MODELLING OF INTENSIVE CARE UNITS AND OPERATING THEATRE IN PUBLIC HOSPITALS

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ABSTRACT
An advanced simulation model encompassing public hospitals’ intensive care units and operating theatres is developed in this paper. The parameters and constraints within the system and their effects on dependent variables are analysed. It was found that statistically significant distributions could be fitted to most of the parameters in the model. ARENA simulation package was chosen because of its flexibility and visual nature and is used to describe and analyse the system. Results of a significant numerical investigation at a public hospital are also presented. The model is used to develop a decision support system to establish the benefit of operational changes and/or as a planning tool.

Key Words: Health Care Systems, Simulation.

1. INTRODUCTION
The efficiency of public hospitals in Australia or anywhere in the world is of utmost importance to the people who use them. The state of public hospital waiting lists for elective surgery is one of the major issues highlighted by the media in Australia. This study aims to develop a general model encompassing hospitals’ Intensive Care Unit (ICU) and Operating Theatres (OT). It will be possible to modify the parameters of the model easily to evaluate their effects on a number of dependent variables within the model. The model parameters include; arrival rate distributions, lengths of stay distributions, number of beds in the ICU, number of OTs, etc. The dependent variables include; number of rejected patients, ICU utilization rates, patient waiting times, etc.

An advanced simulation model will be developed to approximate the ICUs and OTs of the Princess Alexandra Hospital. Numerical analysis will be performed for this example to show the effect of parameters within the model on dependent variables.

A patient arriving at the ICU may be from one of five sources. These are; Ward (W), Accidents and Emergencies (AE), Operating Theatre Emergency (OM), Operating Theatre Elective (OE), Other Hospitals (OH)

Arriving patients are classified as either elective surgery admissions or acute admissions, based mainly on their arrival source. All patients requiring elective surgery and those patients
transferred from other hospitals requiring elective surgery comprise the elective surgery admissions. The remaining arrivals make up the acute admissions. This distinction is made because the ICU is separated into two parts to handle these different admissions.

The ICU has a total of sixteen beds. During the week there are four beds allocated to elective surgery admissions in the **Elective ICU** and twelve beds for acute admissions in the **Acute ICU**. Over the weekend the Elective ICU is closed to new admissions as elective surgery is only scheduled during the week and then only during business hours. The Acute ICU operates normally throughout the entire week and it can receive admissions at any time.

When the number of requested admissions to either ICU exceeds the number of available beds the admitting consultant is responsible for deciding which patients are admitted. A number of factors are considered to prioritise admission and these are different for each ICU.

The Acute ICU admission priorities are dependent on the:
- hospital the patient is referred from;
- availability of required tertiary level care in other part of South-East Queensland; and
- source of patient, whether they are an in-patient or emergency admission.

Patients that cannot be admitted to the Acute ICU are transferred to another hospital.

The Elective ICU admission priorities are dependent on the:
- need for multiple surgical teams during surgery;
- number of previous surgery reschedules;
- urgency of surgery;
- in-patient cases that cannot be sent home; and
- amount of time spent waiting.

A public hospital provides $n$ OT pods. Pods provide are grouped by the type of surgery that it is used for. These pods are only operational during business hours on weekdays. If there are no beds available in a particular ICU then the patient cannot proceed to the OT and their surgery is cancelled.

Patients that utilise the theatre pods may not require intensive care and may only need a lower level of care in one of the hospitals Ws. Therefore not all patients using the theatre pods pass through the ICU, this study is limited to those patients that do pass through the ICU.

Elective patients arriving at the Elective ICU that are unable to be accepted have their surgery **rescheduled** for a later date. The maximum time until their surgery is rescheduled is based on their clinical urgency category. Acute patients arriving at the Acute ICU that are unable to be accepted are **rejected** from the system. This means that they will be transferred to another hospital for care. The number of patients that have to be rescheduled or rejected is one of the performance indicators of the hospital and it is expected that this number be minimised. When a surgery is rescheduled it causes many costly effects to the hospital and the patient. For example the hospital has to cancel resources previously allocated to the cancelled surgery. All process is summarised in Figure 1.
2. PAST RESEARCH

Two areas of literature were reviewed that provided an insight into the system modeled. These are investigations that use simulation methods to describe an ICU and/or OTs and general investigations relating to bed allocation and waiting lists in public hospitals.

2.1 General Hospital

(Kusters et al. 1996) developed a model to predict the effects of decisions on resources to aid a human in admission planning with three goals in mind. These are to

- optimise patient throughput by minimizing waiting times;
- maximise hospital resource utilization;
- optimise availability of emergency services.

The study included an analysis of the number of beds, OT facilities and nursing staff. It was found that patients could be categorised by the combination of their final diagnosis and the surgical procedure undertaken. A correlation between the combination of gender and admitting source with length of stay was also observed.

Queuing theory models were also developed specifically for this system to describe bed availability, OT availability and nurse workload. Using these the decision support system was able to predict, with very low error, the number of available beds and also OT availability.

(Lapierre et al. 1999) focused on balancing the number of beds between specialty units so that demand in each unit was met “most of the time”. These units were the different medical and surgical specialties that comprised the hospital. New hourly census data was collected for this model as the current census-at-midnight data did not account for patients with short length of stays.

A time series model was also developed based on the analysis of the hourly census data. It was applied to the perinatal unit to determine the best allocation of beds between its subspecialties. The results of the model influenced the hospital to reallocate the number of beds within this unit.

A study by (Vissers 1998) developed a decision support system to aid in regular revision of resource allocation between specialties to uniformly spread the resource utilization. These resources included beds, OTs, specialists, and nursing staff. Resources were categorised as

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**Figure 1. General ICU and OT Process Diagram**
either leading or following. The leading resources act as triggers for utilization of following resources. The specialist is one of the more important leading resources in a hospital.

The decision support system mentioned was based on a sensitivity analysis of the system. This determined that bed numbers were the bottleneck in the hospital studied, and the allocation of beds was given higher priority over other resources. Based on the findings of this investigation beds were reallocated between specialties.

(Kapadia et al. 2000) investigated the duration of stay of patients in a pediatric ICU using discrete time Markovian processes. A high, medium or low severity of illness scores was assigned to patients daily using PRISM scores. A PRISM score takes into account 14 weighted variables to determine a risk of mortality.

