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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, 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.

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

 $MASE = mean(|q_t|) (2)$

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 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 daysof-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.

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

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).

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

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.

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

where *n* is initial replication number, *i* is required replication number, *S* is standard deviation, γ' is "adjusted" relative error and \overline{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 $n_Y^*(Y)$ is less than or equal to Y' 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).

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

(4) Graphs of moving averages of $\overline{Y}_i(w)$ 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.

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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, |
|----------|------------|------------|------------|--------------|-----------|-------|-------------|
| | 1 | | | | 0 1 | () | |

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 | \checkmark | V | \checkmark | 2 months | 10 | V | Simul8 |
| Oh et al. (2016) | Deterministic | 5 months | Х | Х | Х | Х | 2 days | 5 | \checkmark | Arena |
| Al-Refaie et al. (2014) | Stochastic | NG | Х | Х | Х | Х | NG | 10 | Х | NG |
| Wang et al. (2012) | Deterministic | 1 month | √ - by presumptive | Х | Х | Х | NG | NG | V | Simul8 |
| Gul et al. (2012) | Stochastic | NG | Х | Х | Х | Х | NG | NG | \checkmark | ServiceModel |
| Virtue et al. (2011) | Deterministic | 12 months | Х | Х | Х | Х | 24 hours | 50 | Х | Simul8 |
| Ozdagoglu et al. (2009) | Stochastic | 33 days | Х | Х | V | V | 3 days | 10 | Х | Arena |
| Medeiros et al. (2008) | NG | 1 month | Х | Х | Х | Х | NG | 30 | Х | Arena |
| Meng and Spedding (2008) | Stochastic | 1 month | Х | Х | Х | Х | NG | NG | Х | MedModel |
| Duguay and Chetouane (2007) | Stochastic | 90 days | Х | Х | Х | Х | NG | 10 | \checkmark | Arena |
| Gunal and Pidd (2006) | Stochastic | 2 months | Х | Х | Х | Х | Х | 50 | Х | Micro Saint Sharp |
| Ruohonen and Teittinen (2006) | Stochastic | 2 weeks | X | X | X | X | NG | NG | V | MedModel |
| Komashie and Mousavi (2005) | Stochastic | NG | Х | Х | Х | Х | NG | NG | Х | 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

| Equalating matheda | Forecasting models | Forecast accuracy (MASE) | | | |
|----------------------------|----------------------------|--------------------------|----------------|--|--|
| Forecasting methous | Forecasting models | 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 | <i>t</i> Test value | <i>t</i> Critical value | Average number of patients (monthly) | 99% Confidence interval |
|-------------------|------------------------|-------------------------|--------------------------------------|----------------------------|
| Forecasted demand | 2.25 | 3.11 | 6781 | (6358, 7204) |

| | | | | Distributions a | nd parameters | | |
|---------------------|---------------------------------|--------------------------|------------------------------|------------------------------|--------------------------|--------------------------|------------------------------|
| Simulation's period | | Case 1 | Case 2 | Case 3 | Case 4 | Case 5 | Case 6 |
| | | (Base model) | (5% Increase) | (10% Increase) | (15% Increase) | (20% Increase) | (25% Increase) |
| Warm Up Period | December 2012 – January 2013 | | | Poisson (λ | =5.9355) | | |
| | 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 $(\lambda=5.7000)$ | 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) |
| Data Collection | 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) |
| Period | 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 5. Monthly distributions of interarrival times based on days-of-weeks pattern

