Demand and Capacity Modelling for Acute Services using Discrete Event Simulation

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Abstract

Increasing demand for services in England with limited healthcare budget has put hospitals under immense pressure. Given that almost all National Health Service (NHS) hospitals have severe capacity constraints (beds and staff shortages) a decision support tool (DST) is developed for the management of a major NHS Trust in England. Acute activities are forecasted over a 5 year period broken down by age groups for 10 specialty areas. Our statistical models have produced forecast accuracies in the region of 90%. We then developed a discrete event simulation model capturing individual patient pathways until discharge (in A&E, inpatient and outpatients), where arrivals are based on the forecasted activity outputting key performance metrics over a period of time, e.g., future activity, bed occupancy rates, required bed capacity, theatre utilisations for electives and non-electives, clinic utilisations, and diagnostic/treatment procedures. The DST allows Trusts to compare key performance metrics for 1,000’s of different scenarios against their existing service (baseline). The power of DST is that hospital decision makers can make better decisions using the simulation model with plausible assumptions which are supported by statistically validated data.

Keywords: Simulation, Decision Support System, Hospital Capacity, Hospital Resources

1. Introduction

Given the ever increasing demand with severe capacity (e.g. beds) and financial constraints (economic downturn) it is clear that current acute services will continue to struggle and need to make sure that resources are utilised in the most effective manner. Acute services would need to improve the efficiency of the current delivery of services (e.g. elective and non-elective admissions). The efficiency needs to be achieved by enhancing the match of capacity and demand. More importantly the service would need to model the level of resources needed by patients in acute services as a function of demand factors (e.g. population projections by age group, Office of National Statistics (ONS) growth rates) with a range of supply issues. In this context, it is vital to understand the patient pathway in order to demonstrate the full impact of change. Note that patient pathway is a timeline on which every event relating to patients' treatment, such as consultations, diagnosis, treatment, medication, hospitalisation, is entered (Department of Health, 2007) and should show all the care received by the patient as they move towards the point of intervention, and after. It is our argument that once we understand current practices and possible defects in a pathway, we can affect changes that will make the pathway more efficient and mitigate capacity and financial constraints. This will ensure that National Health Service (NHS) Trusts can better understand the complexities of their existing system and understand its inner working.

There are four key challenges to this:

1) The development of statistical models for the entire Trust (at specialty level, age and ONS growth adjusted) that are able to forecast demand at a sufficient level of accuracy, e.g., minimum 90% forecast accuracy.
2) The development of a discrete event simulation model that captures individual patient's footsteps in acute services (inpatient, outpatient and A&E), from arrival to

discharge. All input parameters must be statistically validated (e.g. length of stay, waiting times, revenues, number of beds/theatres/clinic slots/staff, etc.) in order to build realistic and valid simulation models.

3) The development of a user friendly decision support toolkit with relevant simulation controls to enable users to interact with the model by enabling them to make necessary changes to the input parameters, comparing the baseline vs. intervention, focusing on key performance metrics, such as activity at specialty level, bed occupancy rates, required bed capacity, theatre utilisations, clinic utilisations, staff utilisation, diagnostic/treatment procedure counts, revenues and many more.
4) The development of an Excel spreadsheet that collates all key performance metrics (i.e. outputs from the simulation) for the chosen specialties (and for the whole Trust), comparing the two scenarios (baseline vs. intervention) for a period of time (i.e. the next 5 years).

It is clear from the literature review presented in the next section and authors' domain knowledge, to date no model has been developed and implemented within an NHS Trust tackling all the above specified challenges within a single Decision Support Tool (DST) framework. The current study has two objectives: firstly, to explore the impact of a range of changes to the acute services pathway using DES and to explore the utility of this approach in a large NHS Trust. Secondly, to develop a user friendly DST (a further development on the DES model) with relevant simulation controls for decision makers in this NHS Trust. The objective here is to get users to interact with the model by enabling them to make necessary changes to the input parameters, so that the model can be stress tested with a customized set of results, focusing on activity, bed occupancy rates, resource utilization, theatre/clinic utilisations, diagnostic/treatment procedure counts, revenue and many more. These indicators are thought to be valuable for key decision makers in the process of commissioning and re-designing services, and help them understand the interaction between key decision variables.