325 patients were observed and these were split into 2 groups. One used for estimating the discrete Markov process and the other to validate the results gained from the first set against. The Markov process was used to find a relationship between the severity of illness on consecutive days. It was assumed that the change in severity is independent of time, and hence changes can be described by a transition probability matrix.

Using this method the difference between the observed and expected overall duration of stay in the system was found to be negligible. This type of modeling allows hospitals to give patients an expected length of stay and predict when the severity of illness of a patient is likely to change. Also knowing the likelihood of a change will allow staff and resources to be better scheduled to treat patients.

2.2 Simulation Literature Review

The complex nature of hospitals with the interaction of many random occurrences lends itself particularly well to analysis by simulation. A study by Kozan and Gillingham (1997) used simulation to change parameters to find a solution to meet desired levels. Two ways to approximate an ideal solution of no patients waiting and total resource availability were examined. This study was used as a starting reference of this simulation work.

A small amount of research that analyses the efficiency of the ICUs has used simulation methods. Mainly arrival distributions, distinct sources of arrivals, service times or lengths of stay were investigated. For example (Kim et al. 1999; Kim et al. 2000; Kim et al. 2002). have written a number of papers in the area of ICU simulation. Each new paper has built on the findings of the previous. The specific system modelled was that of a public hospital in Hong Kong. (Ridge et al. 1998) is another author in this area and his research has a similar scope to that of Kim’s papers (1999, 2000, 2002). The main differences between the two authors works are that Kim focused on just the ICU while Ridge included the OT and also allowed rescheduling of elective surgery cancellations.

Each of the authors identifies elective surgery patient arrivals as the major complicating factor in the smooth running of an ICU. Furthermore the aim of reducing rescheduled elective surgeries is at the detriment to the service of patients from other sources and a balance needs to be found.

The goals of the first paper by (Kim et al. 1999) were to determine if the ICU currently had sufficient capacity and to discover ways to improve ICU performance in general. To do this they needed to establish the major patient sources, find arrival and length of stay distributions for each source and then verify that the simulation developed was a good approximation of the real world system. The major sources were determined by Kim (1999) to be from wards internally at the hospital, Accidents and Emergencies (AE), Operating Theatre – Emergency (OM) patients and Operating Theatre – Elective (OL) patients. Out of a total 882 patient arrivals, 390 were from Ws, 194 from AE, 90 from OM and 208 from OL.
The arrival rates and length of stays of the first 3 sources, Ws, AE, and OM were well fitted by Poisson distributions. However the OL source could not be fitted by this distribution. For simplicity in developing a queuing theory model they used a worst-case scenario Poisson distribution to approximate the two characteristics of the OL source. It was also noted that compared to other sources, OL patients required less time in the ICU and a lower variation in length of stay times was found.

Six months worth of data formed the basis of the analysis for the three papers written by Kim et al. It was assumed that the shape of the arrival and length of stay distributions would stay the same for any six month period, with the only difference being a change in the parameters of the distribution. This ignored any seasonal variation in arrival rates.

The simulation was run for a six month period. Using Poisson arrivals showed a similar number of treated patients from the first 3 sources and a much higher number of patients treated from the OL source. Specifically the number treated increased from the observed value in the data of 150 to 270. This confirmed that the ICU currently had sufficient capacity.

As OL patients are scheduled in advance they thought it more plausible to fit them to a uniform distribution. By doing this they found that waiting times could be reduced by two thirds without significantly reducing the number of patients treated.

The simulation showed a relatively low bed utilization rate of 69% with high maximum queue length which suggested that current capacity problems were due to an imbalance of the supply and demand of beds at certain times. This provided the basis for the second paper (2000) which investigated new bed reservation schemes.

These schemes were of two types, **Dependency Unit** (DICU) and **Flexible Bed Allocation** (FBA). The DICU scheme allocated a fixed number of beds for OL patients whereas the FBA scheme allocates a different number of beds to OL patients depending on the day of the week.

As this study was more focused on elective surgery patients a more accurate description of their arrival and service time distributions needed to be found. It was found that the arrival times for the OL were related to their length of stay. A weighted combination of 3 gamma distributions, each representing a range of length of stay times was found to fit the arrival rate data.

Four FBA schemes were compared to the DICU scheme. The first reserves beds exclusively for OL patients. The next two take advantage of the fact that elective surgery patients seldom arrive on weekends. The second allows patients from the AE source to use the beds on Friday and Saturdays, with the third allowing anyone to use them during these days. The fourth scheme shares the reservation of beds between patients from both OL and OM sources.

These schemes were evaluated using a number of factors including bed utilization, average waiting time, and number of patients treated and rejected.

It was found that DICU lowered cancelled surgeries by reducing the standard of service for other patients. Comparatively the exclusive reservation FBA scheme also lowered cancelled surgeries with less negative effect on the standard of service of other patients.

(Kim et al. 2002) extended the FBA scheme to compare 1 and 2 week scheduling windows. The main focus was again to reduce the number of cancelled elective surgeries without negatively impacting the standard of service of other patients. Scheduling windows take advantage of the fact that patients from the OL have their surgeries scheduled more than one week in advance.

Scheduling windows provide a certain number of available beds to OL patients over a 1 or 2 week period that are booked in advance. If the beds are not filled by booking then they can be used by other sources. Uniform and varying allocation schemes were compared and the 2,1,1,1,2; 2 week quote scheme gave the lowest number of cancelled surgeries and least
waiting times of all schemes. This scheme allocates 2 beds on Monday and Friday, and 1 bed on Tuesday, Wednesday and Thursday with bookings taken for beds over a 2 week period.

(Ridge et al. 1998) aimed to develop a simulation model verified by queuing theory methods to maximise bed utilisation and minimise the number of emergency transfers. It was discovered that there were 3 factors that complicated the model. They were that

- emergency patients arrive at random which may cause a build up of emergency queues;
- elective patients are constrained by surgeon hours, theatre space, and free beds in the ICU; and
- different patient types have different length of stay distributions.

The hospital studied had one ICU and elective patients were only accepted if two or more beds were free, otherwise their surgery was rescheduled. They could only be rescheduled a maximum of two times. Other patients were transferred to another hospital if no beds were free.

This study used 5 years of past data, again any seasonal or annual variation was not taken into account.

