Near Real-Time Bed Modelling Feasibility Study

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ABSTRACT

Hospital bed management is crucial to ensure that patients do not have to wait for the right bed for their care. A simulation model has been developed that mimics the bed management rules applied to the Trauma & Orthopaedic wards of a busy Welsh hospital. The model includes forecasting methodologies to predict the number of emergency admissions, split by gender. The model uses near real-time admission data to see whether patients will be admitted to a given ward on a given day in a 7-day planning horizon. The one-week feasibility pilot study examined the accuracy and usability of the tool. The study has shown that it is possible to correctly predict the short-term processes of a Trauma & Orthopaedic bed management system by accurately forecasting arrivals, using known data and statistical distributions to predict patient length of stay, and applying generic bed management rules to dictate their placement.

KEYWORDS

bed management; simulation modelling; forecasting; emergency; elective

1. Introduction

Hospital beds are one of the most expensive forms of health care and their effective management is crucial to ensure efficient use and availability so that patients in need of acute care do not have to wait for the right bed. Work to date indicates that hospitals struggle to manage bed capacity (Akcali, Cˆot´e, and Lin (2006)) and many plan their beds based on average demand (Harper (2002)), using deterministic spreadsheets rather than on the real life variation in patient types, arrivals and length of stay (LOS) which is better modelled using simulation. This means that their plans underestimate variation in patient demand leading to an underestimation of patients queueing in the system. Hospital beds are generally managed by specialty and patients can be allocated a bed outside their speciality area when their own specialty is full. The research evidence shows that patients in a non-ideal bed placement, are likely to stay longer in hospital and twice as likely to die (Alameda (2009); Beckett (2014); Blay (2002); Santamaria (2014)). The aim of the simulation model discussed here is to improve planning thereby improving patient flow through the hospital.

The primary goal of the feasibility study described here is to prove the ability to use a daily extract of data to drive a simulation that will in turn assist in managing beds within the Trauma & Orthopaedic (T&O) specialty. The secondary goal is to gain feedback on the live simulation to determine what a tool of this nature would need to be able to do to be considered useful. The paper aims to highlight the usefulness of a short-term bed-planning tool within a busy T&O department that schedules both emergency and elective operations on a daily basis. The bed-planning tool provides an operational solution for ward managers planning their inpatient services. The tool combines discrete event simulation and traditional forecasting to provide the most accurate picture of the current bed stock and the number of patient admissions over the next 7 days. The paper is based on the development of the simulation model for Aneurin Bevan University Health Board which was undertaken between June 2016 and June 2017.

1.1. Background

Managing demand and capacity with variation is a complex task. Discrete event simulation can assist in providing evidence that helps in managing the demand and capacity associated with a system. Cardiff University and Aneurin Bevan University Health Board (ABUHB) were aware of a number of hospital bed management projects that SIMUL8 Corporation had supported and were keen to examine the benefits of a similar approach within the health board. Each bed management project used a similar methodology and had led to a template simulation model for long-term planning – Bed.P.A.C. The abbreviations P.A.C stand for Predict, Act, Communicate. The simulation model required a simple data upload and produces results for bed planners without users needing to learn to build simulations (Wight, 2017). The long term planning simulation shows the required bed numbers by specialty. It uses: patient arrivals (modelled by hour of the day and day of the week), numbers of midnight stays by day and time of arrival and a daily discharge profile. Constraining the simulation by the number of beds demonstrates the expected number of patients located on other wards (termed outliers), elective cancellations and wait times.

Hospitals have been using the long-term simulation for annual planning and to test the likely impact of improvement strategies. Table 1 shows a summary statistics and a bed utilisation projection from a typical run of the Bed.P.A.C model.

Table 1. Results summary with 18 beds

Total	95% LC	Avg.	95% UC
Demand	1,536	1,548	1,559
Admissions	1,129	1,140	1,152
Total Outliers	393	407	422
Avg. LOS	5	5.0	5
% Utilisation	88	88.8	89

Discussion with hospitals revealed that there was also a strong interest in short term bed capacity predictions. With the support of a Scottish Enterprise SMART (Small firms Merit Award for Research and Technology) grant, SIMUL8 was able to work with Aneurin Bevan University Health Board to develop and test a short-term predictive simulation which is presented here.

1.2. A Joint Project between an Embedded Modelling Group and SIMUL8

In terms of the collaboration with ABUHB, SIMUL8 worked with the Aneurin Bevan Continuous Improvement team (ABCi), which has both improvement practitioners and mathematical modellers, and members of the Information Department (responsible for providing the data). Improvement practitioners support clinical and management staff within the health board to undertake projects that might improve the performance of a department or enhance the staff or patient experience following the change put in place. The feasibility study began in June 2016 with a collaboration with the Isle of Wight NHS Trust before kicking off with ABUHB in mid-September with an initial scoping meeting, outlining the purpose and scope of the study.