2. Review of Literature and Modelling Methodologies

A number of models have been developed to tackle some of the challenges presented in the previous section (Harper and Shahani (2002), Gallivan et al (2002), Utley et al (2003), Vasilakis et al (2008)). Demand and capacity planning in healthcare, more specifically in hospitals, has been a topic in Operations Management (OM) and Operational Research (OR) context for many years. Vissers and Beech (2005) presented a review of OM concepts which can be applied in healthcare. These concepts can be used for allocation and utilization of hospital resources, hospital production and capacity planning, admission planning, patient mix optimization, master scheduling of medical specialists and scheduling outpatient appointments. At the core of these concepts, there is a "patient flow" concept which is, as described in (Hall et al, 2006), the study of how patients move through the healthcare system. Patient flows are partly dependent on the process of care and decisions taken by medical staff, and partly inherent uncertainties of healthcare processes (Cote (2000), Harper (2002)). Note that the demand, or the rate of patient flow, is affected by seasonal and local factors including types of services offered by a hospital (Alexopoulos, 2008).

Although deterministic capacity models can be applied in hospitals (Vissers, 1998), most academic studies consider the stochastic nature of hospitals. Queuing and simulation are popular approaches for modelling. For example, Worthington (1991) demonstrated how queuing models can be used to plan patient waiting lists in hospitals. An influential paper in this field is Bagust et al (1999), which reports a simulation of inpatient beds for emergency admissions, concluding that the risk of a hospital bed shortage is low when mean bed occupancy remains under 85%. This simple yet effective model demonstrates that bed crises occur not necessarily because of poor management but because of the nature of stochastic arrivals. Zonderland and Boucherie (2012) provide a review and details of the queuing network models in healthcare. In a recent study, Pitt et al (2015) reviews the role of modelling and simulation for policy making in health service delivery and design.

Discrete Event Simulation (DES) and System Dynamics (SD) are the two popular simulation methodologies. DES has the ability to model individual patients and their unique trajectories as they flow through the care system and to incorporate a large number of different patient attributes such as age, gender and disease stage. It allows for the running of the model over extended time horizons. Patients move through the model and they can experience events at any discrete point in time. Moreover, DES provides the flexibility to incorporate capacity and resource constraints explicitly and to capture the "competition" between competing modelled entities for access to limited resources (Robinson, 2004). Gunal and Pidd (2010) provides a review of the literature on DES for performance modelling in hospitals. Katsaliaki and Mustafee (2011) presented simulation applications in healthcare. Among many other examples, Rohleder et al (2011) used DES to diagnose the causes of poor patient flow and to identify improvement measures in an outpatient orthopaedics clinic. Additionally, Gunal (2012) present the guidelines for developing simulation models for hospitals, not only using DES but also using SD and an emerging methodology, Agent Based Simulation (ABS).

SD divides populations into large homogenous groups, where each group of patients in the same clinical/care state is represented by the same variable state. The modelling of patients flows then aims to track the transition of these groups of patients between the variable states and not the flow of each individual patient within the population (Brailsford, 2004). The SD process includes two phases: (i) The first phase is qualitative in which the system's elements are determined and possible cause-effect links are mapped in the form of interconnected feedback loops, and (ii) the second phase, which involves the translation of the qualitative structure into a quantitative simulation model, in which the different stocks (variable states) and flows are identified and relationships among them formally quantified. The simulation model can be then used for 'what-if' scenarios to investigate possible outcomes of different policy interventions and understand the relationship between the structure of a system and its behaviour ((Sterman, 2000), Lane and Oliva, 1998)).

Because of these unique advantages, there has been a steady stream of SD applications in health care management in general and in health systems where patients' flows are significant in particular. In this context, SD has been successfully applied to model transmission dynamics of diseases such as Tuberculosis and HIV/AIDS ((Reda et al 2010), (Atun et al 2007), Dangerfield et al, 2001), dengue fever (Dunham and Galivan, 1999) and variant Creutzfeld Jakob Disease (Bennett et al 2005). Other applications focused on issues such as the analysis of demand management in accident and emergency (Lane et al, 2000) and reconfiguration of health services (Taylor and Dangerfield, 2005).

