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Improving hospital bed utilisation through simulation and optimisation in South African Public Hospitals

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Abstract

South African public hospitals have a shortage of hospital beds and struggle to allocate patients to beds and keep track thereof. This contributes to inefficient utilisation of limited hospital capacity. In literature, this problem is called the *bed management problem with specific focus on bed allocation*.

Different techniques have been studied in literature in an attempt to solve this problem. Various models have been created to solve this problem using exact solution modelling. These attempts have failed because the problem is to complex to solve with currently available exact solvers within an acceptable operations time. A heuristic and simulation models have also been developed to solve this problem with success. A comparison between these techniques show that agent based simulation modelling is the best suited for this specific problem.

This report addresses this problem by creating a bed management model, using agent-based simulation, that will better match patients to beds and therefore maximise the capacity utilisation of a South African Public Hospital.

Agent based simulation allows each patient's characteristics and needs to be taken into account and match it to a bed that will fulfil the patients needs. This simulation method lends the required flexibility to the model to be able to test individual as well as combined allocation rules.

In order to match a patient and to a bed, certain bed allocation rules should be adhered to. These allocation rules are studied by using conceptual models. Seven individual allocation rules are tested. These rules include allocation according to patient characteristics, reservation of beds for elective patients, and allocating more than one patient to a bed.

In order to be able to compare the results obtain from the conceptual models a basic first come, first served model is created. All the rules are a variation of this rule. Two reservation techniques are tested. Reservations according to elective patient schedule outperforms reservation of a fixed number of beds for the exclusive use by elective patients.

Allocation according to age and gender perform the same as the the first come, first served rule. These rules should, however, not be judged solely on performance. Adult patients should be separated gender for protection as well as to ensure that the patient's stay is comfortable. Children are not as sensitive to this rule. But it is imperative that children and adults be separated for the protection of the children.

Allocation according to patient criticality and allocating more than one patient to a bed also perform better than the first come, first served model. These rules

are not the most important to implement and can be used if the hospital's policies allow for it.

Combinations of the rules are further tested in a case study done at Mamelodi Hospital. Three rule sets were created. The results show that all three rules sets perform better than the current system that Mamelodi Hospital uses. This is partially due to the models tracking which beds are available and which are occupied.

Of the three rule sets, Rule set 3 provides the most satisfactory results. This model takes into consideration all of the most important rules and creates focussed units within the hospital. Male and female adult patients are allocated to wards according to their needs and children and babies are also assigned to the correct wards to receive specialised care. This rule set also gives preference to emergency patients and beds can be reserved for elective patients. Rooms can be used for isolation purposes to protect other patients from infections or diseases. This model also allows patients to be transferred between wards.

Different allocations rules are applicable to different patients. Implementing the right combinations of rules, similar to those used in Rule set three, will improve bed utilisation. Better tracking of beds will also improve bed utilisation and the patients hospital experience.

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Chapter 1

Introduction

1.1 Background

An estimated 82.4% of the South African population make use of public health services (Health Systems Trust, 2012), while the remaining 17.6% make use of private health care. The public health sector is under immense pressure due to an increase in the number of people with HIV/Aids from 4 million in 2002 to 5.28 million in 2013 (Statistics South Africa, 2013), an increase in general population and a shortage of resources, such as beds, telemetry, funds and staff (Meyer, 2010, p. 9). It is estimated that a further 60 000 beds are required country wide in an attempt to improve the standard of public health services and relieve the pressure on the hospitals.

1.1.1 Structure of the Public Health sector

The South African Public Health sector has a hierarchical referral structure between the hospitals and clinics (Mojaki et al., 2011), as shown in figure 1.1.

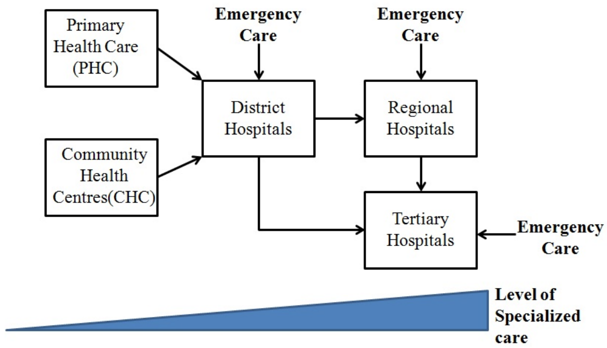

Figure 1.1: Hierarchical referral structure of public hospitals

All patients must first receive primary care at a clinic or health centre where initial diagnosis and treatments are conducted (Cullinan, 2006). If required, patients are then referred to a district hospital to be admitted. If the patient requires more specialised care, they will be transferred to a tertiary or regional hospital. The district, tertiary and regional hospitals all have an Emergency Department through which patients can also be admitted.

1.1.2 Admission of patients

An outpatient is a patient who visits a medical facility for treatment but is not hospitalised for an over-night stay. Inpatients are admitted to the hospital and stay for one or more nights before being discharged.

In South Africa, inpatients can be admitted to a hospital in one of three ways:

1. elective patient being admitted for a surgery that has been scheduled in advance;
2. emergency patient being admitted from the Emergency Department for urgent medical treatment;
3. urgent referral from General Practitioners (GP), Community Health Centres (CHC) or Primary Health Care (PHC) clinics.

Figure 1.2 is a simplified illustration of a patient's journey:

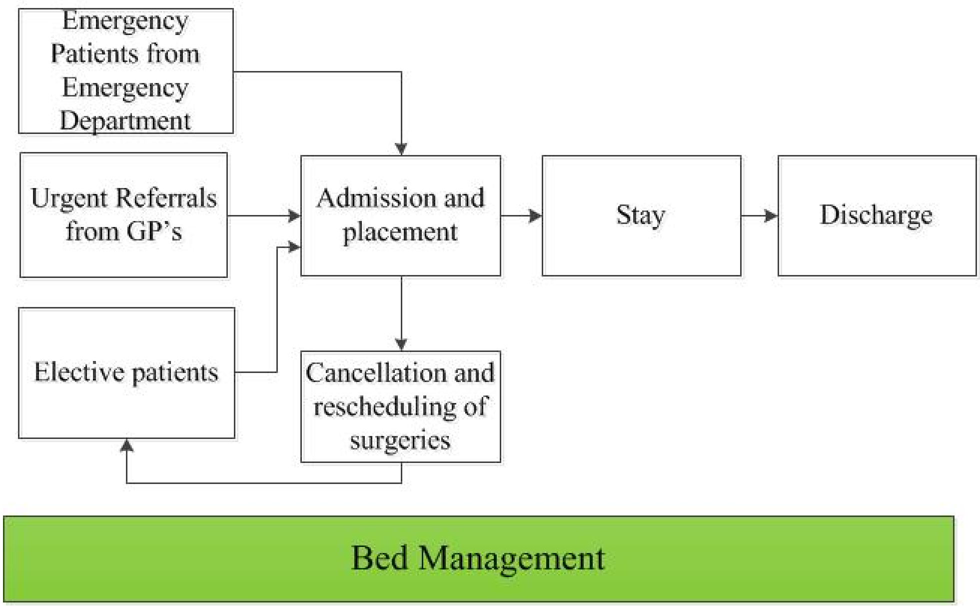

Figure 1.2: Simplified illustration of the patients journey (Proudlove et al., 2003)

Schmidt et al. (2013) suggested that between 30% and 80% of patients are elective, depending on the medical department that they are assigned to. These admissions can be planned in advance. Demeester et al. (2010) defines inpatient admissions scheduling as a facility allocation decision and that the maximisation of the hospital's capacity depends on two main sources of variability:

- Emergency admissions cannot be planned and slack capacity must be available to admit these patients.
- A patient's Length of Stay (LoS) is inherently uncertain and can therefore only be estimated.

Elective patients are tentatively allocated to a bed in a ward by a bed manager before arriving, but emergency patients and emergency referrals have precedence over elective patients (Schmidt et al., 2013). Hospitals have a fixed number of beds and if there is a shortage, elective surgeries are rescheduled.

1.1.3 Units and wards

Hospitals consist of independent units which are visited by patients according to the level of specialised care required and their individual pathology (Paulussen et al., 2006). Patients usually stay in wards and go to ancillary wards for various treatments or procedures. The type of units in a hospital depends on the type and size of the hospital, therefore not all hospitals will have all of the units or wards. Not all units have beds for patients to stay in but rather are units where treatments are done.

According to Roger (2011) the following is a list of units where patients can possibly be allocated to a bed:

Cardiology

The Cardiology Unit provides care for patients with any heart or circulation related diseases and also acts as an intermediate care unit for patients transferred from the ICU after receiving cardiac treatments and who have recovered sufficiently (UW Health, 2014).

Intensive Care (Adult, Paediatric and Neonatal)

This unit cares for the most critically ill patients. It has a limited number of beds and the patients receive specialised care from specialist doctors and nurses.

The Neonatal ICU takes care of babies between the ages of 1 to 30 days but usually these wards only admit newborn babies who have not yet been discharged after birth. The Paediatric Unit cares for children between the ages of 30 days and 12 years and the Adult Unit cares for patients older than 12 years.

Gastroenterology
This discipline specialises in the treatment of bowel-related diseases. These patients cannot be allocated to wards where other patients have open wounds because of the high risk of infection for the other patients.

General Surgery
The General Surgery ward caters for patients who have received a wide range of minor surgeries. This unit tends to have a high turnover of patients who only stay for a few hours or overnight.

Gynaecology
The Gynaecology Department treats problems of the female urinary tract and reproductive organs.

Obstetrics, Maternity and Neonatal Department
The Obstetric Unit care for women and prenatal foetuses. The Maternity Department cares for women during childbirth and provides postnatal care. The Neonatal Department is attached to the Maternity Wards and has a number of cots to which the newborn babies can be allocated. The most hospitals have the policy that the mothers and babies should be kept together, where possible.

Nephrology and Urology
This department deals with kidney related problems. The patients in these departments can either be hospitalised for a short period, such as three days, when receiving minor treatments or for longer periods of time if the patient is on dialysis and waiting for a transplant.

Oncology
Oncology cares for patients who have been diagnosed with cancer. These patients receive radiotherapy and chemotherapy. They require specialised care from nurses and doctors and are closely linked to the Surgical Departments. Patients can be admitted for a single day treatment or for longer periods, depending on how critical the patient is.

Orthopaedics
Orthopaedics treats ailments of the muscles, joints, bones, ligaments, tendons, and nerves.

Paediatrics

This unit cares for children between the ages of 30 days and 12 years with all kinds of pathologies.

1.1.4 Length of Stay (LoS)

When a patient is admitted to hospital, not all the necessary medical treatments are always known at the start of the patient's stay (Paulussen et al., 2006). New findings during the patient's treatment might change the priority group of the patient, giving rise to more treatments or complications. This causes variability to occur in the Length of Stay of the patient.

Marazzi et al. (1998) did extensive research on three widely used distributions to assist bed managers to better predict their patient's LoS and make more informed decisions. The Weibull, log normal and gamma distributions were examined within each Diagnosis Related Group (DRG). DRG is a system that was developed in 1975 by YALE University to accurately describe all patient care types in an acute care hospital. Hospital cases are divided into 467 groups to help the healthcare industry to better understand the needs of their patients with regard to products and assigning a basic cost to each group. Marazzi et al. (1998) concluded that the log normal distribution fitted the most of the data because LoS is a short period for most of the patients.

Statistics South Africa (2004) indicated that patients' stay in special hospitals is longer than in district or regional hospitals because they have special needs. Table 1.1 is an extract of the study that shows the average and variation in the length of stay of patients in public hospitals in the City of Tshwane following a Weibull distribution.

Hospital	Average length of stay
George Mukhari	7.9
Pretoria Academic	5.7
Kalafong	6.5
Mamelodi	2.1
Pretoria West	2.7
Total	6.0

Table 1.1: Average length of stay in public hospitals in the City of Tshwane (Statistics South Africa, 2004)

1.1.5 Bed utilisation

Bed capacity is a limited resource in all hospitals (Schmidt et al., 2013). As reported in The Herald, Durban's Addington Hospital has 135 beds that are fully occupied at all times (Cullinan, 2006). Chris Hani Baragwanath Hospital in Soweto has only eighteen intensive care beds to serve a community of more than two million. This over population results in patients being discharged before they have fully recovered in order to make beds available for more critical patients. The standard of healthcare at Chris Hani Baragwanath Hospital ranges between world-class and life-threatening because there is a shortage of trained staff and available beds.

The shortage of beds causes the allocation of patients to beds to become problematic. Cases have been reported where patients share beds, are allocated to mattresses in hallways, or simply can not be admitted (Viljoen, 2005). Halata (2013) reported that a shortage of beds at Kimberley Hospital causes patients to be left on ambulance stretchers, patient trolleys or in wheelchairs because patients cannot be allocated to beds. Chris Hani Hospital also had cases where newborn babies were allocated to boxes in the Maternity Wards due to a shortage of cribs caused by budget cuts (Musgrave, 2007). On the other hand, there are instances where beds are left unoccupied because utilisation of beds is not monitored effectively (Mashaba, 2007). It is in many cases the responsibility of doctors and nurses to allocate a patient to an appropriate bed and to keep track of beds that have been filled or are possibly available.

Through interviews it became clear that in most public hospitals there is no central computer system that tracks beds or supports bed managers when doing allocation. When patients are admitted, the relevant ward is telephoned. The head nurse or an available doctor searches the wards for an open bed or moves patients around in an attempt to find a bed that will fulfil the patient's needs. If the patient cannot be admitted to a ward, the patient is either referred to another hospital or it is attempted to admit the patient to another ward.

Allocation is mainly based on certain characteristics of a patient, such as age, gender, pathology, and what type of medical treatment is required (Bachouch et al., 2012). In some hospitals patient preference in terms of room requirements is also taken into account (Schmidt et al., 2013).

According to hospital management and doctors interviewed, hospitals are designed to accommodate a fixed number of beds. Each bed must have the right resources, such as oxygen access, communication to the nursing station and telemetry. To compensate for the shortage of beds in public hospitals, extra beds are placed in the wards and in departments such as Paediatrics or Neonatal ICU. In some cases, up to three patients can be placed into one bed or crib if the demand for beds exceeds the actual supply. Therefore, not all the beds have the required resources to serve each patient's needs. When allocating patients to beds, these needs should be taken into consideration and the patient must be allocated to a bed which can fulfil these needs.

Patients are allocated to wards where beds are available, even if it is not the correct unit under which the patient should receive treatment. These patients must be transferred to the appropriate ward when beds become available.

Statistics South Africa (2004) showed in the Provincial Profile Report that, on average, the hospitals in Gauteng had a bed occupancy rate of 73%. Of all the hospitals, Mamelodi Hospital had the highest occupancy of 105% on average. This high rate can be attributed to patients sharing beds or admitting more patients than the number of available beds. The high occupancy rates cause difficulties in the optimisation of capacity utilisation when manual allocations of beds are made.

South African public hospitals have a shortage of hospital beds and struggle to allocate patients to beds and keep track thereof. This contributes to inefficient utilisation of limited hospital capacity. In literature, this problem is called the *bed management problem with specific focus on bed allocation.* This problem strives to optimally allocate patients to a hospital's scarce resources (Paulussen et al., 2006).

Different techniques have been studied in literature in an attempt to solve this problem. Bachouch et al. (2012), Demeester et al. (2010) and Schmidt et al. (2013) use mathematical programming to form a supporting tool that can be used by nurses when bed allocations are made. These models fall short because when the experiments are made larger to resemble a real life hospital the model takes too long to reach a feasible solution. Demeester et al. (2010) also attempt to use a heuristic model to shorten the solution time. This model is successful in assigning patients in a short amount of time. Schmidt et al. (2013), Seung-Chul et al. (2000) and Paulussen et al. (2006) found simulation modelling to be more flexible than the other techniques. Length of Stay, patients' possible demise and recovery, movement between wards and more allocation rules can be taken into account. Agent-based simulation modelling, as used by Paulussen et al. (2006), gives the most accurate depiction of reality. A patient's Length of Stay varies as new information about their health becomes available. The discharge times can therefore be updated and decisions can be made based on when the bed will become available. The agent based model can also solve the problem in a short time irrespective of the size of the experiment.

1.2 Research design

The aim of this report is to create a generic bed management model that will better match patients to beds and therefore maximise the capacity utilisation of a South African public hospital.

The model will take into account the needs, personal preferences and priority of each patient and allocate the patient to a bed that will best match their specific needs. Length of Stay (LoS) will be assigned to a probability distribution that correctly depicts the inherent variation. The uncertainty with respect to the patients' recovery will also be taken into account. Attention will be given to patient flow within the hospital.

Agent-based simulation will firstly be used for smaller experiments to establish what the reaction of the model will be if different characteristics of the inputs are changed. These smaller experiments will also be used to duplicate previous research to establish whether the similar results are obtained. Secondly, using experimental data a larger agent based simulation will be used to test three different collections of rules. The reaction of the model will be observed, as well as which group will maximise capacity utilisation.

Actual historical data from Mamelodi District Hospital will be used as a case study to show that the findings of this project are applicable to South African state hospitals.

1.3 Document structure

To start addressing the problem, the next chapter provides a literature review. The role of bed management, how admission and scheduling of patients take place, and how patients are currently allocated are investigated first. To provide a basis for determining which solution method should be used to solve the patient bed allocation problem, an overview of various allocation methods is given.

Chapter 3 contains conceptual models to test the influence of all the basic models. Each model is tested and a conclusion is reached based on the results. The results of each conceptual model is compared to the results of the other models to establish which rule is the most effective and has the largest impact on the system.

Three rule sets are compiled and tested in Chapter 4 based on the results from Chapter 3 in an attempt to solve the bed allocation problem. The results of the rules are compared and a conclusion is reached on which rule set performs the best. Reasoning in favour of some rules are also taken into consideration.