The initial steps involved obtaining the health board data and having discussions with both the T&O directorate and the Information Department to explain the the model's purpose and data requirements. By November 2016, the data had been acquired and validated prior to the development of the short-term simulation model. The data was examined to ensure that it was in the correct format for the model, that there were no duplicate records and that all the date and time entries were correct. The data was also sense-checked to make sure that there were no situations where the data showed two patients occupying the same bed at the same time or a patient leaving before they had arrived. The data was also examined in terms of the appropriate bed-management rules to ensure that female patients were not placed on a male ward or vice versa. In February 2017, a workshop was delivered where the long-term model was demonstrated and how it could be adapted for near real-time bed planning purposes. The 5-day pilot study was arranged for the last week in April 2017 at the Royal Gwent Hospital, Wales, UK.

2. Related Work

Similar planning problems can be broadly broken into two streams: i) Related work on mathematical programming applied to operational planning problems in which bed capacity is constrained and ii) Discrete-event simulation models in which inpatients allocate scarce bed capacity.
To discover related work in both streams, the taxonomy from Hulshof, Kortbeek, Boucherie, and Hans (2012) was very useful. They categorise Operational Research and Management Science literature into health care services such as ambulatory, inpatient, and residential care. Because of the Trauma & Orthopaedic specialty and inpatients, our related work focuses on inpatient and surgical care services and is why we excluded work on, for example, residential care services. As a result, operational planning problems in which mathematical programming has been used whereby bed capacity is constrained is provided in Table 2.

Table 2. Related work on mathematical programming applied to planning problems in which bed capacity is constrained

Inpatient or surgical care services	Augusto, Xie, and Perdomo (2010); Cardoen and Demeulemeester (2011); Cardoen, Demeulemeester, and Beli¨en (2009a, 2009b); Ceschia and Schaerf (2011, 2014); Chow, Puterman, Salehirad, Huang, and Atkins (2011); Conforti, Guerriero, Guido, Cerinic, and Conforti (2011); Conforti et al. (2011); Demeester, Souffriau, De Causmaecker, and Vanden Berghe (2009); Fei, Meskens, and Chu (2010); Gartner and Kolisch (2014); Gartner, Kolisch, Neill, and Padman (2015); Gartner and Padman (2019); Guinet and Chaabane (2003); Jebali, Alouane, Atidel, and Ladet (2006); Min and Yih (2010); Ozkarahan (2000); Range, Lusby, and Larsen (2014); Testi and Tanfani (2009); Turhan and Bilgen (2017)

The majority of these papers use linear programming approaches to tackle the patient-to-bed assignment which had been addressed by Demeester et al. (2009) and then extended by, for example, Range et al. (2014). This is, however, different to the Bed PAC tool because of the bed-assignment policies built-in into the simulation model which are located on an operational online planning level.

Our second stream of related work focuses on discrete-event simulation modelling. Bed capacity planning problems have been widely considered, including for example by Harper and Shahani (2002). The authors examine what the likely bed requirements for a specialty bed-pool will be over time including the relationship with other hospital specialty bed-pools. Furthermore, they analyse what effects changing various admission rules may have on the efficiency of the bed-pool and include refusals (transferred or deferred patients) which is similar to our model.

Another relevant paper is Landa, Sonnessa, T`anfani, and Testi (2014) which considers emergency and elective patients that require a bed during their hospital stay. The case study describes the development of a DES model used as a decision support tool to optimise the use of available resources and aid bed management. The tool has also been used to consider the effects of different bed management policies on the patient and the hospital in terms of flow. Moreover, it mentions bed management rules to manage patient flow in relation to performance measures. The difference to our paper is that we use forecasting methods within the model to predict demand and specify ward-specific patient subgroups.

Finally, Monks et al. (2016) model one specialty which consists of different patient subgroups. Patients are located on multiple wards and, similar to our work, the authors use SIMUL8 as the software package to model the problem and run scenarios. Given that in our study we are focused on Trauma & Orthopaedics, this means that for example patients have different length of stay distributions, which in turn impacts on bed utilisation.

3. Data

The information and data required to build and run the simulation model comprises of four distinct sets:

- Bed base layout
- Bed management rules
- Historical transaction log
- Scheduled elective plan

The bed base layout and bed management rules are required in order to build the structure of the simulation as well as the logic that determines how patients move within it. The bed base layout contains details of the number of beds and how they are split into single occupancy cubicles and multi-occupancy bays, and then arranged into larger wards. The bed management rules convey how patients arrive into the bed base, where they should ideally be placed and where they should be sent if the ideal placement is not available.