ABS views the world differently to DES and SD. An Agent is an autonomous entity which has the ability to make decisions and therefore the focus in ABS is to model how a decision is made. Individual behaviour of an agent is modelled and then multiple entities are sent to the environment in order for them to interact with each other and with the environment (Macal and North, 2010). The interactions determine the holistic behaviour. ABS is used frequently in modelling spread of a disease (Laskowski et al 2011) however there are examples in hospital context in modelling demand where patient choice is significant (Knight, 2012).

Out of the three simulation approaches (DES, SD and ABS), we have chosen to develop our model using DES as it allows for the running of the model over extended time horizons and enables tracking of individual patients footsteps in service and the ability to incorporate capacity and resource constraints, hence capturing reality within a software environment

(Simul8). Furthermore, it is an approach well understood and accepted by the NHS community, including clinicians, nurses, service managers and senior executives.

3. High level description of the decision support tool

This demand and capacity planning simulation tool was developed to be used by a large NHS hospitals trust to facilitate change and transformation with the aim of benefiting patients and the Trust. As the envisaged end users were not meant to be simulation experts we designed and implemented from the outset, a graphical user interface to facilitate the running of the simulations by non-experts and without the need for resorting to the research team for future experimentation. Figure 1 shows a high level representation of the resultant simulation-based DST. The tool is made up of eight sets of key inputs (identified at the conceptualisation phase in collaboration with the Trust and logically grouped) and eight sets of key outputs which are considered to be the key performance indicators of the system's operation. The tool comes pre-populated with values for all the input parameters as these were estimated through rigorous analyses of the national English Hospital Episodes Statistics (HES) dataset and additional data provided by the Trust. The end users however, are able to change the values of the input parameters according to the configurations of their services. Two sets of input parameters can be entered, namely scenario 1 (baseline model), and scenario 2 the experiment (or intervention). The scenarios are then compared with respect to key performance indicators (or outputs) as stated in Figure 1.

Inputs are related to patient demand, physical capacity, personnel capacity, financial and uncontrolled system parameters. Forecasted patient demand by specialty is used to create patients in the hospital simulation. Bed, theatre and outpatient clinic capacities are the key physical capacities in a hospital and are directly related to hospital performance. Another key capacity is the number of personnel who work in the hospital. Revenues are linked to

Healthcare Resource Groups (HRG) tariffs and are the key determinants of hospital's revenue. Most of these inputs can be controlled by hospital management, however there are some inputs which are uncontrollable and stochastic by nature. Length of stay (LoS), waiting times and percentages of diagnostic and treatment procedures are such variables. These are related to patient case mix.

The DST generates five sets of outputs for each specialty over a five year period: patient activity, beds and theatres, clinics and procedures, personnel activity and financial reporting. Patient activity outputs include the number of elective admissions, non-elective admissions, accident and emergency (A&E) attendances and outpatient attendances, cancellations and did not attends. The 10 specialties are general medicine, general surgery, trauma and orthopaedics, maternity, urology, ophthalmology, paediatrics, gynaecology, gastroenterology and cardiology. Note that these specialties were chosen by the Trust as they cover 85% of inpatient admissions and 51% of outpatient attendances, where the majority of revenue is generated from these specialties.

Bed and theatre activity outputs are utilisation of beds and theatres. DST calculates the number of beds required to sustain a target level of bed usage. Furthermore, clinic utilisation in outpatients and the number of diagnostic and treatment procedures are presented. A detailed breakdown of revenue for inpatients and outpatients is provided for each year.

4. Forecasting demand and parameter estimation

We extracted data relevant to the Trust from HES dataset covering financial years 2009/10-2012/13. Monthly admissions for inpatient electives, non-electives, A&E attendances, outpatient attendances, did not attend (DNA) and cancellations broken down by age groups (0-18, 19-64, 65-84 and 85+) were extracted for each specialty. Similar data was extracted for

CCG level admissions and attendances. The HES dataset contains personal, medical and administrative details of all patients admitted to, and treated in, NHS hospitals in England.

Figure 1: A high-level representation of the simulation-based DST for Demand and Capacity Planning of NHS Trusts

Using the statistical software R (library package *forecast*), for each specialty we developed four models for electives (one for each age group), 4 for non-electives, 4 for outpatient attendances, 4 for DNAs and 4 for cancellations (i.e. 20 models for each specialty in total). The forecasted activity was then adjusted for ONS growth rates and collated to estimate future activity for 2013-14 to 2018-19 (6 year forecast).

