A decision support system for demand and capacity modelling of an accident and emergency department

Accident and emergency (A&E) departments in England have been struggling against severe capacity constraints (e.g. beds, staff and budget). In addition, A&E demand for admissions have been increasing year on year. In this study, our aim was to develop a decision support system combining discrete event simulation and comparative forecasting techniques for the better management of the Princess Alexandra Hospital (PAH) in England. We used the national hospital episodes statistics (HES) dataset including period April, 2009 to January, 2013. Two demand conditions are considered: (1) The expected demand condition is based on A&E demands estimated by comparing four forecasting methods and validated within a confidence interval range of 99%, and (2) The unexpected demand is based on the closure of a nearby A&E department due to budgeting constraints, hence the model should be able to estimate the impact this may have on the A&E department. We developed a discrete event simulation model where statistical distributions (i.e. waiting time for treatment and overall waiting time) are based on age groups. Key performance metrics such as capacity, demand coverage ratio (DCR), utilization rates of staff and financial outputs are generated based on six "what-if" scenarios under the expected and unexpected demand conditions. The experimental results clearly illustrate that the A&E department will not be able to cope with the demand in most of the unexpected demand conditions although it has the ability of balancing demand and capacity under the expected demand condition. Additional resources tested in the scenarios will not be sufficient to cope with all demands in Case 5 (20% increase in demand) and Case 6 (25% increase in demand) although they do provide efficient delivery of healthcare in the A&E department under the expected demand conditions. This study contributes to the knowledge of simulation modelling in healthcare systems by modelling demand and capacity by combining discrete event simulation and comparative forecasting. This paper presents a crucial study which will enable service managers and directors of hospitals to foresee their activities in future and form a strategic plan well in advance.

Keywords: demand and capacity modelling; discrete event simulation; forecasting; accident and emergency department; healthcare; decision support system

1. Introduction

Accident and emergency (A&E) units are the busiest departments within hospitals working under immense financial pressures resulting in shortage of clinicians, nurses, beds and equipment. For the last decades, A&E departments in the United Kingdom (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 (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 2017a).

The population has been increasing and ageing around the world, which causes increasing demands on hospitals (Hong and Ghani, 2006). The considerable increase (i.e. approximately 23.5% from 2006/07 to 2016/17 financial year) in the number of admissions has been observed in the UK A&E departments (National Health Services England, 2014 and 2017a). In addition, the bed occupancy rates of hospitals in the UK from 2010/11 to 2016/17 financial year have presented an upward trend on occupied beds used overnight and day only, 4.87% and 13.51%, respectively. (National Health Services England, 2017b).

Proportion of the younger population is decreasing compared to an increasing proportion of the elderly population. According to Cracknell (2010), the 65 years and over age group in the UK was around 10 million (a 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, n.d.). Therefore, resources (e.g. staff, beds) may not be sufficient to meet demand for A&E, 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 A&E departments will continue to struggle (i.e. longer waiting times) to use their resources efficiently. Due to increasing demand, hospital administrations will need to provide higher productivity rates by enhancing the match of demand and capacity of A&Es. Therefore, key decision makers would need to model the level of resources needed by patients in A&E 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.

In this study, the objective is to develop a demand and capacity model for an A&E department by combining the methods of quantitative forecasting and discrete event simulation techniques. Using the English Hospital Episodes Statistics dataset, we forecasted daily A&E demand by comparing four forecasting methods and selected the best model according to the forecast accuracy measure. The forecasted demands are then inputted into the simulation model under the expected demand condition. In addition, we have also considered unexpected demand conditions as requested by the Directors of the hospital, and examined the impact of the closure of a nearby A&E department at another hospital. We obtained the unexpected demand by increasing the expected demand by various rates. Capacity of the A&E has been investigated through the simulation model for future years. We have taken many inputs into account including demographic features (age groups, gender), staff shifts, number of resources (doctors, nurses, beds, triage rooms and clinic rooms), salary of human resources, cost of treatment, distributions (investigation for treatment (severity of injuries), waiting time for treatment and overall waiting time) and laboratory tests. We established distributions based on age groups, so that the related times vary, hence a more robust model could be built. In addition, we tested several 'what-if' scenarios in order to observe how performance metrics are changed. Thus, many outputs have been computed under expected and unexpected demand conditions: capacity (number of patients discharged), utilisation rates of doctors, nurses and beds, demand coverage ratio (DCR), financial implications, and many more.

The first contribution to knowledge is the development of a decision support system combining discrete event simulation and comparative forecasting in modelling demand and capacity. To our knowledge, the literature does not contain such an extensive study which has successfully combined these two approaches. Therefore, we generate A&E demand using forecasting techniques, including the seasonal and trend decomposition using loess (STLF) method, which has not been applied within the healthcare context. The objective is to enable service managers to better understand future demand and act accordingly to prevent issues related to system performances and capacity. We then take into account the request from the hospital management to evaluate possible demand increases in the case of the closure of an A&E department at a nearby hospital. Thus, we model unexpected demand conditions by increasing the expected demand by various rates determined in case studies. As a result, service managers will be prepared against possible increasing demand. If they project that demand would increase in future years according to the results of this study, they might need to increase staffing level (i.e. additional staff). Therefore, they will prevent increasing staff utilization rates and staff will continue to work without severe workloads.

Almost all of the discrete event simulation oriented research papers do not provide further details in relation to the practical aspects of simulation modelling, for example the validation process, how to determine the warm-up period, calculating the optimal number of replications (i.e. trials), etc. We therefore provide a step by step guide to modelling A&E and thus an opportunity for researchers, practitioners and analysts to replicate our study within their setting.

Section 2 reviews the literature on forecasting and discrete even simulation; Section 3 presents a flow diagram for the step by step guide. Section 4 shows how A&E demand is forecasted. Section 5 illustrates the conceptualised patient pathway, develops the model, showcases the validation stage in greater detail; Sections 6 and 7 discusses results and presents the conclusion, respectively.

2. Literature Review

2.1. Forecasting A&E demand

Many studies have been conducted using time series analysis to forecast patient demand (see Table 1). 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. 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. 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). 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 others on estimating A&E demand.

Table 1 gives detailed information of the literature related to the forecasting hospital demand. We have drawn on the literature to select forecasting methods to be used in the study. We have used three forecasting methods (ARIMA, exponential smoothing and multiple linear regression) since they have been widely used and recommended as the best methods in the literature. One of the contributions of this study is the use of 'the seasonal and trend decomposition using loess function (STLF) method; we tried this method because the hospital data contains both trend and seasonal components. In the study, we include a section comparing the performance of forecasting methods. Most importantly, as shown in Table 3, the STLF method has better forecast accuracy than ARIMA and exponential smoothing methods which have been widely used in the literature. The STLF is a different forecasting approach which has not previously been applied to forecast demand for A&E. According to Hyndman and Athanasopoulos (2014, p. 163), the STL method is a reliable technique to separate time series datasets into seasons and trends. This method is explained in Section 4.

2.2. Discrete Event Simulation Modelling

Simulation is an approach which allows characteristic features of any system to be built into a computer environment and for experiments to be conducted (Pidd, 2004, p. 3 – 4). Simulation gives useful results to users. Some of its advantages, according to Banks et al. (2005, p. 6) 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, p. 9-10) states that simulation is cheaper than real experiments 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 many times.

As can be seen from the literature review, health care services are systems where simulation techniques have been carried out extensively. This situation is confirmed by Pidd (2004, p. 5) who stresses that simulation in an appropriate implementation allows the restricted resources of hospitals to be effectively used in healthcare services.

One of the most widely used application areas of simulation methods is the accident and emergency department (A&E) as seen in the literature review study conducted by Gul and Guneri (2015). 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 A&Es by means of triage systems which classify patients according to their urgency. Existing vs. re-designed triage systems have been compared by a number of researchers (Connelly and Bair, 2004; Medeiros et al., 2008; Ruohonen & Teittinen, 2006; Gunal & Pidd, 2006). On the other hand, some studies focus on classifying and prioritizing patients, for instance (Ozdagoglu et al., 2009; Virtue et al., 2011). A number of studies in the literature have developed systems of A&Es by means of scenarios. Alternative scenarios are generated and compared by measuring the performances of A&Es, for example, (Komashie & Mousavi, 2005; Duguay & Chetouane, 2007; Meng & Spedding, 2008; Gul et al., 2012; Wang et al., 2012; Ahmad et al., 2012; Gul and Guneri, 2012; Al-Refaie et al., 2014; Oh et al., 2016).

A&Es have been exhaustively investigated by many researchers around the world, with the aim of assisting key decision makers to find the most effective and efficient way of running their service. For instance, redesigned triage systems, tackled by means of what-if scenarios and prioritized patients according to their health status. These studies have a number of limitations, firstly the number of staff in each shift are generally assumed to be fixed, and secondly, the lack of availability of real data to capture reality within A&E. In some cases, data is 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 or reliable. Table 2 compares the current study with previous studies related to A&E departments.

Simulation modelling has been developed as an alternative solution method in different departments of hospitals. Within this framework, inpatient and outpatient departments have been considered as study areas. VanBerkel and Blake (2007) examined a general surgery’s practice in order to reduce waiting times and operation room times, and according to their findings long waiting times were associated with the number of beds. In this study, it is suggested that alternative scenarios must be combined to decrease patient waiting times. Rohleder et al. (2011) measured performance of an outpatient pathway at an orthopaedic department. A combination of optimum number of staff, patient schedules and staff punctuality was tested. As a result, significant reductions in waiting times and total patient times were found. Zhu et al. (2012) analysed how two growth rates in demand changed the optimum bed numbers in an intensive care unit. Demir et al. (2017) developed a decision support tool to better understand future key performance metrics of 10 specialities of a hospital. Hospital demand was estimated for the next 6 years by assuming population growth rates of the catchment area which the hospital serves.

Bed capacity issues of healthcare services are directly proportional to patient demands, making it difficult for healthcare planners to manage services. Therefore, service managers are forced to take precautions, such as the reallocation of beds, building new departments with an increased capacity. Vasilakis and El-Darzi (2001) analysed the crises coming in sight during winter seasons and revealed the available bed capacity *"before crisis"* and *"during crisis"*. Cochran and Bharti (2006) reallocated beds at an obstetrics hospital and increased the bed capacity by a small rate to enable more patients to be admitted. Levin et al. (2008) found that determining the optimal capacity of cardiology enables a reduction in admission times of A&E.

The contribution of this study to the field of simulation modelling in healthcare systems is as follows: (1) we develop a decision support system which combines discrete event simulation technique and comparative forecasting method to specify demand and capacity of a healthcare department (A&E). To determine scientifically the A&E demand for expected demand conditions, we compare four forecasting methods and select the best model instead of relying on a single forecasting method. (2) In comparison with existing studies, this study provides a step by step guide presented in

Section 3 to simulating an A&E department, explaining all steps in greater detail, including the model validation stage, warm-up period, and the optimum replication number. In the majority of instances, researchers, practitioners and analysts find it difficult to replicate a study, hence our objective was to provide all the details to ensure our model can be replicated in other settings.

3. The Decision Support System

In this study, we develop a decision support system (DSS) combining comparative forecasting techniques and discrete event simulation for demand and capacity planning in an A&E department. For this, the projected 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 two techniques are combined in Fig 1. We extracted all required A&E data from the 'big data' corresponding to the hospital of interest, i.e., 248,910 A&E arrivals (with 86 variables) over the period of the study. The required data was 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 were embedded into our A&E simulation model. The model then generated future levels of key output metrics (i.e. capacity, demand coverage ratio, bed occupancy rate, utilization rates of doctors and nurses, total revenue and surplus). All steps mentioned in the flow diagram are explained in Section 4 and 5 in greater detail.