The data provided by the historical transaction log and scheduled elective plan is then used to build the statistical distributions and forecasts applied to the LOS calculation and the patient arrivals process. The historical transaction log is a record of patient arrivals and movements within a specialty bed base, including where and when patients were within the system as well as patient information such as gender, age, specialty, and admission method type. The arrivals process is broken down into the two admission method types, emergency and elective. Elective arrivals are known in advance and thus this method simply uses the scheduled elective plan to dictate how many electives are planned each day for each gender. Emergency arrivals are unknown and therefore a forecasting tool was built to predict the number of arrivals in the forthcoming week by using three years of historical demand (prior to the date the model was run) for each gender. The forecasting tool considers three different traditional methods: Simple exponential smoothing, double exponential smoothing and Holt-Winters. Each method requires the estimation of one or more smoothing parameters; carried out using the Solver Add-In feature in Excel. The methods were applied to the historical data. The model needs to consider day of the week and patient gender and forecasts the two gender populations separately as the hospital has separate wards for male and female patients (Bilgin, Demeester, Misir, Vancroonenburg, and Berghe (2012); Ceschia and Schaerf (2016)). In total, 42 different forecast models were considered and the best one chosen for each data set (according to patient gender and day of the week). The novelty of the approach discussed here has been to link traditional forecasting techniques with simulation to optimise the performance metrics of the model.

4. Method – The Simulation Model

Figure 1 shows a diagram of the implementation of the simulation model in SIMUL8.

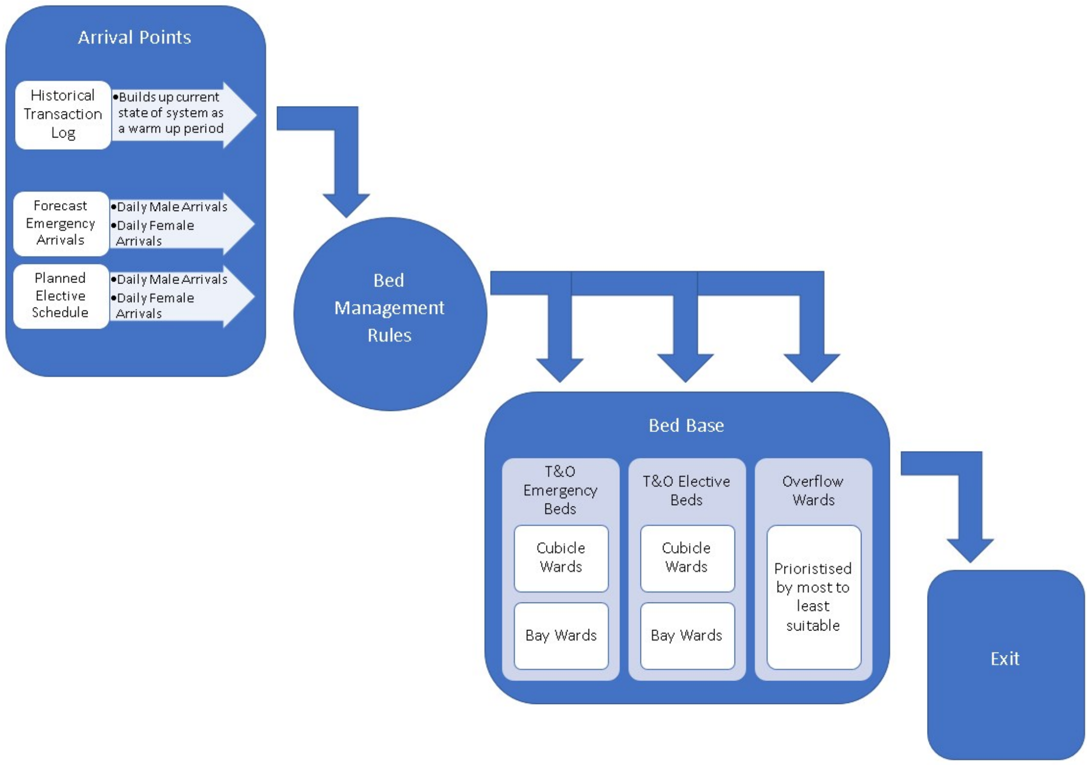

Figure 1. Diagram of the implementation in SIMUL8.

The simulation uses the current state of the system as a starting point and forecasts emergency arrivals based on daily male and female arrivals. In addition, the planned elective admissions are incorporated into the planning. Then, with the bed management rules, the bed base is filled where it is decided whether patients go into cubicle, bay or overflow wards. Figure 2 shows a screenshot of the simulation model at midnight on 25th April 2017.