Models are selected based on the best compromise between model complexity and goodness-of-fit according to Akaike's information criterion, Bayesian information criterion and forecast accuracy measures, i.e., mean error, root mean squared error, mean absolute error, mean percentage error, mean absolute percentage error and mean absolute scaled error. When 2013-14 forecasted activity was compared with the actual activity, our forecast accuracy was in the region of 90-99%.

In addition to demand forecasting many parameters were estimated and distributions were identified for each specialty, such as the distribution of length of stay (LoS) for electives and non-electives; average LoS; distribution of waiting times for elective admissions and outpatient appointments; average number of follow-ups per patient; annual theatre capacity (in sessions) for electives and non-electives; average number of theatre procedures per session for electives and non-electives; average HRG tariffs for electives, non-electives and outpatient attendances, and the top 10 diagnostic and treatment procedures in terms of frequency of use carried out in inpatient and outpatients. These are crucial statistics to ensure that the Trusts activity and processes are captured within the simulation environment and the outputs are reliable, robust and accurate.

5. The Decision Support Tool

5.1. Overview

The DST is designed and implemented with key decision makers in mind, including service managers, clinicians, financial planners and information analysts without the need for a technical intermediary. As a result, the front interface and the simulation controls are simple, concise and fit for purpose. Users are able to make necessary changes in the input parameters (demand and capacity inputs). A dashboard is available for each specialty (see Figure 2 – Maternity as an example). High level results are provided on the dashboard and detailed sets of results are exported to an Excel file (a worksheet for each specialty). Simulation controls are on the right of the dashboard, where the *Demand* button enables users to test scenarios associated with the demand aspect of the specialty, i.e., scenario 1 is the forecasted demand for each of the 5 years (for electives, non-electives, attendances, DNAs and cancellations) and reflects the "as-is" case, and scenario 2 is the experimentation which reflects the "what-if" case. The *Manage* button allows users to test the capacity aspect of the specialty, namely staff, bed and clinic capacity, length of stay and waiting time, theatre utilisation and revenue. Note that scenario 1 inputs are pre-populated through extensive analysis of HES and data provided by the Trust.

Figure 2: Maternity dashboard as an example

5.2.Model Structure

In the background of the DST, to generate values on the dashboards, a simulation model runs with the specified inputs. A process diagram of the model is provided in Figure 3 for the four selected specialties and for inpatient pathways only. The Figure is simple in the sense that it only depicts high level processes and shows the holistic view. For example, the A&E department is conceptualized as a hub for emergency patients, whereas in reality this department has complex processes; triage, doctor consultations, treatment, diagnostics tests etc. Likewise, inpatient departments for each specialty are conceptualized as single processes as if they were simple input-output systems. Outpatient clinics are modelled in a similar way to inpatient departments.

Finding the right level of detail in simulation models of complex systems, such as hospitals, has been an issue for modellers, as more detail requires more data (Gunal and Pidd, 2011). A modellers' task is to find a good balance of what is to be included and excluded in the model. If more details are added, more inputs will be required in the model, which will then initiate the search for reliable data and also slow-down the model's execution time. In our model, we picked the right level of detail for our purposes since we aimed at evaluating high level use of resources.

Figure 3: Model structure – Elective and Non-elective Inpatients

5.3.Model validation

The model validation process was carried out by comparing the expected number of arrivals over a 5-year period using the known data in the actual care system, with the simulation results. The simulated values were consistent with historical data. This approach is known as Black-Box Validation technique and it is commonly used to validate simulation models

(Law, 2007). The model is assumed as an unknown black-box and its input-output relation is only compared with the actual system. Statistical tests showed that there is no significant difference between the model's output and the real system's output.

We also conducted White-Box Validation in which the internal working of each model component was tested. This method was used during the model development phase and includes unit-level checks. For example, in demand generation processes, the model was run to check that it is generating as many patients as expected.

Another useful technique to validate simulation models is to achieve face validity (whether the model appears reasonable on the face of it). The model was shown to each Trust staff member individually and then within a workshop. The model structure was confirmed to be highly representative of the real world acute care system by all NHS Trust staff in the individual meetings and during the workshop where the whole group was present. In general, the continuous engagement of the staff throughout the study increased significantly the confidence in the validity of the model.