Chapter 5 concludes the document by summarising the research conducted and providing the proposed solution. Finally, suggestions for further research are discussed.

Chapter 2

Literature Review

Bed allocation and admission scheduling are well documented in literature. It is called the *bed management problem with specific focus on bed allocation.* Hospitals are continuously pressured to use all resources more efficiently to reduce cost for the hospitals and patients.

According to Proudlove et al. (2003) the responsibilities of bed management include allocating patients to beds, tracking empty beds, calculating when beds will become available and overseeing transfers of patients to another department or hospital. Therefore, it is reasonable to assume that bed management influences the capacity utilisation of the hospital and should strive to optimally allocate beds. Schmidt et al. (2013) state that operations management and strategic planning is an important task in a hospital and that bed management is a subtask of this.

Manual bed management techniques are the most widely used technique in public hospitals. Patient assignment to beds is based on business rules, how critical the treatment is and the patient's room preferences (Schmidt et al., 2013). This technique has also been used in an attempt to improve the hospital's capacity utilisation. A shortfall of this technique is that it is based on the assumption of a fixed Length of Stay for all the patients, without considering the variability that exists in the Length of Stay or the possible demise of the patient.

2.1 Mathematical programming

Mathematical programming is one of the best known branches of operations research, the scientific approach to decision making concerned with optimally allocating limited resources to different competitive activities whilst adhering to a set of constraints (Winston and Venkataramanan, 2003). Mathematical programming uses mathematical models to assist in making decisions or to understand a situation better.

2.1.1 Integer model

An integer linear program is a linear program in which some or all of the variables are non-negative integers (Winston and Venkataramanan, 2003).

A generic model for allocating acute and elective patients is based on integer linear planning, taking into account that the allocation rules and constraints have been developed by Bachouch et al. (2012). Their model aims to improve capacity utilisation at an operational level and was conducted at Saint Joseph's Hospital, which has 350 beds and some specialised wards. The following rules are considered in this model:

- Patients will not be transferred between wards.
- Length of Stay is deterministic and known.
- A window in which each patient has to be admitted is defined. The start and end times of a acute patient's window are the same in order to express urgency.
- Patients of different gender cannot share a room.
- Rooms are double or single rooms.
- Due consideration is given to compatibility of pathology when assigning patients to double rooms. Contagious patients are assigned to a room alone.

The model is formulated as follows:

Set of patients $i \in \boldsymbol{P} = 1, .., N$

Set of days $t \in \boldsymbol{D} = 1, .., T$

Set of beds $l \in \boldsymbol{B} = 1, .., L$

debut_i earliest hospitilisation window of patient i;

tard_i latest hospitilisation window of patient i;

Sex_i gender of patient i;

P_i pathology of patient$i$;

C_i contagiousness of patient i;

LoS_i Length of stay of patient i;

T2A_i rates of activity of patient i;

H   cost of each day a patient is late being admitted;

HV   very high value;

J_i beginning of hospitalisation period for patient i;

fin_i end of stay period for patient i such as $fin_i = J_i + LoS_i - 1$;

Bed availability

$$B_{lt} = \begin{cases} -2 & \text{if bed } l \text{ is assigned to a man during period } t; \\ 1 & \text{if bed } l \text{ is available during period } t; \\ 2 & \text{if bed } l \text{ is assigned to a woman during period } t \end{cases}$$

Bed location

$$B_{ll'} = \begin{cases} 1 & \text{if bed } l \text{ and } l' \text{ are in the same double room or if bed } l \text{ is located} \\ & \text{in a single room } (l = l'); \\ 0 & \text{otherwise} \end{cases}$$

If a bed is available within a certain pathology

$$PB_{lt} = \begin{cases} P_i & \text{if bed } l \text{ has previously been assigned to patient} \\ & i \text{ who has pathology } P_i \text{ during period } t; \\ 0 & \text{if bed } l \text{ is available during period } t \end{cases}$$

Allocation of a patient to a bed for a time frame

$$X_{ilt} = \begin{cases} 1 & \text{if patient } i \text{ is assigned to bed } l \text{ during period } t; \\ 0 & \text{otherwise} \end{cases}$$

Patient assignment to bed

$$A_{il} = \begin{cases} 1 & \text{if patient } i \text{ is assigned to bed } l; \\ 0 & \text{otherwise} \end{cases}$$

Transfer variable

$$REFUS_i = \begin{cases} 0 & \text{if patient } i \text{ is assigned to a bed;} \\ LoS_i & \text{otherwise} \end{cases}$$

The objective function aims to minimise costs incurred when a patient is admitted late and the cost when a patient cannot be admitted.

$$Minz = \sum_{i \in P} (J_i - debut_i) \times H + \sum_{i \in P} (REFUS_i / LoS_i) \times T2A_i \tag{2.1}$$

Subject to: Constraints (2) and (3) ensure that the patient is assigned to only one period over entire Length of Stay.

$$\sum_{i \in B} X_{ilt} \leq 1 \quad \forall i \in P, \forall t \in D \tag{2.2}$$

$$\sum_{i \in P} X_{ilt} \leq 1 \quad \forall l \in B, \forall t \in D \tag{2.3}$$

Equations (4) and (5) ensure that a patient is allocated to a bed that is available.

$$\sum_{l \in B} \sum_{t \in debut_i}^{T} X_{ilt} + REFUS_i = LoS_i \quad \forall i \in P \tag{2.4}$$

$$\sum_{l \in B} \sum_{t \in debut_i}^{T} (X_{ilt} \times (B_{lt} - 2) \times (B_{lt} + 2))/(-3) = LoS_i \times A_{it} \quad \forall i \in P \tag{2.5}$$

The start and end times of Length of Stay is calculated by constraints (6) and (7). Equation (8) calculates the actual Length of Stay.

$$\sum_{t \in B} t \times X_{ilt} + (1 - X_{ilt}) \times HV \geq J_i \quad \forall i \in P \forall t \in D \tag{2.6}$$

$$\sum_{t \in B} t \times X_{ilt} \geq fin_i \quad \forall i \in P \forall t \in D \tag{2.7}$$

Constraints (9) and (10) enforce that the starting of the patient's stay is within the window in which he or she must be admitted. Emergency patients must be admitted immediately.

$$fin_i = J_i + LoS_i - 1 \quad \forall i \in P \tag{2.8}$$

$$J_i \geq debut_i \quad \forall i \in P \tag{2.9}$$

$$J_i \geq tard_i \quad \forall i \in P \tag{2.10}$$

Equations (11), (12), (13) and (14) ensure that patients can share a room with patients of the same gender.

$$\sum_{i \in PC_i=2} (X_{ilt} \times S_i - Xil't \times S_i) \geq -1 \quad \forall l, l' \in B, l \neq l', \forall t \in D, \forall M_{ll'} = 1 \tag{2.11}$$

$$\sum_{i \in PC_i=2} (X_{il't} \times S_i) \times B_{lt} \leq 2 \quad \forall l, l' \in B, l \neq l', \forall t \in D, \forall M_{ll'} = 1 \tag{2.12}$$

$$\sum_{i \in PC_i=2} (X_{il't} \times S_i) \times B_{lt} \geq -1 \quad \forall l, l' \in B, l \neq l', \forall t \in D, \forall M_{ll'} = 1 \tag{2.13}$$

$$\sum_{i \in PC_i=2} (X_{ilt} \times P_i - Xil't \times P_i) \leq 1 + \big(1 - \sum_{i \in PC_i=2} X_{il't}\big) \times HV \tag{2.14}$$

$$\forall l, l' \in B, l \neq l', \forall t \in D, \forall M_{ll'} = 1$$

Equations (15), (16), (17) and (18) ensure compatibility of pathologies.

$$\sum_{i \in PC_i=2} (X_{ilt} \times P_i - Xil't \times P_i) \geq -1 - \big(1 - \sum_{i \in PC_i=2} X_{ilt}\big) \times HV \tag{2.15}$$

$$\forall l, l' \in B, l \neq l', \forall t \in D, \forall M_{ll'} = 1$$

$$PB_{lt} - \sum_{i \in PC_i=2} X_{il't} \times P_i \leq 1 + \big(1 - \sum_{i \in PC_i=2} X_{il't}\big) \times HV \tag{2.16}$$

$$\forall l, l' \in B, l \neq l', \forall t \in D, \forall M_{ll'} = 1$$

$$PB_{lt} - \sum_{i \in PC_i=2} X_{il't} \times P_i \geq -1 - \big(1 - \sum_{i \in PC_i=2} X_{il't}\big) \times HV \tag{2.17}$$

$$\forall l, l' \in B, l \neq l', \forall t \in D, \forall M_{ll'} = 1$$

$$B_{l't} \times \big(\sum_{i \in PC_i=1} X_{ilt} + \sum_{i \in P} X_{il't}\big) \leq 1 \tag{2.18}$$

$$\forall l, l' \in B, l \neq l', \forall t \in D, \forall M_{ll'} = 1$$

Contagious patients are assigned to an isolation room by (19) and (20).

$$B_{l't} \times \Big(\sum_{i \in PC_i = 1} X_{ilt} + \sum_{i \in P} X_{il't} \Big) \geq 0 \tag{2.19}$$

$$\forall l, l' \in B, l \neq l', \forall t \in D, \forall M_{ll'} = 1$$

$$X_{ilt} \in 0, 1 \quad \forall i \in P, \forall l \in B, \forall t \in D \tag{2.20}$$

$$A_{il} \in 0, 1 \quad \forall i \in P, \forall l \in B \tag{2.21}$$

$$REFUS_i \geq 0 \quad \forall i \in P \tag{2.22}$$

$$J_i \geq 0 \quad \forall i \in P \tag{2.23}$$

$$fin_i \geq 0 \quad \forall i \in P \tag{2.24}$$

Experiments are run using this model over a period of fourteen days with four types of pathologies and twenty-five beds (ten double rooms and five single rooms). Fifteen, twenty, thirty and forty patients are used in each experiment. The results show that the model is an accurate representation of the chosen rules used to allocate patients to beds and that the model can be used by nurses to support them in making decisions regarding bed allocations.

Binary integer programming is a special case of integer programming where the variables are binary.

Schmidt et al. (2013) uses a binary integer program to model the assignment and scheduling of patients to beds. Patients' preferences and costs resulting from admitting a patient to a specific department or ward are taken into account. If a patient cannot be admitted a large penalty cost is awarded. The aim is to improve the efficiency and effectiveness of bed management.

Schmidt et al. (2013) have realised that LoS is an important factor that influences capacity utilisation. LoS should be adjustable over the patient's stay. LoS is modelled as a log-normal distribution. The expected available beds are calculated based on expected LoS of the patients already assigned to the ward. The mathematical program is formulated as follows:

Set of patients preferences $\quad b \in \boldsymbol{B} = 1, .., x$

Set of patients $\quad i \in \boldsymbol{P} = 1, .., n$

Set of wards $\quad j \in \boldsymbol{J} = 1, .., m$

Set of days of admissions $\quad t \in \boldsymbol{T} = 1, .., k$

U_{jtb} number of beds used in ward j, fulfilling patients prefernce b at date t;

V_i Length of stay of patient i;

$E(U_{jtb})$ Expected number of used beds in ward j, fulfilling patients prefernce b at date t ;

$E(V_i)$ Expected length of stay of patient i;

K_{jb} Bed capacity of ward j, fulfilling patient prefernce b;

$c_{jtb} = \frac{E(U_(jtb)}{K_(jb)}$ Cost of assignment to ward j, fulfilling patients prefernce b at date t;

C_i Treating clinic of patient i;

m_α affinity weight factor;

m_β ward usage weight factor;

m_γ ward usage change weight factor;

m_δ admission delay weight factor;

$$x_{ijt} = \begin{cases} 1 & \text{if patient } i \text{ is admitted to ward } j \text{ at time } t) \\ o & \text{otherwise} \end{cases}$$

Mappings:

$AFF : S \times K \to [0, 1]$ Mapping of the affinities between wards and clinics;

$Cons : P \times B \to P$ Mapping of the patients who demand the preference $b \in B$;

$Cons : S \times B \to S$ Mapping of the wards satisfying patient preference $b \in B$;

$L_{max} : P \to T]$ Mapping of maximal LoS of a patient within the set P;

$Prio : P \to [0, 1, 2, 3]$ Mapping of patients to their treatment priority;

$$\min z = \sum_{b \in B} \sum_{i \in Cons(P,b)} \sum_{j \in Cons(s,b)} \sum_{t \in T} x_{ijt} \times (m_\alpha \times AFF(C_i, j) \tag{2.25}$$

$$(m_\alpha \times AFF(C_i, j) \tag{2.26}$$

$$+m_\beta \times (\sum_{m=t} [E(V_i)] c_{j,m,b}) \tag{2.27}$$

$$+m_\gamma \times (\sum_{m=t} [E(V_i)] \mid c_{j,m+1,b} - c_{j,m,b} \mid) \tag{2.28}$$

$$+m_\delta \times \frac{1}{1 + Prio(i)} \times (1 - \frac{1}{1 + \sqrt{t}})) \tag{2.29}$$

The objective function aims to minimise assignment costs. These costs includes the cost when a patient cannot be assigned to the correct ward, the cost of the patient being allocated to the ward, the cost of changing wards and the cost incurred for delay in admittance. Some of the constraints are:

$$\sum_{i \in Cons(P,b)} \sum_{j \in S} \sum_{t \in T} x_{ijt} =\mid Cons(P, b) \quad \forall b \in B \tag{2.30}$$

Constraint (2.30) ensures that an admission date and ward will be assigned to each patient.

$$\sum_{j \in S} \sum_{t \in T} x_{jit} \leq 1 \quad \forall b \in B \quad \forall i \in Cons(p, b) \tag{2.31}$$

Constraint (2.31) no more than one admission date and one ward can be assigned to each patient.

$$\sum_{i \in Cons(P,b)} \sum_{t_1 = max(0, t - L_{max}} x_{ijt_1} \leq K_{jb} - E(U_{jtb}) \quad \forall b \in B \quad \forall j \in Cons(S, b) \quad \forall t \in T \tag{2.32}$$

Equation (3.31) ensures that the capacity of the ward will never be exceeded.

Schmidt et al. (2013) concludes that there exists a great need for decision-support tools when bed allocations are made. The exact solution is feasible but it may take a long time to solve the problem.

Demeester et al. (2010) examine two methods that assist bed managers in allocating a patient to the appropriate bed and satisfying as much of the patient's needs as possible. The first is an integer linear program applied to a generated set of data and the second method is a heuristic approach. The heuristic approach is discussed later in this literature review.

Length of Stay depends on the sub-specialism a patient is assigned to and is generated randomly based on a normal distribution. The patient's needs, such as room preference, oxygen requirements and telemetry, are taken into consideration when allocation is done. The allocation rules that are taken into consideration by (Demeester et al., 2010) are divided into soft and hard constraints.

Hard constraints are rules that have to be adhered to in order to find a feasible solution.

- The room must be available for the duration of the patients stay.
- Length of Stay is a fixed period that can only be amended by the responsible doctor.
- Different patients cannot be assigned to the same bed for the same time slot.
- Male and female patients may not share the same room.
- Patients are assigned to departments depending on their age.
- Medical treatment requires that the patient is assigned to a room with special equipment.
- Quarantine of patients is allowed.

Soft constraints do not have to be satisfied when allocation is done, but the quality of the solution will improve when as many as possible are satisfied.

- Patients have the choice of a single room, twin room or ward.
- Patients are allocated to the correct department.
- Unplanned transfers to other wards should be kept to a minimum.

The model uses a generated set of data. The model has six departments which can accommodate patients from one major specialism and two minor specialisms. Every department has between twenty and thirty rooms. In each department there are at most five single rooms, five to ten double rooms, and the remaining rooms have four beds.

The patients are randomly assigned to a specialism and room preference. Length of Stay is generated based on a normal distribution with a mean of five and standard deviation of three. Sixty new patients are generated for each new day of the planning period.

Unfortunately, the full model is not included in the published article. The objective function aims to minimise the penalty incurred when patients are assigned to the wrong room and for each transfer.

The integer linear program did not find a feasible solution within a satisfactory amount of time. The bed assignment application should take very little time in computing a solution. For this reason, this method is not a feasible solution and therefore the heuristic method is considered in an attempt to find a better solution.

2.2 Heuristics

A heuristic is a problem-solving technique which gives a solution that is not guaranteed to be optimal (Winston and Venkataramanan, 2003). This technique is used when classic methods fail to find an exact solution, exhaustive searches are impractical or a satisfactory answer is required in a short frame of time.

The second method Demeester et al. (2010) used is a tabu search algorithm hybridised with a token-ring approach. Tabu search is a meta-heuristic developed by Glover in 1986 (Winston and Venkataramanan, 2003). This heuristic uses long-term and short-term memory to avoid entrainment in cycles by forbidding certain moves. The next iteration will be moved away from points previously used. The short-term memory lets the heuristic move away from local optimum, whilst the long-term memory allows searches to be conducted in the most promising neighbourhood (Demeester et al., 2010). The memory is created by recording previous moves in a tabu list. Initially this algorithm makes a course examination of the solution space. This step is called diversification. Candidate locations are then identified and more focused searches are started to produce local solutions. This step is called intensification. If a better solution is found, the list is shortened. On the other hand, if a better solution is not found the list is lengthened to escape local optimum.

The token ring algorithm creates a logical ring in which each neighbourhood is assigned a position in the ring (New Mexico State University, 2014). Each neighbourhood knows which neighbourhood is next in line. The ring is initialised by giving neighbourhood 0 a token. This token is then circulated. When a neighbourhood receives a token, it checks whether the process can go into a critical region, in this case, whether the solution is approaching a better solution than previously recorded in the tabu list. If so, it enters the region and iterates until no more improving moves can be made. The token then exits the neighbourhood. No other neighbourhood can use the same token to enter a critical region (Demeester et al., 2010). When the final neighbourhood cannot be improved, the algorithm iterates through the first neighbourhood again.