A $(M_i/M/s):(NPRP//\infty//\infty)$ (see page 14 for explanation of Kendall notation) queuing model was compared to the simulation model with some simplification to validate that the simulation was working correctly. The simulation model developed by Ridge was similar to that of Kim with the addition of rejected OL patients having their surgery rescheduled for a later date.

Some sensitivity analysis was performed to ascertain the effects that important variables had on the system. These variables were the number of beds in the ICU, length of reschedule times and the number of beds reserved for emergency admissions. The results were intended to be used as part of a decision analysis tool to decide allocation of beds. While the main focus was on the number of emergency patient transfers it was concluded a more effective patient admission scheduling system could benefit the hospital being analysed.

A study undertaken by (Moreno et al. 1999) developed a simulation model of an entire hospital. The overall aim was to develop a decision analysis tool that would help to minimise average waiting time for each unit within the hospital.

To model this system a process-oriented approach was taken instead of the classical unit-oriented approach. This recognises that the hospital is comprised of many specialised units that are used by the patient in different combinations to provide them with an overall service. If each unit were optimised individually the overall system would not operate optimally. This is because each unit is competing for shared resources, so the system needs to be analysed as a whole to provide the best service for each patient.

The Modsim simulation package was chosen over the MEDMODEL software as it allowed a much more generalised model to be created. In this case the model developed is expected to describe any hospital. The simulation developed allowed administration to

- obtain information about the hospital state through reports and graphs;
- experiment with different control actions.

It is expected that this system will be able to help improve hospital management, billing, patient treatment, etc.

### 3. SIMULATION MODEL

The aim of the simulation model was to develop a more accurate approximation to the real life situation and to be able to see the effect that new parameters have on the variables in the system.
3.1 Assumptions

The OT in this model does not split itself up into groups that treat each type of surgery. The model just provides $n$ identical servers within the OT resource. Each server is forced to stop processing to simulate its inability to operate outside of business hours and on weekends.

Each ICU has a small queue, however the OT has an infinite queue length. This is done because patients attempting to enter the OT have already been accepted into the ICU and should not be rejected from the system after this happens.

Patients arriving for each source that requires surgery are assigned a clinical urgency rating. This rating quantifies the risk of the patient dying as a result of being rejected from the system without receiving care. These ratings are used as priorities in the queues of each of the ICUs. Those sources that do not require surgery are given a rating equivalent to the middle category to compete with other patients within the queue.

3.2 Parameters and Variables

The advanced model provides the following parameters;

- arrival rate distributions for each source;
- ICU length of stay distributions for each source;
- OT length of stay distributions for OL and OM patients;
- number of beds in each ICU;
- number of OT pods;
- reschedule wait time for OL patients;
- proportions of
  - surgical urgency categories for OL and OM patients;
  - emergency, elective and other patients from OH source;
  - number of OT visits for OL and OM patients.

After running the simulation the user is are able to gather the following statistics

- max, min, average queue wait time for each ICU;
- max, min, average queue length;
- number of patients arriving from each source and ASA;
- max, min, average time in the system;
- number rejected or rescheduled from each source and ASA;
- number discharged for each source and ASA;
- ICU utilization rates;
- OT utilization rate.
3.3 Model Operation

The ARENA software generates arriving patients at each of the sources. In Figure 3.3 above the source modules are indicated by a green border. When a patient arrives at the system it is assigned a number of attributes which are

- source;
- ICU length of stay;
- OT length of stay;
- Number of surgeries;
- Clinical urgency category; and
- Arrival time.

All arriving patients are counted on arrival and sorted by their source and urgency category. Similarly all patients discharged or rejected are counted and sorted by their source and urgency category. Each ICU can have a different sized queue and a different queue discipline to determine which patients should be accepted. Elective patients are only allowed to arrive on weekdays and during normal operating hours. To choose modules we use the arrival time of the patient to determine if they should be accepted or not.

The Elective and Acute ICU and OT resources are shown at the bottom of the simulation model. Each of these has an available number of beds or operating pods. The OT can specify downtimes to restrict operations from only occurring between normal operating hours.

Arriving patients attempt to seize an ICU resource when they get to a seize module, these seize modules are indicated by a red border. Acute patients unable to seize an Acute ICU bed are counted and rejected. Elective ICU patients are also counted, but are delayed for a certain time dependent on their urgency category. After this delay their arrival time is reset and they attempt to seize an ICU bed again.

Once a surgical patient has seized an ICU bed they attempt to seize an OT pod. The OT has an infinitely sized queue. When the patient enters the OT they are delayed for the time in their OT length of stay attribute, after which they release the OT pod.
Non-surgical patients and surgical patients that have completed their surgery are delayed for the time in the ICU length of stay attribute. They then release the ICU bed seized.

Surgical patients may require multiple surgeries. Before releasing the ICU bed the value of their number of surgeries attribute is checked to determine if another surgery is required. If it is the attribute is decremented and they return to the OT queue, if not they release the ICU bed and are discharged.

4. DATA ANALYSIS

This study now focuses on the ICU and OTs at the Princess Alexandra Hospital. The Princess Alexandra Hospital is a 550 bed tertiary teaching hospital located in Brisbane Queensland Australia. Its main purpose is to serve the southern suburbs of Brisbane. Services provided include Acute, Medical, Rehabilitation, Surgical, Mental and Allied Health with particular expertise in spinal injury treatment.

The ICU admits approximately 1800 surgical and medical patients per year. These are not only direct referrals from within the hospital, or in-patients, but also include intra-hospital transfers from hospitals all over Queensland and northern New South Wales.

Data used in this project was collected over a 3 month period. The original format of the data was separated into days. Each day showed the cumulative history of a patient that was in the ICU at some period of time during that day. This data included 16 common fields for each patient as well as 23 fields for each visit to the OT before an ICU stay. Excel spreadsheets were used to store the data collected and separate files were created for each month.

Operation Type, Intra-Hospital Transfer Prior to ICU and Operation Type were used to determine the source of each patient. If there were entries in the Intra-Hospital Transfer Prior to ICU field then the patient was put into the OH source. If the patient was listed as Elective in the first Operation Type field then they were put into the OL source, if this field showed Emergency then they were put into the OM source. Of the remaining patients if the Hospital Admission Ward listed Emergency Department then they were put into the AE source, all remaining patients were put into the W source.