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 |
| | Case 2 | 5% Increase |
| | Case 3 | 10% Increase |
| Unexpected demand | 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 |
|-------------------|----------------|----------|-------------------------|-------------------------|------------------------|------------------------|--------------------------|------------------------|
| | | 01 | 20708 | 20709 | 20475 | 20459 | 20460 | 20459 |
| | | ×- | (20667, 20749) | (20661, 20756) | (20368, 20583) | (20352, 20567) | (20352, 20567) | (20352, 20567) |
| | | Q2 | (20825, 20010) | 20884 | 20815 | 20814 | 20814 | 20814 |
| | | | 20616 | 20582 | 20476 | 20482 | 20481 | 20482 |
| Expected demand | Case 1 | Q3 | (20520, 20712) | (20480, 20684) | (20443, 20510) | (20447, 20515) | (20447, 20517) | (20447, 20517) |
| condition | (Base model) | 04 | 20144 | 20161 | 19971 | 19967 | 19967 | 19967 |
| | | Q4 | (20065, 20224) | (20088, 20234) | (19907, 20035) | (19903, 20031) | (19903, 20031) | (19903, 20031) |
| | | Total | 82340 | 82336 | 81737 | 81722 | 81722 | 81722 |
| | | | (82076, 82604) | (82057, 82614) | (81487, 81989) | (81469, 81975) | (81469, 81975) | (81469, 81975) |
| | | DCR (%) | 99.95 | 99.94 | 99.21 (08.01.00.52) | 99.20 | 99.20 | (08 80 00 50) |
| | | | 21058 | 21056 | 21196 | 21184 | 21184 | 21184 |
| | | Q1 | (21014, 21101) | (21003, 21109) | (21156, 21237) | (21144, 21225) | (21143, 21226) | (21143, 21226) |
| | | 02 | 21202 | 21187 | 21754 | 21754 | 21754 | 21754 |
| | | Q2 | (21157, 21247) | (21136, 21238) | (21717, 21791) | (21717, 21791) | (21717, 21791) | (21717, 21791) |
| | | 03 | 21021 | 21002 | 21442 | 21438 | 21438 | 21438 |
| | Case 2 | | (20976, 21065) | (20959, 21044) | (21390, 21494) | (21388, 21489) | (21387, 21488) | (21387, 21488) |
| | (5% merease) | Q4 | (19858-20059) | (19852 20086) | (20466, 20590) | (20469-20602) | (20469, 20602) | (20469-20602) |
| | | | 83240 | 83214 | 84920 | 84912 | 84912 | 84912 |
| | | Total | (83006, 83472) | (82949, 83477) | (84728, 85112) | (84718, 85106) | (84716, 85107) | (84716, 85107) |
| | | DCP (%) | 97.15 | 97.12 | 99.11 | 99.10 | 99.10 | 99.10 |
| | | DCR (70) | (96.88, 97.42) | (96.81, 97.43) | (98.89, 99.33) | (98.88, 99.33) | (98.87, 99.33) | (98.87, 99.33) |
| | | Q1 | 21376 | 21379 | 22320 | 22560 | 22560 | 22560 |
| | | | (21329, 21423) | (21530, 21428) | (22289, 22551) | (22521, 22599) | (22521, 22600) | (22521, 22600) |
| | | Q2 | (21331, 21412) | (21348, 21441) | (22475, 22535) | (22682, 22749) | (22683, 22748) | (22683, 22748) |
| | | 00 | 21213 | 21214 | 22282 | 22062 | 22063 | 22063 |
| | Case 3 | Q3 | (21154, 21272) | (21170, 21258) | (22219, 22345) | (22021, 22104) | (22021, 22105) | (22021, 22105) |
| | (10% Increase) | 04 | 18613 | 18643 | 22029 | 21784 | 21783 | 21783 |
| | | V | (18512, 18714) | (18526, 18759) | (21960, 22098) | (21753, 21814) | (21753, 21813) | (21753, 21813) |
| | | Total | 82574 | 82631 | 89136 | 89121 | 89121 | 89121 |
| | | | (82327, 82820) 91.91 | (82373, 82880) 91.97 | (88943, 89329) | (88970, 89203) | (88977, 89203) | (88977, 89203) |
| | | DCR (%) | (91.64, 92.18) | (91.69, 92.26) | (99.00, 99.43) | (99.04, 99.36) | (99.04, 99.36) | (99.04, 99.36) |
| | | 01 | 21433 | 21430 | 22045 | 23440 | 23448 | 23448 |
| | | QI | (21366, 21499) | (21358, 21501) | (21980, 22110) | (23373, 23506) | (23386, 23511) | (23386, 23511) |
| | | 02 | 21562 | 21552 | 21766 | 24401 | 24392 | 24392 |
| | | | (21514, 21610) | (21516, 21589) | (21700, 21833) | (24316, 24486) | (24301, 24483) | (24301, 24483) |
| Unexpected demand | Case 4 | Q3 | (21390, 21455) | (21346, 21448) | (22049, 22136) | (23818 24104) | (23810, 24112) | (23810, 24112) |
| condition | (15% Increase) | | 15848 | 15798 | 18666 | 23187 | 23187 | 23187 |
| | · · · · | Q4 | (15738, 15958) | (15665, 15931) | (18475, 18858) | (23003, 23370) | (23003, 23370) | (23003, 23370) |
| | | Total | 80265 | 80177 | 84569 | 94989 | 94988 | 94988 |
| | | 1000 | (80008, 80523) | (79885, 80468) | (84204, 84937) | (94510, 95466) | (94500, 95476) | (94500, 95476) |
| | | DCR (%) | 83.79 | 83.70 | 88.28 | 99.16 | 99.16 | 99.16 |
| | | | 21616 | 21626 | 21845 | 24175 | 24178 | 24178 |
| | | Q1 | (21579, 21653) | (21589, 21662) | (21764, 21926) | (24114, 24235) | (24115, 24242) | (24115, 24242) |
| | | 02 | 21653 | 21668 | 21749 | 24349 | 24367 | 24367 |
| | | Q2 | (21614, 21691) | (21618, 21718) | (21686, 21811) | (24243, 24455) | (24255, 24479) | (24255, 24479) |
| | 0.5 | Q3 | 21551 | 21539 | 21724 | 24379 | 24381 | 24381 |
| | (20% Increase) | | (21508, 21593) | (21492, 21585) | (21662, 21/85) | (24265, 24493) | (24274, 24488) | (24274, 24488) |
| | (2070 mercase) | Q4 | (14902, 15165) | (14893 15157) | (16786 17078) | (24433 24559) | $(24425 \ 24564)$ | $(24425 \ 24564)$ |
| | | T (1 | 79854 | 79858 | 82250 | 97399 | 97421 | 97421 |
| | | 1 otal | (79603, 80103) | (79591, 80123) | (81898, 82600) | (97054, 97742) | (97068, 97773) | (97068, 97773) |
| | | DCR (%) | 81.08 | 81.09 | 83.52 | 98.90 | 98.92 | 98.92 |
| | | | (80.83, 81.34) | (80.82, 81.36) | (83.16, 83.87) | (98.55, 99.25) | (98.56, 99.28) | (98.56, 99.28) |
| | | Q1 | 21574 | 21578 | 21/12 (21655-21760) | 24194 (24131 24257) | 24189 (24117 - 24261) | 24189 (24117 24261) |
| | | - | 21515, 21054) | 21525, 21054) | 21614 | 24135 | 24134 | 24134 |
| | | Q2 | (21533, 21639) | (21522, 21636) | (21550, 21679) | (24020, 24250) | (24024, 24244) | (24024, 24244) |
| | | 02 | 21663 | 21678 | 21579 | 24137 | 24147 | 24147 |
| | Case 6 | Q3 | (21607, 21720) | (21618, 21739) | (21515, 21643) | (24039, 24236) | (24050, 24244) | (24050, 24244) |
| | (25% Increase) | 04 | 13768 | 13748 | 15470 | 23999 | 24027 | 24027 |
| | | χ. | (13613, 13922) | (13618, 13877) | (15200, 15741) | (23858, 24139) | (23888, 24165) | (23888, 24165) |
| | | Total | 78267 78914) | 10000 (78282 78885) | 00373 (79920 80832) | 90400 (96048 96882) | 90497 (96078 96915) | 90497 (96078 96915) |
| | | | 77.16 | 77.15 | 78.91 | 94.71 | 94.74 | 94.74 |
| | | DCR (%) | (76.84, 77.48) | (76.86, 77.45) | (78.47, 79.36) | (94.30, 95.12) | (94.33, 95.15) | (94.33, 95.15) |