The solution to this approach is given in a two-dimensional matrix. Each row represents a bed in a department and each column represents a night. If a patient is placed within the matrix it is shown as a 1. The number of nights is the number of nights the patient will be staying in the hospital. Each matrix is a department and the collection of matrices represents the hospital (Demeester et al., 2010). A small hospital of three departments is experimentally created.

A patient is modelled as a set of objects called a "patient stay part". Each object is a night's stay. Patients are assigned to beds according to the hard and soft constraints mentioned previously.

Demeester et al. (2010) describe the neighbourhoods moves that are considered in this study as follows:

1. Swap-beds neighbourhood: In this neighbourhood, only patient stay parts can be moved or exchanged in the same department. Patients can only be moved to different rows (beds) and not different columns (nights). The algorithm searches for any empty matrix element in the same column and places the patient stay part into it. the matrix contains only 1/0 values.

2. Move-patient-to-another-department neighbourhood: Different departments can serve the same specialism. A patient can be moved to another department with the same specialism if the current department is full. At the start of an iteration, the algorithm selects a department with the most patients and moves one of the patients to another department. Yet again, only the bed can be influenced by the move, while the nights cannot be influenced.

3. Move-patient-to-same-department neighbourhood: In this neighbourhood all the patient stay parts are moved to empty beds in the same department.

4. Move-best-patient-to-another-department neighbourhood: As in the second neighbourhood, a patient is selected and moved to another department. But it chooses the best patient to move from a list, rather than selecting the patient randomly.

Various experiments are run using this method, comparing the results with the results found using a tabu search algorithm hybridised with a variable neighbourhood decent. The two algorithms work on the same principles, except the time when the algorithm moves to another neighbourhood differs. The variable neighbourhood algorithm goes to a new neighbourhood when one non-improving move is made. The token ring approach changes when a certain number of non-improving moves are made.

The tabu search algorithm hybridised with a token ring continuously produced better results. Demeester et al. (2010) finds that the algorithm produces fast and satisfactory results. It can successfully be used to assist bed managers, balance patients across the different departments and improve the hospital's performance in terms of patients' waiting list and bed utilisation. A shortcoming of this study is that emergency patient admissions and ICU Departments are not considered.

The existing model's neighbourhoods should also be improved to allow patients to be moved in a time dimension to simulate rescheduling of elective patients.

2.3 Simulation modelling

Simulation modelling is the reproduction of a dynamic real world process to create a model that can be experimented with to depict how the system will react to changes. Different software tools have been created to assist in creating these models, such as ARENA, SIMIO, Siemens Tecnomatix Plantsimulation and AnyLogic. Each of these software packages has been developed for a certain goal. The most common goal is the improvement of production systems. Simulation can be used to depict any system and to study the influence of certain decisions on this system. Different simulation methods exist. Two popular methods are discrete event simulation and agent based simulation.

Simulation modelling is used to show that reserving some beds in an ICU Ward for exclusive use of elective surgeries will minimise the number of surgeries that have to be cancelled because of emergency admissions (Seung-Chul et al., 2000). This model serves as a decision support model for bed managers. Two reservation techniques are tested with the simulation model to generate data for evaluation of performance by criteria based on ICU and other patients' requirements. The two methods that are tested is a dependency unit attached to the surgery department and reserving some beds in the ICU for the exclusive use of elective patients. Using simulation modelling, this model is given the flexibility to be able to transfer patients from an ICU to another ward when a patient requires allocation that is a higher medical priority, given that the patient being transferred is medically stable.

Seung-Chul et al. (2000) found that in a typical public hospital in Hong Kong patient flow into the adult ICU comes from four sources, as depicted in the following figure 2.1.

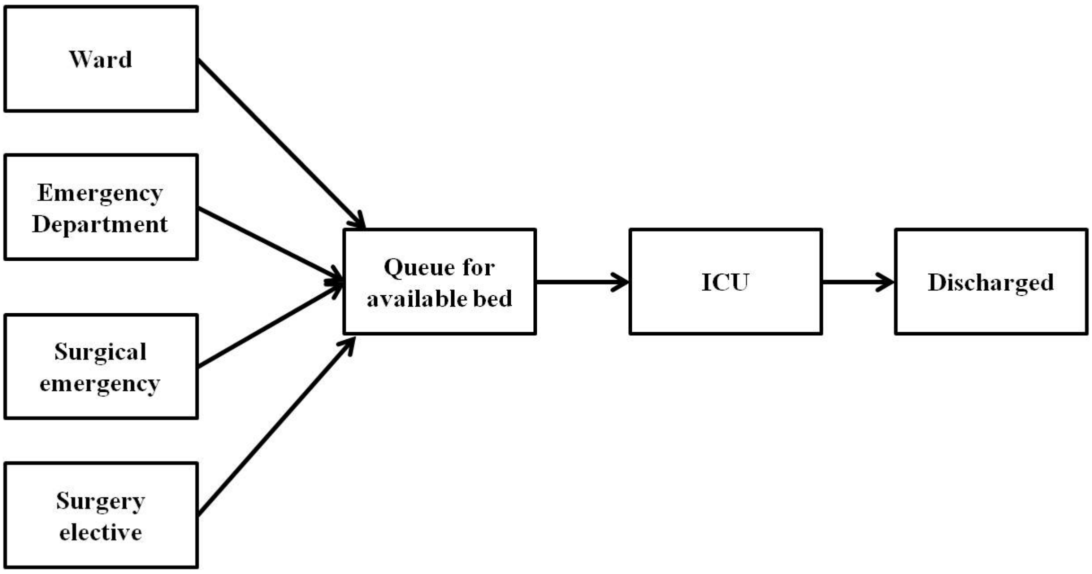

Figure 2.1: General model of an ICU (Seung-Chul et al., 2000)

When an ICU patient is discharged from the ICU, he is rarely immediately also discharged from the hospital but rather transferred to a High Care Unit. From the High Care Unit a patient moves to a ward, from where he or she is usually discharged.

Seung-Chul et al. (2000) uses the following process in the decision to admit a patient from surgery elective patients to the ICU:

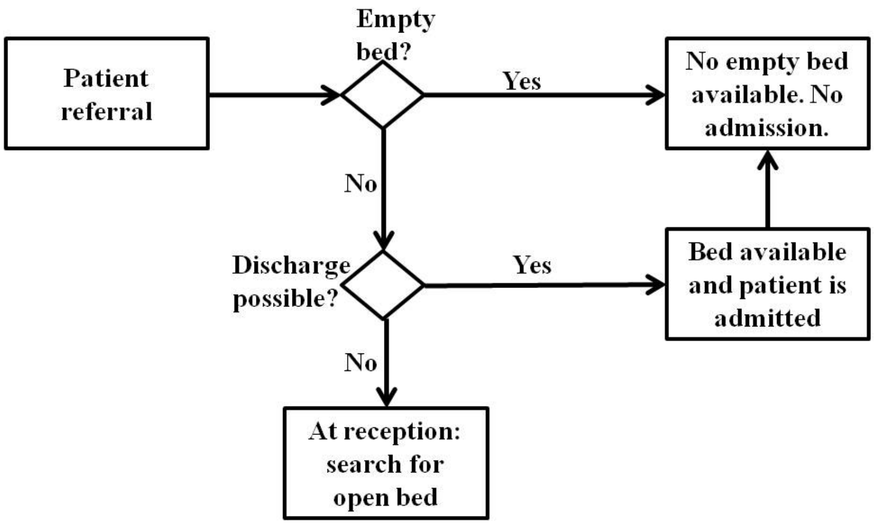

Figure 2.2: General process for deciding whether to admit a patient to the ICU (Seung-Chul et al., 2000)

Four reservation strategies are tested using the flexible bed allocation method (Seung-Chul et al., 2000). The first strategy represents the current system as a control for the outputs of the other strategies. Strategy 2 experiments with reserving of different number of beds for exclusive use by elective surgery patients. The other strategies aim to exploit the fact that elective surgeries are seldom scheduled for weekends. This allows patients who do not qualify for use of the reserved beds to be allocated to these beds over weekends when unreserved beds are not available.

Data collected over six months are used in the model (Seung-Chul et al., 2000). Some of the variables obtained from the data include arrival rate, survival rate, admission rates and length of stay. Distributions are assigned to each variable.

To validate the model, the simulation is run for an experimental period of twenty years. The data obtained from the model correspond with the actual data (Seung-Chul et al., 2000). The system performance is measured by seven outputs. These outputs are bed utilisation, average number and average time of patients waiting in system and queue, number of surgeries cancelled and number of patients admitted.

The results of the simulation model shows that the dedicated ICU does not outperform the current system. The dedicated ICU only reduces the number of cancelled surgeries but causes other services to perform worse (Seung-Chul et al., 2000).

An experiment is created to test the impact of the flexible bed allocation technique. The strategies are tested by increasing the number of reserved beds from one to five in increments of one (Seung-Chul et al., 2000). It is found that three reserved beds significantly decrease the number of cancelled elective surgeries with little impact on the queue length. The three-bed reservation technique is used to compare the results of the four strategies. Bed utilisation for the four strategies is slightly higher than the current system and the number of cancelled surgeries is markedly lower. None of the strategies is markedly better than the other strategies.

Seung-Chul et al. (2000) concludes that none of the tested techniques is a dominant solution to the problem. This study identifies some positive aspects for using simulation modelling in the attempt to solve the bed allocation problem:

- Different experiments can easily be created and compared.
- No hospital ward will be empty at the start of an experiment. The simulation model allows a warm-up period for the system, where some beds and wards are filled to be able to obtain realistic results.
- The simulation model can be run for a longer simulation time.
- The required flexibility is lent to the model in terms of Length of Stay, arrival rates and possible demise of patients.

2.4 Agent based simulation modelling

Agent based simulation modelling is a "decentralised, individual-centric" approach to modelling (AnyLogic, 2014). Other simulation modelling techniques are system focused. An agent can be people, products, vehicles or anything that performs activities and has certain behaviours. These agents are placed in an environment and are connected to other agents. The simulation will then depict the individual behaviour and interactions between the agents.

Paulussen et al. (2006) uses an agent-based approach to lend the required flexibility to patient scheduling in ancillary units. An ancillary unit is a support unit where patients can go for treatments or tests. Patient's Length of Stay in hospitals vary with the type of disease, duration of treatments and as complications arise. An agent-based approach allows each object to be represented by a single agent with its own goal and the agents can react with the needed flexibility to changes. The objects in this study are the resources in ancillary units and the patients. The changes that can occur are due to new information that is available on the patient's health whether it is a speedy improvement or a decline in health. The goal of the patients is to minimize their length of stay and the resources aim to minimize their idle time.

The patients and resources are modelled as autonomous agents (Paulussen et al., 2006). This means that the patients and resources have the freedom to act independently. In this model the economic concept of mutual selection is used to assign patients to resource time slots. Mutual selection occurs if the patient tries to obtain the required resources and the resources attempt to provide services to the most deserving patient, based on certain criteria. An auction-based coordination mechanism is created to evaluate which patients' bid is the highest for a time slot. A utility function is used by the patient agents to measure what the value of a time slot is and to generate a bid.

A utility function is a mathematical function that ranks alternatives according to the patient's preferences (Paulussen et al., 2006). The preferences are formed to minimise the patient's Length of Stay or to improve their health. The more critical the patient's health becomes, the longer the patient will stay in the hospital or the higher their priority class will become. Therefore the patient's bid will become higher. The resource must then give the time slot to the highest bid (sickest patient). This is the basic principle for an auction-based coordination mechanism.

Paulussen et al. (2006) use various experiments to evaluate and benchmark the performance of the multi-agent system. The hospital size, durations of treatments and probability for an emergency case are varied to test the reaction of the model and are compared to the results obtained from a model using the priority rule strategy currently used in hospitals. The multi-agent model improves the current patient schedule practice in hospitals and provides the required flexibility.

Agent based simulation has all the positive aspects of simulation modelling but is focused on the individual instead of the system. Hospitals must serve each patient as an individual and not as a system. Agent based simulation will better allocate patients to beds because each patient's needs and characteristics can be taken into account as well as the characteristics of each bed. Agent based simulation also lends the model the required flexibility. Each patient's Length of Stay can differ and can react as new information on the person's health becomes available. The model can also react in a proactive manner to disturbances, such as an influx in emergency patients. When creating an agent based simulation model, caution must be given when the bed agent is created. The bed cannot make decisions and the model must depict reality as closely as possible.

Agent based simulation will be used in the next section to demonstrate what the influence of allocation rules will be on the system, because each patient can be modelled as an autonomous object with the ability to react to its environment. This method of simulation will also make it easier to collect and compare data from multiple simulation iterations.

Chapter 3

Studying Rule-Based Components

In this section, basic allocation rules are tested on a small scale model with six beds to establish what the influence of the individual rule is on the system without added noise or influence of other rules. The basic models are created in Anylogic using agent based simulation.

3.1 Basic model

3.1.1 Agents

In the basic model there exist four types of agents: main, patients, beds, and reception. Each of these agents has their own characteristics and behaviours.

Main

Main, as seen in figure 3.1, is the principle view of the model where the layout of the beds and movement of patients can be observed.

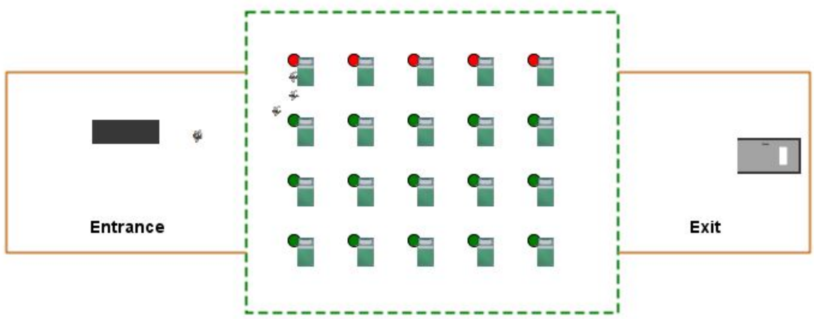

Figure 3.1: Main agent forming the principle view of the model

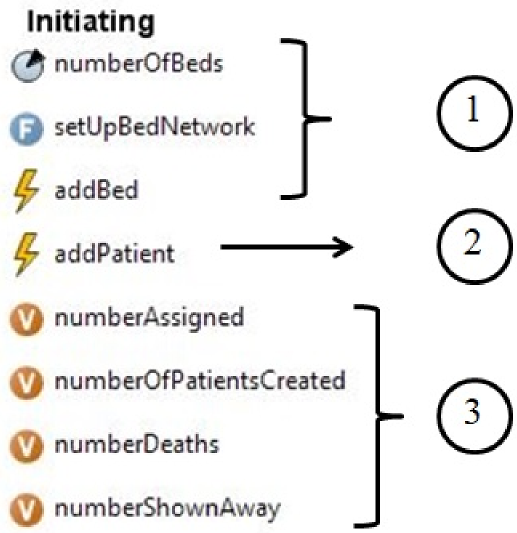

Figure 3.2: Main agent initiating variables and parameters

Figure 3.2 shows the initiating variables and parameters of the model. Collection 1 creates beds at the start of the simulation run and places them in the locations specified in the function. All conceptual models will have six beds. Collection 2 is an event that adds patients throughout the model to simulate patients arriving at the hospital. For the conceptual models it is assumed that patients' inter arrival time is exponentially distributed with a mean of 8 hours. Patients arrive at the entrance and are then sent to different locations. The flow of patients will be explained in the patient agent. Collection 3 includes variables that collects data on patients according to their assignment status. These variables will be used to compare the outputs of the different conceptual models.

Beds

Figure 3.3 illustrates the bed agent's logic. The bed can either be occupied or unoccupied. When a patient is allocated to the bed, the patient identification number is stored in patientId variable. The bed also has parameters such as gender and pathology. These parameters will be used if the gender or pathology of the patient is used to allocate a patient to a bed with similar gender or pathology.

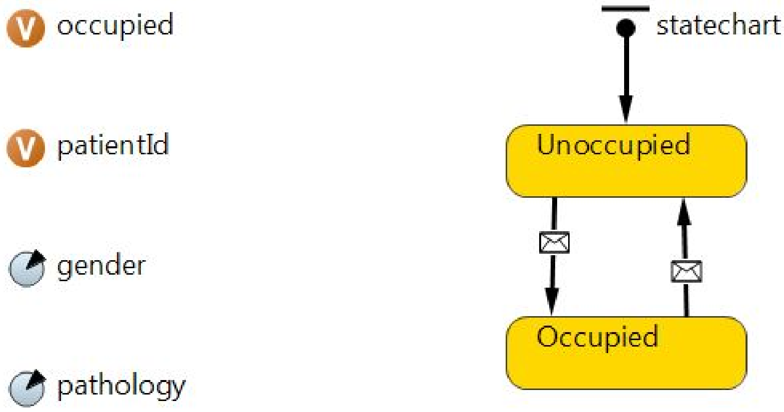

Figure 3.3: State chart and parameters of the bed agent

Figure 3.4 shows the animation of the beds. When a patient is assigned to a bed, the status of the bed changes from unoccupied to occupied. The colour of the circle above the bed changes from green for unoccupied to red for occupied. Similarly, the colour changes from red for occupied to green for unoccupied when the patient is discharged.