6. Scenario Planning

The DST can be used for evaluating effects of changes in input parameters on model outputs. Since the DST has many input parameters, we systematically altered some of them to evaluate likely changes in the Trust in the future. These changes are mostly related to patient demand, increase in non-elective patients and patients over the age of 75.

We created 6 scenarios as illustrated in Table 1. In scenarios 1 and 5, we increased and decreased non-elective admissions by 5%, respectively. Nearby hospital (Chase Farm) has recently closed their Accident and Emergency services and as a result the Trust expects a 5% increase in non-elective admissions. In scenario 5, however, an improvement policy is tested in which a decrease by 5% is anticipated. In this scenario, the Trust is considering establishing a new fast-track urgent care model for patients under 75.

In scenarios 2, 3 and 4, effects of the Trust's "Frail elderly model at Torbay" is evaluated. Due to this change, in Scenario 2, non-elective admissions for patients over 75 are expected to decrease by 10%. In scenario 3, the average length of stay of patients over 75 is expected to decrease by 20% and in scenario 4 the percentage of patients who are readmitted is expected to decrease by 10%. Finally, the Trust wanted to consider what would happen if elective capacity were increased by 5% (scenario 6).

In our experimental design, we created the scenarios in a cumulative manner, for example, the changes made for scenario 2 include the changes made in scenario 1. This means that scenario 6 includes all the changes in the previous scenarios. By designing the scenarios this way, we are able to find out the scenarios which cause the most significant effect.

Scenario no.	**Change in**	**Direction of change**	**% of change**	**Rationale**
1	Non-elective admissions	Increase	5	The Trust gains market share in non-elective services from nearby closures
2	Non-elective admissions for those over 75	Decrease	10	Frail elderly model at Torbay is implemented to 50% effectiveness
3	Non-elective length of stay for those over 75	Decrease	20	Frail elderly model at Torbay is implemented to 50% effectiveness

4	Non-elective readmissions for those over 75	Decrease	10	Frail elderly model at Torbay is implemented to 50% effectiveness
5	Non-elective admissions	Decrease	5	The Trust implements single urgent care model for those under 75 with 50% effectiveness
6	Elective admissions	Increase	5	The Trust increases its elective activity across the board

Table 1: Scenario planning

7. Results

Due to the stochastic nature of the model, we ran each scenario 10 times and collected relevant output statistics.

It is rather cumbersome to interpret all outputs generated from the model. As a result we illustrate two key performance metrics of interest, the required bed capacity and theatre session utilisation (within a session more than one patient can be surgically operated). Required bed capacity is the total number of beds that is required by the hospital in order to meet elective and non-elective patient demand. These figures are aggregates of ten specialties. Total session utilisation output shows the number of sessions that the operating theatre is used for. It is again the aggregate of ten specialties. The simulation period was 5 years since it is plausible to compare the effects of changes in the long run. Rather than presenting the absolute figures of the output variables, we demonstrate the amount of change in a 5-year horizon.

Figure 4: Percentage of increase in required bed capacity and total session utilisation of operating theatres at the end of 5-year period.

In all scenarios (see Figure 4), the required bed capacity has increased by around 16%. This suggests that over a 5 year period the hospital needs to consider increasing bed capacity in any case. Considering scenario 1, 5% increase in non-electives will result in 17% increase in bed requirement. As it is clear from scenario 2, even if the elderly demand decreases by 10%, required bed capacity will still be high since scenario 2 includes the change in scenario 1. Likewise, the decreases in scenario 3, 4, and 5 will result in just 1% decrease in required bed capacity. Total theatre session utilization figures are stable around 5.9% in all scenarios, however, some minor increases can be observed in scenarios 4 to 6. Although the peak at scenario 5 is not significant, this is due to the increase in day-case elective patients who need an operation. If the Trust implements a single urgent care model for those under the age of 75 with 50% effectiveness, theatre session utilisation increases, whilst required bed capacity remains stable.

The interaction effects between the two outputs should be noted. One would expect similar patterns from these variables, for example when theatre utilisation increases bed requirement should increase too. Given the stochastic nature of the model and the Trust as a system our result suggests that they can behave differently.