The Input Analyser tool, which is a part of the simulation package Arena, was used to fit distributions to the data. This tool allowed comparison between goodness of fit of different statistical distributions to each dataset. The Chi Square Test was used as the deciding factor as to whether a given dataset could have been generated by a particular statistical distribution. A p-value of < 0.005 indicates that the data could have been generated by a particular distribution.

4.1 Arrival Rates

The inter-arrival times for the AE, OH and OM sources were all able to be fit by the negative exponential distribution. The remaining Acute source, W with only 7 observations over the 57 day period did not provide any statistically significant results. This source was assumed to have inter-arrival rates described by a negative exponential distribution with an average as estimated by the failed data fit to bring it in line with other sources.

Arrivals for the Elective ICU could only occur between 7am and 8pm on weekdays. To account for this the first arrival for each week was given an inter-arrival time equal to its arrival time minus the time at 7am Monday morning. By fitting a distribution to this data it will allow us to generate arrivals at all times while discarding those that are outside of business hours and still retain the expected number of arrivals each day. A negative exponential distribution was found to fit the inter-arrival times of the Elective ICU patients.

A daily variation in the number of patients arriving at the Elective ICU prompted investigation to fit distributions to each day. Inter-arrival times of only two days out of five...
could be described by a negative exponential arrival rate and it was deemed that no statistically significant results could be obtained from the small amount of observed data.

### Table 4.1. Analysis results for inter-arrival rates by Source

<table>
<thead>
<tr>
<th>Source</th>
<th>Distribution</th>
<th>p-value</th>
<th>Accepted</th>
<th>Square Error</th>
<th># observations</th>
</tr>
</thead>
<tbody>
<tr>
<td>AE</td>
<td>EXP(1.74)</td>
<td>&lt; 0.005</td>
<td>Yes</td>
<td>0.002873</td>
<td>27</td>
</tr>
<tr>
<td>OM</td>
<td>EXP(1.95)</td>
<td>&lt; 0.005</td>
<td>Yes</td>
<td>0.006767</td>
<td>28</td>
</tr>
<tr>
<td>OH</td>
<td>EXP(1.65)</td>
<td>&lt; 0.005</td>
<td>Yes</td>
<td>0.000946</td>
<td>34</td>
</tr>
<tr>
<td>W</td>
<td>EXP(4.56)</td>
<td>&gt; 0.005</td>
<td>No</td>
<td>0.058176</td>
<td>5</td>
</tr>
<tr>
<td>OL</td>
<td>EXP(0.374)</td>
<td>&lt; 0.005</td>
<td>Yes</td>
<td>0.049293</td>
<td>92</td>
</tr>
</tbody>
</table>

### 4.2 Lengths of Stay in the Operating Theatre

In the case of the Princess Alexandra Hospital it has 20 OT pods are grouped as follows:
- 4 for Day surgery, Ophthalmology.
- 3 for Orthopaedics, hands, elbows, shoulder, spine.
- 5 for Emergency, general, gynaecology.
- 6 for Neuro, urology, vascular, plastics
- 2 for Cardiac and cardiac thoracic.

There was not enough data to determine length of stay distributions for each type of surgery, so the analysis did not use this information.

The length of stay for Elective surgery patients was well fit by a Log-Normal distribution. However a lack of data for the Emergency surgery patients prevented this data from being fitted. By grouping the length of stays of both Elective and Emergency surgery patients it was found that it could be well described by a Log-Normal distribution.

It was also thought that the lengths of stays of patients requiring surgery may be related to their surgical urgency category, however this was not found to be true.

### Table 4.2. Analysis results for OT LOS

<table>
<thead>
<tr>
<th>Source</th>
<th>Distribution</th>
<th>p-value</th>
<th>Accepted</th>
<th>Square Error</th>
<th># observations</th>
</tr>
</thead>
<tbody>
<tr>
<td>OM &amp; OL</td>
<td>LOGN(0.236, 0.0958)</td>
<td>&lt; 0.005</td>
<td>Yes</td>
<td>0.061275</td>
<td>79</td>
</tr>
</tbody>
</table>

### 4.3 Lengths of Stay in the ICU

The lengths of stay of the OM and OL sources could be fitted separately while the other sources were not able to be fitted significantly. The OM source was fitted by a negative exponential distribution while the OL source was fitted by an Erlang distribution with k parameter 9. Similarly with the length of stay in the OT it was thought that the length of stay in the ICU may be related to the surgical urgency category of the patient. Again no statistically significant results were found that supported this claim.

By combining all patients that do not require surgery it was found that their length of stay in the ICU could be fitted by a negative exponential distribution.

### Table 4.3. Analysis results for ICU LOS

<table>
<thead>
<tr>
<th>Source</th>
<th>Distribution</th>
<th>p-value</th>
<th>Accepted</th>
<th>Square Error</th>
<th># observations</th>
</tr>
</thead>
<tbody>
<tr>
<td>AE &amp; OH &amp; W</td>
<td>EXP(3.61)</td>
<td>&lt; 0.005</td>
<td>Yes</td>
<td>0.015429</td>
<td>32</td>
</tr>
<tr>
<td>OM</td>
<td>EXP(3.09)</td>
<td>&lt; 0.005</td>
<td>Yes</td>
<td>0.018885</td>
<td>28</td>
</tr>
<tr>
<td>OL</td>
<td>ERLA(0.0826, 9)</td>
<td>&lt; 0.005</td>
<td>Yes</td>
<td>0.065819</td>
<td>65</td>
</tr>
</tbody>
</table>
4.4 Other Proportions

A discrete distribution was used to describe the number of stays for elective and emergency surgery patients. It was found that the proportions for each of these groups were different. Also emergency patients may require up to 3 separate surgical procedures, whereas elective patients may only require up to 2 procedures.

Similarly discrete distributions were used to describe proportions of surgical urgency categories to patients requiring surgery and also to separate patient types arriving from the OH source.

| Table 4.4. Proportion of OT stays by Source |
| Source | 1 OT stay (%) | 2 OT stays (%) | 3 OT stays (%) |
| OM | 73.3 | 20.0 | 6.7 |
| OL | 96.9 | 3.1 | 0.0 |

| Table 4.5. Proportion of ASA category by Source |
| Source | ASA 2 (%) | ASA 3 (%) | ASA 4 (%) | ASA 5 (%) |
| OM | 8.7 | 21.7 | 60.9 | 8.7 |
| OL | 10.3 | 63.2 | 26.5 | 0.0 |

| Table 4.6. Proportion of patient type from OH |
| Source | Elective (%) | Emergency (%) | Non-Surgery (%) |
| OH | 11.4 | 31.4 | 57.2 |

5. SOLUTION

The arrivals data provided did not include those patients rejected from the system. It was found that adding an extra patient every 2 days gave realistic ICU utilization and rejection rates.