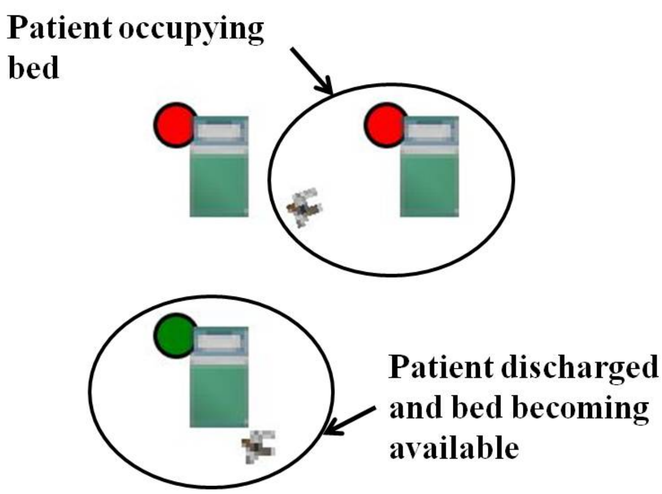

Figure 3.4: Bed animation showing occupied and unoccupied beds

Patients

The patient agents have the characteristics shown in figure 3.5. These parameters are used to allocate patients to the appropriate beds.

Figure 3.5: Patient agent characteristics

Figure 3.6 illustrates the patient's journey through the hospital. Patients arrive at the reception with an exponential inter arrival time with a mean of 8 hours. The patients queue for reception. When the patient is first in line, reception searches through the available beds to find a bed matching the patient's criteria. If there is a bed available the patient is admitted and sent to the bed. If no bed is available, the patient is shown away. In the conceptual models, the patients cannot wait for a bed to become available.

Once admitted, the patient stays in the hospital for a time period known as the LoS. The LoS is modelled as a Weibull distribution (gamma = 2.5, beta = 2, minimum = 0). Using these parameters for the Weibull distribution ensures that on average the patients are in the hospital for 2.5 days. The patient can either recover fully or can die due to complications. The probability that a patient will die is 10%. If the patient's stay at the hospital is complete, the patient is discharged and the bed becomes available again.

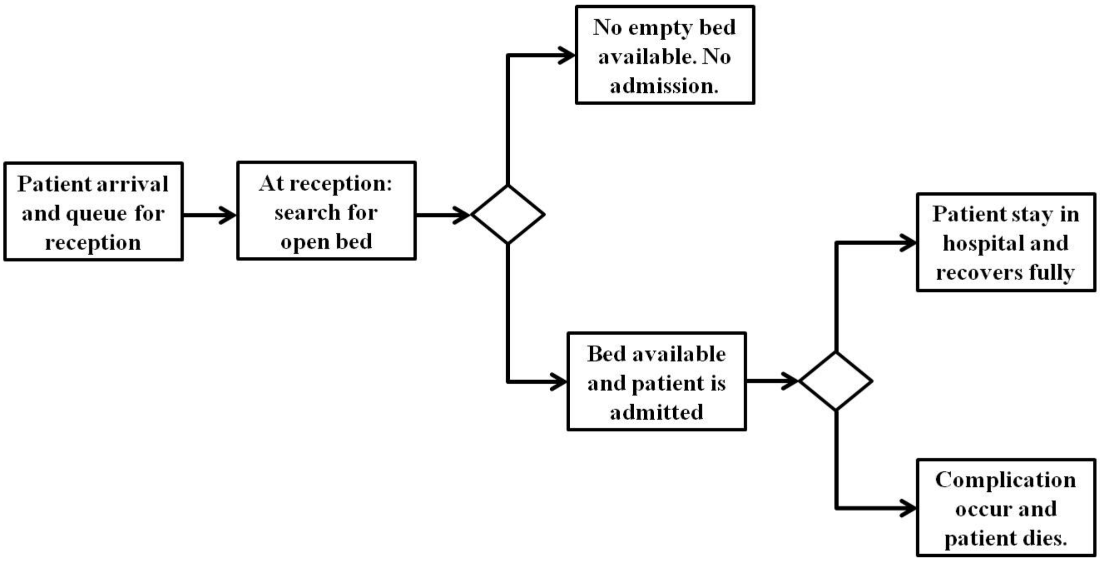

Figure 3.6: Basic patient flow

When the patient reaches the reception desk the model searches through all the beds to find an available bed that matches the patient's criteria. The basic search function is as follows:

```
Result: Patient assigned to bed
for beds 1 to 6 do
    integer i = number of beds;
    if bed is unoccupied and patient is not assigned to bed then
        bed is now occupied;
        patient is assigned;
        record which bed is assigned to patient in variable bedId;
        record which patient is assigned to bed in variable patientId;

        send a message to patient state chart to change state;
        send a message to bed state chart to change state from unoccupied
        to occupied;
        break function;
    end
    if All beds are occupied and patient is still not assigned then
        send a message to patient state chart that there are no beds
        available;
    end
end
```

Algorithm 1: Basic find bed function

Data collection and model comparison

The conceptual models will be compared on the basis of the number of patients that were allocated to beds during the simulation run. To ensure that the results can be compared, the following standards will be maintained:

- Number of beds: 6
- Run time: 500 units of time
- To be able to compare results the of the rules a fixed seed of 2 will be used in each experiment. Rhis will ensure that any difference in the results are due to the influence of the rules and not the influence of randomness on the model. As a further experiment each rule will also be run using a random seed value to test how the rule set will react with fluctuation of arrivals and different Lengths of Stay.
- Length of Stay distribution will be the same for all models
- Patients will arrive with an inter arrival time exponentially distributed with a mean of 8 hours
- Probability of demise will be 10% for all models
- Only one conceptual rule will be tested per model
- Number of iterations: 20

3.2 Conceptual models

3.2.1 First come, first served

This model will be based on the basic conceptual model as described above. No regard is given to the criticality of patients, pathology, age, or gender. The patient who arrives first is helped first. If a bed is available the patient is allocated to the bed, otherwise the patient cannot be admitted and is shown away.

Results

Figure 3.7 shows the typical results obtained during a simulation run from Any-Logic. From the figure it can be seen that data are collected on number of patients allocated, number of deaths, and number of patients shown away. This data, as well as total number of patients created, are used to analyse how well the rule functions. From the figure 3.7 it can be seen that on average there are between one and two patients assigned to the hospital at any given time. It rarely occurs that there is a shortage of beds and patients have to be shown away.

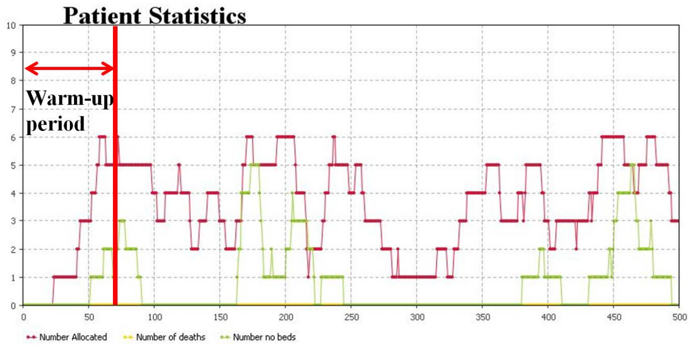

Figure 3.7: Typical patient statistics during a single simulation run

Table 3.1 show the results obtained from the fixed seed model and table 3.2 shows the average and standard deviations of the results obtained from the first come, first served rule using random seed. Figure 3.8 indicates all data collected on a histogram for all twenty runs using random seed.

Number of patients	Result
Arrived at Hospital	71
Admitted	36
Number referred to another hospital	35

Table 3.1: Results obtained from twenty simulation runs for first come, first served rule using fixed seed

Variable	Average	Standard deviation
Number arrived at hospital	63.7	7.07
Number admitted	41.60	2.50
Number of deaths	3.75	2.02
Number referred to another hospital	22.10	5.74

Table 3.2: Results obtained from twenty iterations of first come, first served rule with a random seed

On average, 65% of patients are assigned to beds and 35% are shown away. If on average 41.6 patients are assigned to 6 beds, it means that each bed has an average of 6.93 patients per 500 time units (hours). On average, a patient stays 2.5 days in a bed before being discharged. Therefore, each bed is utilised for 415.8 hours, giving the average bed utilisation as 83.16%.

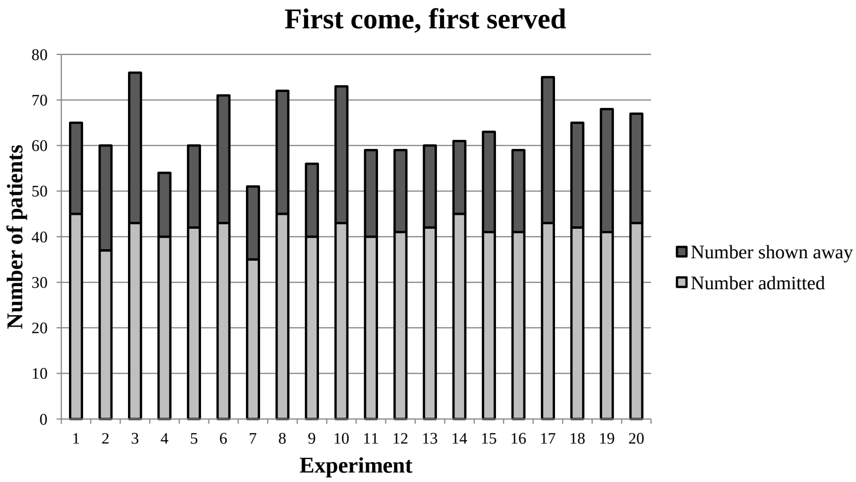

Figure 3.8: Results obtained from twenty simulation runs for first come, first served rule using random seed

Observations

From figure 3.7 it can be seen that the model takes on average 60 time units to reach a stable phase. The first 60 units are referred to as a warm-up period. The warm-up period is the time required for the model to reach normal conditions (SIMUL8, 2014). In this case, it is the time required for the beds to become full and reach a stable state. In no hospital will all beds be empty at the start of any day. Therefore the model must first reach a stable state in order to accurately represent reality.

3.2.2 Reservation of some beds for elective patients

In this conceptual model some beds are be reserved for the exclusive use of elective patients. Emergency patients or inpatients cannot use these beds. Experiments are run for reservation of 1 to 5 beds which are reserved exclusively for elective patients. The results of this model should be compared to results obtained from reserving beds for elective patients as they are scheduled.

Ryan et al. (2010) showed in their study of the characteristics of hospital admissions that 28% of all patients admitted to hospitals are elective patients. The basic find bed function is modified in the following way:

```
Result: Patient assigned to bed
if Patient is elective then
    for beds 1 to number of elective beds do
        if bed is unoccupied and patient is not assigned to a bed then
            bed is now occupied by patient;
            patient is assigned to bed;
            record which bed is assigned to patient in variable bedId;
            record which patient is assigned to bed in variable patientId;
            send a message to patient state chart to change state;
            send a message to bed state chart to change state from
            unoccupied to occupied;
            break function;
        end
        if All elective beds are occupied and patient is still not assigned then
            send a message to patient state chart that there are no beds
            available;
        end
    end
end
if Patient is not elective then
    for beds al non-elective beds do
        if bed is unoccupied and patient is not assigned to a bed then
            bed is now occupied;
            patient is assigned;
            record which bed is assigned to patient in variable bedId;
            record which patient is assigned to bed in variable patientId;
            send a message to patient state chart to change state;
            send a message to bed state chart to change state from
            unoccupied to occupied;
            break function;
        end
        if All non-elective beds are occupied and patient is still not assigned
        then
            send a message to patient state chart that there are no beds
            available;
        end
    end
end
```
Algorithm 2: Basic find bed function modified to allocate patients according to whether patient is an elective patient

Example of the results obtained from the experiments

Table 3.3 shows the average and standard deviations of the results obtained from the model considering reservation of a fixed amount of beds for elective patients when allocations are done. In this model two beds are reserved for exclusive use by elective patients. Figure 3.9 indicates all data collected on a histogram for this experiment's twenty runs. This is a representation of the type of data collected. The results for all the experiments are shown in 3.10

Variable	Average	Standard deviation
Number arrived	63.80	8.22
Number admitted	36.60	3.08
Number of deaths	3.10	2.03
Number referred to another hospital	27.20	7.14

Table 3.3: Results obtained from twenty simulation runs for model considering reservation of beds for elective patients using random seed

On average, 57.37% of patients are assigned to beds and 42.63% are shown away. Of the 36.60 patients assigned to beds, on average 10.50 are elective patients and 26.10 are non-elective patients. Table 3.4 indicates the average bed occupancy for the 500 hours and the bed utilisation for reservation of elective beds allocations rule.

Patient	No. of beds	Bed occupancy for run	Bed utilisation (hours)	Bed utilisation (%)
Elective	2	5.25	315	63
Non-elective	4	6.53	391.5	78.3

Table 3.4: Bed utilisation for reservation of some beds for elective patients using random seed

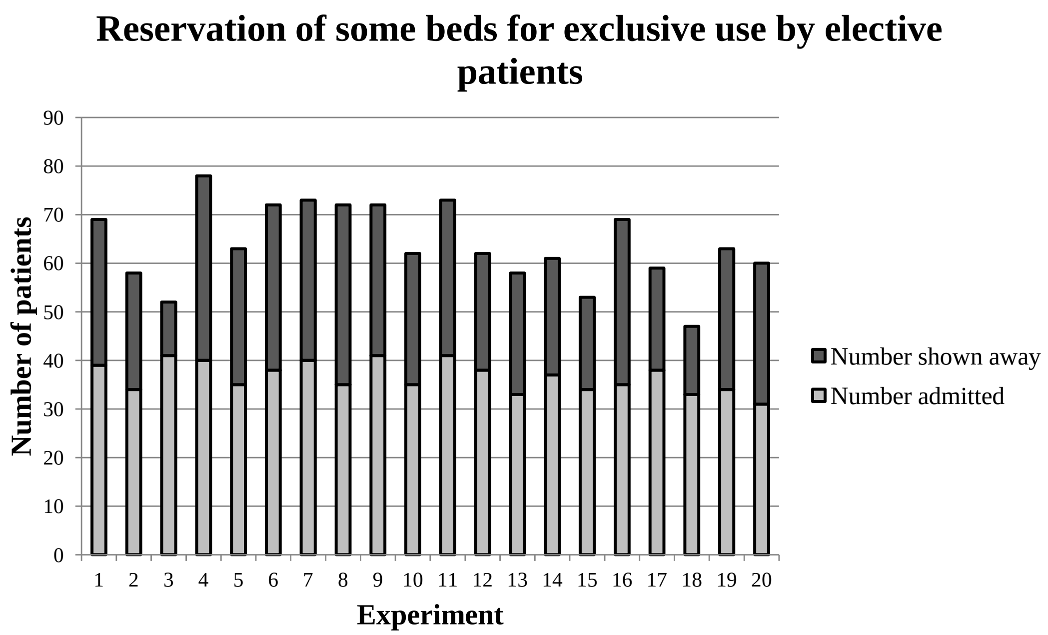

Figure 3.9: Results obtained from twenty simulation runs for model considering reservation of beds for elective patients using random seed

Results from all experiments

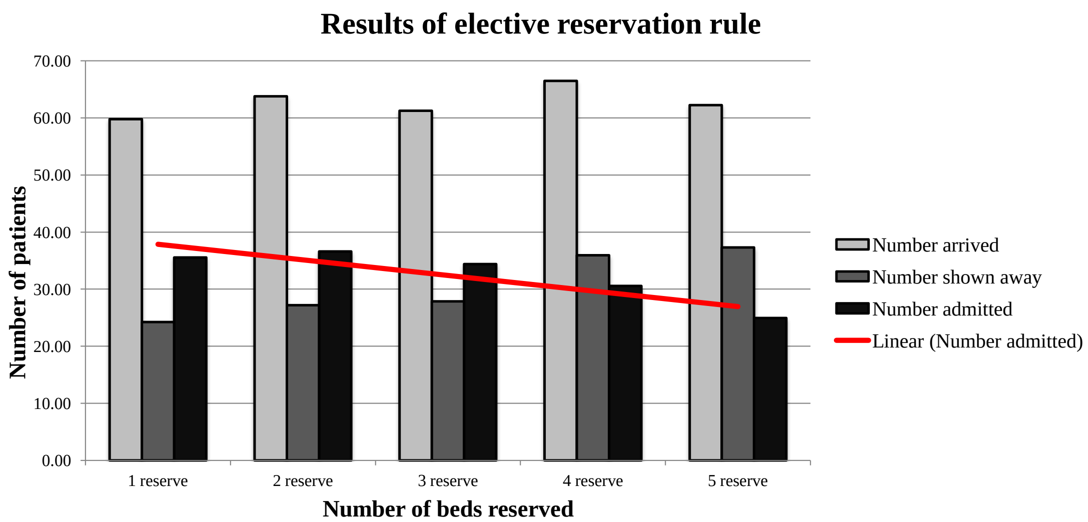

Figure 3.10: Results obtained from all experiments for the model considering reservation of beds for elective patients using random seed

Number of patients	Reserve 1	Reserve 2	Reserve 3	Reserve 4	Reserve 5
Arrived at Hospital	71	71	71	71	71
Admitted	28	25	19	16	10
Number referred to another hospital	22	25	32	39	43

Table 3.5: Results obtained from twenty simulation runs for reservation of some beds for the exclusive use of elective patients using fixed seed

Discussing and conclusion

The results of the experiments, as can be seen in figure 3.10, seem to be very close. Reservation of one or two beds gives the best results. Reservation of one bed shows away the least number of patients, whilst reservation of two beds assigns the most patients.

On closer inspection of all the results reservation of one bed allocates 5.70 elective patients on average and 29.85 non-elective patients of the 35.55 patients admitted. Reservation of two beds assigns 10.5 elective patients and 26.10 non-elective patients of the 36.60 patients admitted.

