83.92	11	4	4
8	Geriatric Medicine	-	8077	84.99	157	51	51
9	Obstetrics	-	7686	83.37	49	16	16
	Total	11946	37290	-	512	31	167

BOR: Bed occupancy rate, NB: Number of beds, NC: Number of Consultants, NDEP: Number of discharged elective patients, NDNEP: Number of discharged non-elective patients, NN: Number of nurses

Appendix 50

The results of the FSO approach for the Experiment 6

Code	Name	NDEP	NDNEP	BOR	NB	NC	NN
1	General surgery	3677	3880	84.30	64	21	21
2	Trauma & Orthopaedics	3473	1629	84.44	50	16	16
3	General Medicine	1558	9545	84.75	122	39	39
4	Cardiology	1031	1298	83.30	33	11	11
5	Paediatrics	280	2328	81.61	12	4	4
6	Gynaecology	1647	2276	80.84	16	5	5
7	Others	395	776	84.69	11	4	4
8	Geriatric Medicine	-	8154	84.72	159	51	51
9	Obstetrics	-	7760	84.17	49	16	16
	Total	12061	37646	-	516	31	167

BOR: Bed occupancy rate, NB: Number of beds, NC: Number of Consultants, NDEP: Number of discharged elective patients, NDNEP: Number of discharged non-elective patients, NN: Number of nurses

Appendix 51

The results of the FSO approach for the Experiment 7

Code	Name	NDEP	NDNEP	BOR	NB	NC	NN
1	General surgery	3711	3917	83.79	65	21	21
2	Trauma & Orthopaedics	3506	1644	83.56	51	16	16
3	General Medicine	1572	9635	84.85	123	40	40
4	Cardiology	1041	1310	84.07	33	11	11
5	Paediatrics	283	2350	82.39	12	4	4
6	Gynaecology	1662	2298	81.61	16	5	5
7	Others	399	784	78.43	12	4	4
8	Geriatric Medicine	-	8231	84.99	160	51	51
9	Obstetrics	-	7833	84.97	49	16	16
	Total	12174	38002	-	521	31	168

BOR: Bed occupancy rate, NB: Number of beds, NC: Number of Consultants, NDEP: Number of discharged elective patients, NDNEP: Number of discharged non-elective patients, NN: Number of nurses

Appendix 52

The results of the FSO approach for the Experiment 8

Code	Name	NDEP	NDNEP	BOR	NB	NC	NN
1	General surgery	3746	3953	84.57	65	4	21
2	Trauma & Orthopaedics	3539	1659	84.33	51	3	17
3	General Medicine	1587	9725	84.96	124	7	40
4	Cardiology	1050	1322	84.84	33	2	11
5	Paediatrics	286	2372	83.17	12	1	4
6	Gynaecology	1678	2319	82.36	16	1	5
7	Others	402	791	79.12	12	1	4
8	Geriatric Medicine	-	8308	84.72	162	9	52
9	Obstetrics	-	7906	84.04	50	3	16
	Total	12288	38355	-	525	31	170

BOR: Bed occupancy rate, NB: Number of beds, NC: Number of Consultants, NDEP: Number of discharged elective patients, NDNEP: Number of discharged non-elective patients, NN: Number of nurses

Appendix 53

The results of the FSO approach for the Experiment 9

Code	Name	NDEP	NDNEP	BOR	NB	NC	NN
1	General surgery	3781	3990	84.07	66	4	21
2	Trauma & Orthopaedics	3571	1675	83.49	52	3	17
3	General Medicine	1602	9815	84.38	126	7	40
4	Cardiology	1060	1335	83.15	34	2	11
5	Paediatrics	288	2394	83.93	12	1	4
6	Gynaecology	1693	2341	83.13	16	1	5
7	Others	406	798	79.83	12	1	4
8	Geriatric Medicine	-	8385	84.98	163	9	52
9	Obstetrics	-	7979	84.82	50	3	16
	Total	12401	38712	-	531	31	170

BOR: Bed occupancy rate, NB: Number of beds, NC: Number of Consultants, NDEP: Number of discharged elective patients, NDNEP: Number of discharged non-elective patients, NN: Number of nurses

Appendix 54

The results of the FSO approach for the Experiment 10

Code	Name	NDEP	NDNEP	BOR	NB	NC	NN
1	General surgery	3815	4026	84.82	66	4	21
2	Trauma & Orthopaedics	3604	1690	84.24	52	3	17
3	General Medicine	1616	9905	84.48	127	7	41
4	Cardiology	1070	1347	83.90	34	2	11
5	Paediatrics	291	2416	84.71	12	1	4
6	Gynaecology	1709	2362	83.89	16	1	6
7	Others	410	806	80.63	12	1	4
8	Geriatric Medicine	-	8462	84.73	165	9	53
9	Obstetrics	-	8052	83.92	51	3	17
	Total	12515	39066	-	535	31	174