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 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





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

| Inputs Estimates Distributions References - Available demand (2012/13) see Table 5 see Table 5 HES dataset - Norder of beds 22 Fixed Local data - Number of beds 22 Fixed Local data - Number of clinic rooms 4 Fixed Local data - Number of dectors 12 Fixed Local data - Number of funces 21 Fixed DoH (2013 and 2014) - VB01Z £235 £237 Fixed DoH (2013 and 2014) - VB02Z £235 £210 Fixed DoH (2013 and 2014) - VB03Z £151 £130 Fixed DoH (2013 and 2014) - VB04Z £151 £130 Fixed DoH (2013 and 2014) - VB05Z £12 £110 Fixed DoH (2013 and 2014) - VB06Z £11 £113 Fixed | | | | D f |
|--|---|---------------------------|------------------------|-----------------------------|
| Patient inputs- Available demand (2012/13)see Table 5see Table 5HES dataset- Number of beds22FixedLocal data- Number of triage rooms5FixedLocal data- Number of clinic rooms4FixedLocal data- Number of doctors12FixedLocal data- Number of doctors12FixedLocal data- Number of doctors12FixedLocal data- Number of nurses21FixedLocal data- Number of nurses21FixedLocal data- Number of Doctors12FixedLocal data- Number of Doctors12FixedDoH (2013 and 2014)- VB01Z£235 + £237FixedDoH (2013 and 2014)- VB02Z£235 + £210FixedDoH (2013 and 2014)- VB04Z£151 + £164FixedDoH (2013 and 2014)- VB05Z£151 + £161FixedDoH (2013 and 2014)- VB05Z£151 - £1130FixedDoH (2013 and 2014)- VB05Z£121 - £110FixedDoH (2013 and 2014)- VB07Z£112 - £110FixedDoH (2013 and 2014)- VB07Z£2552 - £2563AverageNHS Digital (2013 and 2014)- Average monthly payment to a doctor£6178 - £6274Average- Average monthly payment to a doctor£6178 - £6274Average- Average monthly payment to a unexe£2552 - £2563Average- Age group 1 (0 - 15)23%Multinomial <td< td=""><td>Input parameters</td><td>Estimates</td><td>Distributions</td><td>References</td></td<> | Input parameters | Estimates | Distributions | References |
| - Available demain (2012/15) see Table 5 see Table 5 see Table 5 N/A Physical inputs - - - - Namber of beds 22 Fixed Local data - Number of beds 22 Fixed Local data Local data - Number of beds 21 Fixed Local data - Number of clinic rooms 4 Fixed Local data - Number of dectors 12 Fixed Local data - Number of fuces 21 Fixed Local data - Number of fuces 12 Fixed Dolf (2013 and 2014) - VB012 £235 - £237 Fixed Dolf (2013 and 2014) - VB022 £151 - £164 Fixed Dolf (2013 and 2014) - VB052 £151 - £130 Fixed Dolf (2013 and 2014) - VB052 £112 - £119 Fixed Dolf (2013 and 2014) - VB052 £1212 - £110 | Patient inputs | T 11 6 | T 11 5 | |
| - Forecasted year (2015) (4) see Table 3 see Table 3 N/A Physical inputs 22 Fixed Local data - Number of bridge rooms 5 Fixed Local data - Number of diring rooms 4 Fixed Local data - Number of doctors 12 Fixed Local data - Number of doctors 12 Fixed Local data - Number of nurses 21 Fixed Doft (2013 and 2014) - VB0/2 £235 £237 Fixed Doft (2013 and 2014) - VB0/2 £151 £164 Fixed Doft (2013 and 2014) - VB0/2 £151 £1730 Fixed Doft (2013 and 2014) - VB0/2 £151 £1130 Fixed Doft (2013 and 2014) - VB0/2 £112 £110 Fixed Doft (2013 and 2014) - VB0/2 £2525 £2563 Average NHS Digital (2013 and 20 - Average monthly payment to a doctor< | - Available demand $(2012/13)$ | see Table 5 | see Table 5 | HES dataset |
| Provided inputs22FixedLocal dataNumber of friage rooms5FixedLocal dataNumber of clinic rooms4FixedLocal dataStaff inputs4FixedLocal dataNumber of nurses12FixedLocal dataNumber of nurses21FixedLocal dataRevenues in the A&E (HRG Codes for severity of2012/13 - 2013/14FixedLocal dataVB01Z£235 - £237FixedDoH (2013 and 2014)- VB02Z£235 - £210FixedDoH (2013 and 2014)- VB04Z£151 - £164FixedDoH (2013 and 2014)- VB04Z£151 - £130FixedDoH (2013 and 2014)- VB05Z£151 - £110FixedDoH (2013 and 2014)- VB06Z£81 - £102FixedDoH (2013 and 2014)- VB07Z£151 - £119FixedDoH (2013 and 2014)- VB08Z£112 - £119FixedDoH (2013 and 2014)- VB07Z£12 - £110FixedDoH (2013 and 2014)- VB07Z£12 - £110FixedDoH (2013 and 2014)- VB07Z£12 - £110FixedDoH (2013 and 2014)- VB07Z£112 - £110FixedDoH (2013 and 2014)- VB07Z£252 - £253AverageNHS Digital (2013 and 20- Average monthly payment to a doctor£6178 - £6274Average- Average monthly payment to a nurse£252 - £253Average- Age group 1 (0 - 15)23%Multinomial- Age group 2 (16 - 35)28%Mult | - Folecasted year (2015/14) | see Table 5 | see Table 5 | IN/A |
| - Number of linger coms 122 Priced Local data - Number of linger coms 4 Fixed Local data - Number of linger coms 4 Fixed Local data - Number of doctors 12 Fixed Local data - Number of nurses 21 Fixed Local data - Average monthly payment to a doctor for S- f6078 - f | Physical inputs | 22 | Firred | L agal data |