8. Conclusions

The current tool addresses a top-of-the-agenda issue in healthcare management as it focuses on the policies related to service re-design and how they have an impact on the demand and capacity of health and social care systems. The importance of the DST can be appreciated in the current context of increasing demand on health service provision at the time when we are moving to the new reality of tighter public finances and the resulting pressure to improve the effectiveness and efficiency of healthcare provision and delivery.

The tool allows decision makers to better understand the operation of the system in relation to key performance metrics associated with detailed breakdown of activity, resource utilisation (theatres, clinics, staff, and beds), diagnostic/treatment procedures, and many more. The ease of use of the tool with the relevant set of exported results means that senior decision makers could be more proactive with an evidence based approach in re-designing their services to find the most efficient and effective delivery of care.

The authors have first-hand experience of the frustrations that can sometimes accompany planning and approving new services in healthcare systems. Often changes are introduced without proper consideration of the impact on the service. It is also often the case that those people working in the healthcare system know how they would like to improve the service they deliver, but lack the expertise to frame those improvements in a manner that will allow a strong case to be made to board-level executives and holders of budgets. This tool therefore has been designed to allow 'non-simulation experts' to test change on the pathway in a validated simulation that will present the impact of changes in a way that can be easily understood by both the executive and specialists. It is the intention that this will facilitate service planning and decision making and speed up the pace of change in hospitals. The DST is currently being used by a major NHS Trust to facilitate service change and transformation.

Future work could explore additional ways in which the current model could incorporate individual patient characteristics which may alter patient pathways (e.g. disease severity, age group, gender, etc.) and explore the impact on activity results and capacity metrics.

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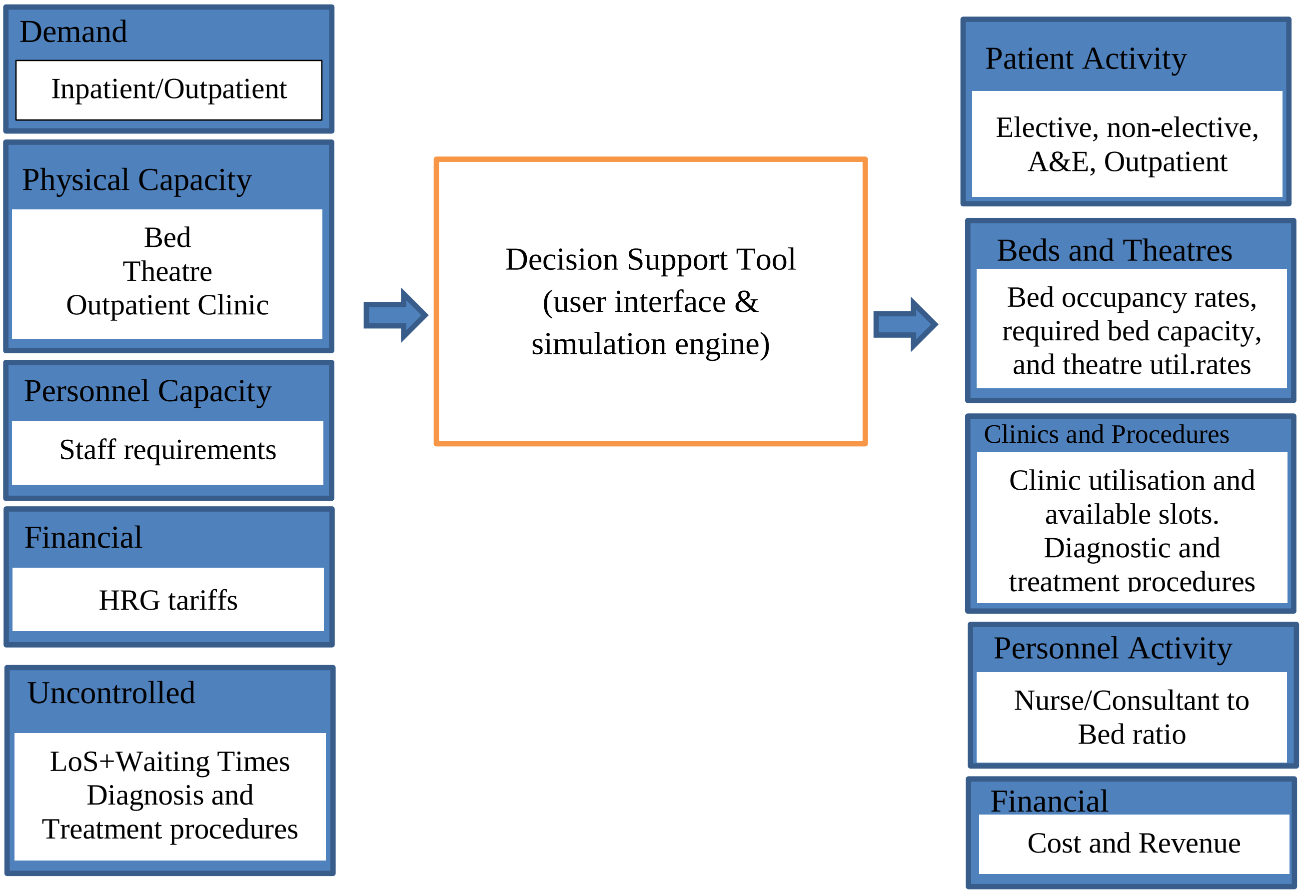