4. Forecasting A&E demand

Daily demand of the A&E department is predicted by using quantitative forecasting methods since patient admissions are used as an input to the simulation model. This study has been carried out in the A&E department of the Princess Alexandra Hospital working 24/7 in England. In this study, 46-months of data was used for the period April, 2009 – January, 2013 and the data was extracted from the national hospital episodes statistics. The data was divided into two: the training set (April, 2009 – January, 2012) and the validation set (February, 2012 – January, 2013).

Many forecasting methods have been compared in A&E demand forecasting in the literature. As seen in Table 1, the autoregressive integrated moving average (ARIMA), exponential smoothing (ES) and multiple linear regression have been widely used. On the other hand, Hyndman and Athanasopoulos (2014, p. 163) 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. Thus, we have compared the method with three other methods.

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 and Athanasopoulos, 2014, p. 213). 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, p. 270). Exponential smoothing 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, Wheelwright and Hyndman, 1998, p. 140). 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 (Makridakis, Wheelwright and Hyndman, 1998, p. 241). Stepwise linear regression, which is one of multiple linear regression methods, selects the explanatory variables relevant to the dependent variable from the initial model including all explanatory variables. In this study, the stepwise linear regression involves the use of dummy variables. For example, the stepwise linear regression model for the daily estimation includes days of week, months of year, variables related to UK public holidays (a holiday, a day before a holiday and a day after a holiday). The STLF method converts data to seasonal data using STL (The Seasonal and Trend Decomposition using Loess) decomposition. A non-seasonal forecasting technique is used to get the estimated values. The estimated values are then re-seasonalized by using the "the last year of the seasonal component" (Hyndman et al., 2016). In this study, the following functions in R are applied in order to select the best ARIMA, ES, the STLF methods and stepwise linear regression, respectively: the auto.arima(), the ets(), the stlf() functions (Hyndman and Khandakar, 2008), and the stepAIC() functions (Ripley et al. 2016).

4.1. Choosing the best forecasting method

In this study, an A&E demand for projection is obtained from forecasting techniques instead of using presumptive demand to embed it as input in simulation model. Therefore, forecasting and simulation is combined for the development of the decision support system in demand and capacity modelling. Thus, four forecasting methods are used: ARIMA, ES, Stepwise Linear Regression and STLF. Using these methods, the daily A&E demand is estimated. At this point, 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 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.

$$q_t = \frac{e_t}{\frac{1}{n-1}\sum_{i=2}^{n}|Y_i - Y_{i-1}|} \quad (1)$$

$$\text{MASE} = \text{mean}(|q_t|) \quad (2)$$

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

According to Table 3, the stepwise linear regression is the best method judging by the lowest MASE value with 0.8651. As a result, this means that the daily A&E demand will be forecasted using the stepwise linear regression method.

One of the important issues in forecasting is to validate the forecasts. We use a paired t test (see Eq. (4) for the formula) for validation of forecasts and compare the actual data and forecasted demand from the regression model for the validation set period (February, 2012 – January, 2013) in forecasting process. Table 4 shows that the forecasted demand is validated at 99% confidence interval.

In order to estimate the distribution of interarrival times to be used as input in the simulation model, daily A&E demand is forecasted by using the developed stepwise linear regression model for the period February, 2013 – January, 2014. The distributions related to patient arrivals are explained in Section 5.3.

5. Discrete Event Simulation Modelling

In our study, patient arrivals, investigation for treatment (severity of injuries) waiting time for treatment, treatment time and overall waiting time are probabilistic and thus, statistical distributions are considered. In addition, patient arrivals and processes of the hospital are discrete and have discrete time intervals. 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 way of simulating complex patient pathways (Davis et al. 2014). In the light of these reasons, DES method is applied and Simul8 software is used in our study.

5.1. Data

The data used in the simulation model is obtained in two ways: firstly, the following are derived using the national hospital episodes statistics (HES) dataset covering period April 2009 to January 2013: patient arrival date and time, demographic features, treatment time, conclusion time, laboratory tests and discharge destination. The local data was provided by the hospital, that is, the number doctors, nurses, beds, triage room, etc. In addition, all input parameters and their references are given in Appendix 1.

5.2. Conceptualization of the A&E department

To develop 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, p. 35 – 36). This means that firstly, a hospital should be conceptualized and after that, a simulation model should be developed.

The conceptualization stage is required to understand the system better and build a simulation model correctly. In this study, the A&E is conceptualised in high level and presented in Fig. 2. The conceptualised A&E model is validated in collaboration with directors of the hospital (i.e. clinical directors, director of finance, turnaround director) and consultants in the hospital. In this pathway, four different patient arrivals are shown: patients can be referred from GPs, self-admission, by ambulance, or referral from educational establishments and general dental practitioner. Patients are registered and pre-assessment process (triage process) 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.

5.3. Inputs – Outputs

In this study, inputs and outputs are shown in Fig. 3. We used five types of inputs: patient input (patient demand by forecasting), physical inputs (beds, triage and clinic rooms), staff inputs (doctors, nurses), financial inputs (Healthcare Research Groups (HRG) tariff, payments to doctors and nurses indicated in NHS Staff Earnings Publications) and other inputs (distributions, all laboratory tests, shifts, demographic features, such as age groups and gender). Healthcare Research Groups (HRGs) is an indicator which classifies similar clinic "conditions" or "treatments" in terms of level of resources used in healthcare systems (NHS England, 2017). In this study, reference costs based on HRG (NHS Digital, n.d.) are used to estimate average revenue of the A&E. Appendix 1 shows all input parameters, estimates, distributions and references.

All laboratory tests (X-ray, electrocardiogram, haematology, biochemistry, urinalysis and others) in the A&E department are taken into account. Number of resources provided by the hospital are used as inputs in the simulation model (see Appendix 1).

Two age groups (i.e. 20-40, 80+) correlate with waiting times for treatment in A&E departments compared against age group of 40-60. 10%-demand increase by younger group means a 0.49% increase on the performances related to waiting times in A&Es. In addition to this, same increase on demand by elderly group causes a 1% decrease on the performances (Monitor, 2015). We therefore established the distributions based on age groups because the relevant times vary according to age group. Distributions for “waiting time for treatment” and “waiting time for discharge” are computed. Appendix 2 illustrates values of goodness of fit (i.e. Kolmogorov Smirnov and Anderson Darling) for 18 different distributions of “waiting time for treatment” for each age group. The best fitting distributions for each age group are selected judging by the lowest goodness of fit value, which are highlighted in bold and their parameter values are stated in Appendix 2. Probability density function graphs for the best fitting distributions of “waiting time for treatment” for each age group are given in Appendix 3.

Appendix 4 illustrates values of goodness of fit (i.e. Kolmogorov Smirnov and Anderson Darling) for 18 different distributions of “waiting time for discharge” (by each age group). The best fitting distributions for each age group are selected judging by the lowest goodness of fit value, which are highlighted in bold and their parameter values are stated in Appendix 4. Probability density function graphs for the best fitting distributions of “waiting time for discharge” (by each age group) are given in Appendix 5.

We established the observed frequency distributions 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 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). This risk adjustments enable us to better capture detailed treatment processes within A&E, financial implications, impact on resources, etc.

We calculate daily average interarrival times of the A&E by dividing total time of a day by daily demand estimated by the stepwise linear regression model. This procedure is applied for each day of a month. After that, monthly distribution was calculated using that daily average interarrival times we calculated for that month. Therefore, we generate all monthly distributions of the interarrival times based on days-of-weeks pattern by using EasyFit software for each case study. The EasyFit software selects the best distribution according to goodness of fit (i.e. Kolmogorov Smirnov and Anderson Darling) (Mathwave Technologies, n.d.). Table 5 gives the monthly distributions of patient interarrival times used in this study. For example, as seen from Table 5, patients arrive to the A&E in accordance with the Poisson Distribution (λ=6.2667) for the period (April, 2013) whereas they arrive to the A&E according to the Geometric Distribution (p=0.13478) for the period (March, 2013) in Case 1.

As seen from Fig. 3, we obtain four kinds of outputs from this study: patient outputs (capacity), physical outputs (bed utilization rates, demand coverage ratio), staff outputs (staff utilization rates) and financial outputs (average revenue, cost and surplus). Outputs are obtained quarterly and annually. We developed an output metric: Demand coverage ratio (DCR). Therefore, we can measure the percentage of patients admitted to an A&E and discharged with available resources. Its formula is shown in Eq. (3). This output shows the A&E's ability to meet demand. For example, 100% DCR means that all patient demands are met with the available resources, whereas DCR would be less than 100% depending on the number of patients who are not discharged from A&E.

$$DCR = \frac{Number\ of\ patients\ who\ are\ discharged}{Number\ of\ patients\ who\ are\ admitted\ to\ the\ A\&E} \quad (3)$$

Our financial outputs are associated with NHS Staff Earnings Publications by applying payments to doctors and nurses determined in NHS Staff Earnings Publications (NHS Digital, 2013 and 2014) when calculating average cost of treatment. On the other hand, NHS reference costs (Department of Health, 2013 and 2014) are considered as revenue to estimate average revenue of the A&E department.

5.4. Simulation Model

The conceptualization stage enables us to better understand the system prior to developing the simulation model. As presented in Fig. 4, the A&E simulation model is modelled using Simul8 simulation software. The "AandE Arrival" entry point is made up of four arrival modes (i.e. GP referral, self referral, emergency and other) as shown in Fig. 2. Patients arrive at A&E according to the distribution of the interarrival times specified in Table 5. Patients are labelled in terms of age group and gender according to their statistical distributions. Patients wait for pre-assessment which is normally carried out by a nurse and a label related to severity of injuries is assigned to patients for triage process. Patients are then asked to further wait to be seen by an A&E doctor according to a waiting time distribution as indicated in Appendix 2. In the 'AandE Treatment' work centre, if a doctor wants a further investigation, patients are referred to the laboratory area such as X-Ray, electrocardiogram and so on. An investigation bundle is assigned to each patient according to the distribution obtained from data. For example, if a patient has investigation1 (X-Ray) and investigation2 (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". Then, patients are discharged based on healthcare provider's decision by "AandE Discharged" using five discharge modes as shown in Fig. 2 (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 waiting times: 1) Waiting for pre-assessment (triage), 2) Waiting time for treatment (by clinician), 3) Waiting time for discharge (post treatment), 4) Overall waiting time, i.e. from arrival to discharge. Relevant distributions have been established for (1), (2) and (3) whereas (4) is an output. In the data collection period of the model, overall waiting time (4) is obtained by adding (1), (2) and (3).

5.5. Verification and validation

The simulation model is verified by a number of directors in the hospital. The model is run for the period February, 2012 – January, 2013 and the simulation results (number of admission, waiting time for treatment and overall waiting time) are obtained for validating the model. We have compared these simulation results and actual values by using a paired *t* test which is determined as a formula in Eq. (4).

$$t_0 = \frac{\bar{d} - \mu_d}{S_d / \sqrt{K}} \quad (4)$$

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, p. 377). As a result, the model is validated since *t* test values ($|t_0|$) are less than or equal to *t* critical values ($t_{\alpha/2,K-1}$) at 95% significance level. Table 6 presents the results of the validation test.