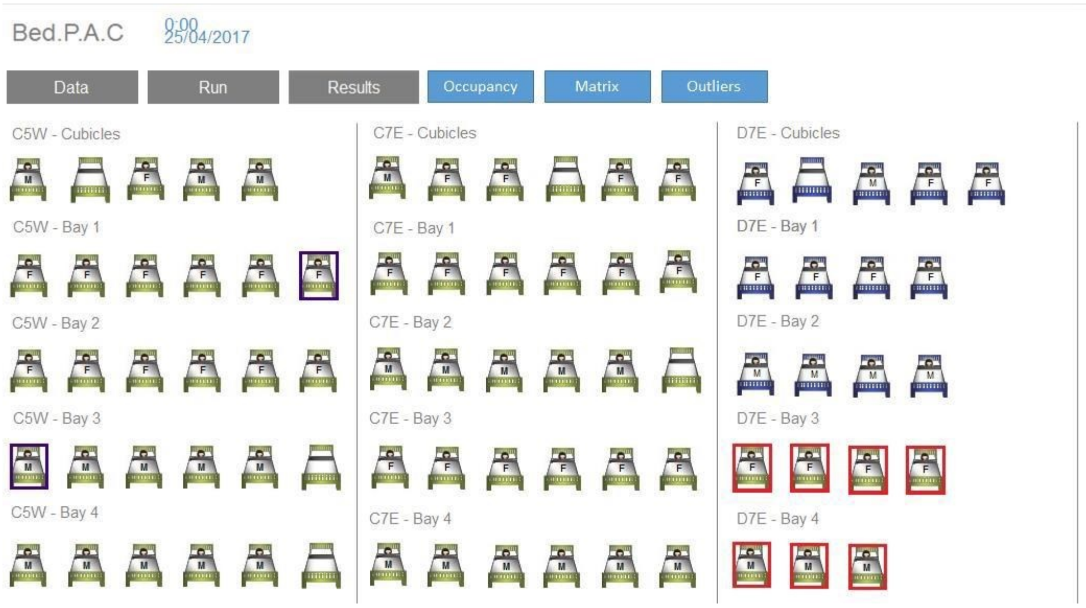

Figure 2. Screenshot of the SIMUL8 Short Term Bed Planning Tool.

Each of the T&O wards at the Royal Gwent Hospital are shown. Male beds are labelled with an "M" and female with an "F". Wards are split into single occupancy cubicles and multi-occupancy bays. The bed management rules within the simulation model relate to the division of the wards into bays. Green beds are assigned emergency beds and blue beds are assigned elective beds. When a patient enters a bed assigned to an admission type that is not theirs the colour will be changed to theirs but a red box will be displayed to indicate that they are encroaching on beds not assigned to that admission type. When a patient who is not from the T&O specialty enters the T&O assigned wards a purple box will be displayed to indicate as such.

As the model runs the screen dynamically changes showing the beds emptying or filling over time. Results are fed through to Excel spreadsheets that can be analysed after the model has run. Table 3 provides an overview of data fields included in the model.

Table 3. Data fields included in the model

Bed Base Layout	Historical Transaction Log	Scheduled Elective Plan
Hospital Site	Unidentifiable Patient ID	Ward Name/Number
Ward Name/Number	Hospital Site Code	Bed Name/Number
Bed Name/Number	Ward Name/Number	Planned Admission Date
Occupancy Type (Cubicle or Bay)	Bed Name/Number	Admission Time
Assigned Admission Method (Elective or Emergency)	Date Admitted To Hospital	Unidentifiable Patient ID
	Date Entered Bed	Sex

Date Left Bed	Referral Date
Discharge Date	Planned Operation Date
Estimated Date of Discharge Original	Service Name
Estimated Date of Discharge Latest	Priority
Outcome	Patient Classification (Inpatient or Day case)
Specialty Name Sex Age Admission Method (Elective or Emergency) Patient Classification (Inpatient or Day case) Admission Reason	Admission Reason

5. The feasibility study

The setup and execution of the feasibility study followed a process which can be summarized in Figure 3.

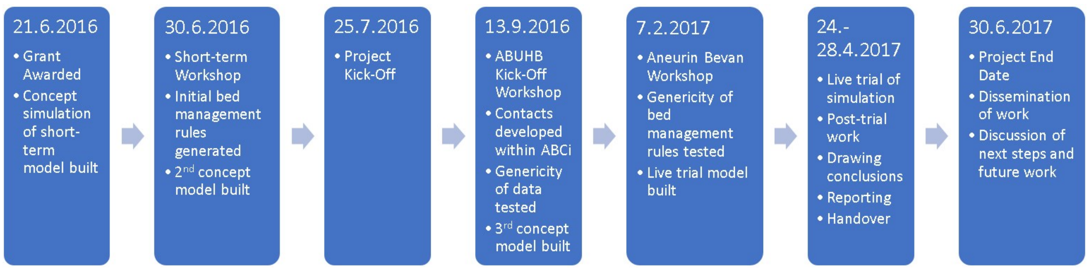

Figure 3. Flow chart describing the feasibility study

In a first step, a concept simulation model was built, followed by a workshop in which bed management rules were discussed such that the simulation model represents current policy. Afterwards, the project was started including tests in close collaboration with senior managers followed by the build and test of the live model. Finally, the results were discussed and next steps were outlined.

5.1. Forecasting Model Verification and Validation

The simulation tool relies on a variety of forecasting approaches to forecast the number of male and female emergency admissions arriving on a daily basis. This is then used as one of the data inputs for the simulation that then runs forward for 7 days to predict the effect on the T&O bed base. Work had been undertaken using data collected from 1/4/2013 – 31/10/2016 provided by ABUHB to validate the forecasting methods. The trial data sets were refined to the 3 years of data prior to the date of data retrieval (i.e. 25/4/2014 – 24/4/2017 for the first day of the trial). The start and end dates were then incremented by one on each successive day of the trial.