Figure 1: A high-level representation of the simulation-based DST for Demand and Capacity Planning of NHS Trusts

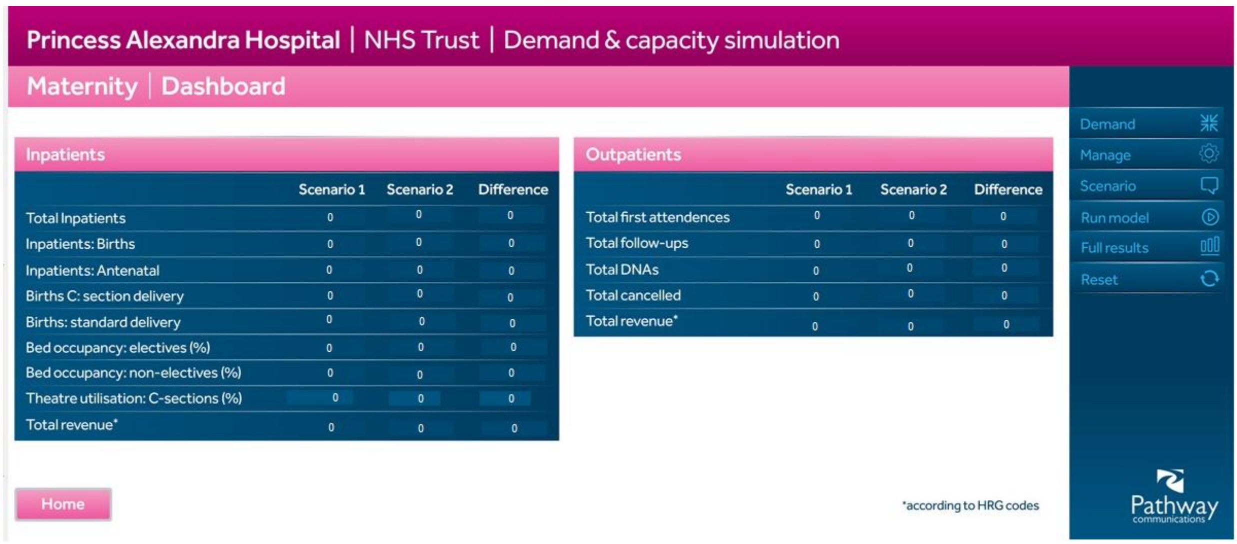

Figure 2: Maternity dashboard as an example

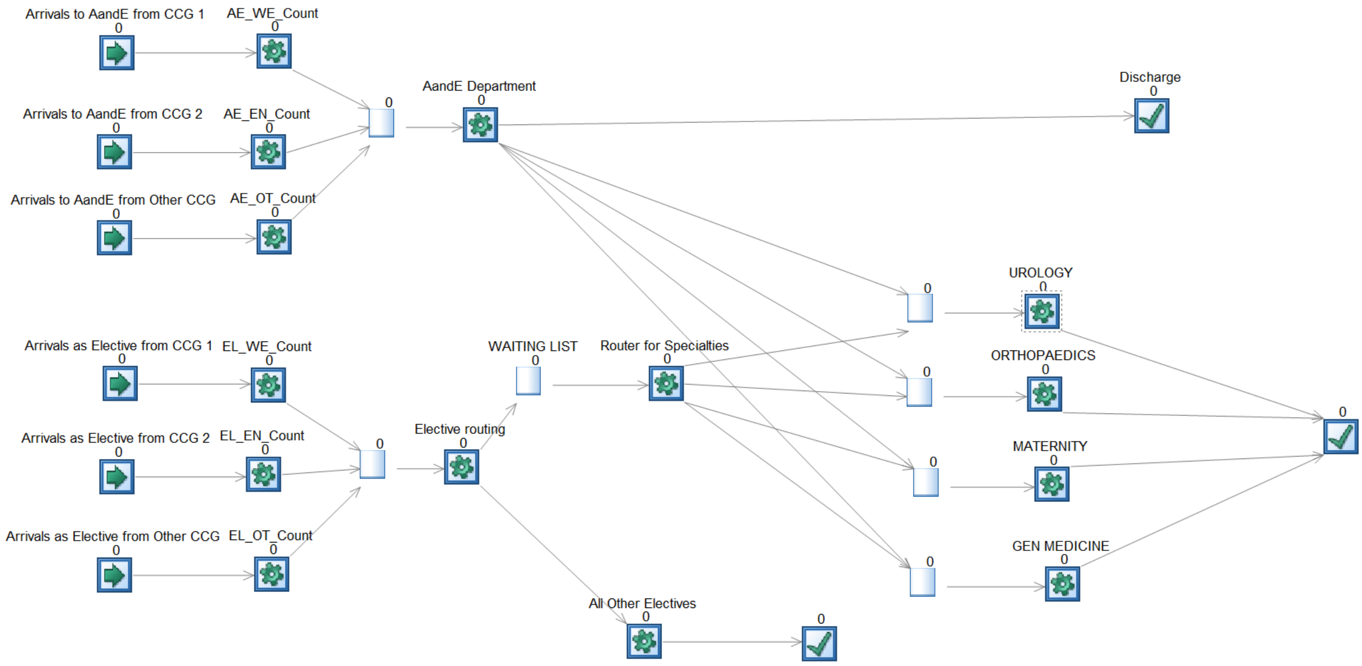