5.6. Determination of replication number and warm-up period

Using Fixed-Sample-Size Procedure, we calculate the optimum replication number for the simulation model. Eq. (5) presents formula for fixed-sample-size procedure.

$$n_\gamma^*(\gamma) = min\left\{i \geq n; \frac{t_{i-1,1-\alpha/2}\sqrt{S^2(n)/i}}{|\bar{X}(n)|}\right\} \leq \gamma' \quad (5)$$

where *n* is initial replication number, *i* is required replication number, *S* is standard deviation, γ' is “adjusted” relative error and $\bar{X}$ is average estimates of key parameter (Law and Kelton, 2000, p. 513). It is recommended that $\gamma \leq 0.15$ and at $n_0 \leq 10$ (Law and Kelton, 2000, p. 515). Minimum value of replication number is chosen as optimum replication number if $n_\gamma^*(\gamma)$ is less than or equal to γ'(Law and Kelton, 2000, p. 513). In this study, initial replication number is determined as 10 and we calculate $n_\gamma^*(\gamma)$ is less than or equal to γ' for the key performance metrics (i.e. average waiting time and average length of stay). As a result, we use the optimum replication number as 10 replications in our simulation model.

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 ($\bar{Y}_i$) of a key performance metric (i.e. waiting time) is averaged. (3) Moving averages of $\bar{Y}_i$(w) by using formula in Eq. (6).

$$\bar{Y}_i(\mathrm{w}) = \begin{cases} \frac{\sum_{s=-w}^{w} \bar{Y}_{i+s}}{2w+1} & if\ i = w+1, \dots, m-w \\ \frac{\sum_{s=-(i-1)}^{i-1} \bar{Y}_{i+s}}{2i-1} & if\ i = 1, \dots, w \end{cases} \quad (6)$$

(4) Graphs of moving averages of $\bar{Y}_i$(w) are obtained for each key performance metric. Then, the point where moving averages are smoothed is selected (Law and Kelton, 2000, p. 520-521).

In this study, the warm-up period is investigated for key performance metrics (i.e. waiting time for treatment and overall waiting time). In the simulation model, the warm up period consists of two months: December 2011 (31 days) and January 2012 (31 days) and totally the warm up period is 62.

5.7. Case Study

We have compared four forecasting methods and selected the one giving the best forecast accuracy measure. By using the forecasting method selected, we estimate daily A&E demand and compute monthly patient interarrival times to embed in the simulation model as input. In this study, six case studies are developed as given Table 7. Case 1 (Base model) consists of only A&E demand obtained from the stepwise linear regression model. Capacity for Case 1 is modelled and the simulation model including warm-up period is run 10 times (replication is 10 according to the Fixed-Sample-Size Procedure). Therefore, Case 1 is investigated under expected demand conditions since forecasting provides the foreseen demand of the A&E department. Following the request of the management of hospital, we also examine how the balance of demand and capacity is affected in case the nearby hospital is closed. In this situation, more patients than expected will visit the A&E department. Thus, we examine these possible increases under unexpected demand conditions. Case studies covering Case 2 to Case 6 are developed based on the Base Model (Case 1). For example, the A&E demand in

Case 2 is 5% higher than in Case 1. Five different increases in demand levels are taken into account to observe possible effects on the A&E's performance.

In addition, we generate 'what-if' scenarios by considering the bottlenecks in the A&E department. In this regard, we develop six scenarios (see Table 8) related to how demand is met with additional resources. Each scenario contains previous scenarios cumulatively. For example, Scenario 3 includes Scenario 1 and 2. Scenario 1 is the base model (demand is provided by forecasting method). Scenario 2 includes increase in overall waiting time by 20% since possible increases in demand could provide longer length of stay. In Scenario 3, an additional X-Ray is added to the A&E system in addition to Scenario 2. In Scenario 4, a total of 3 nurses are employed, i.e. one nurse for each shift. Thus, we investigate how capacity is affected by this additional resource and whether performance metrics (i.e. utilization rates of nurses and beds) are increased or not. Scenario 5 has one additional bed in comparison with Scenario 4. Finally, Scenario 6 involves an additional doctor per shift compared with Scenario 5. Each scenario is analysed under expected and unexpected demand conditions and therefore, simulation outputs determined in Fig. 2 are calculated.

6. Results and Discussion

Simulation is a technique which has been widely used in different research areas and provides better management performance and decision support systems to the related companies or organisations by means of operational research. However, simulation on its own uses sampling from historical data distributions but does not deal with upward trends in some inputs such as demand. Such disadvantages must be avoided, particularly when simulation is used in strategic planning. The simulation technique therefore needs to be combined with forecasting methods in order to estimate the values of parameters for projection. It should be looked at what constitutes a good criterion for comparing forecasting methods, if one undertook a similar study. This is in fact an outstanding issue in the field of forecasting – there is no universally accepted measure of forecast accuracy. In fact, it seems to depend on the research area and the characteristics of the data used. The existence of particular features in the data, such as trend and seasonality, may lead to the use of certain types of forecasting techniques. Therefore, in this study, ARIMA, exponential smoothing and multiple linear regression methods are selected since these methods have been widely used and recommended as the best methods in the literature as mentioned in Section 2.1. In addition, the STLF method was also compared with the others because the hospital data contains both trend and seasonal components.

This study presents a decision support system to modelling demand and capacity compared to other studies in the literature. It combines discrete event simulation technique and quantitative forecasting in order to investigate demand and capacity of the A&E department by using 46-months of 'big' data. In this study, we use demand obtained by quantitative forecasting instead of using presumptive rates in the simulation model. We took all the laboratory processes with more than 18 tests into account in the simulation model. To develop the model that captures variation (uncertainty), statistical distributions are based on age groups so that the related times vary according to age groups. In addition, the warm-up period is determined by using Welch's method and it is added to the run length of the model. Therefore, we ensure that the system's queues are embedded in the model to behave as under normal conditions and it is run before collecting statistical results from the model. To prevent any correlations among the results of key performance metrics and reduce variance, we specify optimum replication number as 10 replications.

Demand coverage ratio (DCR) is a metric that showcases whether the hospital is able to cope with the expected and unexpected demand for A&E. The A&E has an ability in meeting demand if the DCR is around 100%. It means that available resources are sufficient to provide efficient delivery of health care in the A&E department. Otherwise, the management of the department (i.e. service managers and directors of the hospital) will need to take necessary actions against the projected demand.

In Table 9, capacity amounts are given quarterly and annually under expected and unexpected demand conditions. Firstly, the Demand Coverage Ratio (DCR) is more than 99% which means future demand is met with available resources in each scenario under the expected demand condition. In Case 2, a 5%-increase in demand causes a little reduction in meeting demand. However, this problem is removed by additional resources in Scenario 3 to 6. As the unexpected demand rises, the capability of the A&E department in meeting the demand decreases. For example, the capability in coping with demand result in the reduction by around 8%, 16%, 19% and 23% in Case 3, 4, 5 and 6 respectively in Base Scenario. An additional X-Ray is enough to achieve around 100% DCR in Case 3 although it is not adequate for Case 4, increasing DCR 83.70% to 88.28%. In addition to an additional X-Ray, an additional nurse per shift is required to meet demand in Case 4. Scenarios increase the DCR 81.08% to 98.92% in Case 5. However, all scenarios are insufficient to meet all unexpected demand in Case 5. Likewise, more planning for additional reinforcements is required in order to achieve 100% DCR in Case 6. Around 5% of the demand is not met in Case 6 despite all the listed additional resources being applied.

Fig. 5 to 9 present comparative graphs which shows the outputs of this study and how performance metrics are changed through scenarios. These graphs use two vertical axes: The axis on the left of the graph represents the Demand Coverage Ratio (DCR) as plotted using “bars” whereas the vertical axis on the right is the annual capacity in the A&E represented using “lines”. Note that in Fig. 5, out of the six scenarios only 3 lines are shown. Scenario 1 - 2 and Scenario 4 - 6 overlap as they produce identical outputs. Fig. 5 compares capacity (number of patients discharged) and demand coverage ratios (DCR) under expected (Case 1) and unexpected (other Cases) demand conditions. The A&E department’s capacity reaches the peak in each case when Scenario 6 is applied. The increase in demand results in decrease in DCR in Scenario 1 and 2. On the other hand, Scenario 3 is not able to prevent a decrease in DCR in the last three cases even with rises in DCR in the first three cases.

Fig. 6 illustrates comparison of capacity (number of patients discharged) and utilization of beds in A&E. Scenario 2 increases use of beds as additional resources (X-Ray and nurse) are integrated in to the system; the utilization of beds increase since more patients occupy more beds. In Scenario 5, as expected the addition of a bed has slightly decreased the utilization of beds. On the other hand, utilization rates of beds exceed 90% in Case 4 to 6. The A&E department’s management should take some precautions to avoid capacity issues before facing severe demands as in Cases 4 to 6.

Fig. 6 and 7 illustrate the results related to utilization rates of human resources (doctors and nurses). Utilization rates of doctors are around 84% and rise to over 90% in Case 4, 5 and 6. Likewise, utilization rate of nurses is roughly 100%. In every case, Scenario 6 includes an additional doctor per shift in the system and reduces the utilization substantially. We should be aware that scenarios such as Scenario 4 increases staffing costs. Although Scenario 4 employs an additional nurse per shift, the utilization rates of nurses remain higher in Case 4, 5 and 6.

In this study, HRG Tariff is used to calculate revenue for the A&E department for the period (February, 2012 – January, 2013). The hospitals revenue is proportional to the number of patients treated in A&E depending on patient severity, whereas for costing we have only considered staff costs. Staff cost is calculated by multiplying the number of hours treated by staff with unit cost of staff per hour. Surplus is derived by deducting costs from revenues and calculated on a quarterly and annually basis. Fig. 8 presents comparative results of average revenue and surplus. Scenarios which increase the number of patients admitted provides A&E with the highest revenue. Due to increased capacity, Cases 4, 5 and 6 dramatically increases revenue under the unexpected demand conditions. However, Scenarios 4 and 5 gives higher surplus than Scenario 6 due to doctor's salary.

7. Conclusion

We developed a decision support system which discrete event simulation was combined with comparative forecasting technique to model demand and capacity of the A&E department of the Princess Alexandra Hospital in England in this study. For this, we prepared a step by step guide as presented in the decision support system illustrating how the two techniques are combined. We have compared four forecasting methods (ARIMA, exponential smoothing, stepwise linear regression and the STLF method which has not previously applied to forecast A&E demand) and selected the best according to a forecast accuracy measure. We estimated daily A&E demand using stepwise linear regression and developed two demand conditions, namely the expected demand condition based on predicted activity, and the unexpected demand condition as requested by the hospital management in the case of closure of an A&E department at a nearby hospital. We then modelled capacity of A&E using discrete event simulation under expected and unexpected demand conditions.

The experimental results clearly illustrate that the A&E department will not be able to cope with the demand in most of the unexpected demand conditions although it has the ability of balancing demand and capacity under the expected demand condition. Additional resources tested in the scenarios will not be sufficient to cope with all demands in Case 5 (20% increase in demand) and Case 6 (25% increase in demand) although they do provide efficient delivery of healthcare in the A&E department under the expected demand conditions.