| - Number of Linker of clinic rooms 3 1 Ked Local data - Number of altine rooms 4 Fixed Local data Staff inputs 21 Fixed Local data - Number of detors 21 Fixed Local data - Number of nurses 21 Fixed Local data Financial inputs 2 2012/13 - 2013/14 Fixed Local data - 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 - £102 Fixed DoH (2013 and 2014) - VB06Z £81 - £102 Fixed DoH (2013 and 2014) - VB08Z £112 - £119 Fixed DoH (2013 and 2014) - VB08Z £112 - £110 Fixed DoH (2013 and 2014) - Average monthly payment to a doctor £6178 - £6274 Average NHS Digital (2013 and 2014) - Average monthly payment to a doctor £6178 - £6274 Average NHS Digital (2013 and 2014) - Average monthly payment to a doctor £6178 - £6274 Average NHS Digital (2013 and 2014) <td>- Number of triage rooms</td> <td>5</td> <td>Fixed</td> <td>Local data</td> | - Number of triage rooms | 5 | Fixed | Local data |
| - Value of the roots - 4 - Fixed - Local data - Number of doctors 12 Fixed Local data - Number of doctors 21 Fixed Local data - Number of nurses 21 Fixed Local data Financial inputs 2012/13 - 2013/14 - Local data - VB01Z £235 - £237 Fixed DoH (2013 and 2014) - VB02Z £235 - £210 Fixed DoH (2013 and 2014) - VB05Z £151 - £164 Fixed DoH (2013 and 2014) - VB05Z £151 - £130 Fixed DoH (2013 and 2014) - VB05Z £151 - £110 Fixed DoH (2013 and 2014) - VB06Z £151 - £110 Fixed DoH (2013 and 2014) - VB05Z £151 - £110 Fixed DoH (2013 and 2014) - VB06Z £112 - £110 Fixed DoH (2013 and 2014) - VB07Z £112 - £110 Fixed DoH (2013 and 2014) - 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) - Average monthly payment to a nurse £2552 - £2563 Average NHS Digital (2013 and 2014) 2 | - Number of clinic rooms | 5 | Fixed | Local data |
| Starting of • Number of doctors12FixedLocal data• Number of nurses21FixedLocal dataFinancial inputs Revenues in the A&E (HRG Codes for severity of injuries):2012/13 – 2013/14FixedDoH (2013 and 2014)• VB01Z£235 - £237FixedDoH (2013 and 2014)• VB02Z£235 - £237FixedDoH (2013 and 2014)• VB02Z£235 - £237FixedDoH (2013 and 2014)• VB04Z£151 - £164FixedDoH (2013 and 2014)• VB05Z£151 - £139FixedDoH (2013 and 2014)• VB06Z£151 - £102FixedDoH (2013 and 2014)• VB07Z£112 - £110FixedDoH (2013 and 2014)• VB07Z£112 - £110FixedDoH (2013 and 2014)• VB08Z£112 - £110FixedDoH (2013 and 2014)• Costs in the A&E: • - Average monthly payment to a doctor£6178 - £6274Average• Average monthly payment to a nurse£2552 - £253AverageNHS Digital (2013 and 20• Average monthly payment to a nurse£2552 - £253AverageNHS Digital (2013 and 20• Cender1Age group 3 (36 - 50)16%MultinomialHES dataset• Age group 3 (36 - 50)16%MultinomialHES dataset• Age group 5 (65+)12%MultinomialHES dataset• Laboratory process: • Laboratory process:11%11%MultinomialHES dataset• Laboratory service1.12%MultinomialHES dataset <td>- Number of chine rooms</td> <td>4</td> <td>Fixed</td> <td>Local data</td> | - Number of chine rooms | 4 | Fixed | Local data |
| - Number of nurses 12 Fixed Local data Financial inputs Revenues in the A&E (HRG Codes for severity of injuries): 2012/13 - 2013/14 Fixed DoH (2013 and 2014) - VB01Z £235 - £237 Fixed DoH (2013 and 2014) - VB02Z £235 - £237 Fixed DoH (2013 and 2014) - VB03Z £151 - £164 Fixed DoH (2013 and 2014) - VB04Z £151 - £130 Fixed DoH (2013 and 2014) - VB05Z £151 - £130 Fixed DoH (2013 and 2014) - VB06Z £81 - £102 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 NHS Digital (2013 and 2014) - 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) 1. Male 47% Multinomial HES dataset Age group 1 | - Number of doctors | 12 | Fixed | Local data |
| Financial inputs $L1$ FixedDolf (2013 and 2014)Revenues in the A&E (HRG Codes for severity of injuries): $2012/13 - 2013/14$ FixedDolf (2013 and 2014)· VB01Z£235 - £237FixedDolf (2013 and 2014)· VB02Z£235 - £210FixedDolf (2013 and 2014)· VB03Z£151 - £164FixedDolf (2013 and 2014)· VB05Z£151 - £130FixedDolf (2013 and 2014)· VB06Z£112 - £119FixedDolf (2013 and 2014)· VB06Z£12 - £119FixedDolf (2013 and 2014)· VB07Z£112 - £119FixedDolf (2013 and 2014)· VB08Z£112 - £110FixedDolf (2013 and 2014)· VB08Z£112 - £110FixedDolf (2013 and 2014)· Average monthly payment to a doctor£6178 - £6274AverageNHS Digital (2013 and 2014)· Average monthly payment to a nurse£2552 - £2563AverageNHS Digital (2013 and 2014)· Cotter inputsDemographic features: - GenderNerageNHS Digital (2013 and 2014)1. Age groups 11. Age group 1 (0 - 15)23%MultinomialHES dataset1. Age group 3 (36 - 50)16%MultinomialHES dataset4. Age group 4 (51 - 65)12%MultinomialHES dataset5. Age group 5 (65+)21%MultinomialHES dataset1. What percentage of patients are referred21%MultinomialHES dataset | - Number of nurses | 21 | Fixed | Local data |
| Revenues in the A&E (HRG Codes for severity of injuries):2012/13 - 2013/14 £235 - £237FixedDoH (2013 and 2014)· VB01Z£235 - £237FixedDoH (2013 and 2014)· VB03Z£151 - £164FixedDoH (2013 and 2014)· VB04Z£151 - £119FixedDoH (2013 and 2014)· VB05Z£151 - £119FixedDoH (2013 and 2014)· VB06Z£151 - £119FixedDoH (2013 and 2014)· VB07Z£112 - £119FixedDoH (2013 and 2014)· VB08Z£112 - £119FixedDoH (2013 and 2014)· VB08Z£112 - £110FixedDoH (2013 and 2014)· VB08Z£112 - £110FixedDoH (2013 and 2014)· Average monthly payment to a doctor£6178 - £6274Average· Average monthly payment to a nurse£2552 - £2563Average· Average monthly payment to a nurse£2552 - £2563Average· Average monthly payment to a nurse£2552 - £2563Average· Age group 1 (0 - 15)23%MultinomialHES dataset2. Age group 2 (16 - 35)23%MultinomialHES dataset3. Age group 4 (51 - 65)12%MultinomialHES dataset4. Age group 4 (51 - 65)12%MultinomialHES dataset1. Laboratory process: - Laboratory service11%11%11%1. What percentage of patients are referred21%MultinomialHES dataset | Financial innuts | 21 | 1 IACU | |