5.2. Simulation Model Verification and Validation

The location data within the historical transaction log was validated against the provided bed base layout, which was taken as being an accurate representation of the current system. The historical transaction log was cleaned and verified by inspecting values and information within the dataset. Erroneous values were removed from the dataset. The frequency of such errors was minimal and varied between data extracts. The generated bed management rules were validated by running the historical transaction log through a test simulation to dynamically examine the recorded behaviours. The analysis showed that the identified rules were being adhered to sufficiently for the rules to be deemed correct. Additionally, a consistency check was carried out for the scheduled elective plan.

Work prior to the trial identified the majority of the data fields needed to run the simulation. However, a few were added after the workshop just before the offset of the trial:

- The expected date of discharge (EDD) which had been added to the data request but not fully analysed before the trial began.
- Data relating to a patient's presenting complaint (captured in a free-text field) would identify particular cohorts of patients that might have a longer LOS on the ward.

As the forecasts need to be useful to those that manage the beds within a healthcare setting, one purpose of the 5-day trial was to identify the best setting in which to display the information from the tool to the right people in the most suitable format. Throughout the week, members from SIMUL8 attended a variety of site and planning meetings to see where the tool could be used within the health board and which type of staff would find the tool useful. The site manager meetings were attended to understand the process of bed management. These meetings occur three times a day (at 8:30, 12.00 and 15:30) and focus on the planning of patient flow through the whole hospital over the next 3 to 4 hours. This is aimed at making sure that they are well prepared approaching the evening shift to in turn allow them to carry that situation into the next day. These meetings last for roughly 15 minutes and require the attendance of key staff from across the hospital to bring currently up to date, clinical-level data. This information is then used to make decisions, such as whether to open additional extra capacity beds or if there is a need to move staff around to match the differing levels of patient activity across the hospital.

The ward manager meetings were attended to understand how planning is handled internally to the T&O wards. These meetings occur once daily (at 13.00). The focus of this meeting is to provide an update on the recent admissions and discharges and then use that information to plan staffing across the T&O wards to ensure patient safety. An extra meeting was also arranged with the T&O Assistant Directorate Manager to gain his views on the potential value of a predictive short-term bed planning tool in his role and the two aforementioned site and ward manager meetings.

Coupled with the challenge that the data is in the right format for the tool, is the added challenge that the data needs to reflect the most up to date information. Staff from the ABUHB Information Services team flagged the potential problem that the databases feeding the simulation model might not necessarily be up to date at the point of extraction. This was monitored during the 5-day trial and the week following the completion of the study.

Each day the updated data extract needed for the simulation model was received at 08:30, analysed and fed into the model. To monitor and analyse the severity of the data delay due to the data cycle time a comparison was made using each day's provided extract against the previous day's extract (for example, using Tuesday's data to look for information that should have been known on Monday). In this manner four comparisons were created (Tue:Mon, Wed:Tue, Thu:Wed, Fri:Thu) using the five daily extracts from the trial. Within these comparisons the differences that were searched for included: Admissions, Patient Movements and Discharges. In addition, the length of time it took for this previously unknown information to become available was tracked as it was possible that the cycle time of data went beyond a single day.

6. Results – Simulation Model

The results output built into the simulation tool was developed based on feedback received from the workshop held with ABUHB in February 2017. In this workshop it was decided that the output should be clear and easy to understand for staff using the tool. For this reason, results produced by averaging multiple runs of the simulation are rounded to the nearest whole patient and confidence limits are not shown.

For the live trial two distinct methods of displaying the results were used, the first being a specialty or ward overview approach that provided key performance indicators and the second being a bed base occupancy approach that showed how much free capacity was available. Results from an example simulation run are used here for demonstration purposes. The results displayed for the whole specialty view for each day of the simulation include:

- Number of admissions for each admission method type (emergency and elective) in total and by gender
- Number of discharges for each admission method type in total and by gender
- Number of outliers for emergency admissions in total and by gender
- Number of cancelled elective admissions in total and by gender
- Average daily bed occupancy O_a for each admission method type. The occupancy is calculated as follows: Let T be the set of micro-periods during each day with cardinality $|\mathrm{T}| = T$ and let o_t be the occupancy in each period $t \in \mathrm{T}$. Then, the daily occupancy is calculated as given in Equation (1).

$$O_a = \sum_{t=1}^{T} \frac{o_t}{T} \qquad (1)$$

- A 'traffic light' colour code representation of average daily bed occupancy for each admission method type

For example, on Monday the simulation model predicted an average bed occupancy of 95% for the emergency patients and 97% for the electives. The results displayed for the ward-based view for each day of the simulation include:

- Number of admissions for each T&O ward (C5W, C7E and D7E) in total
- Number of discharges for each ward and in total
- Number of expected discharges (using the Expected Date of Discharge (EDD) data) for each ward in total

- Midnight bed occupancy for each ward (typically used as a key measure within the hospital; the model could give the occupancy over time but managers are more interested in this metric which they can use as a benchmarking figure with other hospitals in the region).
- A 'traffic light' colour code representation of midnight bed occupancy for each ward.

The daily results for the whole T&O specialty are shown in Figure 4.