The results from all experiments with a fixed seed shown in table 3.5 indicate that the number of patients that can be admitted to the hospital declines as the number of reserved beds inclines. The best reservation techniques are to reserve one bed for the exclusive use of elective patients.

A hospital's objectives have to be considered when choosing whether to reserve 16.67% or 33.33% of its beds for elective patients. If the hospital receives more emergency patients, management may choose to reserve fewer beds to ensure more beds are available for emergency patients and fewer surgeries are cancelled. The hospital will also consider the type of ward when selecting this technique. It may be more applicable to a surgical ward.

3.2.3 Reservation of beds as elective patients are scheduled

This model will reserve beds for scheduled arrival of elective patients. It will take into consideration when a bed will become available and when a patient is scheduled to be admitted. If the release time of the bed is before the arrival time of the patient, the bed is reserved for the patients arrival and no patient can be allocated to this bed.

This occurrence is modelled in AnyLogic by creating two types of patients: elective and non-elective. The elective patients are created with an add patient event as in the base case model but is not admitted or shown away when the patient arrives. On creation, an elective patient requests reservation of a bed for his or her scheduled arrival. The modified find bed function searches through all the beds to find a bed that will be available for the scheduled arrival date. If a bed is available it is reserved for the arrival of the patient. If no bed is available for the scheduled arrival, the patient is shown away.

A bed may be occupied when it is reserved, but once reserved, no patient can be allocated to it. The patient must therefore be scheduled to arrive within a day of creation, otherwise all beds will be reserved and no patients can be admitted. As in the fixed reservation technique, elective patients will be 28% of all patients.

The modified find bed algorithm for elective patients:

```
Result: Patient assigned to bed
if Patient is elective then
    for beds 1 to 6 do
        if bed is unoccupied at scheduled arrival time and patient is not
        assigned to bed then
            bed is reserved;
            patient is assigned to bed;
            record which bed is assigned to patient in variable bedId;
            record patient ID in resevationID variable;
            send a message to patient state chart to change state from
            waiting for a bed to scheduled arrival;
            send a message to bed state chart to change state to reserved;
            break function;
        end
        if All beds are occupied at scheduled arrival time and patient is still
        not assigned then
            send a message to patient state chart that there are no beds
            available;
        end
    end
end
```

Algorithm 3: Modified find bed function to search for a bed that is available at scheduled arrival time of elective patient

Results from all experiments

Table 3.6 shows the results for the model considering reservations of beds according to patient schedule using a fixed seed. Table 3.7 shows the average and standard deviations of the results obtained from the model using a random seed. Figure 3.11 indicates all data collected on a histogram for this experiment's twenty runs.

Number of patients	Result
Arrived at Hospital	71
Admitted	41
Number referred to another hospital	19

Table 3.6: Results obtained from twenty simulation runs for the model considering reservation of beds using fixed seed

Variable	Average	Standard deviation
Number arrived	61.50	7.78
Number admitted	47.05	4.88
Number of deaths	3.20	2.07
Number referred to another hospital	13.15	6.48

Table 3.7: Results obtained from twenty simulation runs for model considering reservation of beds using random seed

On average, 76.5% of patients are assigned to beds and 23.5% are shown away. Of the 56.15 patients assigned to beds, on average 6.00 are elective and 41.05 are non-elective. During the experiment, each bed had an average of 7.84 patients. If each patient stays for 2.5 days the beds are utilised for 470,5 hours or 94.1% of the time.

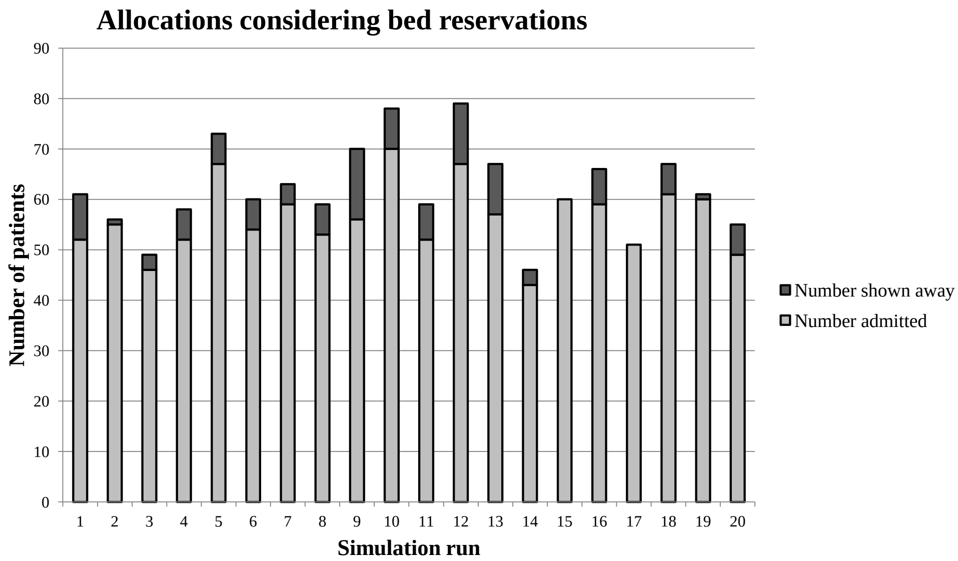

Figure 3.11: Results obtained from twenty simulation runs for model considering reservation of beds using random seed

Discussion and conclusion

The results of this model indicate that bed utilisation is very high, with each bed being occupied 94.1% of the time. The number of patients assigned is also high. From 3.11 it can be seen that the number of patients assigned and shown away as a percentage of all the patients created remains relatively constant for each experiment.

3.2.4 Allocation according to patient characteristics: Age

This model will take into consideration the age of the patient when allocations are done. Patient age is calculated with a gamma distribution with shape parameter of 11 and scale parameter of 2 (Statistics South Africa, 2013). Adults are patients who are older than thirteen years. Patients dedicated to the children's beds are younger than thirteen years. The basic find bed algorithm is modified in die following manner:

```
Result: Patient assigned to bed
if Patient is older than 13 years then
    for beds 1 to 4 do
        if bed is unoccupied and patient is not assigned to bed then
            bed is now occupied;
            patient is assigned;
            record which bed is assigned to patient in variable bedId;
            record which patient is assigned to bed in variable patientId;
            send a message to patient state chart to change state;
            send a message to bed state chart to change state from
            unoccupied to occupied;
            break function;
        end
        if All adult beds are occupied and patient is still not assigned then
            send a message to patient state chart that there are no beds
            available;
        end
    end
end
if Patient is younger than 13 years then
    for beds 5 do
        if bed is unoccupied and patient is not assigned to bed then
            bed is now occupied;
            patient is assigned;
            record which bed is assigned to patient in variable bedId;
            record which patient is assigned to bed in variable patientId;
            send a message to patient state chart to change state;
            send a message to bed state chart to change state from
            unoccupied to occupied;
            break function;
        end
        if All paediatric beds are occupied and patient is still not assigned
        then
            send a message to patient state chart that there are no beds
            available;
        end
    end
end
```

Algorithm 4: Basic find bed function modified to allocate patients according to age

The number of beds dedicated to each age group will be varied to estimate what number of beds allocated to each group will give the best answers. The experiments are run as follows:

- Adults: 6 beds. Children: 0 bed
- Adults: 5 beds. Children: 1 bed
- Adults: 4 beds. Children: 2 beds
- Adults: 3 beds. Children: 3 beds
- Adults: 2 beds. Children: 4 beds
- Adults: 1 beds. Children: 5 beds
- Adults: 0 beds. Children: 1 beds

Example of the results gathered from the simulation model

Table 3.8 shows the average and standard deviations of the results obtained from the model, considering age when allocations of patients are done. In this model, adults have 5 beds and children have 1 bed. Figure **??** indicates all data collected on a histogram for this experiment's twenty runs. This is a representation of the type of data collected. The results for all the experiments are shown in 3.12.

Variable	Average	Standard deviation
Number arrived	60.55	6.72
Number admitted	37.85	2.83
Number of deaths	3.85	2.03
Number referred to another hospital	22.70	5.81

Table 3.8: Results obtained from twenty simulation runs for model considering age as a rule using random seed

On average, 54% of patients are assigned to beds and 46% are shown away. Of the 33.5 patients assigned to beds, on average 28.70 are adults and 4.80 are children. Table 3.9 indicates the average bed occupancy for the 500 hours and the bed utilisation for age based allocations.

Patient	No. of beds	Bed occupancy for run	Bed utilisation (hours)	Bed utilisation (%)
Adult	4	7.18	430.8	86.16
Children	2	2.4	144	28.8

Table 3.9: Bed utilisation for age based allocations using random seed

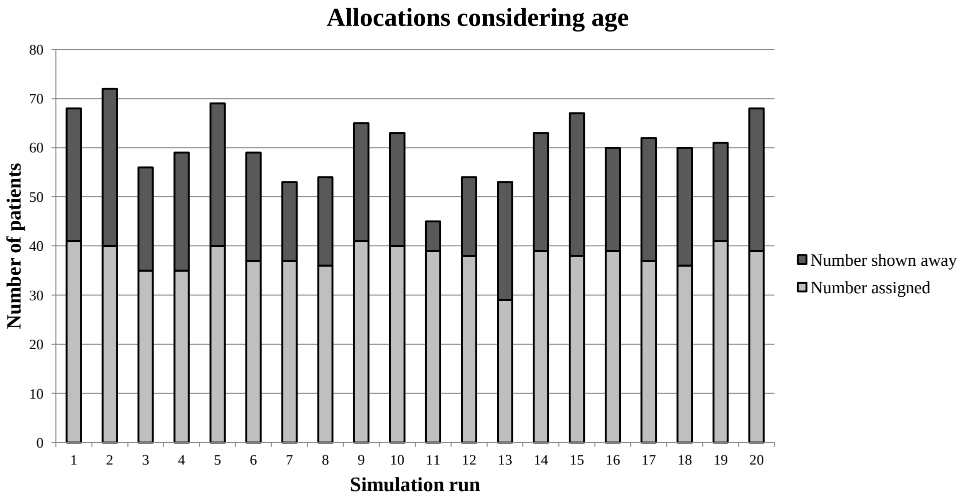

Figure 3.12: Results obtained from twenty simulation runs for model considering age as a rule using random seed

Results from all experiments

Number of patients	6 Adult, 0 Child	5 Adult, 1 Child	4 Adult, 2 Child	3 Adult, 3 Child	2 Adult, 4 Child	1 Adult, 5 Child	0 Adult, 6 Child
Arrived at Hospital	71	71	71	71	71	71	71
Admitted	38	34	32	25	19	12	5
Number referred	33	37	39	46	52	59	66

Table 3.10: Results obtained from twenty simulation runs for model considering age as rule using fixed seed

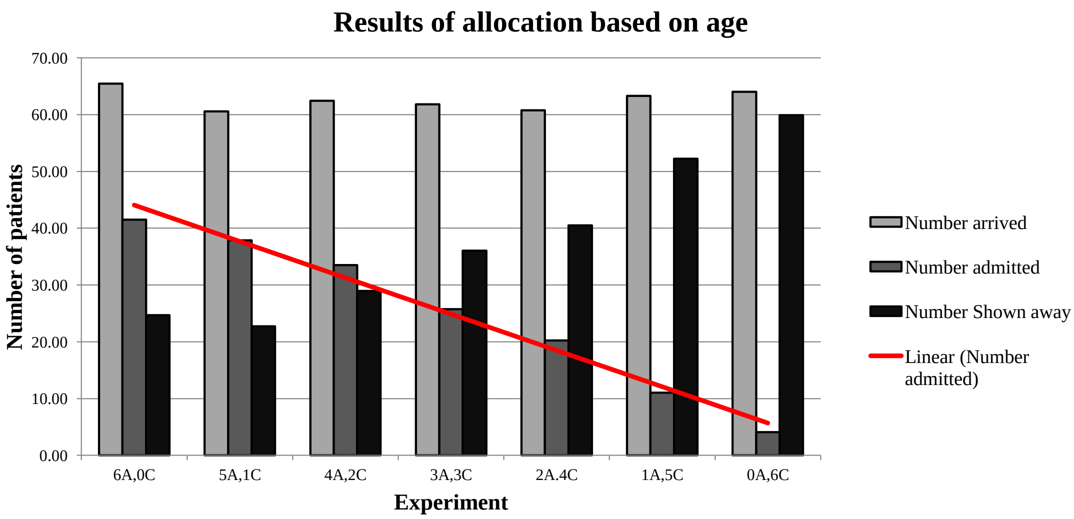

Figure 3.13: Results obtained from all experiments for the model considering age as allocation rule using random seed

Discussion and conclusion

From figure 3.13 and table 3.10 it can be seen that the number of patients assigned to a bed decreases as the number of children's beds increases. The highest amount of allocation occurs when there are no children's beds. This result may seem logical because children are a small amount of the total population and therefore hospitals will have more adult patients.

Having no children's beds is not a practical solution, seeing that hospitals must be able to accommodate children in the paediatric wards. The best result is to have five adult beds and one children's bed.

3.2.5 Allocation according to patient characteristics: Patient criticality

This model will take into consideration the criticality of the patient when allocations are done. A criticality of 1 means that a patient has to be admitted to the hospital within the next 4 to 6 hours. The patient is kept in a stable condition in the Emergency Department until a bed can be found. A criticality of 2 means the patient must be admitted within the next 7 to 24 hours and a criticality of 3 can be admitted after 24 hours.

When the patients arrive at the hospital, they are placed in a queue to wait for an open bed. Patients with a criticality of 1 go to the front of the queue. Patients with a criticality of 2 are placed behind criticality 1 patients in the row, and criticality 3 patients can be allocated only if there are no criticality 1s and 2s waiting for a bed.

In AnyLogic the find bed basic function is moved to the reception agent and a linked list collection is created to simulate a queue. When a patient arrives, they are placed in the queue as described above.

Results

Table 3.11 show the results for the model using fixed seed and table 3.12 shows the average and standard deviations of the results obtained from the model considering patient criticality when allocations of patients have been done. Figure 3.14 indicates all data collected on a histogram for all twenty runs.

Number of patients	Result
Arrived at Hospital	71
Admitted	36
Number referred to another hospital	35

Table 3.11: Results obtained from twenty simulation runs for the model considering patient criticality using fixed seed

Variable	Average	Standard deviation
Number arrived	63.30	7.92
Number admitted	40.50	3.75
Number of deaths	3.75	2.00
Number shown away	22.80	7.13

Table 3.12: Results obtained from twenty simulation runs for model considering patient criticality as allocation rule using random seed

On average, 63.98% of patients are assigned to beds and 36.02% are shown away. Of the 40.50 patients assigned to beds, on average 7.90 have a criticality of 1. Bed occupancy for this rule is 6.75 and the beds are utilised for 405 hours (81%).

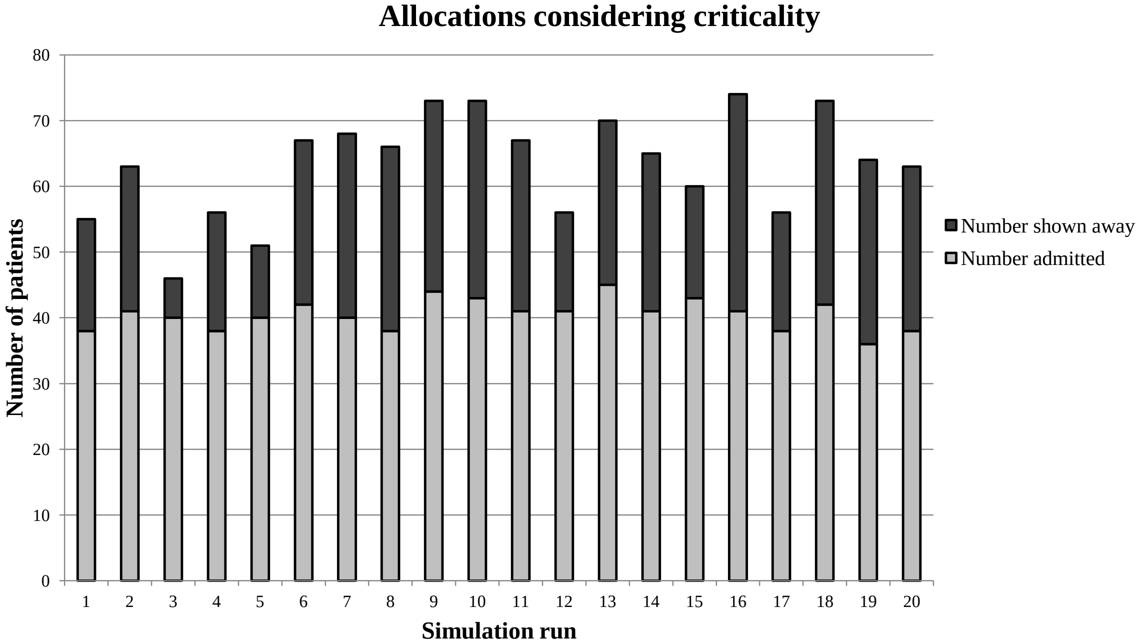

Figure 3.14: Results obtained from twenty simulation runs for model considering patient criticality as allocation rule using random seed

Observations

This rule is used very widely in hospitals. It is imperative that the most critical patients receive priority above all other patients because they require specialist care to ensure that they survive. The negative side of implementing this rule is that a non-critical patient can receive a status of 1 or 2 as a result of favouritism. If this rule is implemented, strong control mechanisms should be put in place to ensure that patients are classified correctly.