| $\begin{array}{c c c c c c c c c c c c c c c c c c c $ | Revenues in the A&E (HRG Codes for severity of | | | |
| VB01Zf $225 - f 237$ FixedDoH (2013 and 2014)- VB02Zf $2235 - f 210$ FixedDoH (2013 and 2014)- VB03Zf f f f f f f f f f f f f f f f f f f | iniuries): | 2012/13 - 2013/14 | | |
| $\begin{array}{c c c c c c c c c c c c c c c c c c c $ | - VB01Z | £235 - £237 | Fixed | DoH (2013 and 2014) |
| \cdot VB03Z£151 - £164FixedDoH (2013 and 2014) \cdot VB04Z£151 - £130FixedDoH (2013 and 2014) \cdot VB05Z£151 - £130FixedDoH (2013 and 2014) \cdot VB06Z£81 - £102FixedDoH (2013 and 2014) \cdot VB07Z£112 - £119FixedDoH (2013 and 2014) \cdot VB07Z£112 - £110FixedDoH (2013 and 2014) \cdot VB07Z£112 - £110FixedDoH (2013 and 2014) \cdot VB08Z£112 - £110FixedDoH (2013 and 2014) $costs in the A&E:\cdot\cdot\cdot\cdot Average monthly payment to a doctor£6178 - £6274Average\cdot Average monthly payment to a nurse£2552 - £2563Average\cdot Average groups\cdot\cdot\cdot\cdot Gender\cdot\cdot\cdot\cdot Age group 1 (0 - 15)23%Multinomial\cdot Age group 2 (16 - 35)23%Multinomial\cdot Age group 4 (51 - 65)12%Multinomial\cdot Age group 5 (65+)21%Multinomial\cdot Laboratory process:\cdot\cdot\cdot Laboratory service\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot$ | - VB02Z | £235 - £210 | Fixed | DoH (2013 and 2014) |
| \cdot VB04Z£151 - £139FixedDoH (2013 and 2014) \cdot VB05Z£151 - £130FixedDoH (2013 and 2014) \cdot VB06Z£112 - £110FixedDoH (2013 and 2014) \cdot VB07Z£112 - £119FixedDoH (2013 and 2014) \cdot VB08Z£112 - £110FixedDoH (2013 and 2014) $Costs in the A&E:ft12 - £110FixedDoH (2013 and 2014)- Average monthly payment to a doctor£6178 - £6274AverageNHS Digital (2013 and 2014)- Average monthly payment to a nurse£2552 - £2563AverageNHS Digital (2013 and 2014)Demographic features:- Gender- AverageNHS Digital (2013 and 2014)1. Male47%MultinomialHES dataset- Age groups- Age group 1 (0 - 15)23%Multinomial1. Age group 2 (16 - 35)28%MultinomialHES dataset4. Age group 4 (51 - 65)12%MultinomialHES dataset4. Age group 5 (65+)21%MultinomialHES dataset4. Ag$ | - VB03Z | £151 - £164 | Fixed | DoH (2013 and 2014) |
| - VB05Z $\pounds 151 - \pounds 130$ FixedDoH (2013 and 2014)- VB06Z $\pounds 81 - \pounds 102$ FixedDoH (2013 and 2014)- VB07Z $\pounds 112 - \pounds 119$ FixedDoH (2013 and 2014)- VB08Z $\pounds 112 - \pounds 110$ FixedDoH (2013 and 2014)Costs in the A&E: $\pounds 112 - \pounds 110$ FixedDoH (2013 and 2014)- Average monthly payment to a doctor $\pounds 6178 - \pounds 6274$ AverageNHS Digital (2013 and 20- Average monthly payment to a nurse $\pounds 2552 - \pounds 2563$ AverageNHS Digital (2013 and 20- Average monthly payment to a nurse $\pounds 2552 - \pounds 2563$ AverageNHS Digital (2013 and 20- Average monthly payment to a nurse $\pounds 2552 - \pounds 2563$ AverageNHS Digital (2013 and 20- Average monthly payment to a nurse $\pounds 2552 - \pounds 2563$ AverageNHS Digital (2013 and 20- Average monthly payment to a nurse $\pounds 2552 - \pounds 2563$ AverageNHS Digital (2013 and 20- Average monthly payment to a nurse $\pounds 2552 - \pounds 2563$ AverageNHS Digital (2013 and 20- Average monthly payment to a nurse $\pounds 2552 - \pounds 2563$ AverageNHS Digital (2013 and 20- Average monthly payment to a nurse $\pounds 2552 - \pounds 2563$ AverageNHS Digital (2013 and 20- Gender1Male 47% MultinomialHES dataset- Age group 1 (0 - 15)23%MultinomialHES dataset2. Age group 2 (16 - 35)28%MultinomialHES dataset3. Age group 4 (51 - 65)12%MultinomialHES dataset <tr< tr="">4. Age group</tr<> | - VB04Z | £151 - £139 | Fixed | DoH (2013 and 2014) |
| - VB06Z \pounds 81 - \pounds 102FixedDoH (2013 and 2014)- VB07Z \pounds 112 - \pounds 119FixedDoH (2013 and 2014)- VB08Z \pounds 112 - \pounds 110FixedDoH (2013 and 2014)Costs in the A&E: \pounds 112 - \pounds 110FixedDoH (2013 and 2014)- Average monthly payment to a doctor \pounds 6178 - \pounds 6274AverageNHS Digital (2013 and 20- Average monthly payment to a nurse \pounds 2552 - \pounds 2563AverageNHS Digital (2013 and 20- Average monthly payment to a nurse \pounds 2552 - \pounds 2563AverageNHS Digital (2013 and 20- Other inputs-AverageNHS Digital (2013 and 20- Gender1. Male47%MultinomialHES dataset- Age group 1 (0 - 15)23%MultinomialHES dataset2. Age group 2 (16 - 35)28%MultinomialHES dataset3. Age group 3 (36 - 50)16%MultinomialHES dataset4. Age group 4 (51 - 65)12%MultinomialHES dataset5. Age group 5 (65+)21%MultinomialHES dataset4. Aboratory process:-21%MultinomialHES dataset1. What percentage of patients are referred-10%MultinomialHES dataset | - VB05Z | £151 - £130 | Fixed | DoH (2013 and 2014) |