Select:
Trauma Orthopaedics

Emergency	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
Avg. Bed Occupancy	95%	96%	95%	95%	93%	92%	92%
TOTAL							
Admissions	7	5	8	7	7	5	5
Discharges	6	8	8	9	10	6	5
Outliers	0	1	1	0	0	0	0
MALE							
Admissions	4	2	5	3	3	3	2
Discharges	3	4	4	4	5	3	2
Outliers	0	0	1	0	0	0	0
FEMALE							
Admissions	3	3	3	4	4	2	3
Discharges	3	4	4	5	5	3	3
Outliers	0	0	0	0	0	0	0

Elective	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
Avg. Bed Occupancy	97%	91%	84%	80%	71%	64%	50%
TOTAL							
Admissions	4	6	5	3	1	2	0
Discharges	3	6	4	5	4	4	1
Cancelations	0	0	0	0	0	0	0
MALE							
Admissions	1	3	3	0	1	1	0
Discharges	0	2	1	2	1	2	1
Cancelations	0	0	0	0	0	0	0
FEMALE							
Admissions	3	3	2	3	0	1	0
Discharges	2	4	3	3	2	2	1
Cancelations	0	0	0	0	0	0	0

Figure 4. Daily results for the whole T&O specialty.

Figure 5 shows the bed occupancy on each ward (e.g. 96% on C5W, 96% on C7E and 91% on D7E on Monday) and the number of admissions and discharges each day.

Trauma Orthopaedics *Emergency*							
C5W	**Monday**	**Tuesday**	**Wednesday**	**Thursday**	**Friday**	**Saturday**	**Sunday**
Bed Occ at 00:00	96%	95%	97%	97%	94%	94%	95%
Admissions	2	2	3	2	2	2	2
Discharges	2	2	2	2	3	2	1
EDD Discharges	1	1	1	1	1	1	0
C7E	**Monday**	**Tuesday**	**Wednesday**	**Thursday**	**Friday**	**Saturday**	**Sunday**
Bed Occ at 00:00	96%	94%	93%	91%	89%	89%	90%
Admissions	4	2	3	3	4	3	3
Discharges	3	3	4	4	4	3	2
EDD Discharges	2	2	2	2	2	1	1
Elective							
D7E	**Monday**	**Tuesday**	**Wednesday**	**Thursday**	**Friday**	**Saturday**	**Sunday**
Bed Occ at 00:00	91%	81%	79%	73%	61%	51%	45%
Admissions	1	2	3	3	2	2	1
Discharges	2	4	4	4	4	5	2
EDD Discharges	2	2	2	2	2	1	1

Figure 5. Daily results – ward based view.

The second method is available only for a whole specialty level and the results displayed for each day of the simulation include:

- Number of free beds available at the start of the day for each admission method type by type of bed and gender
- Number of admissions for each admission method type by gender
- Number of discharges for each admission method type by gender
- Number of free beds available at the end of the day for each admission method type by type of bed and gender
- A 'traffic light' colour code representation of number of free beds available at the end of the day for each admission method type Detailed results including patient gender are shown in Figure 6.

Select: *Trauma Orthopaedics*							
Emergency	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
Starting Free Beds	4	2	3	2	3	4	4
Unassigned Cubicle Beds	2	1	1	1	1	1	1
Unassigned Bays Beds	0	0	0	0	0	0	0
Male	1	1	1	1	1	2	2
Female	1	1	1	1	1	1	2
Expected Admissions	7	5	8	7	7	5	5
Male	4	2	5	3	3	3	2
Female	3	3	3	4	4	2	3
Expected Discharges	6	8	8	9	10	6	5
Male	3	4	4	4	5	3	2
Female	3	4	4	5	5	3	3
Free Beds End	2	3	3	3	4	5	4
Unassigned Cubicle Beds	1	1	1	1	1	1	1
Unassigned Bays Beds	0	0	0	0	0	0	0
Male	1	1	1	1	2	2	2
Female	1	1	1	1	2	2	1

Elective	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
Starting Free Beds	0	2	4	4	5	8	10
Unassigned Cubicle Beds	0	0	1	1	1	1	2
Unassigned Bays Beds	0	0	0	0	0	1	1
Male	0	1	1	1	2	2	3
Female	0	1	2	3	3	4	4
Expected Admissions	4	6	5	3	1	2	0
Male	1	3	3	0	1	1	0
Female	3	3	2	3	0	1	0
Expected Discharges	3	6	4	5	4	4	1
Male	0	2	1	2	1	2	1
Female	2	4	3	3	2	2	1
Free Beds End	2	4	4	5	8	10	11
Unassigned Cubicle Beds	0	1	1	1	1	2	2
Unassigned Bays Beds	0	0	0	0	1	1	2
Male	1	1	1	2	2	3	3
Female	1	2	3	3	4	4	3

Figure 6. More detailed results including patient gender.

For example, on Monday there are 4 free beds at the start of the day, 7 expected admissions, 6 expected discharges and 2 free beds at the end of the day on the emergency ward. Having the results presented in a dashboard (see Figures 4, 5 and 6) allows the ward manager to see at a glance whether the bed occupancy is at an acceptable level and whether any cancellations or outliers have occurred as a result of limited bed availability.