This extra 0.5 of a patient each day was split up and added to the W, AE, OH and OL sources that provide the arrivals to the Acute ICU. It was divided according to the proportion of patients observed arriving from each source. The new inter-arrival rate was found by inverting the current arrival rate to obtain the number of arrivals per day, adding 0.5 * proportion of arrivals for each source and inverting again to obtain the new inter-arrival time.

The arrival rates were modified and are shown in the following table.

| Table 5.6. Calculated Inter-Arrival Rates |
| Source | Current Distribution | Proportion of Arrivals (%) | New Distribution |
| W | EXPO(4.56) | 6.3 | EXPO(3.99) |
| AE | EXPO(1.74) | 29.5 | EXPO(1.38) |
| OH | EXPO(1.65) | 33.7 | EXPO(1.29) |
| OM | EXPO(1.95) | 30.5 | EXPO(1.50) |

The OT was initially set at 10 theatre pods which is a high number for just ICU patients. This ensures that the OT does not affect any other variables in the model at this stage.

5.1 Arrivals

It would be expected that the number of patients accepted into the system be similar to the simple simulation model. This would also be the case for queue length, waiting times, and utilization rates for the Acute ICU, but not necessarily for the Elective ICU.

Arrival rates of all Acute sources were up to a combined 130.25 compared to the 98 in the observed data. This difference was expected as the arrival rates were increased. By summing
all Acute arrivals and subtracting the extra half a patient each day the combined arrivals came down to 101.75, which is acceptably close to 98 patients.

Running the simulation with the default parameters showed that the number of the Elective arrivals was just 71, well below the expected value of 93.

In total 165.1 elective surgery patients arrived before being filtered based on their arrival time to only allow those patients, into the system, that arrived during business hours on a weekday. Only 71 patients were allowed through, this is 42% of the total patients.

Arrivals are only let through in 65 out of a total 168 hours in a week (so only 39% of the time). These percentages are very similar and confirm that the filtering logic is working correctly and that either the arrival rate needs to be increased or the amount of time that elective patients are let through needs to be increased.

If the amount of time was to increase alone, it would need to increase by 6 from 13 to 19 hours to allow the required amount of patients into the system.

Alternatively if the arrival rate was to increase alone and with the current filtering of 39% of patients we would need 216 arrivals over 57 days or 3.8 per day giving an inter-arrival rate of 0.268 days per patient.

It was decided to change both of these so that only small changes in each were needed. The allowable hours per day were increased by 2 and the inter-arrival rate was decreased to 0.274 days per patient. These changes increased the number of arrivals from 71 to 99 and these new parameters were accepted.

5.2 Waiting queue

The length of the simulation runs was now increased from 57 days to the full 6 month period. Queue statistics were then gathered for both the Elective and Acute ICU’s.

Table 5.1. Queue statistics

<table>
<thead>
<tr>
<th>ICU</th>
<th>Average Queue Length</th>
<th>Average Wait Time (min)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Elective</td>
<td>0.125</td>
<td>100</td>
</tr>
<tr>
<td>Acute</td>
<td>0.09</td>
<td>65</td>
</tr>
</tbody>
</table>

The average queue length value is not a true indication of the length of the queue that an arriving patient will see, because arrivals do not occur all week.

5.3 Total Time in System

The total time in the system is the time that passed from when the patient arrives at the system until they are discharged. This time includes queue waiting time, and length of stay in the ICU and OT. Acute patients stay on average 3.9 days in the system while Elective patients stay just 1.2 days.

5.4 Reschedule/Rejection

The number of rescheduled elective patients is much lower than that observed in the data with just 4.3 patients being rescheduled in a 6 month period. The number of rejected acute patients at 2.95 is also much lower than that found in the simple simulation model which has the same number of arrivals and the same sized waiting queue.

The only difference between these models is the total time patients spend in the system which for the advanced model was found to be slightly lower for both elective and acute patients.

The total time in the system is mainly dependent on the length of stay in the ICU and OT. These parameters were found to be fit well by their relevant distributions. Also by splitting the total time in the system into the time spent in the ICU and the time spent in the OT the length of stay time should be more accurate.
6. SENSITIVITY ANALYSIS

In this section sensitivity analysis was performed to determine the effect of changing specific parameters in the system on output variables in the proposed models. The simulation model parameters that were modified in this sensitivity analysis were the arrival rates of patients and the number of beds. Their effect on average queue length, average queue waiting time, ICU utilization and reschedule/rejection rates are investigated.

All other model parameters were kept the same as those found in Section 5.1. This analysis was only performed on the Acute and Elective ICUs and parameters directly affecting it. The number of beds in the Acute ICU is currently 12. In this analysis the number of beds was varied between 9 and 15. The sensitivity analysis of the arrival rate of patients arriving at the Acute ICU was varied from -20% to +20% of the current arrival rate in steps of 5%.

It would be expected that similar results for both the Acute and Elective ICUs would be observed if the same analysis was done on each. The only dependence between the two ICU’s is the OTs, however it would be expected that changes to the elective surgery patients would have a greater effect on the OT as they account for approximately half of all arrivals and all require time in the OT.

The number of beds in the Elective ICU is currently 4. In this analysis the number of beds was varied between 1 and 6. The inter-arrival rate of the OL source was modified to allow 1 extra patient to arrive every 1, 2, 3, and 4 days and for 1 less patient to arrive every 1, 2, 3 and 4 days. The inter-arrival rates that were used are as follows.