| - VB07Z · VB08Z $\pounds 112 - \pounds 119$ $\pounds 112 - \pounds 110$ FixedDoH (2013 and 2014)Costs in the A&E: · Average monthly payment to a doctor $\pounds 6178 - \pounds 6274$ $\pounds 2552 - \pounds 2563$ AverageNHS Digital (2013 and 2014)Other inputs Demographic features: · Gender $\pounds 2552 - \pounds 2563$ AverageNHS Digital (2013 and 2014)1. Male 47% S.MultinomialHES dataset2. Female 53% MultinomialHES dataset2. Age groups1. Age group 1 (0 - 15) 23% MultinomialHES dataset3. Age group 3 (36 - 50) 16% MultinomialHES dataset4. Age group 4 (51 - 65) 12% 12% MultinomialHES dataset5. Age group 5 (65+) 21% MultinomialHES dataset4. Age group 5 (65+) 12% MultinomialHES dataset3. Age group 5 (65+) 12% MultinomialHES dataset4. Age group 5 (65+) 12% MultinomialHES dataset4. Age group 5 (65+) 12% MultinomialHES dataset5. Age group 5 (65+) 21% MultinomialHES dataset6. Age group 5 (65+) 21% MultinomialHES dataset6. Age group 5 (65+) 12% MultinomialHES dataset7. Age group 5 (65+) 12% MultinomialHES dataset8. Age group 5 (65+) 12% MultinomialHES dataset9. Age group 5 (65+) 12% MultinomialHES dataset9. Age group 5 (65+) 21% MultinomialHES dataset< | - VB06Z | £81 - £102 | Fixed | DoH (2013 and 2014) |
| \cdot VB08Z£112 - £110FixedDoH (2013 and 2014)Costs in the A&E: - Average monthly payment to a doctor - Average monthly payment to a nurse£6178 - £6274AverageNHS Digital (2013 and 20Other inputs Demographic features: - Gender $1.Male$ 47%MultinomialHES dataset2. Female53%MultinomialHES dataset2. Age groups 2.49 group 1 (0 - 15)23%MultinomialHES dataset3. Age group 2 (16 - 35)28%MultinomialHES dataset4. Age group 4 (51 - 65)16%MultinomialHES dataset5. Age group 5 (65+)21%MultinomialHES dataset4. Aboratory process: - Laboratory service1. What percentage of patients are referred21%Multinomial | - VB07Z | £112 - £119 | Fixed | DoH (2013 and 2014) |
| Costs in the A&E: - Average monthly payment to a doctor£6178 - £6274 £2552 - £2563AverageNHS Digital (2013 and 20 NHS Digital (2013 and 20 | - VB08Z | £112 - £110 | Fixed | DoH (2013 and 2014) |
| - Average monthly payment to a doctor£6178 - £6274 £2552 - £2563AverageNHS Digital (2013 and 20 NHS Digital (2 | Costs in the A&E: | | | |
| - Average monthly payment to a nurse£2552 - £2563AverageNHS Digital (2013 and 20Other inputsDemographic features: - Gender- Gender1. Male47%MultinomialHES dataset2. Female53%MultinomialHES dataset- Age groups23%MultinomialHES dataset1. Age group 1 (0 - 15)23%MultinomialHES dataset2. Age group 2 (16 - 35)28%MultinomialHES dataset3. Age group 3 (36 - 50)16%MultinomialHES dataset4. Age group 4 (51 - 65)12%MultinomialHES dataset5. Age group 5 (65+)21%MultinomialHES datasetLaboratory process: 1. What percentage of patients are referred21%MultinomialHES dataset | Average monthly payment to a doctor | £6178 - £6274 | Average | NHS Digital (2013 and 2014) |
| Other inputsDemographic features: - Gender1.Male2.Female2.Female- Age groups1. Age group 1 (0 - 15)23%MultinomialHES dataset2. Age group 2 (16 - 35)28%MultinomialHES dataset3. Age group 3 (36 - 50)16%4. Age group 4 (51 - 65)12%MultinomialHES dataset5. Age group 5 (65+)21%Laboratory process: - Laboratory service1. What percentage of patients are referred | - Average monthly payment to a nurse | £2552 - £2563 | Average | NHS Digital (2013 and 2014) |
| Demographic features: - GenderMultinomialHES dataset1.Male47%MultinomialHES dataset2.Female53%MultinomialHES dataset- Age groups1Age group 1 (0 - 15)23%Multinomial1. Age group 2 (16 - 35)28%MultinomialHES dataset3. Age group 3 (36 - 50)16%MultinomialHES dataset4. Age group 4 (51 - 65)12%MultinomialHES dataset5. Age group 5 (65+)21%MultinomialHES datasetLaboratory process: 1. What percentage of patients are referred1HES dataset | Other inputs | | | |
| - Gender47%MultinomialHES dataset1. Male47%MultinomialHES dataset2. Female53%MultinomialHES dataset- Age groups123%MultinomialHES dataset2. Age group 2 (16 - 35)28%MultinomialHES dataset3. Age group 3 (36 - 50)16%MultinomialHES dataset4. Age group 4 (51 - 65)12%MultinomialHES dataset5. Age group 5 (65+)21%MultinomialHES datasetLaboratory process:121%MultinomialHES dataset1. What percentage of patients are referred1111 | Demographic features: | | | |
| 1.Male47%MultinomialHES dataset2.Female53%MultinomialHES dataset- Age groups1. Age group 1 (0 - 15)23%MultinomialHES dataset2. Age group 2 (16 - 35)28%MultinomialHES dataset3. Age group 3 (36 - 50)16%MultinomialHES dataset4. Age group 4 (51 - 65)12%MultinomialHES dataset5. Age group 5 (65+)21%MultinomialHES datasetLaboratory process:1. What percentage of patients are referred1. Wat percentage of patients a | - Gender | | | |