Figure 3: Model structure – Elective and Non-elective Inpatients

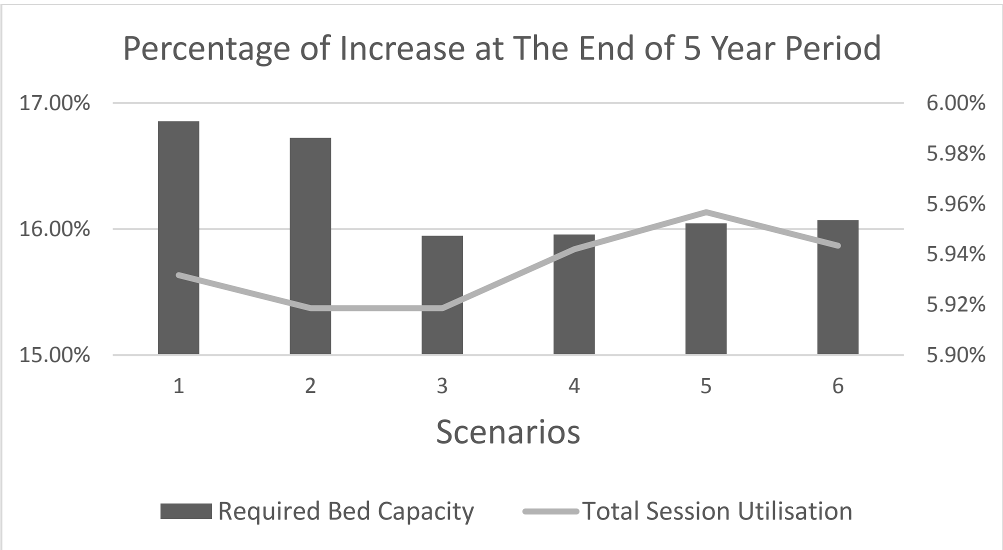

Figure 4: Percentage of increase in required bed capacity and total session utilisation of operating theatres at the end of 5-year period.