The existing A&E models were developed based on historical data, where no projections about the future had been made. Given that there is a year on year increase in A&E admissions, this is a crucial piece of information which is missing for modelling purposes. However, our A&E model (combined with forecasting) included demand inputs estimated by forecasting techniques using big data. In addition, it explored the demand-capacity balance and determined key performance metrics for the next period. The A&E model analysed how the unexpected demands are met by testing cumulative scenarios. It therefore provides a crucial decision support for A&E service managers and hospital management. This study suggests that hospitals should take an integrated approach to capturing demand and capacity using forecasting and simulation. Moreover, hospitals should stress test their systems using such techniques, as it is a useful approach to test complex systems, as illustrated above.

This article will inevitably provide many benefits to management of NHS Trusts. In relation to practical implications, the management is able to foresee patient demands for their hospital in future years and test whether they are able to cope with demand with resources at their disposable. Therefore, this will enable key decision makers to be alerted well in advance if performance targets and patient needs cannot be achieved.

In addition, decision makers can observe the impact of possible changes in resources (i.e. staff, beds, rooms) and how it effects the performance of A&E in the safety of a simulation environment. The results will bring a different perspective to the management in terms of strategic planning (both short and long term) and encourage them to develop a realistic plan. In conclusion, this study provides a crucial and practical decision support tool for hospital managers, which will benefit patients, taxpayers, the NHS and beyond.

A limitation of the study is that we did not take account of triage system's interactions with other departments (e.g. the medical assessment unit) which may impact activity and utilisation of resources. We will consider this aspect of the A&E system in our future simulation models. Further research will involve the development of similar models for outpatient and inpatient specialities which are in interaction with the A&E department.

References

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, 62-73.

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, 9-19.

Al-Refaie, A., Fouad, R. H., Li, M. & Shurrab, M. (2014). Applying simulation and DEA to improve performance of emergency department in a Jordanian hospital. *Simulation Modelling Practice and Theory*, 41, 59-72.

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

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, 48-53.

Blunt, I. (2014). Focus on: A&E attendances: why are patients waiting longer? Retrieved from http://www.qualitywatch.org.uk/sites/files/qualitywatch/field/field_document/QW%20Focus%20on%20A%26E%20attendances%20%28for%20web%29.pdf, accessed 21 June 2017.

Boutsioli, Z. (2010). Forecasting the stochastic demand for inpatient care: the case of Greek national health system. *Health Services Management Research*, 23, 116-120.

Boutsioli, Z. (2013). Estimation of unpredictable hospital demand variations in two Piraeus public hospitals, Greece. *Journal of Hospital Administration*, 2, 126-137.

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, 83-90.

Cochran, J. K. & Bharti, A. (2006). Stochastic bed balancing of an obstetrics hospital. *Health Care Management Science*, 9, 31-45.

Connelly, L. G. & Bair, A. E. (2004). Discrete event simulation of emergency department activity: a platform for system-level operations. *Academic Emergency Medicine*, 11, 1177-1185.

Cracknell, R. (2010). *The ageing population*. Key issues for the new parliament 2010, 44.

Davis, S., Stevenson, M., Tappenden, P. & Wailoo, A. J. (2014). NICE DSU technical support document 15: Cost-effectiveness modelling using patient-level simulation. Retrieved from http://www.nicedsu.org.uk, accessed 4 July 2017.

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

Demir, E., Gunal, M. & Southern, D. (2017). Demand and capacity modelling for acute services using discrete event simulation. *Health Systems*, 6, 33-40.

Department of Health. (2013). Reference costs 2012–13. Retrieved from https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/261154/nhs_reference_costs_2012-13_acc.pdf, accessed 26 May 2017.

Department of Health. (2014). Reference costs 2013–14. Retrieved from https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/380322/01_Final_2013-14_Reference_Costs_publication_v2.pdf, accessed 26 May 2017.

Duguay, C. & Chetouane, F. (2007). Modeling and improving emergency department systems using discrete event simulation. *Simulation*, 83, 311-320.

Gneiting, T. (2011). Making and evaluating point forecasts. *Journal of the American Statistical Association*, 494, 746-762.

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, 1-18 (in Turkish).

Gul, M. & Guneri A. F. (2012). A computer simulation model to reduce patient length of stay and to improve resource utilization rate in an emergency department service system. *International Journal of Industrial Engineering*, 19 (5), 221-231.

Gul, M. & Guneri, A. F. (2015). A comprehensive review of emergency department simulation applications for normal and disaster conditions. *Computers & Industrial Engineering*. 83, 327-344.

Gunal, M., & Pidd, M. (2006, December). 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.). *39th Winter Simulation Conference* (pp. 446-452). Monterey, USA.

Hamm, C. (2010). The coalition government's plans for the NHS in England. *British Medical Journal*, 341, 3790.

Hong, N. C., & Ghani, N. A. (2006, June). A Model for Predicting Average Ambulance Service Travel Times in Penang Island. *Proceedings of the 2nd IMT-GT Regional Conference on Mathematics, Statistics and Applications*. Penang Island.

Hyndman, R. J., O'Hara-Wild, M., Bergmeir, C., Razbash, S. & Wang, E. (2016). Package 'forecast'. Retrieved from https://cran.r-project.org/web/packages/forecast/forecast.pdf, accessed 26 May 2017.

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

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

Hyndman, R. J. & Koehler, A. B. (2006). Another look at measures of forecast accuracy. *International Journal of Forecasting*, 22, 679-688.

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

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, 159-170.

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, 158-165.

Komashie, A., & Mousavi, A. (2005, December). Modelling emergency departments using discrete event simulation techniques. In M. E. Kuhl, N. M. Steiger, F. B. Armstrong, & J. A., Joines (Eds.). *38th Winter Simulation Conference* (pp. 2681-2685). Orlando, USA.

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

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, 1202-1209.

Makridakis, S., Wheelwright, S. C. & Hydnman, R. J. (1998). *Forecasting Methods and Applications*. New York: John Wiley & Sons.

Marcilio, I., Hajat, S. & Gouveia, N. (2013). Forecasting daily emergency department visits using calendar variables and ambient temperature readings. *Academic Emergency Medicine*, 20, 769-777.

Mathwave Technologies (n.d.). How to select the best fitting distribution using the goodness of fit tests. Retrieved from http://www.mathwave.com/articles/distribution-fitting-goodness-of-fit.html, accessed 26 May 2017.

Medeiros, D. J., Swenson, E., & DeFlitch, C. (2008, December). 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.). *41st Winter Simulation Conference* (pp. 1526-1531). Miami, USA.

Monitor (2015). A&E delays: Why did patients wait longer? Our econometric analysis. Retrieved from https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/457824/AE_delay_econometric_model_final_document.pdf, accessed 17 November 2018.

National Health Services England. (2014). A&E Attendances and Emergency Admissions and Bed Availability and Occupancy. Retrieved from https://www.england.nhs.uk/statistics/statistical-work-areas/ae-waiting-times-and-activity/, accessed 2 June 2014.

National Health Services England. (2017a). A&E Attendances and Emergency Admissions and Bed Availability and Occupancy. Retrieved from https://www.england.nhs.uk/statistics/statistical-work-areas/ae-waiting-times-and-activity/, accessed 9 July 2017.

National Health Services England. (2017b). Bed Availability and Occupancy. Retrieved from https://www.england.nhs.uk/statistics/statistical-work-areas/bed-availability-and-occupancy/, accessed 26 May 2017.

NHS Digital (2013). NHS staff earnings estimates to June 2013 – provisional, experimental statistics. Retrieved from https://content.digital.nhs.uk/catalogue/PUB116121, accessed 26 May 2017.

NHS Digital (2014). NHS staff earnings estimates to June 2014 – provisional statistics. Retrieved from https://content.digital.nhs.uk/catalogue/PUB14955, accessed 26 May 2017.

NHS Digital (n.d.). Healthcare Research Groups (HRG4). Retrieved from http://content.digital.nhs.uk/hrg4, accessed 26 May 2017.

NHS England (2017). NHS national tariff payment system 2016/17. Retrieved from https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/509697/2016-17_National_Tariff_Payment_System.pdf, accessed 26 May 2017.

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, 29-39.

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, 61-73 (in Turkish).

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

Ripley, B., Venables, B., Bates, D. M., Hornik, K., Gebhardt, A. & Firth, D. (2016). Package 'MASS'. Retrieved from https://cran.r-project.org/web/packages/MASS/MASS.pdf, accessed 26 May 2017.

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, 135-145.

Royal College of Physicians (n.d.). Work and wellbeing in the NHS: why staff health matters to patient care. Retrieved from https://www.rcpsych.ac.uk/pdf/RCP-%20WorkWellbeingNHS.pdf, accessed 23 October 2017.

Ruohonen, T., & Teittinen, J. (2006, December). 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.). *39th Winter Simulation Conference* (pp. 453-458). Monterey, USA.

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.

Tofallis, C. (2015). A better measure of relative prediction accuracy for model selection and model estimation. *Journal of the Operational Research Society*, 66, 1352-1362.

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, 373-385.

Vasilakis, C. & El-Darzi, E. (2001). A simulation study of the winter bed crisis. *Health Care Management Science*, 4, 31-36.

Virtue, A., Kelly, J., & Chaussalet, T. (2011, December). Using simplified discrete-event simulation models for health care applications. In S. Jain, R. R. Creasey, J. Himmelspach, K. P., & M. Fu (Eds.). *44th Winter Simulation Conference* (pp. 1154-1165). Phoenix, USA.

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, 1314-1322.

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, 134-144.

Table 1. A literature review on forecasting hospital demands using time series analysis, ARMA: Autoregressive moving average, ARIMA: Autoregressive integrated moving average

Author/s (Year)	**Study type**	**Method/s used, Best method (*)**	**Independent variables**
Current Study	Daily	ARIMA Exponential Smoothing Stepwise Linear Regression (*) STLF	Days of week, month of year, a day before a holiday, holiday, a day after a holiday
Aboagye-Sarfo et al. (2015)	Monthly	ARMA Vector-ARMA (*) Exponential smoothing	Time *Dependent Variables:* Age group, place of treatment, triage category, disposition
Bergs et al. (2013)	Monthly	Exponential smoothing	-
Boutsioli (2013)	Daily	ARMA Multiple linear regression	Weekends, summer holidays, official holidays, duty
Marcilio et al. (2013)	Daily	Generalized estimating equation (*) Generalized linear model (*) Seasonal ARIMA	Days, months, public holidays, after and before days of a holiday, temperature
Kam et al. (2010)	Daily	Moving average Seasonal ARIMA Multivariate seasonal ARIMA (*)	Days, months, quarters of years, seasons, weather factors, daily temperature, holidays, near-holidays
Boutsioli (2010)	Daily	Multivariate regression model	Weekends, summer holidays, official holidays, duty
Sun et al. (2009)	Daily	ARIMA (*) General linear model	Days, months, public holidays, weather factors
Jones et al. (2008)	Daily	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)
Champion et al. (2007)	Monthly	ARIMA Single exponential smoothing (*)	-
Batal et al. (2001)	Daily	Stepwise linear regression	Days, months, seasons, holidays, after and before days of a holiday

Table 2. Comparison of studies related to accident and emergency (A&E) department, NG: Not Given