| 2.Female53%MultinomialHES dataset- Age groups1. Age group 1 (0 - 15)23%MultinomialHES dataset2. Age group 2 (16 - 35)28%MultinomialHES dataset3. Age group 3 (36 - 50)16%MultinomialHES dataset4. Age group 4 (51 - 65)12%MultinomialHES dataset5. Age group 5 (65+)21%MultinomialHES datasetLaboratory process:-21%MultinomialHES dataset | 1.Male | 47% | Multinomial | HES dataset |
| - Age groupsMultinomialHES dataset1. Age group 1 (0 - 15)23%MultinomialHES dataset2. Age group 2 (16 - 35)28%MultinomialHES dataset3. Age group 3 (36 - 50)16%MultinomialHES dataset4. Age group 4 (51 - 65)12%MultinomialHES dataset5. Age group 5 (65+)21%MultinomialHES datasetLaboratory process:-21%MultinomialHES dataset1. What percentage of patients are referred | 2.Female | 53% | Multinomial | HES dataset |
| 1. Age group 1 (0 - 15)23%MultinomialHES dataset2. Age group 2 (16 - 35)28%MultinomialHES dataset3. Age group 3 (36 - 50)16%MultinomialHES dataset4. Age group 4 (51 - 65)12%MultinomialHES dataset5. Age group 5 (65+)21%MultinomialHES datasetLaboratory process:121%MultinomialHES dataset1. What percentage of patients are referred111 | - Age groups | | | |
| 2. Age group 2 (16 - 35)28%MultinomialHES dataset3. Age group 3 (36 - 50)16%MultinomialHES dataset4. Age group 4 (51 - 65)12%MultinomialHES dataset5. Age group 5 (65+)21%MultinomialHES datasetLaboratory process:11%MultinomialHES dataset1. What percentage of patients are referred11%1%1% | 1. Age group $1 (0 - 15)$ | 23% | 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 HES dataset 1. What percentage of patients are referred Image of the service Image of the service | 2 Age group 2 $(16 - 35)$ | 28% | Multinomial | HES dataset |
| 4. Age group 4 (51 - 65) 12% Multinomial HES dataset 5. Age group 5 (65+) 21% Multinomial HES dataset Laboratory process: 1 10% Multinomial HES dataset 1. What percentage of patients are referred 1 10% Multinomial HES dataset | 3 Age group 3 $(36 - 50)$ | 16% | Multinomial | HFS dataset |
| 5. Age group 5 (65+) 21% Multinomial HES dataset Laboratory process: 1. What percentage of patients are referred 1. | A = Age group A (51 - 65) | 12% | Multinomial | HES dataset |
| Laboratory process: - Laboratory service 1. What percentage of patients are referred | 4. Age group $4(51-55)$ | 210/ | Multinomial | HES dataset |
| - Laboratory process: - Laboratory service 1. What percentage of patients are referred | J. Age gloup 5 (05+) | 2170 | Wutthoma | TIES dataset |
| 1. What percentage of patients are referred | Laboratory process. | | | |
| 1. What percentage of patients are referred | - Laboratory service | | | |
| | 1. What percentage of patients are referred | | | |
| to the laboratory? 76% Multinomial HES dataset | to the laboratory? | /6% | Multinomial | HES dataset |
| 2. What percentage of patients are not | 2. What percentage of patients are not | | | |
| referred to the laboratory? 24% Multinomial HES dataset | referred to the laboratory? | 24% | Multinomial | HES dataset |
| - Percentage of tests | - Percentage of tests | | | |
| First tests - Second tests - Third tests | First tests - Second tests - Third tests | | | |
| X-Ray 42% - 8% - 12% Multinomial HES dataset | X-Ray | 42% - 8% - 12% | Multinomial | HES dataset |
| Electrocardiogram 13% - 22% - 10% Multinomial HES dataset | Electrocardiogram | 13% - 22% - 10% | Multinomial | HES dataset |
| Haematology 31% - 26% - 26% Multinomial HES dataset | Haematology | 31% - 26% - 26% | Multinomial | HES dataset |
| Biochemistry 1% - 32% - 27% Multinomial HES dataset | Biochemistry | 1% - 32% - 27% | Multinomial | HES dataset |
| Urinalysis $8\% - 7\% - 16\%$ Multinomial HES dataset | Urinalysis | 8% - 7% - 16% | Multinomial | HFS dataset |
| $\frac{1}{2} \frac{1}{2} \frac{1}$ | Others | 5% = 5% = 9% | Multinomial | HES dataset |
| Shifts 3 Eived Level date | Shifts | 2 | Fixed | L ocal data |
| Distributions Distributions | Distributions | 5 | r ixeu | Local data |
| Distributions | Distributions | Encourse and distribution | Encourse and the state | |
| - Severity of injuries Frequency distribution Frequency distribution HES dataset | - Severity of injuries | Frequency distribution | Frequency distribution | HES dataset |
| - Waiting time for pre-assessment 15 minutes Multinomial Expert opinion | - Waiting time for pre-assessment | 15 minutes | Multinomial | Expert opinion |
| - Pre-assessment process 10 minutes Multinomial Expert opinion | - Pre-assessment process | 10 minutes | Multinomial | Expert opinion |
| - Waiting time for treatment See Appendix 2 and See Appendix 2 and HES dataset | - Waiting time for treatment | See Appendix 2 and | See Appendix 2 and | HES dataset |
| Appendix 3 Appendix 3 | | Appendix 3 | Appendix 3 | |
| - Treatment time Frequency distribution HES dataset | - Treatment time | Frequency distribution | Frequency distribution | HES dataset |
| - Waiting time for discharge See Appendix 4 and See Appendix 4 and HES dataset | - Waiting time for discharge | See Appendix 4 and | See Appendix 4 and | HES dataset |
| Appendix 5 Appendix 5 | | Appendix 5 | Appendix 5 | |