3.2.6 Allocation according to patient characteristics: Gender

This model will take into consideration the gender of the patient when allocations are done. It is estimated that 50% of the patients are male and 50% are female. Three of the six beds will be allocated to males and three to females. The basic find bed algorithm is modified in die following manner:

```
Result: Patient assigned to bed
if Patient is male then
    for beds 1 to 3 do
        if bed is unoccupied and patient is not assigned to bed then
            bed is now occupied;
            patient is assigned;
            record which bed is assigned to patient in variable bedId;
            record which patient is assigned to bed in variable patientId;

            send a message to patient state chart to change state;
            send a message to bed state chart to change state from
            unoccupied to occupied;
            break function;
        end
        if All male beds are occupied and patient is still not assigned then
            send a message to patient state chart that there are no beds
            available;
        end
    end
end
if Patient is female then
    for beds 4 to 6 do
        if bed is unoccupied and patient is not assigned to bed then
            bed is now occupied;
            patient is assigned;
            record which bed is assigned to patient in variable bedId;
            record which patient is assigned to bed in variable patientId;

            send a message to patient state chart to change state;
            send a message to bed state chart to change state from
            unoccupied to occupied;
            break function;
        end
        if All female beds are occupied and patient is still not assigned then
            send a message to patient state chart that there are no beds
            available;
        end
    end
end
```

Algorithm 5: Basic find bed function modified to allocate patients according to gender

Results

Table 3.13 shows the results of the model using a fixed seed and table 3.14 shows the average and standard deviations of the results obtained from the model considering gender when allocations of patients are done. Figure 3.15 indicates all data collected on a histogram for all twenty runs.

Number of patients	Result
Arrived at Hospital	71
Admitted	38
Number referred to another hospital	33

Table 3.13: Results obtained from twenty simulation runs for the model considering patient gender using fixed seed

Variable	Average	Standard deviation
Number arrived	63.10	7.1
Number admitted	36.9	3.19
Number of deaths	4.15	2.06
Number referred to another hospital	26.2	5.43

Table 3.14: Results obtained from twenty simulation runs for model considering gender as allocation rule using random seed

On average, 58.5% of patients are assigned to beds and 41.5% are shown away. Of the 36.9 patients assigned to beds, on average 18.70 are male and 18.20 are female. Table 3.15 indicates the average bed occupancy for the 500 hours and the bed utilisation for gender-based allocations.

Patient	No. of beds	Bed occupancy for run	Bed utilisation (hours)	Bed utilisation (%)
Male	3	6.23	373.8	75
Female	3	6.07	364.2	73

Table 3.15: Bed utilisation for gender based allocations using random seed

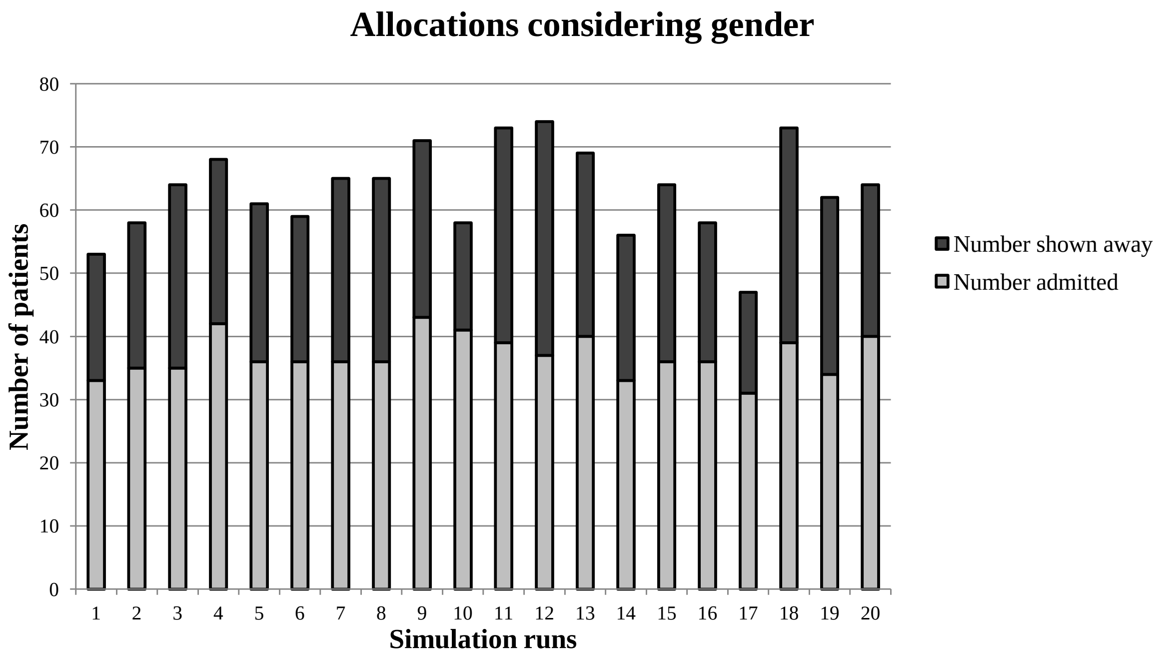

Figure 3.15: Results obtained from twenty simulation runs for model considering gender as allocation rule using random seed

Observations

The results show that the number of male patients is the same as the number of female patients assigned. Consequently, it is unnecessary to experiment with the number of beds assigned to women and men respectively. This rule is regarded as a business rule, seeing as it protects the patients and makes them feel more comfortable during their stay in the hospital.

3.2.7 Allocation of more than one patient to a bed

This model addresses the issue that occurs when all beds are occupied but the patient has to be admitted. More than one patient can then be placed in a single bed. This model considers the capacity of each bed as two. Two patients will only be allocated to a single bed if all others are occupied first. The basic fin bed algorithm has been modified as follows:

```
Result: Patient assigned to bed
for beds 1 to 6 do
    if bed is unoccupied and patient is not assigned to bed then
        bed is now occupied;
        patient is assigned;
        record which bed is assigned to patient in variable bedId;
        record which patient is assigned to bed in variable patientIdFirst;

        send a message to patient state chart to change state;
        send a message to bed state chart to change state from unoccupied
        to occupied;
        break function;
    end
end
for beds 1 to 6 do
    if bed has one patient assigned to it and patient is not assigned to bed
    then
        bed is now occupied by two patients;
        patient is assigned;
        record which bed is assigned to patient in variable bedId;
        record which patient is assigned to bed in variable patientIdSecond;

        send a message to patient state chart to change state;
        send a message to bed state chart to change state from occupied by
        one to occupied by two;
        break function;
    end
    if All beds are occupied by two patients and patient is still not assigned
    then
        send a message to patient state chart that there are no beds
        available;
    end
end
```

Algorithm 6: Basic find bed function modified to allocate more than one patient to the bed

Results

Table 3.16 shows the results obtained from the model using a fixed seed and 3.17 shows the average and standard deviations of the results obtained from the model where more than one patient can be assigned to a bed. Figure 3.16 indicates all data collected on a histogram for all twenty runs.

Number of patients	Result
Arrived at Hospital	71
Admitted	48
Number referred to another hospital	23

Table 3.16: Results obtained from twenty simulation runs for allocations where two patients per bed is allowed using fixed seed

Variable	Average	Standard deviation
Number arrived	63.75	7.55
Number admitted	52.90	5.84
Number of deaths	4.55	2.04
Number referred to another hospital	10.85	9.33

Table 3.17: Results obtained from twenty simulation runs for allocations where two patients per bed is allowed using random seed

On average, 82.98% of patients are assigned to beds and 17.02% are shown away. During the experiment each bed had an average of 8.82 patients. If each patient stays for 2.5 days, the beds are utilised for 529 hours or 105.8% of the time.

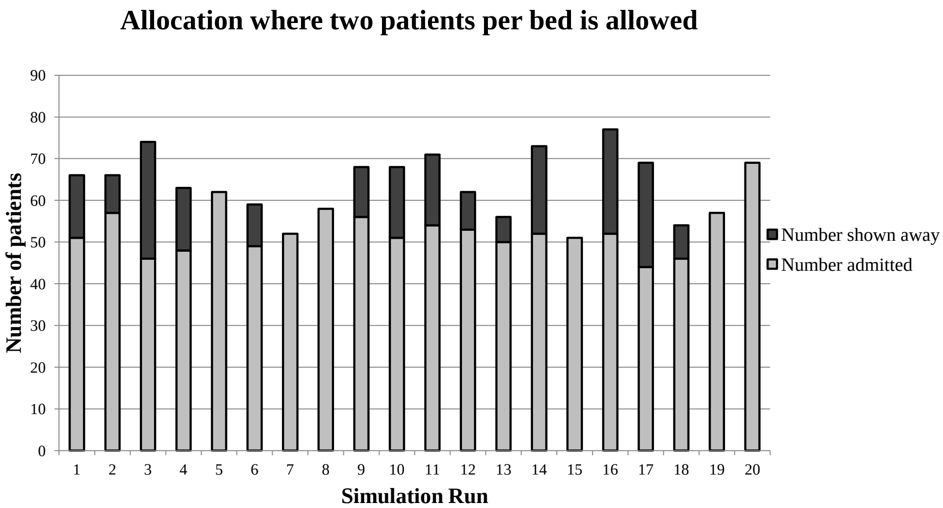

Figure 3.16: Results obtained from twenty simulation runs for model where more than one patient can be allocated to one bed using random seed

Observations

At 105.8% the results show that the bed utilisation is very high. This occurs because more than one patient can be assigned to a bed. This rule will not be feasible in adult wards because adults are too big to be able to comfortably share beds. This occurs mostly in the paediatric and neonatal units.

3.3 Verification and validation

Verification and validation of a simulation model is done throughout the development of the model to ensure that reality is depicted accurately. The results of the model must be accurate to ensure that the correct decisions can be made.

The conceptual models have been verified throughout the process of creation to ensure that the models are error free and that the models match specifications and assumptions. Each conceptual model tests one individual rule to deduce what the impact of the rule will be on the larger system without any added noise and distractions. The same basic model is used for all conceptual models to ensure that the results of the models can be compared because the same assumptions and input parameters are used.

Validation checks the accuracy of the model's result to ensure that the model depicts reality correctly. Assumptions made for the patients' Length of Stay, casualty rates and arrival rates at the hospital are based on data collected from Mamelodi Hospital, as well as from research gathered. Patient flow through the hospital has also been studied through interviews with doctors and nurses, as well as information gathered in the literature review.

All results obtained from the models are based on twenty iterations of each experiment of the respective rule.

3.4 Results

The following results are a comparison of the results obtained from the models using a fixed seed of 2 during the experiments. Table 3.18 shows all the results of the fixed seed models. In each model 71 patients arrived at the hospital. The fixed seed eliminates the effect of randomness on the result.

Rule	Number arrived	Number Admitted	Number Referred to another hospital
Fire come, first served	71	36	35
Reservation of some beds for the exclusive use by elective patients (2 elective, 4 non-elective beds)	71	25	25
Reservation as elective patients are scheduled	71	41	19
Age based rule (5 Adult beds, 1 child bed)	71	34	37
Patient criticality	71	36	35
Gender based rule	71	38	33
More than One	71	48	23

Table 3.18: Results of fixed seed models

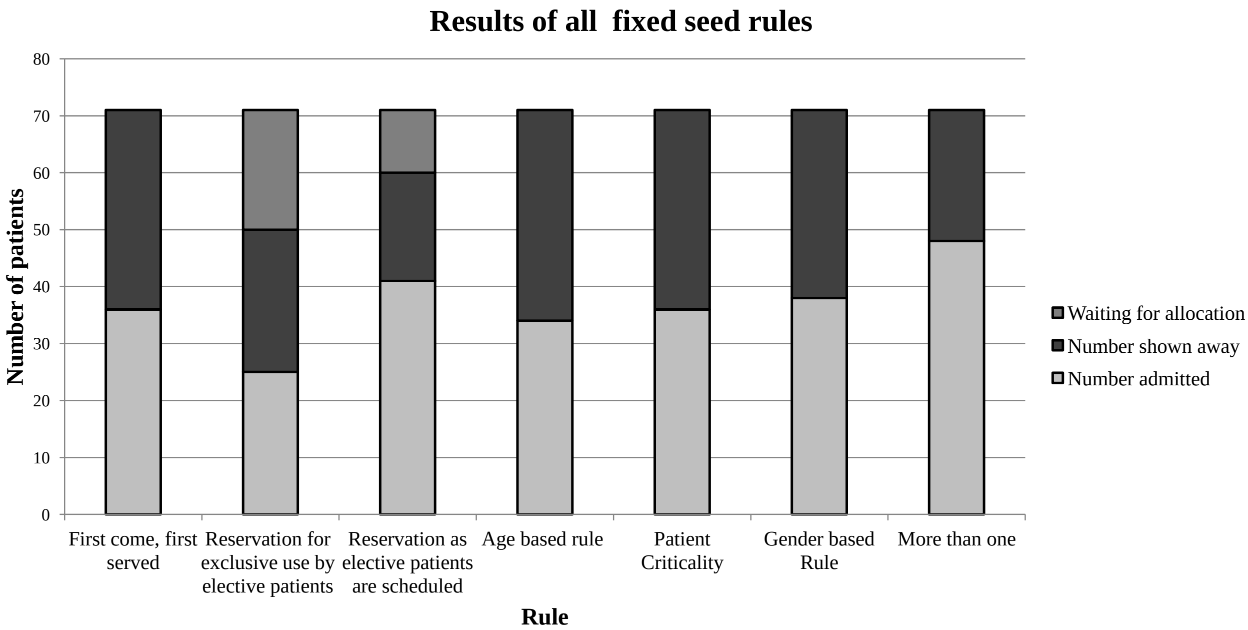

Figure 3.17: Bed utilisation percentage obtained from all results

3.5 Discussion and conclusion

Of the two reservation rules, the reservation of beds according to the patient schedule admits the most patients to beds and refers the least patients to another hospital.Reserving beds according to elective patient schedule allows all beds to be used by all patients.

The first come, first served allocation tends to be a good basis for the comparison of results. Reservation of beds according to a schedule performs better than the first come, first served rule. This is due to the patients not being shown away when a bed is not available for a scheduled patient, but rather that the patient can wait a day before being admitted.

Allocation according to age and gender delivers close results. These rules should, however, not be judged solely on performance. The gender-based rules are usually more applicable to adult patients. Adult patients should be separated for protection as well as to ensure that the patient's stay is comfortable. In the wards, different rooms exist and each room is allocated to a specific gender. This helps in allocating the patients based on gender. According to doctors at Mamelodi Hospital, children are not as sensitive to this rule. But it is imperative that children and adults be separated for the protection of the children.

The rule of allocating patients according to their criticality delivers the same results as the first come, first served rule. This is a very good result and it provides care for the patients that need it the most at the time. This rule will function very well if it is combined with the rule of reserving beds as patients are scheduled. This will allow patients with a criticality of 2 or 3 to wait until a bed becomes available.

Allocating more than one patient to a bed delivers the best results by admitting 48 patients and only referring 23 to another hospital. More patients can stay in the hospital, which increases the bed utilisation. This rule is set up in such a manner that two patients are not assigned to a single bed if there is a bed available. This rule is dangerous to implement because it increases the risk of infection between patients. This rule is mostly implemented in the neonatal wards where twins commonly recover faster and better when they are placed together.

It would be suggested that the above mentioned rule should be applied in the following manner in the case study of Mamelodi Hospital:

- A distinction between patients must be made according to age.
- Adults should be allocated by gender, this rule does not apply to children.

All rules, expect age and gender, must be subordinate to the rule based on patient criticality. This rule will influence the bed utilisation because critical patients tend to have a longer Length of Stay compared to non-critical patients, and elective patients will therefore have to be rescheduled.

Only neonatal patients must be allowed to share beds. Sharing of beds will increase the risk of infection in the hospital above acceptable levels.

In Chapter 4 the above rules are combined into three distinct rule sets to see what the impact of these rules are on the larger system. The rules are tested and the results are compared to evaluate which rule set performs the best. The results are discussed and suggestions are made on the importance of implementing specific rules and a combination of rules.

Chapter 4

Case Study at Mamelodi Hospital

4.1 Introduction to Mamelodi Hospital

Mamelodi Hospital is a district public hospital which is situated in the east of Pretoria. This hospital admits patients from the surrounding areas including Mamelodi, Eersterust, Watloo and Nellmapius. Patients are referred to the hospital from the clinics and can be admitted from the Outpatient Department, Emergency Department or through Inpatient Admissions.

The hospital has 315 beds and 15 wards with different specialities. The hospital admits between 2000 and 3000 patients per month and had an average bed occupancy rate of 66% in the months between March and May of 2014. Some wards had an occupancy of more than 85% with an average Length of Stay of above 7 days.

The basic patient flow is similar to that shown in figure 3.6 in Chapter 3. Minor changes occur for each ward depending on where patients are admitted from and whether they are sent to another ward during their stay in the hospital.

Patients entering the Emergency Department are seen by a casualty officer and are either medical patients or trauma patients. The patient is either referred to a firm (speciality) or treated and sent home. When a firm decides to admit a patient the wards are called to enquire whether there are open beds or to reserve a bed for the patient. If open beds are available the patient is admitted. If no beds are available a bed is reserved and the patient waits to be admitted or the patient is transferred to Steve Biko Academic hospital. Trauma patients currently wait an average of 2 days before being admitted and medical patients wait between 2 to 3 days.

Patients can also be admitted from the Outpatient Department, although this does not occur often (average of 20 patient admitted per month from this department). If a bed is available in the wards the patient is sent to the ward. Otherwise the patient is sent to the Emergency Department to wait for an available bed.

Patients can also be admitted by Inpatient Admissions for scheduled surgeries. Usually when an inpatient is scheduled a bed is reserved in the particular ward for the day that the patient is scheduled to arrive. A patient will only know whether their surgery will take place once they are admitted. The surgery can be rescheduled and the patient must either stay in the hospital until the surgery can take place or the patient is discharged and the surgery is rescheduled.

Some of the common patient flows are shown in the figures below. Each figure depicts a certain ward or collection of wards with common processes.