<table>
<thead>
<tr>
<th>Extra Patient per day</th>
<th>-1.0</th>
<th>-0.5</th>
<th>-0.333</th>
<th>-0.25</th>
<th>0.0</th>
<th>+0.25</th>
<th>+0.333</th>
<th>+0.5</th>
<th>+1.0</th>
</tr>
</thead>
<tbody>
<tr>
<td>Inter-arrival Rate</td>
<td>0.377</td>
<td>0.317</td>
<td>0.302</td>
<td>0.294</td>
<td>0.274</td>
<td>0.256</td>
<td>0.251</td>
<td>0.241</td>
<td>0.215</td>
</tr>
</tbody>
</table>

6.1 Utilisation Rate of ICU

![Figure 6.1. Utilisation Rate of Acute and Elective ICU](image-url)
Table 6.2. Utilisation rates for Acute

<table>
<thead>
<tr>
<th>Arrival Rate Change (%)</th>
<th>Beds 9</th>
<th>-0.2</th>
<th>-0.15</th>
<th>-0.1</th>
<th>-0.05</th>
<th>0</th>
<th>0.05</th>
<th>0.10</th>
<th>0.15</th>
<th>0.2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.768</td>
<td>0.789</td>
<td>0.809</td>
<td>0.829</td>
<td>0.849</td>
<td>0.868</td>
<td>0.886</td>
<td>0.903</td>
<td>0.918</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.718</td>
<td>0.741</td>
<td>0.763</td>
<td>0.786</td>
<td>0.809</td>
<td>0.832</td>
<td>0.854</td>
<td>0.874</td>
<td>0.894</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.668</td>
<td>0.692</td>
<td>0.717</td>
<td>0.742</td>
<td>0.767</td>
<td>0.793</td>
<td>0.818</td>
<td>0.843</td>
<td>0.866</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.621</td>
<td>0.645</td>
<td>0.670</td>
<td>0.697</td>
<td>0.724</td>
<td>0.752</td>
<td>0.780</td>
<td>0.808</td>
<td>0.835</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.578</td>
<td>0.602</td>
<td>0.627</td>
<td>0.653</td>
<td>0.681</td>
<td>0.710</td>
<td>0.740</td>
<td>0.771</td>
<td>0.802</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.539</td>
<td>0.562</td>
<td>0.586</td>
<td>0.612</td>
<td>0.640</td>
<td>0.669</td>
<td>0.700</td>
<td>0.733</td>
<td>0.766</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.504</td>
<td>0.526</td>
<td>0.549</td>
<td>0.574</td>
<td>0.601</td>
<td>0.630</td>
<td>0.662</td>
<td>0.695</td>
<td>0.730</td>
<td></td>
</tr>
</tbody>
</table>

This graph is interesting as it indicates that the utilization rate of the Acute ICU is linearly related to both the arrival rate and the number of beds. An increase in the number of beds gives a similar decrease in utilization rate when compared to decreasing the arrival rate.

Table 6.3. Utilization rates for Elective

<table>
<thead>
<tr>
<th>Extra Patients per Day</th>
<th>Beds 1</th>
<th>-1</th>
<th>-0.5</th>
<th>-0.33</th>
<th>-0.25</th>
<th>0</th>
<th>0.25</th>
<th>0.33</th>
<th>0.5</th>
<th>1</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.979</td>
<td>0.989</td>
<td>0.993</td>
<td>0.995</td>
<td>0.997</td>
<td>0.998</td>
<td>0.999</td>
<td>0.998</td>
<td>0.998</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.718</td>
<td>0.814</td>
<td>0.826</td>
<td>0.838</td>
<td>0.865</td>
<td>0.902</td>
<td>0.906</td>
<td>0.916</td>
<td>0.939</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.498</td>
<td>0.576</td>
<td>0.595</td>
<td>0.623</td>
<td>0.655</td>
<td>0.682</td>
<td>0.687</td>
<td>0.724</td>
<td>0.790</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.380</td>
<td>0.446</td>
<td>0.466</td>
<td>0.488</td>
<td>0.506</td>
<td>0.537</td>
<td>0.547</td>
<td>0.567</td>
<td>0.639</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.296</td>
<td>0.357</td>
<td>0.373</td>
<td>0.384</td>
<td>0.407</td>
<td>0.440</td>
<td>0.445</td>
<td>0.460</td>
<td>0.519</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.250</td>
<td>0.293</td>
<td>0.311</td>
<td>0.318</td>
<td>0.345</td>
<td>0.357</td>
<td>0.368</td>
<td>0.382</td>
<td>0.427</td>
<td></td>
</tr>
</tbody>
</table>

For a fixed number of beds, increasing the arrival rate shows a roughly linear increase in the utilization rate of the Elective ICU. Given a higher number of beds shows a larger gradients as the arrival rate increases.

For a fixed arrival rate the utilization shows an exponential shape with the exception of the step from 1 to 2 beds. This indicates that the queue to the ICU is almost always full when patients are arriving when the ICU has only 1 bed. The utilization rate for 1 bed and any arrival rate is virtually the same at 98-100%

6.2 Patients Treated

Figure 6.2. Patients Treated at Acute and Elective ICU
Table 6.4. Patients Treated in Acute

<table>
<thead>
<tr>
<th>Arrival Rate Change (%)</th>
<th>Beds</th>
<th>-0.2</th>
<th>-0.15</th>
<th>-0.1</th>
<th>-0.05</th>
<th>0</th>
<th>0.05</th>
<th>0.10</th>
<th>0.15</th>
<th>0.2</th>
</tr>
</thead>
<tbody>
<tr>
<td>9</td>
<td>294.5</td>
<td>302.4</td>
<td>310.2</td>
<td>317.8</td>
<td>325.3</td>
<td>332.6</td>
<td>339.5</td>
<td>346.0</td>
<td>351.9</td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>305.8</td>
<td>315.4</td>
<td>325.1</td>
<td>334.9</td>
<td>344.6</td>
<td>354.2</td>
<td>363.5</td>
<td>372.4</td>
<td>380.7</td>
<td></td>
</tr>
<tr>
<td>11</td>
<td>313.1</td>
<td>326.0</td>
<td>335.6</td>
<td>349.3</td>
<td>359.3</td>
<td>371.3</td>
<td>385.3</td>
<td>394.7</td>
<td>408.1</td>
<td></td>
</tr>
<tr>
<td>12</td>
<td>317.5</td>
<td>331.6</td>
<td>342.6</td>
<td>358.0</td>
<td>369.8</td>
<td>384.0</td>
<td>400.6</td>
<td>412.8</td>
<td>429.2</td>
<td></td>
</tr>
<tr>
<td>13</td>
<td>320.0</td>
<td>333.0</td>
<td>346.8</td>
<td>361.5</td>
<td>376.9</td>
<td>393.0</td>
<td>409.7</td>
<td>426.7</td>
<td>443.8</td>
<td></td>
</tr>
<tr>
<td>14</td>
<td>321.3</td>
<td>334.8</td>
<td>349.3</td>
<td>364.8</td>
<td>381.4</td>
<td>399.0</td>
<td>417.6</td>
<td>437.0</td>
<td>456.8</td>
<td></td>
</tr>
<tr>
<td>15</td>
<td>322.0</td>
<td>335.7</td>
<td>350.6</td>
<td>366.7</td>
<td>384.0</td>
<td>402.7</td>
<td>422.8</td>
<td>444.1</td>
<td>466.4</td>
<td></td>
</tr>
</tbody>
</table>

For a given arrival rate, increasing the number of beds shows the number of patients treated increasing more slowly until all patients that arrive are treated. An increase in arrival rate shows an approximately linear increase in the number of patients treated. This indicates that no bottlenecks are created for all arrival rates the number of beds looked at here.