Author/s and Years	Arrival process	Data	Examination of different demand conditions	Waiting time for treatment based on age group	Treatment time based on age group	Overall waiting time based on age group	Warm-up period	Replication number	Shift	Software
Current study	Stochastic	46 months	√ - by forecasting	√	√	√	2 months	10	√	Simul8
Oh et al. (2016)	Deterministic	5 months	X	X	X	X	2 days	5	√	Arena
Al-Refaie et al. (2014)	Stochastic	NG	X	X	X	X	NG	10	X	NG
Wang et al. (2012)	Deterministic	1 month	√ - by presumptive	X	X	X	NG	NG	√	Simul8
Gul et al. (2012)	Stochastic	NG	X	X	X	X	NG	NG	√	ServiceModel
Virtue et al. (2011)	Deterministic	12 months	X	X	X	X	24 hours	50	X	Simul8
Ozdagoglu et al. (2009)	Stochastic	33 days	X	X	√	√	3 days	10	X	Arena
Medeiros et al. (2008)	NG	1 month	X	X	X	X	NG	30	X	Arena
Meng and Spedding (2008)	Stochastic	1 month	X	X	X	X	NG	NG	X	MedModel
Duguay and Chetouane (2007)	Stochastic	90 days	X	X	X	X	NG	10	√	Arena
Gunal and Pidd (2006)	Stochastic	2 months	X	X	X	X	X	50	X	Micro Saint Sharp
Ruohonen and Teittinen (2006)	Stochastic	2 weeks	X	X	X	X	NG	NG	√	MedModel
Komashie and Mousavi (2005)	Stochastic	NG	X	X	X	X	NG	NG	X	Arena

Table 3. Forecast accuracy (MASE) values of this study. ARIMA: Autoregressive integrated moving average, ES: Exponential smoothing, STLF: The function of the seasonal and trend decomposition using loess

Forecasting methods	Forecasting models	Forecast accuracy (MASE)	
		Training set	Validation set
ARIMA	(2, 0, 4)	0.7357	0.9984
ES	ETS (M, N, N)	0.7671	0.9977
Multiple linear regression	Stepwise linear regression	0.7998	0.8651
STLF	STL + ETS (A, N, N)	0.6945	0.9781

Table 4. Validation of the forecasted demand

Parameter	*t* Test value	*t* Critical value	Average number of patients (monthly)	99% Confidence interval
Forecasted demand	2.25	3.11	6781	(6358, 7204)

Table 5. Monthly distributions of interarrival times based on days-of-weeks pattern

Simulation's period		Distributions and parameters					
		Case 1 (Base model)	**Case 2 (5% Increase)**	**Case 3 (10% Increase)**	**Case 4 (15% Increase)**	**Case 5 (20% Increase)**	**Case 6 (25% Increase)**
Warm Up Period	December 2012 – January 2013	Poisson (λ=5.9355)					
Data Collection Period	February 2013	Geometric (p=0.13208)	Poisson (λ=6.2857)	Binomial (n=6, p=0.96753)	Poisson (λ=5.8571)	Geometric (p=0.15556)	Poisson (λ=5.2857)
	March 2013	Geometric (p=0.13478)	Poisson (λ=6.3871)	Poisson (λ=5.9677)	Geometric (p=0.15271)	Poisson (λ=5.3871)	Poisson (λ=5.3871)
	April 2013	Poisson (λ=6.2667)	Poisson (λ=5.9667)	Poisson (λ=5.7000)	Geometric (p=0.15957)	Poisson (λ=5.2667)	Binomial (n=5, p=0.97749)
	May 2013	Poisson (λ=6.3548)	Poisson (λ=6.0645)	Poisson (λ=5.8065)	Geometric (p=0.15736)	Poisson (λ=5.3548)	Poisson (λ=5.1935)
	June 2013	Poisson (λ=6.3000)	Binomial (n=6, p=0.96667)	Poisson (λ=5.7000)	Geometric (p=0.15873)	Poisson (λ=5.3000)	Binomial (n=5, p=0.96038)
	July 2013	Geometric (p=0.13778)	Poisson (λ=6.2581)	Poisson (λ=5.8387)	Geometric (p=0.15578)	Geometric (p=0.15979)	Poisson (λ=5.2581)
	August 2013	Poisson (λ=6.8065)	Geometric (p=0.13596)	Poisson (λ=6.3548)	Poisson (λ=5.9677)	Geometric (p=0.15423)	Poisson (λ=5.3548)
	September 2013	Poisson (λ=6.2667)	Binomial (n=6, p=0.96879)	Poisson (λ=5.6667)	Geometric (p=0.15957)	Poisson (λ=5.2667)	Binomial (n=5, p=0.96287)
	October 2013	Geometric (p=0.13778)	Poisson (λ=6.2581)	Poisson (λ=5.8710)	Geometric (p=0.15578)	Geometric (p=0.15979)	Poisson (λ=5.2581)
	November 2013	Geometric (p=0.13636)	Poisson (λ=6.3333)	Poisson (λ=5.9000)	Geometric (p=0.15464)	Poisson (λ=5.3333)	Poisson (λ=5.3333)
	December 2013	Geometric (p=0.13537)	Poisson (λ=6.3548)	Poisson (λ=5.9032)	Geometric (p=0.15271)	Poisson (λ=5.3548)	Poisson (λ=5.3548)
	January 2014	Poisson (λ=7.0323)	Geometric (p=0.13420)	Poisson (λ=6.2903)	Poisson (λ=6.1613)	Poisson (λ=5.8710)	Geometric (p=0.15897)

Table 6. The results of validation tests

Parameters	***t* Test value**	***t* Critical value**	**Average value (monthly)**	**95% Confidence intervals**
Number of admissions	1.49		7052	(6959, 7144)
Waiting time for treatment	2.02	2.20	64.21	(63.76, 64.67)
Overall waiting time	1.15		153.61	(152.93, 154.29)

Table 7. Case studies

Demand conditions	**Case studies**	**Explanations**
Expected demand	Case 1	Base model
Unexpected demand	Case 2	5% Increase
	Case 3	10% Increase
	Case 4	15% Increase
	Case 5	20% Increase
	Case 6	25% Increase

Table 8. Scenarios in this study

Scenarios	Explanations
Scenario 1	Base model
Scenario 2	Scenario 1 + increase on overall waiting time by 20%
Scenario 3	Scenario 2 + one more X-Ray
Scenario 4	Scenario 3 + one more nurse per shift
Scenario 5	Scenario 4 + one more bed
Scenario 6	Scenario 5 + one more doctor per shift

Table 9. Quarterly and annual capacity (number of patients discharged) and demand coverage ratio (DCR) of the A&E department based on case studies and scenarios at 95% confidence interval, DCR is the percentage of patients admitted to an A&E and discharged with available resources

Demand conditions	Case studies		Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5	Scenario 6
Expected demand condition	Case 1 (Base model)	Q1	20708 (20667, 20749)	20709 (20661, 20756)	20475 (20368, 20583)	20459 (20352, 20567)	20460 (20352, 20567)	20459 (20352, 20567)
		Q2	20872 (20825, 20919)	20884 (20828, 20940)	20815 (20769, 20862)	20814 (20767, 20861)	20814 (20767, 20861)	20814 (20767, 20861)
		Q3	20616 (20520, 20712)	20582 (20480, 20684)	20476 (20443, 20510)	20482 (20447, 20515)	20481 (20447, 20517)	20482 (20447, 20517)
		Q4	20144 (20065, 20224)	20161 (20088, 20234)	19971 (19907, 20035)	19967 (19903, 20031)	19967 (19903, 20031)	19967 (19903, 20031)
		Total	82340 (82076, 82604)	82336 (82057, 82614)	81737 (81487, 81989)	81722 (81469, 81975)	81722 (81469, 81975)	81722 (81469, 81975)
		DCR (%)	99.95 (99.63, 100.00)	99.94 (99.60, 100.00)	99.21 (98.91, 99.52)	99.20 (98.89, 99.50)	99.20 (98.89, 99.50)	99.20 (98.89, 99.50)
Unexpected demand condition	Case 2 (5% Increase)	Q1	21058 (21014, 21101)	21056 (21003, 21109)	21196 (21156, 21237)	21184 (21144, 21225)	21184 (21143, 21226)	21184 (21143, 21226)
		Q2	21202 (21157, 21247)	21187 (21136, 21238)	21754 (21717, 21791)	21754 (21717, 21791)	21754 (21717, 21791)	21754 (21717, 21791)
		Q3	21021 (20976, 21065)	21002 (20959, 21044)	21442 (21390, 21494)	21438 (21388, 21489)	21438 (21387, 21488)	21438 (21387, 21488)
		Q4	19959 (19858, 20059)	19969 (19852, 20086)	20528 (20466, 20590)	20536 (20469, 20602)	20536 (20469, 20602)	20536 (20469, 20602)
		Total	83240 (83006, 83472)	83214 (82949, 83477)	84920 (84728, 85112)	84912 (84718, 85106)	84912 (84716, 85107)	84912 (84716, 85107)
		DCR (%)	97.15 (96.88, 97.42)	97.12 (96.81, 97.43)	99.11 (98.89, 99.33)	99.10 (98.88, 99.33)	99.10 (98.87, 99.33)	99.10 (98.87, 99.33)
	Case 3 (10% Increase)	Q1	21376 (21329, 21423)	21379 (21330, 21428)	22320 (22289, 22351)	22560 (22521, 22599)	22560 (22521, 22600)	22560 (22521, 22600)
		Q2	21372 (21331, 21412)	21395 (21348, 21441)	22505 (22475, 22535)	22715 (22682, 22749)	22715 (22683, 22748)	22715 (22683, 22748)
		Q3	21213 (21154, 21272)	21214 (21170, 21258)	22282 (22219, 22345)	22062 (22021, 22104)	22063 (22021, 22105)	22063 (22021, 22105)
		Q4	18613 (18512, 18714)	18643 (18526, 18759)	22029 (21960, 22098)	21784 (21753, 21814)	21783 (21753, 21813)	21783 (21753, 21813)
		Total	82574 (82327, 82820)	82631 (82373, 82886)	89136 (88943, 89329)	89121 (88976, 89265)	89121 (88977, 89265)	89121 (88977, 89265)
		DCR (%)	91.91 (91.64, 92.18)	91.97 (91.69, 92.26)	99.21 (99.00, 99.43)	99.20 (99.04, 99.36)	99.20 (99.04, 99.36)	99.20 (99.04, 99.36)
	Case 4 (15% Increase)	Q1	21433 (21366, 21499)	21430 (21358, 21501)	22045 (21980, 22110)	23440 (23373, 23506)	23448 (23386, 23511)	23448 (23386, 23511)
		Q2	21562 (21514, 21610)	21552 (21516, 21589)	21766 (21700, 21833)	24401 (24316, 24486)	24392 (24301, 24483)	24392 (24301, 24483)
		Q3	21422 (21390, 21455)	21397 (21346, 21448)	22092 (22049, 22136)	23961 (23818, 24104)	23961 (23810, 24112)	23961 (23810, 24112)
		Q4	15848 (15738, 15958)	15798 (15665, 15931)	18666 (18475, 18858)	23187 (23003, 23370)	23187 (23003, 23370)	23187 (23003, 23370)
		Total	80265 (80008, 80523)	80177 (79885, 80468)	84569 (84204, 84937)	94989 (94510, 95466)	94988 (94500, 95476)	94988 (94500, 95476)
		DCR (%)	83.79 (83.52, 84.06)	83.70 (83.39, 84.00)	88.28 (87.90, 88.67)	99.16 (98.66, 99.66)	99.16 (98.65, 99.67)	99.16 (98.65, 99.67)
	Case 5 (20% Increase)	Q1	21616 (21579, 21653)	21626 (21589, 21662)	21845 (21764, 21926)	24175 (24114, 24235)	24178 (24115, 24242)	24178 (24115, 24242)
		Q2	21653 (21614, 21691)	21668 (21618, 21718)	21749 (21686, 21811)	24349 (24243, 24455)	24367 (24255, 24479)	24367 (24255, 24479)
		Q3	21551 (21508, 21593)	21539 (21492, 21585)	21724 (21662, 21785)	24379 (24265, 24493)	24381 (24274, 24488)	24381 (24274, 24488)
		Q4	15034 (14902, 15165)	15025 (14893, 15157)	16932 (16786, 17078)	24496 (24433, 24559)	24495 (24425, 24564)	24495 (24425, 24564)
		Total	79854 (79603, 80103)	79858 (79591, 80123)	82250 (81898, 82600)	97399 (97054, 97742)	97421 (97068, 97773)	97421 (97068, 97773)
		DCR (%)	81.08 (80.83, 81.34)	81.09 (80.82, 81.36)	83.52 (83.16, 83.87)	98.90 (98.55, 99.25)	98.92 (98.56, 99.28)	98.92 (98.56, 99.28)
	Case 6 (25% Increase)	Q1	21574 (21515, 21634)	21578 (21523, 21634)	21712 (21655, 21769)	24194 (24131, 24257)	24189 (24117, 24261)	24189 (24117, 24261)
		Q2	21586 (21533, 21639)	21579 (21522, 21636)	21614 (21550, 21679)	24135 (24020, 24250)	24134 (24024, 24244)	24134 (24024, 24244)
		Q3	21663 (21607, 21720)	21678 (21618, 21739)	21579 (21515, 21643)	24137 (24039, 24236)	24147 (24050, 24244)	24147 (24050, 24244)
		Q4	13768 (13613, 13922)	13748 (13618, 13877)	15470 (15200, 15741)	23999 (23858, 24139)	24027 (23888, 24165)	24027 (23888, 24165)
		Total	78591 (78267, 78914)	78583 (78282, 78885)	80375 (79920, 80832)	96465 (96048, 96882)	96497 (96078, 96915)	96497 (96078, 96915)
		DCR (%)	77.16 (76.84, 77.48)	77.15 (76.86, 77.45)	78.91 (78.47, 79.36)	94.71 (94.30, 95.12)	94.74 (94.33, 95.15)	94.74 (94.33, 95.15)