ALOS: Average Length of Stay (days).
BOR: Bed Occupancy Rate (%).

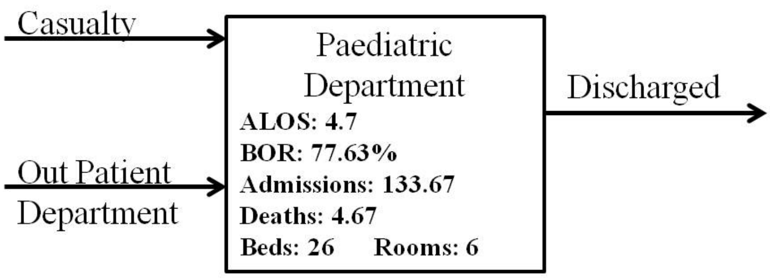

Figure 4.1: Peaditric inflow and outflow

The Paediatrics Department has 26 beds of which 22 are cots, 5 are standard beds and 3 are incubators. The beds are divided into 6 rooms with 4 beds each. One room is an isolation room. Children between the age of 0 to 13 years are admitted to the ward, but babies that are admitted are either not born in the hospital or must be admitted from outside of the hospital.

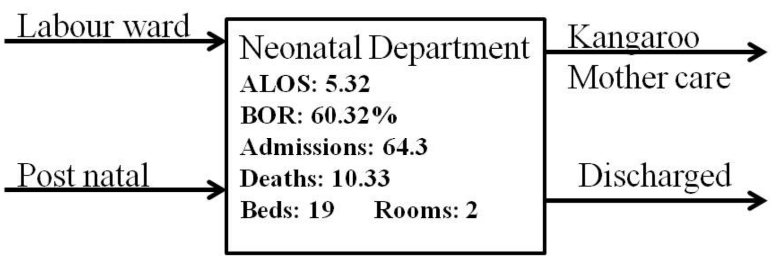

Figure 4.2: Neonatal ICU inflow and outflow

The neonatal ICU falls under the care of the Paediatric Department. This ward is designed for 16 beds, but currently there are 19 incubators in the ward. A lot of shortages occur in this unit because almost all the patients require oxygen and telemetry and only 16 oxygen ports and 16 telemetry machines are available. In this ward more than one patient is placed in a single incubator. The norm is to have two babies per bed and sometimes up to three babies can be placed in a single incubator. Allocations in this ward is done according to the availability of oxygen ports. The patients can be either discharged to home when the baby reaches 1.5 kg or to the Kangaroo Mother Care Unit for further observations.

Expecting mothers enter the Maternity Ward through the Maternity Entrance of the hospital. This unit has 62 beds with an ALOS of 1 day. The mothers are moved from this unit to the Labour Ward as it becomes necessary or to Surgery for a C-section.

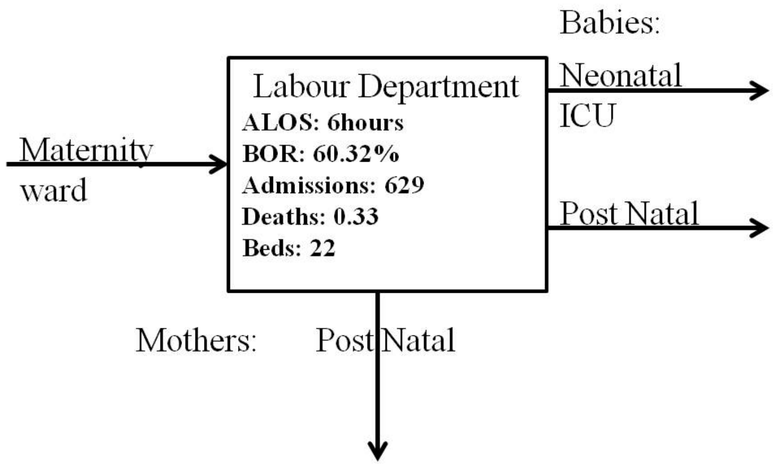

Figure 4.3: Labour ward inflow and outflow

The babies born in the Labour Ward can either be moved with the mother to the Post Natal Ward or to the Neonatal ICU depending on whether complications have arose during birth. On average each mother has only one baby.

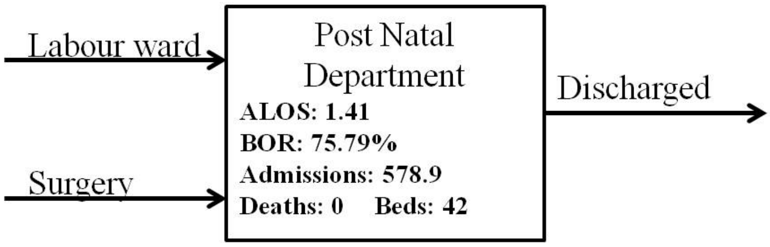

Figure 4.4: Post Natal ward inflow and outflow

In the Postnatal Unit the mothers are allocated to beds and the babies are placed in a crib next to the mother. One of the rooms are occupied by Kangaroo Mother Care patients who stay in the hospital in order to feed their babies either in Neonatal ICU or because the babies are transferred from the Neonatal ICU to the stay with their mothers in this room. Patients are discharged from the hospital.

Mamelodi Hospital has an ICU with 4 activated ICU beds. This unit was created to relieve the pressure from the wards and emergency department when critical patients arrive. The patients that are allocated to this ward have a criticality of 1. Mamelodi hospital does not use the criticality measurement system as described in Chapter 2 and 3. The ALOS is 9.5 days and the ICU treats on average 17 patients per month with a death rate of 1 patient per month.

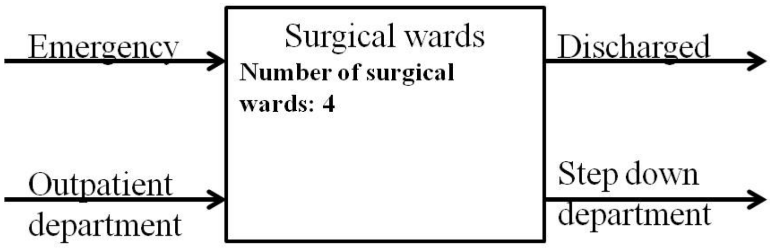

Figure 4.5: Surgical ward inflow and outflow

Mamelodi Hospital has four Surgical Wards as shown in the table 4.1. The Gynaecology Department has only women but the rest of the wards are equally divided between men and women. No sharing of beds are allowed and therefore no shortages of oxygen occur.

Department	Nr of beds	ALOS	BOR	admissions (per month)	deaths (per month)
Gynaecology	32	1.59	42.64	227.33	0.33
Orthopaedics	26	5.61	76.96	104.67	1.00
Surgical 1	32	2.28	47.63	178.33	10.00
Surgical 2	32	6.32	64.74	124.00	26.67

Table 4.1: Surgery wards in Mamelodi Hospital

Mamelodi Hospital also has a Medical Ward where patients who have diseases such as TB, epilepsy and pneumonia are treated. This ward has 42 beds. The beds are divided to 4 per cubicle and 2 side cubicles with to beds each. One of the side cubicles are used as an isolation room. Men and women are allocated to different rooms. Patients are admitted from the Outpatient Department and Emergency Department. If no beds are available patients stay in the Emergency Department until a bed becomes available. The patients are discharged from the hospital or transferred to Step Down ward.

The Step Down Ward is a ward where minimal patient care takes place. This unit has 12 beds, an ALOS of 3.67 days and admits 70 patients per month.

4.2 Three rule sets

The three rule sets that will be tested in this chapter are:

- Rule set 1: First come, first served. The basic find bed function will be used in this model.
- Rule set 2: This rule will consider age, gender, criticality and type of patient (elective, emergency and inpatient). Beds can be reserved for scheduled surgeries. Reservations can be cancelled and the patient must be rescheduled.
- Rule set 3: Will take into consideration all the rules of Rule set 2 but patients will be admitted according to pathology and whether the patient must be isolated. Four types of wards will be considered (Paediatrics, Neonatal ICU, Surgical Ward (2) and Step Down Ward) each with a LoS as determined by the data collected from Mamelodi Hospital. Patients can also be transferred between wards and neonatal patients in the Neonatal ICU can share beds with one other patient.

4.3 Input data and basic model

4.3.1 Input data

Each of the three models will be based on the data received from Mamelodi Hospital on the following four wards, as shown in table 4.2.

Ward	Nr of beds	ALOS (days)	Admissions (per day)	Admissions (%)	Probability of death (%)
Paediatrics	27	4.70	4.46	34.10	3.54
Neonatal	19	5.32	2.14	16.40	15.98
Surgical (2)	32	6.32	4.13	31.60	4.74
Step down	12	3.54	2.30	17.90	0.53

Table 4.2: Data of four wards obtained from Mamelodi Hospital

Each of the wards LoS will be simulated using a Weibull distribution(gamma = ALOS, beta = 2, minimum = 0). Each ward will have the number of beds specified in the above tables. The beds in the Paediatrics Ward and Surgical Ward will be divided into rooms.

These wards where chosen for the case study because these are the areas that experience the most overcrowding or the most rules have to be applied when allocations are made. By including the Step Down Ward the choice between transferring a patient and sending them home is also tested.

4.3.2 Agents

In the case study model six types of agents are used. These agents are main, beds, patients, reception, labour ward, and exit. Each performs certain functions and have their own characteristics and behaviours.

Main

Main, as seen in figure 4.6, is the principle view of the model where the layout of the beds and the movement of patients can be observed.

Figure 4.6: Main view of case study model

The Neonatal ICU is not divided into rooms and patients enter the ward from the labour ward. Neonatal patients can only be admitted if they are born in the hospital or are born in the last hour at one of the clinics. If the baby comes from home he or she must be admitted into the Paediatric Unit.

The Paediatric Unit is divided into six rooms with four beds each and the sixth room with six beds in. Room 5 will be an isolation room. Surgery Ward is divided into nine rooms with room 4, room 8, and room 9 acting as isolation rooms.

The Step Down Ward is not divided into rooms as this does not play a role in allocations within this ward.

All patients, expect neonatal, are admitted through the reception. If no bed is available the patient exits the hospital through the exit.

Beds

Figure 4.7 below shows how the bed agent is set-up for the case study. Each bed is located in a ward and in a specific room if applicable. The gender of the bed and whether the bed is an isolation bed can be set. The allocation variables are activated according to the allocation rule that is applied.

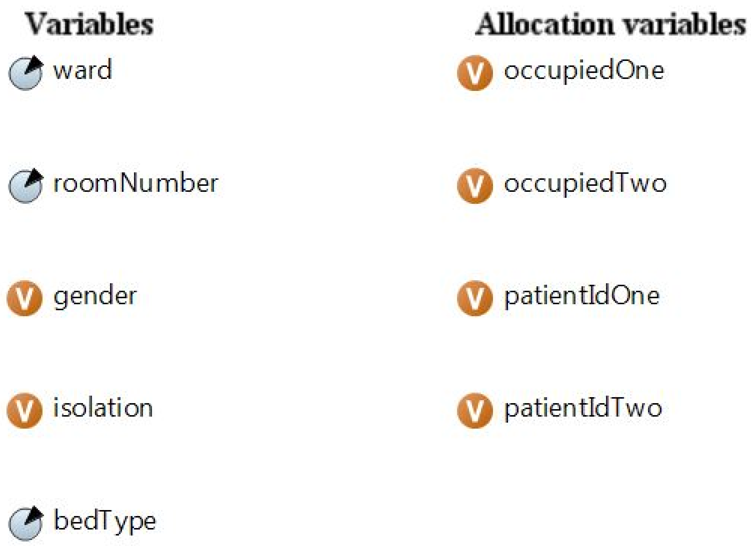

Figure 4.7: Bed agent set-up in case study

As with the bed agents in Chapter 3 the circle above the beds will change colour if the bed is occupied or not. The colour will change to red if the bed is occupied and will turn green if the bed is unoccupied. The colour will change to yellow if the bed is occupied by two patients.

Patients

Each patient has the parameters and variables as shown in figure 4.8. Patient criticality is not currently acknowledged in Mamelodi Hospital. Patient criticality is only divided into two categories: emergency patient (criticality of 1) or non-emergency patient. This causes patient type to be emergency, elective and non-elective patients. The patient must be isolated with a probability of 5% and death probability is dependent on the ward the patient is allocated to.

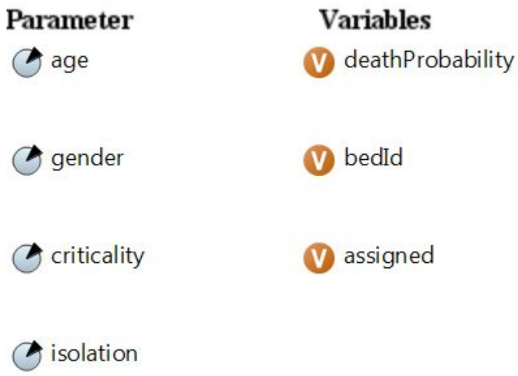

Figure 4.8: Patient agent set-up in case study

Patients arrive at the reception with an exponential inter arrival time with mean of 1.5 hours. The patients queue for reception. When the patient is first in line, reception searches through the available beds to find a bed matching the patients criteria. If there is a bed available the patient is admitted and sent to the bed. Each rule will depict what will happen if there is no bed available.

Reception

The reception is responsible for allocating a patient to a bed when he or she arrives. The patient is placed in a queue in a linked list. Where the patient is placed within the list will depend on the rule set in use. When the patient reaches the front of the queue, reception will search through the beds using a function similar to the basic find bed function used in Chapter 3 to find a bed that will match the patients needs.

4.3.3 The experiments

All experiments will have the following basic structure:

- The model will be run for 2160 time units (hours). This constitutes 3 months of 30 days each.
- To be able to compare results of the rule sets a fixed seed of 2 will be used in each experiment. This will ensure that any difference in results are due to the influence of the rules and not the influence of randomness on the model. As a further experiment each rule will also be run using a random seed value to test how the rule sets will react with fluctuation of arrivals and different Lengths of Stay.

- Each experiment will be run for 25 iterations.
- Number of beds: 88.
- Length of Stay distribution will be based on the data collected from Mamelodi Hospital as shown in table 4.2 for each group.
- Patients will arrive with an inter arrival time exponentially distributed with mean of 0.6667 hours.
- Probability of demise will be based on the group of patient as shown in table 4.2.

4.4 Testing of rules

4.4.1 Rule set 1: First come, First served

This model uses the basic find bed function as described below and which is used in Chapter 3. No other rules such as criticality, pathology, age, or gender are considered in this model. The patient that arrives first is allocated to the first available bed. If no bed is available the patient cannot be admitted.

```
Result: Patient assigned to bed
for beds 1 to 6 do
    integer i = number of beds;
    if bed is unoccupied and patient is not assigned to bed then
        bed is now occupied;
        patient is assigned;
        record which bed is assigned to patient in variable bedId;
        record which patient is assigned to bed in variable patientId;
        send a message to patient state chart to change state;
        send a message to bed state chart to change state from unoccupied
        to occupied;
        break function;
    end
    if All beds are occupied and patient is still not assigned then
        send a message to patient state chart that there are no beds
        available;
    end
end
```

Algorithm 7: Basic find bed function

Results

The results obtained from the experiments using a seed value of two are shown in table 4.3

Number of patients	Result
Arrived at Hospital	1418
Admitted	1418
Deaths	72
Number referred to another hospital	0

Table 4.3: Results obtained from twenty simulation runs for Rule set 1

On average, 100% of patients are assigned to beds and none are shown away. If on average 1418 patients are assigned to 88 beds, it means that each bed has an average of 16.11 patients during the 3 month period.

The results obtained from twenty simulation runs using a random seed value is shown in following table 4.4 and figure 4.9.

Patients	Average number of patients	Standard deviation
Arrived at Hospital	1433.65	30.33
Admitted	1433.65	30.33
Deaths	75.65	7.43
Number referred to another hospital	0	0

Table 4.4: Results obtained from twenty simulation runs for Rule set 1 using a random seed

The results obtained from the experiments using a random seed value also show that a 100% of patients can be admitted at all times. If on average 1433.65 patients are assigned to 88 beds during the 3 month period, each bed accommodates an average of 16.29 patients.