Table 6.5. Patients treated in Elective

<table>
<thead>
<tr>
<th>Extra Patients per Day</th>
<th>Beds</th>
<th>-1</th>
<th>-0.5</th>
<th>-0.33</th>
<th>-0.25</th>
<th>0</th>
<th>0.25</th>
<th>0.33</th>
<th>0.5</th>
<th>1</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1</td>
<td>370.25</td>
<td>417.45</td>
<td>428.75</td>
<td>435.35</td>
<td>460.25</td>
<td>483.20</td>
<td>500.45</td>
<td>509.75</td>
<td>547.15</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>442.15</td>
<td>525.65</td>
<td>529.45</td>
<td>544.45</td>
<td>574.95</td>
<td>611.35</td>
<td>624.95</td>
<td>629.10</td>
<td>690.75</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>448.60</td>
<td>533.90</td>
<td>553.65</td>
<td>578.75</td>
<td>611.30</td>
<td>642.45</td>
<td>653.45</td>
<td>683.10</td>
<td>760.90</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>456.20</td>
<td>541.30</td>
<td>564.20</td>
<td>596.00</td>
<td>617.60</td>
<td>662.60</td>
<td>675.75</td>
<td>697.75</td>
<td>797.15</td>
</tr>
<tr>
<td></td>
<td>5</td>
<td>442.15</td>
<td>538.00</td>
<td>566.95</td>
<td>583.65</td>
<td>615.55</td>
<td>669.80</td>
<td>677.70</td>
<td>702.60</td>
<td>802.65</td>
</tr>
<tr>
<td></td>
<td>6</td>
<td>450.60</td>
<td>523.40</td>
<td>561.00</td>
<td>581.00</td>
<td>626.85</td>
<td>654.75</td>
<td>677.80</td>
<td>699.15</td>
<td>784.25</td>
</tr>
</tbody>
</table>

The number of patients treated or discharged shows the major effects of the bottleneck that occurs at the Elective ICU queue when the number of beds is reduced to 1. There is a significant increase in the number of patients treated when the number of beds is increased to 2.

Changing the arrival rate from -1 to -0.5 extra patients per day and from 0.5 to 1 extra patient per day, for a fixed number of beds, gives a significantly larger increase in the number of patients treated when compared to any other change in arrival rate. Other changes in the arrival rate show a roughly linear change in the number of patients treated.

6.3 Patients Balked vs Patients Treated

The ratio of the number of patients rescheduled versus the number of patients treated yields a useful efficiency rating of the ICU.

![Figure 6.3. Balked/Treated at Acute and Elective ICU](image-url)
Table 6.6. Rejected/Treated from Acute
Arrival Rate Change (%)

<table>
<thead>
<tr>
<th>Beds</th>
<th>-0.2</th>
<th>-0.15</th>
<th>-0.1</th>
<th>-0.05</th>
<th>0</th>
<th>0.05</th>
<th>0.10</th>
<th>0.15</th>
<th>0.2</th>
</tr>
</thead>
<tbody>
<tr>
<td>9</td>
<td>0.095</td>
<td>0.113</td>
<td>0.134</td>
<td>0.159</td>
<td>0.189</td>
<td>0.225</td>
<td>0.267</td>
<td>0.316</td>
<td>0.374</td>
</tr>
<tr>
<td>10</td>
<td>0.055</td>
<td>0.067</td>
<td>0.082</td>
<td>0.100</td>
<td>0.123</td>
<td>0.150</td>
<td>0.183</td>
<td>0.223</td>
<td>0.270</td>
</tr>
<tr>
<td>11</td>
<td>0.030</td>
<td>0.038</td>
<td>0.048</td>
<td>0.061</td>
<td>0.077</td>
<td>0.097</td>
<td>0.122</td>
<td>0.153</td>
<td>0.192</td>
</tr>
<tr>
<td>12</td>
<td>0.016</td>
<td>0.020</td>
<td>0.027</td>
<td>0.035</td>
<td>0.046</td>
<td>0.061</td>
<td>0.079</td>
<td>0.103</td>
<td>0.133</td>
</tr>
<tr>
<td>13</td>
<td>0.008</td>
<td>0.010</td>
<td>0.014</td>
<td>0.020</td>
<td>0.027</td>
<td>0.036</td>
<td>0.049</td>
<td>0.067</td>
<td>0.090</td>
</tr>
<tr>
<td>14</td>
<td>0.004</td>
<td>0.005</td>
<td>0.007</td>
<td>0.010</td>
<td>0.015</td>
<td>0.021</td>
<td>0.030</td>
<td>0.042</td>
<td>0.059</td>
</tr>
<tr>
<td>15</td>
<td>0.002</td>
<td>0.002</td>
<td>0.003</td>
<td>0.005</td>
<td>0.008</td>
<td>0.011</td>
<td>0.017</td>
<td>0.025</td>
<td>0.037</td>
</tr>
</tbody>
</table>

This graph resembles the number of patients rescheduled. For a given arrival rate, increasing the number of beds approximately halves the percentage of patients rejected from the system. Increasing the arrival rate increases the percentage of patients rejected exponentially, but at a lesser rate compared to reducing beds.