BOR: Bed occupancy rate, NB: Number of beds, NC: Number of Consultants, NDEP: Number of discharged elective patients, NDNEP: Number of discharged non-elective patients, NN: Number of nurses

Appendix 55

The results of the FSO approach for the Experiment 11

Code	Name	NDEP	NDNEP	BOR	NB	NC	NN
1	General surgery	3850	4063	84.32	67	4	22
2	Trauma & Orthopaedics	3637	1705	83.40	53	3	17
3	General Medicine	1631	9995	84.59	128	7	41
4	Cardiology	1079	1359	84.65	34	2	11
5	Paediatrics	294	2438	78.91	13	1	4
6	Gynaecology	1724	2384	84.66	16	1	6
7	Others	413	813	81.32	12	1	4
8	Geriatric Medicine	-	8539	84.98	166	9	53
9	Obstetrics	-	8126	84.69	51	3	17
	Total	12628	39422	-	540	31	175

BOR: Bed occupancy rate, NB: Number of beds, NC: Number of Consultants, NDEP: Number of discharged elective patients, NDNEP: Number of discharged non-elective patients, NN: Number of nurses

Appendix 56

The results of the FSO approach for the Experiment 12

Code	Name	NDEP	NDNEP	BOR	NB	NC	NN
1	General surgery	3885	4100	83.84	68	4	22
2	Trauma & Orthopaedics	3670	1721	84.17	53	3	17
3	General Medicine	1646	10085	84.69	129	8	41
4	Cardiology	1089	1371	82.96	35	2	11
5	Paediatrics	296	2460	79.61	13	1	4
6	Gynaecology	1740	2405	80.39	17	1	6
7	Others	417	820	82.03	12	1	4
8	Geriatric Medicine	-	8616	84.73	168	9	54
9	Obstetrics	-	8199	83.80	52	3	17
	Total	12743	39777	-	547	32	176

BOR: Bed occupancy rate, NB: Number of beds, NC: Number of Consultants, NDEP: Number of discharged elective patients, NDNEP: Number of discharged non-elective patients, NN: Number of nurses

Appendix 57

The results of the FSO approach for the Experiment 13

Code	Name	NDEP	NDNEP	BOR	NB	NC	NN
1	General surgery	3919	4136	84.58	68	4	22
2	Trauma & Orthopaedics	3702	1736	84.90	53	3	17
3	General Medicine	1660	10175	84.78	130	8	42
4	Cardiology	1099	1384	83.74	35	2	11
5	Paediatrics	299	2482	80.33	13	1	4
6	Gynaecology	1755	2427	81.12	17	1	6
7	Others	421	828	82.83	12	1	4
8	Geriatric Medicine	-	8692	84.97	169	9	54
9	Obstetrics	-	8272	84.55	52	3	17
	Total	12855	40132	-	549	32	177

BOR: Bed occupancy rate, NB: Number of beds, NC: Number of Consultants, NDEP: Number of discharged elective patients, NDNEP: Number of discharged non-elective patients, NN: Number of nurses

Appendix 58

The results of the FSO approach for the Experiment 14

Code	Name	NDEP	NDNEP	BOR	NB	NC	NN
1	General surgery	3954	4173	84.10	69	4	22
2	Trauma & Orthopaedics	3735	1752	84.09	54	3	18
3	General Medicine	1675	10265	84.88	131	8	42
4	Cardiology	1109	1396	84.47	35	2	12
5	Paediatrics	301	2504	81.03	13	1	4
6	Gynaecology	1771	2448	81.83	17	1	6
7	Others	425	835	83.54	12	1	4
8	Geriatric Medicine	-	8769	84.72	171	10	55
9	Obstetrics	-	8345	83.69	53	3	17
	Total	12970	40487	-	555	33	180

BOR: Bed occupancy rate, NB: Number of beds, NC: Number of Consultants, NDEP: Number of discharged elective patients, NDNEP: Number of discharged non-elective patients, NN: Number of nurses

Appendix 59

The results of the FSO approach for the Experiment 15

Code	Name	NDEP	NDNEP	BOR	NB	NC	NN
1	General surgery	3989	4209	84.83	69	4	22
2	Trauma & Orthopaedics	3768	1767	84.82	54	3	18
3	General Medicine	1690	10355	84.98	132	8	42
4	Cardiology	1118	1408	82.83	36	2	12
5	Paediatrics	304	2526	81.74	13	1	4
6	Gynaecology	1786	2470	82.55	17	1	6
7	Others	69	842	85.00	11	1	4
8	Geriatric Medicine	-	8846	84.97	172	10	55
9	Obstetrics	-	8418	84.42	53	3	17
	Total	12724	40841	-	557	33	180