7. Results - Feasibility 5-day trial

7.1. Demand forecasting

Using the historical data contained within the daily extract of data, forecasts for the emergency admissions into the T&O specialty at the Royal Gwent Hospital were made for male and female patients arriving on each day of the week. Let Y_i be the demand observed from n observations values and let $\hat{Y}_i$ be the predicted demand, our aim is to minimize the Mean Squared Error (MSE) between the observed and predicted demand using equation (2).

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2 \quad (2)$$

Exponential smoothing was chosen as one of the forecasting methods that minimize the MSE. Three years of historical data was used to provide this forecast and the graph of total (male and female) forecast emergency admissions against total actual emergency admissions is given in Figure 7. On average, the weekly error was 0.08 emergency admissions for the best performing forecast method.

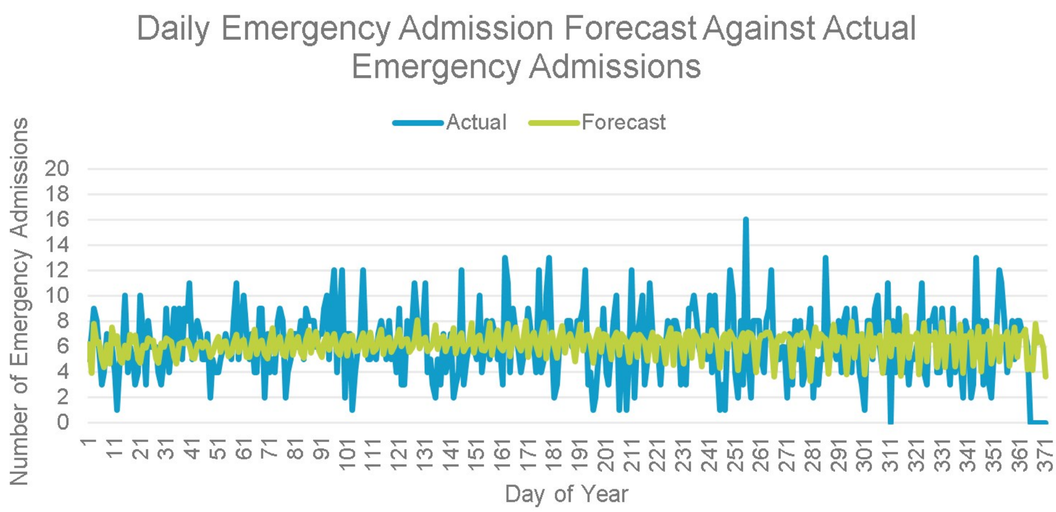

Figure 7. Comparison of the actual and forecast emergency admissions.

7.2. Simulation model verification and results

We ran the simulation model 200 times and averaged the results before presenting them to the decision maker. It is worth mentioning that it would be possible to drill down further into the data to produce non-averaged results if necessary. Figure 8 compares the actual and simulated emergency admissions over the trial period.

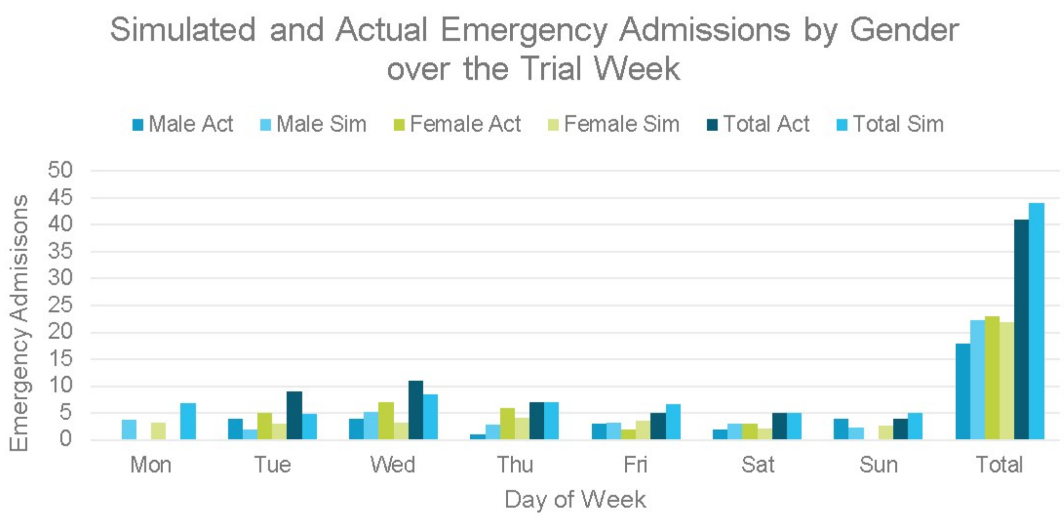

Figure 8. Simulated and actual emergency admissions, by gender, over the trial period.