Table 6.7. Rescheduled/Treated from Elective
Extra Patients per Day

<table>
<thead>
<tr>
<th>Beds</th>
<th>-1</th>
<th>-0.5</th>
<th>-0.33</th>
<th>-0.25</th>
<th>0</th>
<th>0.25</th>
<th>0.33</th>
<th>0.5</th>
<th>1</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1.212</td>
<td>1.486</td>
<td>1.577</td>
<td>1.612</td>
<td>1.821</td>
<td>1.888</td>
<td>1.951</td>
<td>2.014</td>
<td>2.181</td>
</tr>
<tr>
<td>2</td>
<td>0.244</td>
<td>0.371</td>
<td>0.385</td>
<td>0.449</td>
<td>0.528</td>
<td>0.613</td>
<td>0.650</td>
<td>0.714</td>
<td>0.890</td>
</tr>
<tr>
<td>3</td>
<td>0.064</td>
<td>0.102</td>
<td>0.116</td>
<td>0.122</td>
<td>0.163</td>
<td>0.189</td>
<td>0.210</td>
<td>0.234</td>
<td>0.334</td>
</tr>
<tr>
<td>4</td>
<td>0.014</td>
<td>0.028</td>
<td>0.035</td>
<td>0.047</td>
<td>0.054</td>
<td>0.072</td>
<td>0.077</td>
<td>0.076</td>
<td>0.134</td>
</tr>
<tr>
<td>5</td>
<td>0.002</td>
<td>0.008</td>
<td>0.013</td>
<td>0.020</td>
<td>0.017</td>
<td>0.024</td>
<td>0.026</td>
<td>0.031</td>
<td>0.054</td>
</tr>
<tr>
<td>6</td>
<td>0.001</td>
<td>0.002</td>
<td>0.006</td>
<td>0.005</td>
<td>0.006</td>
<td>0.007</td>
<td>0.010</td>
<td>0.011</td>
<td>0.019</td>
</tr>
</tbody>
</table>

This value should be minimised and a realistic figure would be up to 20% of patients rescheduled. As shown in the above graph when the ICU has 1 or 2 beds this ratio is mostly greater than 50%.

By removing 1 and 2 beds from the plot we can see the finer detail in the graph and the alternatives that can be selected to keep this ratio under 20%.

6.4 Summary of Results

Generally for the Elective ICU when changing the number of beds, each variable decreases according to a scaled negative exponential distribution or increases according to a scaled (1 – a negative exponential) distribution. When changing the arrival rate each variable changes according to a linear function. This indicates that the arrival rate would have to change considerably before a new bed is required.

It was found that the variables of average queue length, average wait time and number of rescheduled patients are closely related and any one of these could be used to approximate the other. While minimizing these variables the number of patients treated is decreased so the process of balancing the number of patients treated and the number of patients rejected is the main aim of the hospital.

Taking into account both sensitivity analyses it can be concluded that the system is more sensitive to a change in beds. This indicates that a change in beds will only be required if there is a large increase in arrival rates. We can conclude that the number of beds the hospital has currently allocated to each ICU unit provides a good balance between all of the variables investigated. Furthermore as the data used was only for a short period we can conclude that any small increase in accuracy of the input parameters will have minimal effect on the results observed. This is because the model is less susceptible to small changes in arrival rates.
7. CONCLUSIONS AND FUTURE WORK

A number of models have been proposed to approximate the workings of the ICUs and OTs of a public hospital. The multi-server limited space model is useful to find general queuing information relating to the Elective and Acute ICU’s, with more meaningful results expected to be found for the Acute ICU. But does not provide all the information required and a further study to develop a generalised queuing model specifically for this situation could be undertaken. This would provide in depth information similar to the advanced simulation model and would be applicable to a wide variety of hospitals. For example the diagram below shows a system with an OT decoupled from the ICUs with multiple arrival sources.

Figure 7.1. Tandem queuing system

The Princess Alexandra Hospital was used as a case study for the models developed. It was found that statistically significant distributions could be fitted to most of the parameters of each model. ARENA was found to be a valuable tool to describe the system because of its flexibility and visual nature. Also useful were its input and output analysis tools. It is expected that more complex models could be constructed using this software in the future.

In this study a combination of patients rescheduled and patients treated was found to be a good measure of the efficiency of the Elective ICU. Similarly it is expected that the combination of patients rejected and patients treated could be used as a measure of efficiency for the Acute ICU.

It was also found that varying the number of beds in the each ICU had an exponential effect on variables within the system. Varying the arrival rate in the Acute ICU also had an exponential effect on variables, while varying the arrival rate in the Elective ICU only had a linear effect. This is important in decision making and bed allocation.

A Decision Support System could use the results gained as its basis. By combining the output variables using user specified weightings, different objectives could be minimised or maximised. This would be helpful to determine arrival rates that indicate a new bed is needed, and the best allocation policy between ICU’s, etc.

It is difficult to put a monetary value on the effects of patients that were rescheduled or rejected. The effect of this still needs to be compared in some way to a change in operational procedures or a change in the amount of resources in the system, which have fairly accurate monetary costs associated with them. An investigation into this would aid a decision support system and allow alternatives to be compared quantitatively.

Not all patients utilizing the OT use the ICU and thus were not part of this study. This shows that there are other factors that affect the working of the system studied. Further investigation that incorporates these external factors, using this work as a basis, would be beneficial. Scheduling techniques become more important when widening the scope of study. It would be especially useful for nurse, doctor and operation scheduling. Operating
scheduling is a large problem in itself requiring the organization of surgeons, anesthetists, nurses, specialised equipment, blood, and even organs.

As data was only collected over a small period of time finer details could not be investigated such as the type of surgery that particular patients required. It is thought that the length of stay of patients may be closely related to their surgical urgency category. The type of surgery required may also prove to be related to a patient’s length of stay. This information would prove useful in any scheduling research.

Along with more patient information more detailed information about the processes in the system would allow a more accurate simulation model. This would also lead to comparison of alternative operational procedures.

REFERENCES

In the body of the text, papers or documents are referred to by author's surname with the year of publication. If the reference has more than two authors, only the surname of the first author followed by et al in italics will appear in the body of text.

At the end of the paper, complete references must be given in alphabetical order by author's surname and include: surname(s) and initials of author(s), separated by a comma, year of publication in parenthesis, title of the paper, volume of a journal in bold typeface, title of a journal in italic typeface with title case, and page numbers (for journals); For books and book chapters the publisher and the city of publication must also be indicated. Names of conference proceedings and book titles should be italicised. No lines between references. References should each have a hanging indent of 0.5 cm.