Figure 1. The structure of the decision support system

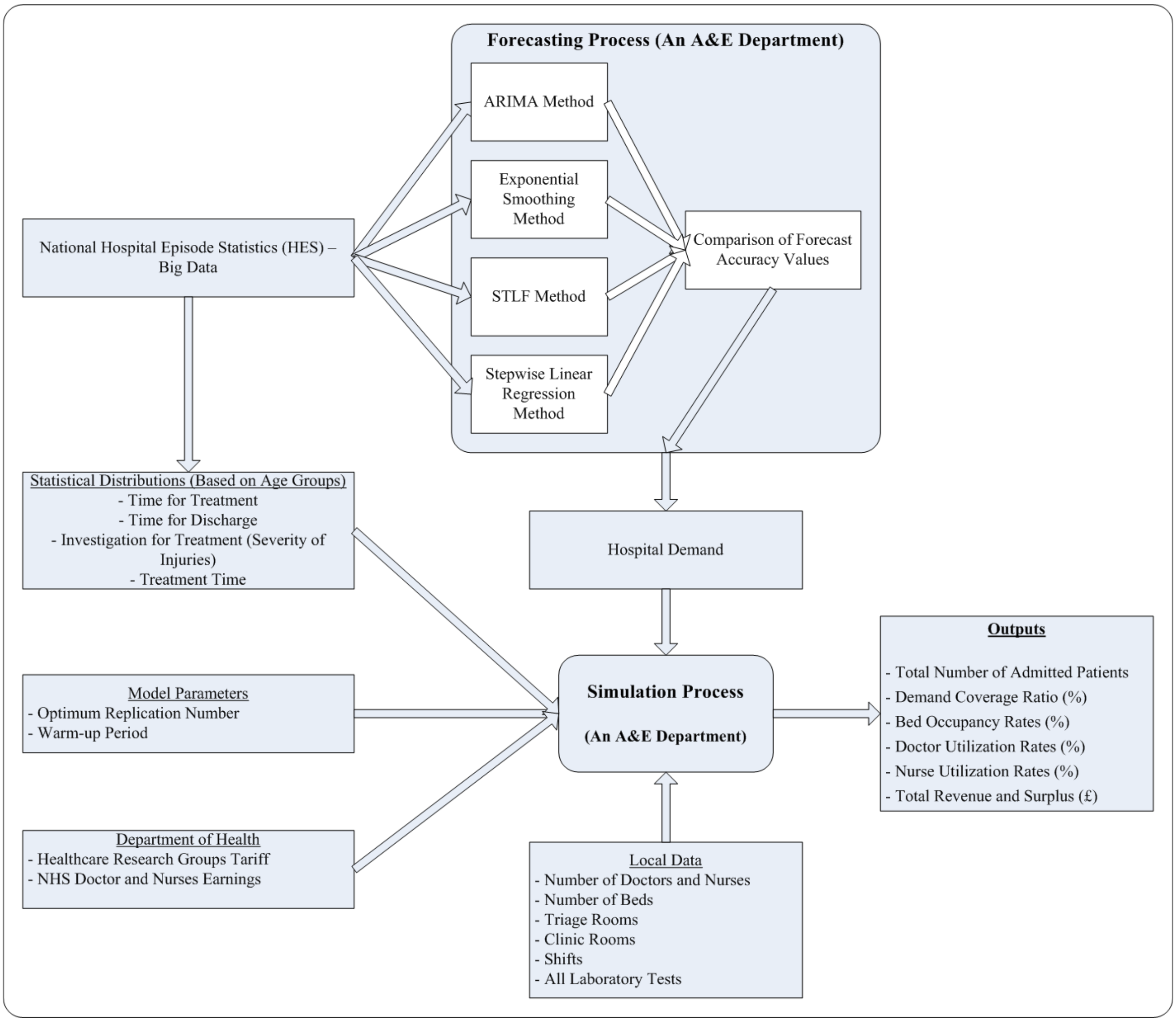


Figure 2. High level conceptualization of the accident and emergency department at the Princess Alexandra Hospital in England