The figure reveals that the daily total of emergency admissions varies between 0 and 16, with an average of 6.1. The daily total forecast varies between 3.3 and 8.4, with an average of 6.2. Further analysis of the errors showed that 96.2% of the daily forecasts are within +/- 5 emergency admissions. Figure 9 provides an overview of the actual and simulated emergency admissions. The figure reveals that the actual and simulated occupancy rates are very close.

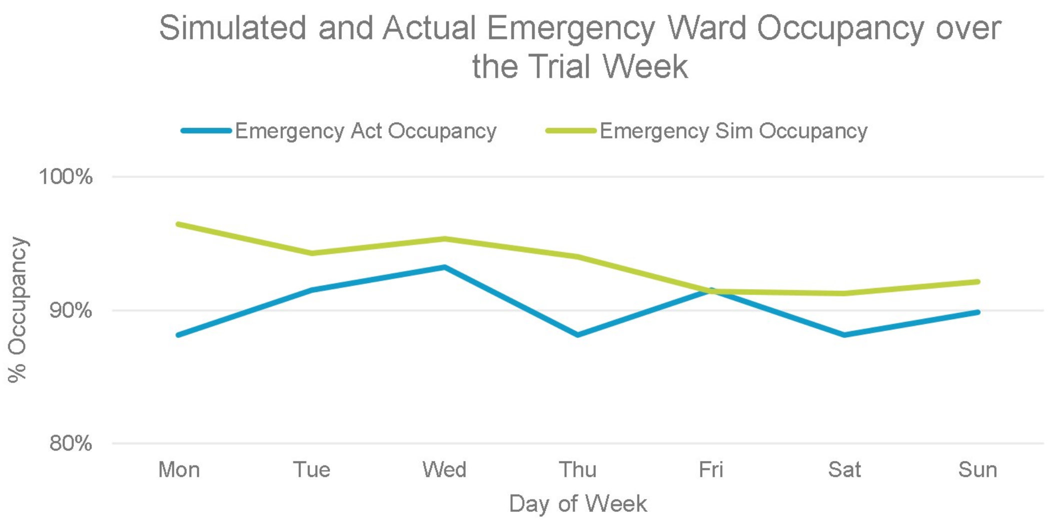

Figure 9. Simulated and Actual Total Occupancy over the week.

The largest disparity occurs on the first day of the trial where in reality there were 0 emergency admissions, a value that occurs only once in the previous year's historical data and thus very much an outlier to the standard values observed. Over the course of the whole week the cumulative simulation emergency admissions were 3 emergency admissions higher than the cumulative actual observed emergency admissions.

The next area to assess was how well the simulation replicates the T&O bed and ward system. The most commonly used Key Performance Indicator (KPI) for assessing a bed base is bed occupancy at midnight and thus this KPI has been measured in the simulation over the trial week and compared against the reality.

Bed occupancy at midnight has been measured in each of the admission type's bed bases, Emergency and Elective as well as in the Overflow Ward built to simulate outliers, which is compared against the number of actual outliers. Finally the whole T&O bed base, including outliers has been measured (see Figure 9).

In the Emergency Ward Occupancy, the simulation closely replicated the actual emergency bed base occupancy, with a marginally higher level of occupancy, decreasing slightly through the week compared to the actual occupancy which remains reasonably steady. In the Elective Ward Occupancy, the simulated and actual occupancy level starts at a similar level at midnight on Monday. As the week progresses, the difference between the two increases.

By combining all areas of the T&O bed base, it is possible to assess how well the system is being replicated as a whole. Figure 9 shows that the simulation is a close representation of reality. The greatest disparity is at midnight on the first day where the difference is 86.7% in reality and 95.0% in the simulation. This difference is almost certainly due to the simulation forecasting 7 emergency admissions on Monday while in reality there was an unusual annual low of 0 emergency admissions that day. It can be concluded that the simulation tool can accurately predict Emergency Ward occupancy but struggles to predict Elective Ward occupancy as well as the number of outliers being placed in the Overflow Ward. Taking a whole T&O system view it can also be said that the simulation tool can accurately predict the Total T&O occupancy.

By analysing the results on a daily basis it is noted that a small number of emergency ward beds are consistently left free while the elective ward is being utilised by emergency patients. This, alongside the midnight occupancy evidence, would suggest that there is an inconsistency with the method by which the simulation outlies patients into the Overflow Ward. In reality these patients are kept within the T&O bed base while the simulation instead finds that they should become outliers and placed elsewhere. This is most likely caused by utilising the shuffling mechanism conducted by the bed managers, where a patient is transferred to a different bed to free up the correct bed for a newly arriving patient.

8. Conclusions

Our overall conclusion is that, with up to date data, the model can be used as a decision support tool for the bed management. The study has also allowed us to identify key data items to track in order to maximise the predictive power of the simulation. The identification of subsets of the specialty cohort within the data, such as hip fracture patients and patient details regarding infection control would provide greater insight to improve bed management and planning.

From staff feedback during the trial, this tool would be most useful in weekly planning and reviewing for continuous improvement rather than for daily use, aimed at using past events to improve future decision making.

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