BOR: Bed occupancy rate, NB: Number of beds, NC: Number of Consultants, NDEP: Number of discharged elective patients, NDNEP: Number of discharged non-elective patients, NN: Number of nurses

Appendix 60

The results of the FSO approach for the Experiment 16

Code	Name	NDEP	NDNEP	BOR	NB	NC	NN
1	General surgery	3886	4246	85.00	69	4	22
2	Trauma & Orthopaedics	2994	1782	85.01	50	3	18
3	General Medicine	1600	10445	85.00	133	8	43
4	Cardiology	967	1420	85.00	35	2	12
5	Paediatrics	307	2548	82.46	13	1	4
6	Gynaecology	1802	2491	37.73	17	1	6
7	Others	431	850	85.01	12	1	4
8	Geriatric Medicine	-	8923	84.72	174	10	56
9	Obstetrics	-	8492	83.58	54	3	18
	Total	11987	41197	-	557	33	183

BOR: Bed occupancy rate, NB: Number of beds, NC: Number of Consultants, NDEP: Number of discharged elective patients, NDNEP: Number of discharged non-elective patients, NN: Number of nurses

Appendix 61

The results of the FSO approach for the Experiment 17

Code	Name	NDEP	NDNEP	BOR	NB	NC	NN
1	General surgery	4039	4283	85.00	70	4	23
2	Trauma & Orthopaedics	2008	1798	85.00	45	3	18
3	General Medicine	1719	10535	84.53	135	8	43
4	Cardiology	1138	1433	84.30	36	2	12
5	Paediatrics	309	2570	83.16	13	1	4
6	Gynaecology	1818	2512	37.50	17	1	6
7	Others	395	857	85.01	12	1	4
8	Geriatric Medicine	-	9000	84.96	175	10	56
9	Obstetrics	-	8565	84.30	54	3	18
	Total	11426	41553	-	557	33	184

BOR: Bed occupancy rate, NB: Number of beds, NC: Number of Consultants, NDEP: Number of discharged elective patients, NDNEP: Number of discharged non-elective patients, NN: Number of nurses

Appendix 62

The results of the FSO approach for the Experiment 18

Code	Name	NDEP	NDNEP	BOR	NB	NC	NN
1	General surgery	4093	4319	84.59	71	4	23
2	Trauma & Orthopaedics	1026	1813	85.00	40	3	18
3	General Medicine	1734	10625	84.63	136	8	44
4	Cardiology	1147	1445	85.00	36	2	12
5	Paediatrics	312	2592	83.88	13	1	4
6	Gynaecology	1833	2534	37.25	17	1	6
7	Others	358	864	85.00	12	1	4
8	Geriatric Medicine	-	9077	84.72	177	10	56
9	Obstetrics	-	8638	83.48	55	3	18
	Total	10503	41907	-	557	33	185

BOR: Bed occupancy rate, NB: Number of beds, NC: Number of Consultants, NDEP: Number of discharged elective patients, NDNEP: Number of discharged non-elective patients, NN: Number of nurses

Appendix 63

The results of the FSO approach for the Experiment 19

Code	Name	NDEP	NDNEP	BOR	NB	NC	NN
1	General surgery	4050	4356	85.00	71	4	23
2	Trauma & Orthopaedics	602	1828	85.01	38	3	18
3	General Medicine	1749	10715	84.72	137	8	44
4	Cardiology	1030	1457	85.00	36	2	12
5	Paediatrics	315	2614	84.60	13	1	4
6	Gynaecology	1807	2555	36.99	17	1	6
7	Others	317	872	85.01	12	1	4
8	Geriatric Medicine	-	9154	84.96	178	10	57
9	Obstetrics	-	8711	84.18	55	3	18
	Total	9870	42262	-	557	33	186

BOR: Bed occupancy rate, NB: Number of beds, NC: Number of Consultants, NDEP: Number of discharged elective patients, NDNEP: Number of discharged non-elective patients, NN: Number of nurses

Appendix 64

The results of the FSO approach for the Experiment 20

Code	Name	NDEP	NDNEP	BOR	NB	NC	NN
1	General surgery	3610	4392	85.00	70	4	23
2	Trauma & Orthopaedics	174	1844	85.01	36	3	18
3	General Medicine	1763	10805	84.81	138	8	44
4	Cardiology	912	1469	85.00	36	2	12
5	Paediatrics	303	2636	85.02	13	1	4
6	Gynaecology	1747	2577	36.76	17	1	7
7	Others	281	879	85.01	12	1	4
8	Geriatric Medicine	-	9231	84.72	180	10	57
9	Obstetrics	-	8784	84.89	55	3	18
	Total	8790	42617	-	557	33	187

BOR: Bed occupancy rate, NB: Number of beds, NC: Number of Consultants, NDEP: Number of discharged elective patients, NDNEP: Number of discharged non-elective patients, NN: Number of nurses