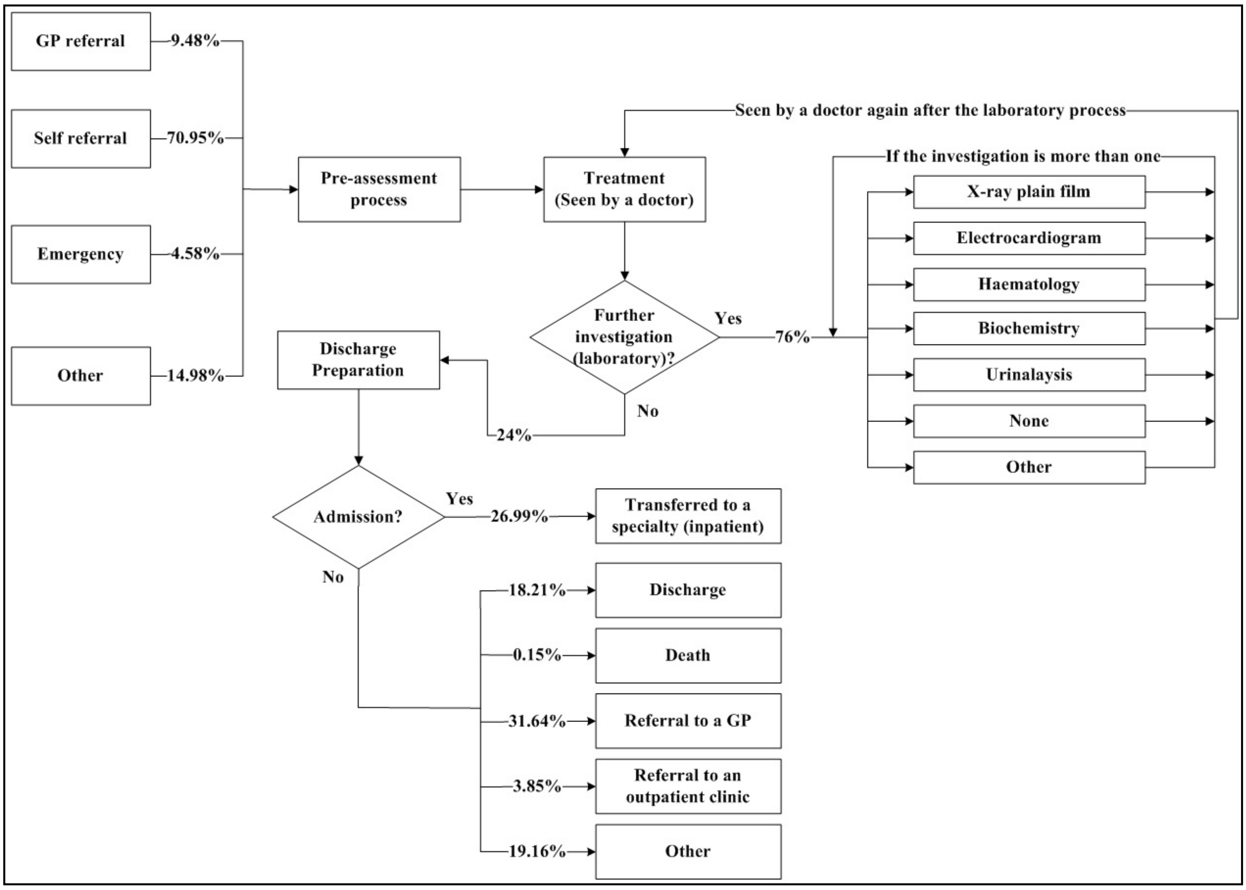


Figure 3. Inputs and outputs, HRG is Healthcare Resource Group

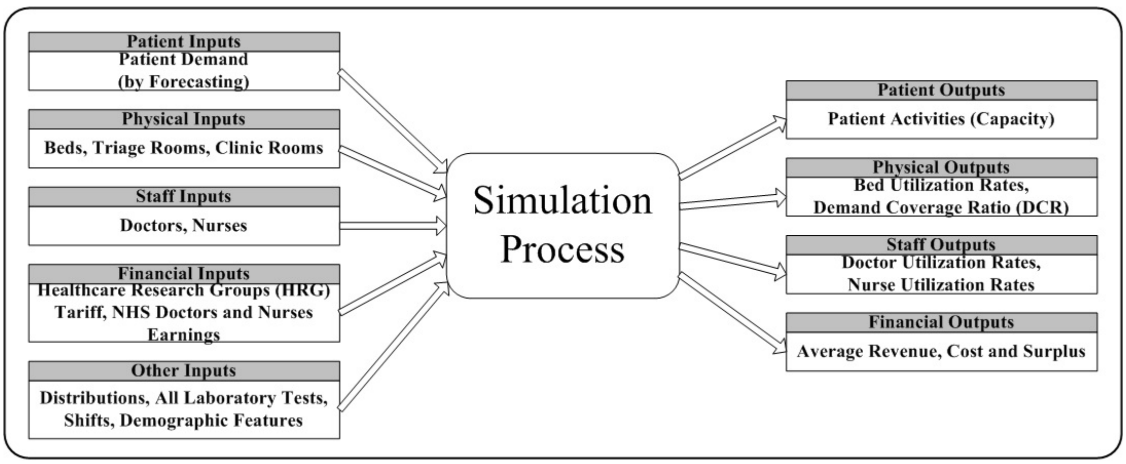


Figure 4. The structure of the A&E simulation model

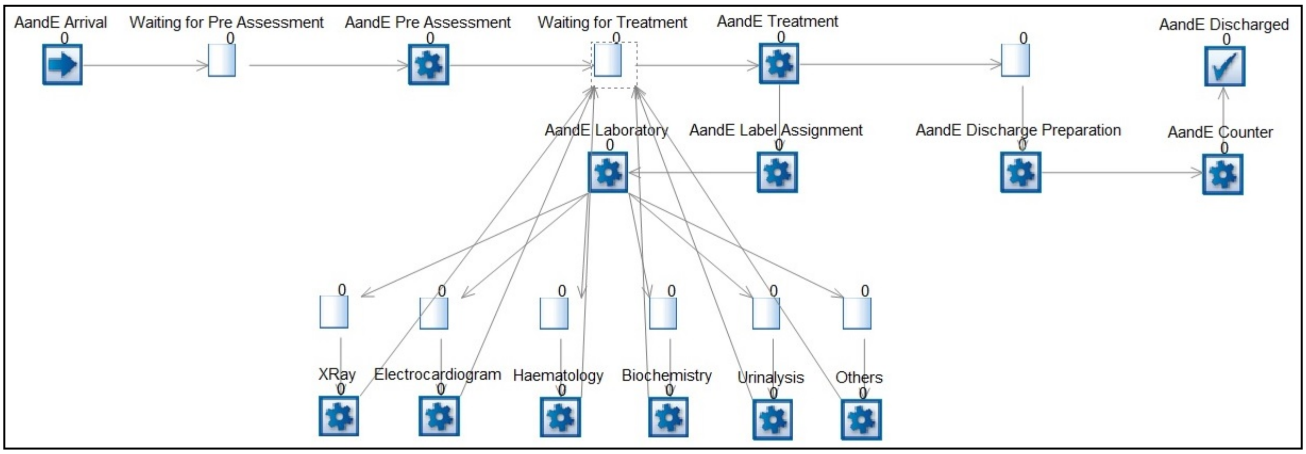


Figure 5. Comparative graphs of demand coverage ratio (DCR) and capacity

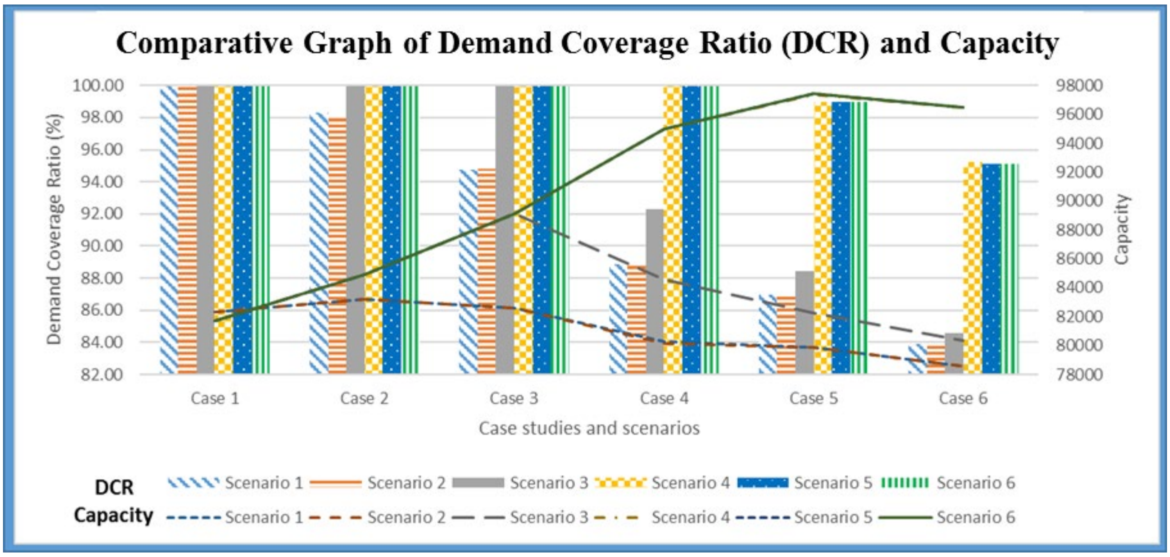


Figure 6. Comparative graphs of utilization rates of bed (URB) and capacity

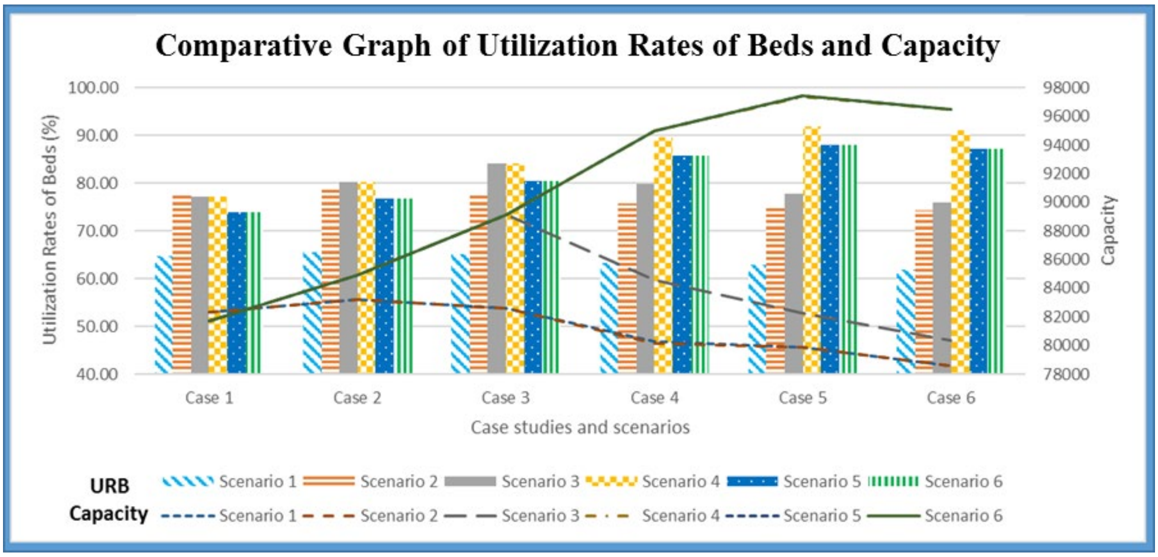


Figure 7. Comparative graphs of utilization rates of doctors (URD) and capacity

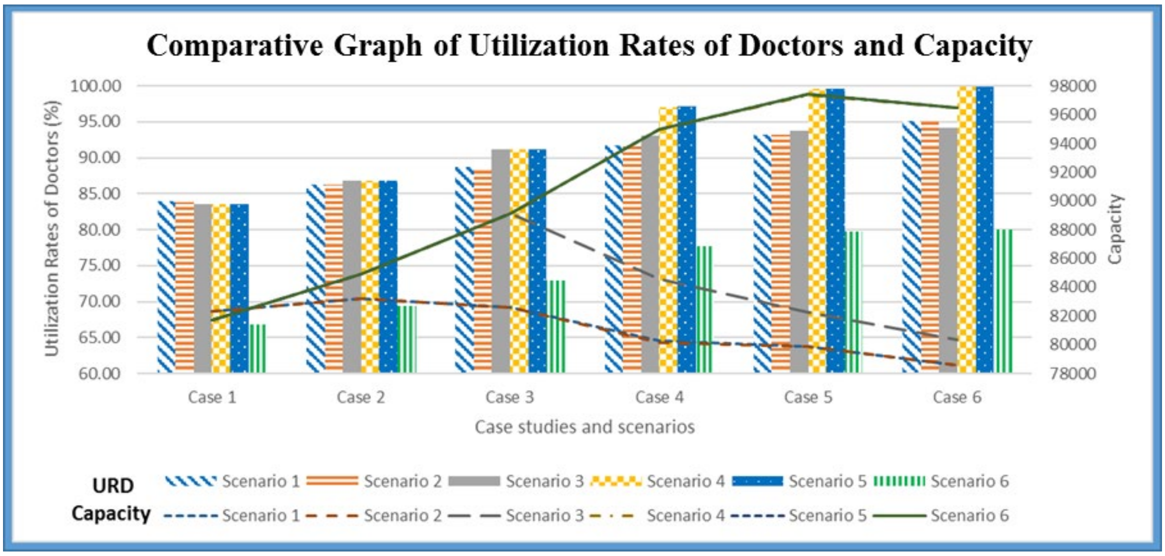


Figure 8. Comparative graphs of utilization rates of nurses (URN) and capacity

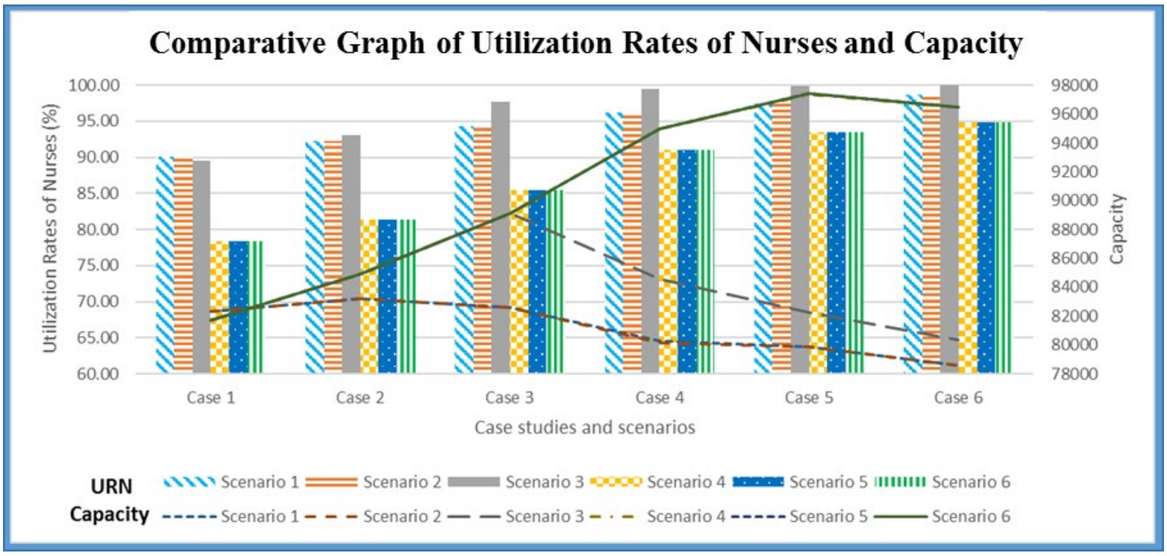
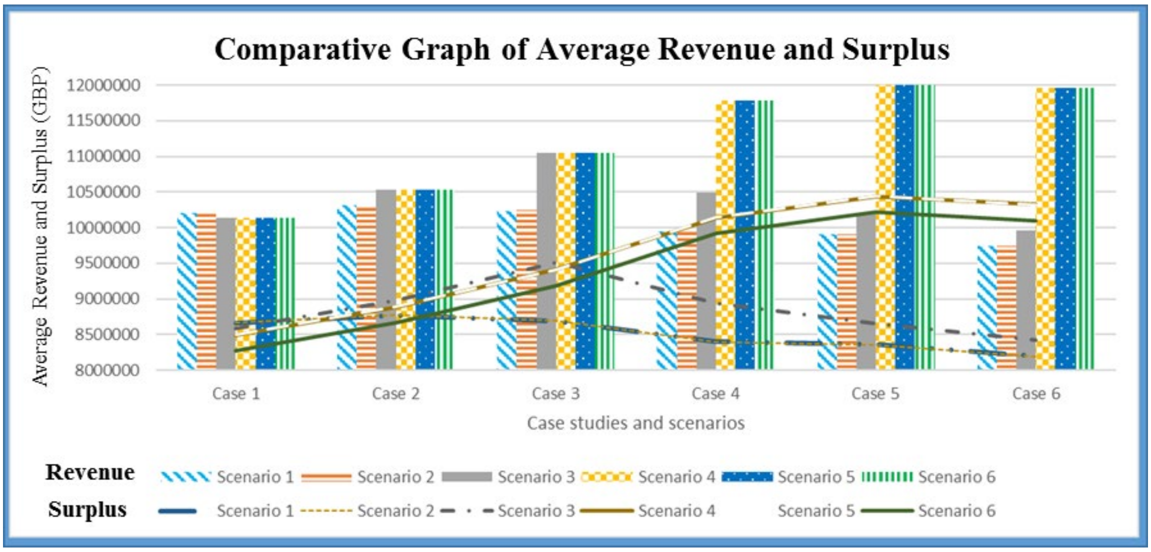