| | Age Group | 1 (0 – 15) | Age Group | 2 (16 – 35) | Age Group | 3 (36 - 50) | Age Group | 4 (51 – 65) | Age Grou | p 5 (65+) |
|-------------------|------------|------------|------------|-------------|------------|-------------|------------|-------------|------------|-----------|
| Distributions | Kolmogorov | Anderson | Kolmogorov | Anderson | Kolmogorov | Anderson | Kolmogorov | Anderson | Kolmogorov | Anderson |
| Distributions | Smirnov | Darling | Smirnov | Darling | Smirnov | Darling | Smirnov | Darling | Smirnov | 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 | 0.02035) | (n=1, p=0 | 0.01572) | (n=1, p=0 | 0.01491) | (p=0.0 | 1289) | (p=0.0 | 1337) |

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



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)

| | Age Group 1 (0 – 15) | | Age Group 2 (16 – 35) | | Age Group 3 (36 – 50) | | Age Group 4 (51 – 65) | | Age Group 5 (65+) | |
|-------------------|----------------------|-----------|-----------------------|-----------|-----------------------|-----------|-----------------------|-----------|-------------------|-----------|
| Distributions | Kolmogorov | Anderson | Kolmogorov | Anderson | Kolmogorov | Anderson | Kolmogorov | Anderson | Kolmogorov | Anderson |
| | Smirnov | Darling | Smirnov | Darling | Smirnov | Darling | Smirnov | Darling | Smirnov | Darling |
| | Statistic | Statistic | Statistic | Statistic | Statistic | Statistic | Statistic | Statistic | Statistic | 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 |

| | | | (a ₁ =0.79911, a ₂ | | |
|------------|---------------------------------------|---|--|-------------|---------------------------------------|
| Parameters | (α =0.6916, β =90.064) | (a= 0.63069, \$= 112.98) | | (p=0.00983) | (a =1.5365, β =85.049) |
| | | | =2.4519E+6, \$= 2.6279E+8) | | |



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