Figure 9. Comparative graphs of average revenue and surplus



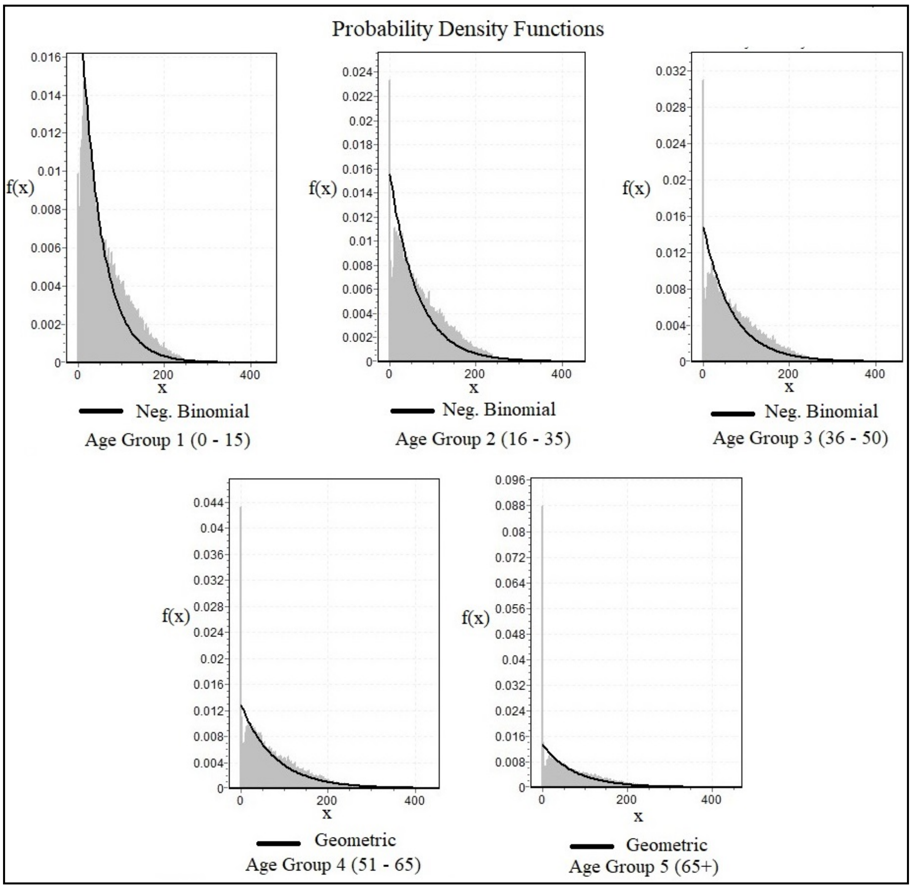
Appendix 1: Inputs parameters of the simulation model, DoH: Department of Health, HES: Hospital episodes statistics, N/A: Not available, NHS: National Health Service

Input parameters	Estimates	Distributions	References
Patient inputs			
- Available demand (2012/13)	see Table 5	see Table 5	HES dataset
- Forecasted year (2013/14)	see Table 5	see Table 5	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)
Costs in the A&E:			
- Average monthly payment to a doctor	£6178 - £6274	Average	NHS Digital (2013 and 2014)
- Average monthly payment to a nurse	£2552 - £2563	Average	NHS Digital (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
- Waiting time for pre-assessment	15 minutes	Multinomial	Expert opinion
- Pre-assessment process	10 minutes	Multinomial	Expert opinion
- Waiting time for treatment	See Appendix 2 and Appendix 3	See Appendix 2 and Appendix 3	HES dataset
- Treatment time	Frequency distribution	Frequency distribution	HES dataset
- Waiting time for discharge	See Appendix 4 and Appendix 5	See Appendix 4 and Appendix 5	HES dataset

Appendix 2: Comparative test results and parameter values of fitting distributions for waiting time for treatment (by each age group)

Distributions	Age Group 1 (0 – 15)		Age Group 2 (16 – 35)		Age Group 3 (36 – 50)		Age Group 4 (51 – 65)		Age Group 5 (65+)	
	Kolmogorov Smirnov	Anderson Darling	Kolmogorov Smirnov	Anderson Darling	Kolmogorov Smirnov	Anderson Darling	Kolmogorov Smirnov	Anderson Darling	Kolmogorov Smirnov	Anderson Darling
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic
Normal	0.12923	2099.70	0.13879	2422.90	0.14521	1454.30	0.16594	1337.60	0.17456	2315.30
Triangular	0.72610	86722.00	0.69821	94712.00	0.69742	55558.00	0.69360	40774.00	0.70196	83634.00
Rounded Uniform	0.17436	16625.00	0.18930	16112.00	0.19679	8996.30	0.22222	5816.10	0.23048	10818.00
Uniform	0.17379	16495.00	0.18657	15988.00	0.19482	8905.70	0.21989	5773.10	0.22971	10754.00
Exponential	0.06663	557.04	0.06177	795.44	0.05583	389.93	0.04596	207.67	0.07516	718.60
Erlang	0.13537	3929.10	0.12344	3171.30	0.10218	1179.80	No fit	No fit	No fit	No fit
Log Normal	0.06010	513.37	0.08475	1577.20	0.09208	1081.20	0.10092	971.83	0.13096	2769.40
Weibull	0.04054	173.41	0.13330	3866.90	0.03498	148.87	0.04517	188.78	0.06858	885.00
Gamma	0.02868	99.90	0.03245	222.74	0.03653	170.08	0.05291	247.91	0.06844	664.64
Beta	0.14541	4822.80	0.08022	8362.60	0.05944	1529.80	0.05865	5705.50	0.08795	12296.00
Pearson V	0.13806	3096.40	0.21034	7659.80	0.22249	4900.40	0.24150	3894.60	0.26344	7804.10
Pearson VI	0.03141	109.18	0.03129	192.54	0.06170	486.27	0.05301	240.84	0.06645	678.68
Gauss	0.10574	3296.20	0.09362	6199.20	0.09447	4531.00	0.09259	4234.40	0.13080	21378.00
Poisson	0.47940	2.9599E+5	0.46884	3.4596E+5	0.46908	2.0249E+5	0.48098	1.4773E+5	0.48196	2.6785E+5
Binomial	No fit	No fit	No fit	No fit	No fit	No fit	No fit	No fit	No fit	No fit
Negative Binomial	**0.02374**	**94.47**	**0.02732**	**155.15**	**0.03375**	**148.45**	No fit	No fit	No fit	No fit
Bernoulli	No fit	No fit	No fit	No fit	No fit	No fit	No fit	No fit	No fit	No fit
Geometric	0.07811	774.29	0.06938	998.22	0.11182	1486.40	**0.03524**	**161.62**	**0.06233**	**477.29**
Parameters	(n=1, p=0.02035)		(n=1, p=0.01572)		(n=1, p=0.01491)		(p=0.01289)		(p=0.01337)	

Appendix 3: Probability density function graphs for distributions of "waiting time for treatment" for each age group



Appendix 4: Comparative test results and parameter values of fitting distributions of waiting time for discharge (by each age group)

Distributions	Age Group 1 (0 – 15)		Age Group 2 (16 – 35)		Age Group 3 (36 – 50)		Age Group 4 (51 – 65)		Age Group 5 (65+)	
	Kolmogorov Smirnov Statistic	Anderson Darling Statistic	Kolmogorov Smirnov Statistic	Anderson Darling Statistic	Kolmogorov Smirnov Statistic	Anderson Darling Statistic	Kolmogorov Smirnov Statistic	Anderson Darling Statistic	Kolmogorov Smirnov Statistic	Anderson Darling Statistic
Normal	0.20660	3499.20	0.21681	4758.40	0.18845	2070.30	0.17422	1357.00	0.10933	1495.20
Triangular	0.70813	98696.00	0.68889	1.1465E+5	0.66845	55713.00	0.65161	34414.00	0.62277	44780.00
Rounded Uniform	0.26538	14884.00	0.27653	14027.00	0.24699	7684.80	0.23098	5817.80	0.14521	11660.00
Uniform	0.26379	14815.00	0.27396	13862.00	0.24492	7679.80	0.22933	5828.70	0.14491	11648.00
Exponential	0.09458	916.43	0.10103	1934.50	0.08063	644.23	0.07091	419.73	0.13337	1978.80
Erlang	No fit	No fit	No fit	No fit	No fit	No fit	No fit	No fit	0.28874	10603.00
Log Normal	0.09328	1614.20	0.08845	1943.00	0.10860	1476.40	0.12836	1393.20	0.17493	4045.80
Weibull	0.06740	305.37	0.06490	454.72	0.06117	375.58	0.08673	452.96	0.14490	2044.90
Gamma	**0.05078**	**278.89**	**0.05633**	**410.83**	0.05852	311.09	0.06349	366.75	**0.08135**	**1333.40**
Beta	0.06579	4573.90	0.06745	19416.00	0.06324	2699.20	0.06462	5746.80	0.15577	9192.60
Pearson V	0.21863	5429.50	0.21196	6395.60	0.22414	4577.20	0.24988	3950.60	0.30445	10262.00
Pearson VI	0.06859	348.64	0.06459	491.18	**0.05849**	**311.08**	0.06760	373.05	0.11909	1678.50
Gauss	0.14898	14917.00	0.16125	21451.00	0.15557	14078.00	0.14419	10511.00	0.12057	20250.00
Poisson	0.52731	3.3229E+5	0.53841	4.4603E+5	0.50976	2.2846E+5	0.48435	1.4293E+5	0.41942	2.0181E+5
Binomial	No fit	No fit	No fit	No fit	No fit	No fit	No fit	No fit	No fit	No fit
Negative Binomial	No fit	No fit	No fit	No fit	No fit	No fit	No fit	No fit	0.29493	11176.00
Bernoulli	No fit	No fit	No fit	No fit	No fit	No fit	No fit	No fit	No fit	No fit
Geometric	0.07952	518.96	0.08804	1279.00	0.06968	424.11	**0.06151**	**319.86**	0.13584	1994.10

Parameters	(α=0.6916, β=90.064)	(α=0.63069, β=112.98)	(α_1=0.79911, α_2 =2.4519E+6, β=2.6279E+8)	(p=0.00983)	(α=1.5365, β=85.049)

Appendix 5: Probability density function graphs for distributions of waiting time for discharge (by each age group)