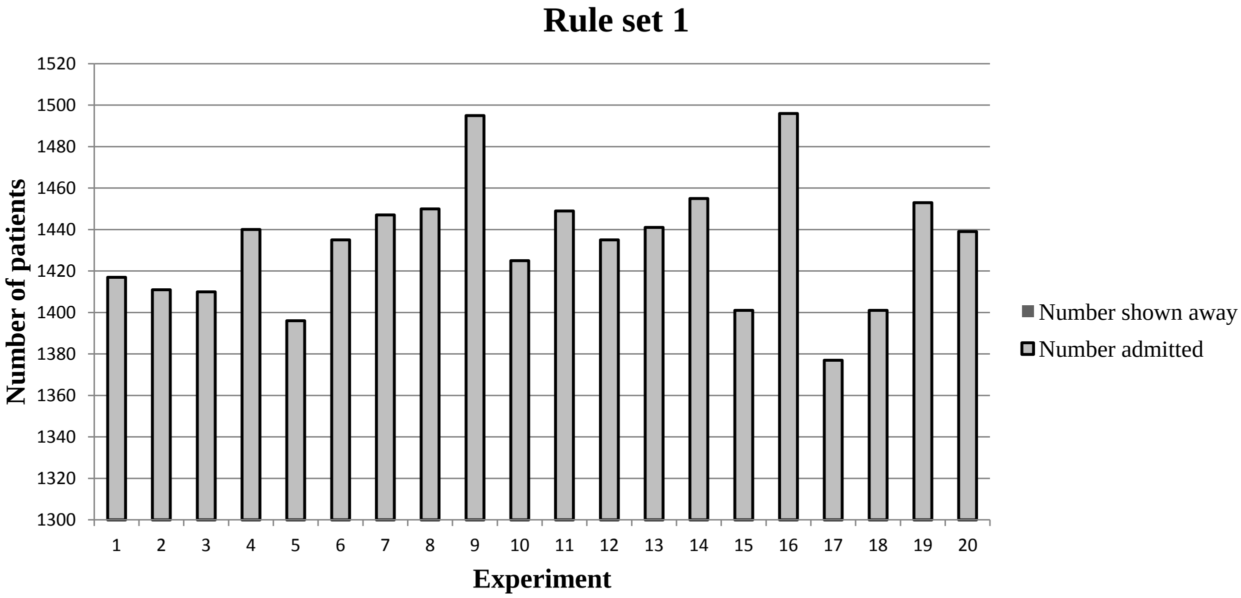

Figure 4.9: Results obtained from twenty simulation runs for Rule set 1 using a random seed

4.4.2 Rule set 2

Rule set 2 model will base allocation of a patient on the age, gender, criticality and type of patient (elective, emergency, and inpatient). The rules are applied by the model using an adapted version of the basic find bed function. The rule applied in this model are explained and listed below:

Number of beds and age:

In Mamelodi Hospital a distinction is made between three age groups: neonatal(new born babies until 30 days), paediatric (30 days old to 13 years), and adults (any person older than 13 years). In this model the Neonatal Unit has 19 beds, Paediatric Unit has 26 beds and the Adult Unit has 44 beds. The number of beds have been determined in accordance to the data collected from Mamelodi Hospital.

Gender

The gender based rule is only applicable to the adult patients. Of the 44 adult beds 22 are female and 22 are male.

Criticality and type of patient

As discussed above in the patient section of Chapter 4 a patient can either be emergency, elective or non-elective. Twenty percent of the patients that are admitted to the hospital are emergency patients. Emergency patients must be admitted into the hospital within the next four hours and will be given preference when a bed becomes available. Twenty-eight percent of the patients are elective patients and are scheduled to be admitted at a certain time, usually two days from the first arrival at the hospital. Beds can be reserved for elective patients for their scheduled arrival. These reservations can be cancelled and rescheduled if an emergency patient requires the bed. Fifty-two percent of patients are non-elective and are admitted as beds become available. In Mamelodi Hospital non-elective patients and some elective patients usually wait in the Casualty Department until a bed becomes available.

The neonatal allocations will only consider emergency patients during admissions because neonatal patients cannot be scheduled for admission before they are born. Adult patients will consider all three types of patients.

Results

Data collected from the experiment using a seed value of two is shown in table 4.5.

Number of patients	Result
Arrived at hospital	1414
Admitted	1403
Deaths	83
Referred to another hospital	11
Number of elective patient rescheduled	7

Table 4.5: Results obtained from twenty simulation runs for Rule set 2

On average, 99% of patients could be admitted to the hospital and 1% are referred to another hospital.

The results obtained from twenty simulation runs using a random seed value is shown in following table 4.6 and figure 4.10.

Patients	Average number of patients	Standard deviation
Arrived at Hospital	1428.85	42.23
Admitted	1407.45	42.41
Deaths	74.65	10.02
Number referred to another hospital	21.40	12.22

Table 4.6: Results obtained from twenty simulation runs for Rule set 2 using a random seed

The results obtained from the experiments using a random seed value show that 98.5% of patients can be admitted and 1.5% are referred to other hospitals. If on average 1407.45 patients are assigned to 88 beds during the 3 month period, each bed accommodates an average of 15.99 patients.

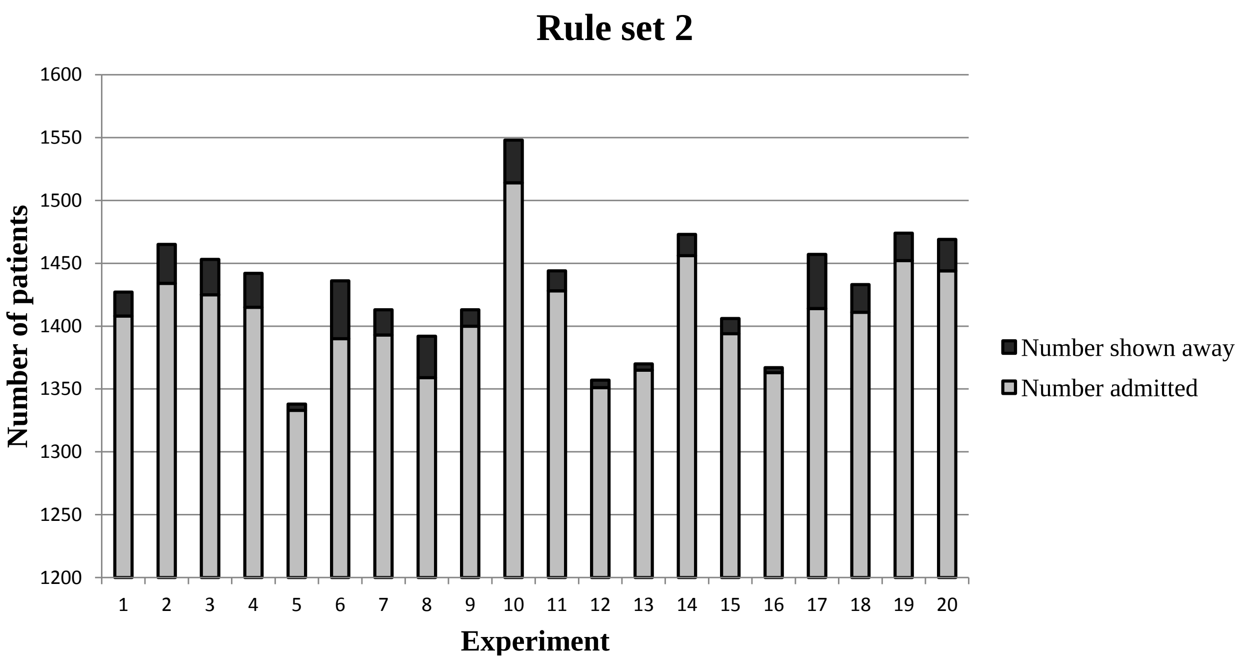

Figure 4.10: Results obtained from twenty simulation runs for Rule set 2 using a random seed

4.4.3 Rule set 3

This rule set will consider all the rules applied in Rule set 2 but will also consider the following additional rules:

Allocation by ward

Patients can be admitted to one of four wards depending on age and pathology. New born babies will be admitted to the Neonatal Ward and children between the ages of 30 days to 13 years are admitted to the Paediatric Ward. The adult patients can either be admitted for the Surgical Ward or the Step Down Ward.

Layout of model

The number of beds in each ward will be based on the data received from Mamelodi Hospital as shown in table 4.2 with a total of 88 beds in the model.

Figure 4.11 show how beds are divided into wards and rooms for this rule set. Room 5 in the Paediatric Ward and room 4, 8, and 9 in the Surgical Ward are isolation rooms. If a patient requires isolation he or she will be allocated to this room. In this model 5% of patients will require isolation in the Surgical and Paediatric Wards. If no isolation patients are occupying the room other patients can be allocated to it.

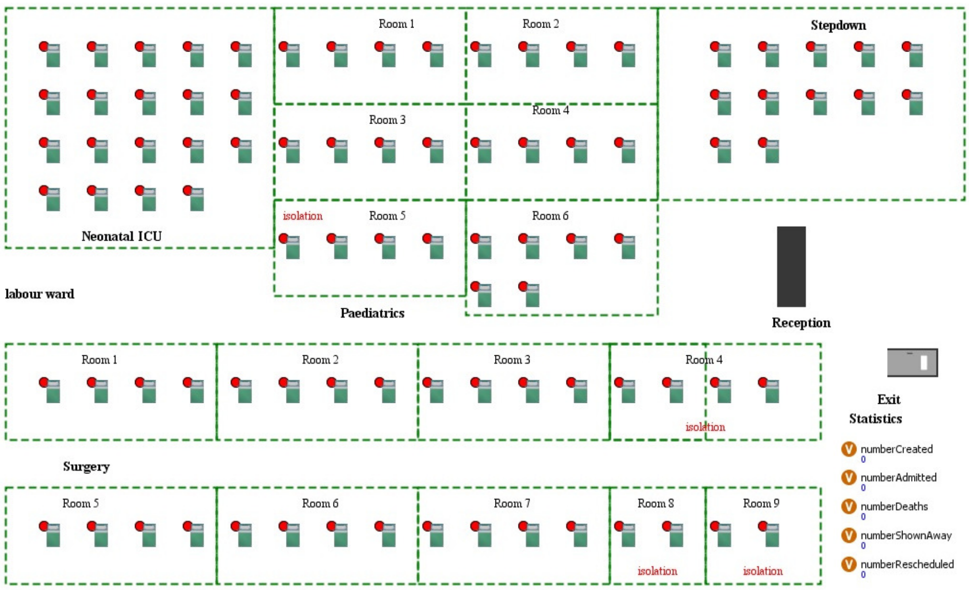

Figure 4.11: Layout of wards in rule set 3

Allocation according to gender will not be considered in the Paediatric and Neonatal Units. In the two adult wards, Surgical (2) and Step Down, patients will be allocated according to gender. Room 1 to 4 in the Surgical Ward are male rooms and rooms 5 to 9 are female rooms. The Step Down Ward has six male and six female beds.

Transfer of patients between wards

Patients can be transferred from the Surgical Department to the Step Down Department if further care is required.

Sharing of beds

Due to the high demand for the neonatal beds and the fact that twin babies recover faster when they are placed in the same bed neonatal patients will be allowed to share beds. This is not an ideal because it increase the hospitals risk for infections. This rule will only be applied if all available beds have been filled.

Results

Data collected from the experiment using a seed value of two is shown in table 4.7.

Number of patients	Result
Arrived at hospital	1383
Admitted	1265
Deaths	70
Referred to another hospital	128
Number of elective patient rescheduled	4
Number of surgical patients transferred to Step Down Ward	10

Table 4.7: Results obtained from twenty simulation runs for Rule set 3

On average, 91.5% of patients could be admitted to the hospital and 8.5% are referred to another hospital.

The results obtained from twenty simulation runs using a random seed value is shown in table 4.8 and figure 4.12.

Patients	Average number of patients	Standard deviation
Arrived at Hospital	1443.6	35.39
Admitted	1327.00	29.39
Deaths	73.40	9.96
Number referred to another hospital	133.10	12.74

Table 4.8: Results obtained from twenty simulation runs for Rule set 3 using a random seed

The results obtained from the experiments using a random seed value show that 91.9% of patients can be admitted and 8.1% are referred to other hospitals. If on average 1327 patients are assigned to 88 beds during the 3 month period, each bed accommodates an average of 15.08 patients.

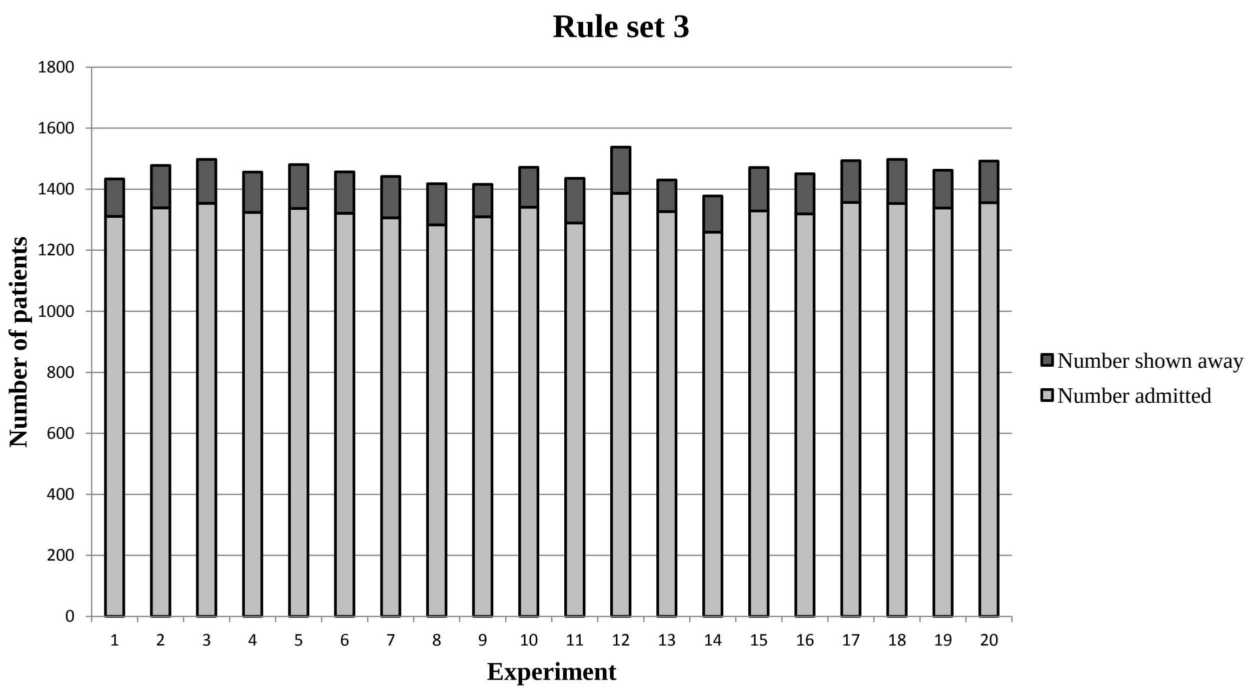

Figure 4.12: Results obtained from twenty simulation runs for Rule set 3 using a random seed

4.5 Verification and validation

Verification and validation of a simulation model is done throughout the development of the models to ensure that they perform as expected. The results of the model must be accurate to ensure that the correct decisions can be made.

The Rule set models have been verified throughout the process of development to ensure that the models are error free and that the rules are applied by the model as expected. Each of the Rule sets are first tested using a constant seed of two to ensure that the results obtained are not a result of the influence of randomness on the models. The Rule sets are tested with a random seed to indicate what the influence of randomness and fluctuation in patient arrivals and Length of Stay will be on the results.

Validation checks the accuracy of the model's result to ensure that the model depicts reality correctly. Assumptions made for the patients' Length of Stay, casualty rates and arrival rates at the hospital are based on data collected from Mamelodi Hospital. Patient flow through the hospital has also been studied through interviews with doctors and nurses, as well as information gathered in the literature review. Not all rules used in the Rule Sets are currently used in Mamelodi Hospital. The goal of this Chapter is to determine what the influence of the rules are and whether better results can be obtained than what the current system currently delivers.

4.6 Results and Discussion

The results of the various Rule sets are very stable. The amount of patient admitted using a constant seed is very close to the number admitted using a random seed as shown in table 4.9.

Rule set	Percentage admitted fixed seed	Percentage shown away fixed seed	Percentage admitted random seed	Percentage shown away fixed seed
Rule set 1	100	0	100	0
Rule set 2	99	1	98.5	1.5
Rule set 3	91.5	8.5	91.9	8.1

Table 4.9: Stability of results obtained from each Rule set

Figure 4.13 shows the results from all the Rule sets. Rule set 1 performs the best by assigning all patients to beds. Rule set 3 performs the worst by only being able to admit a small amount of people.

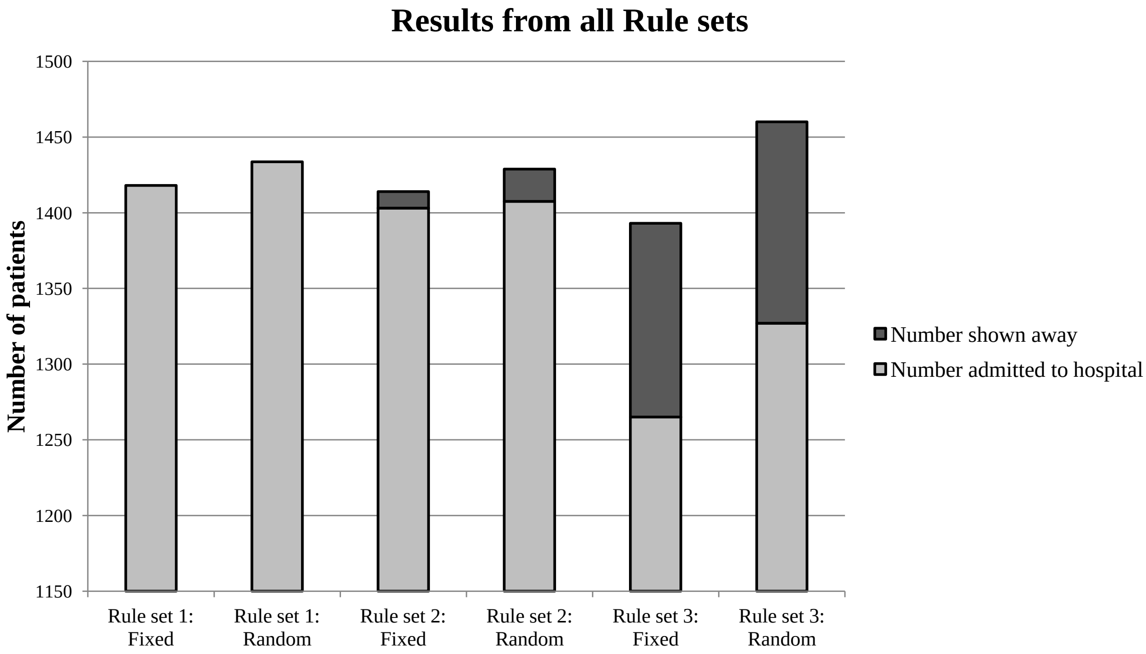

Figure 4.13: Results of all Rule sets

The following table 4.10 compares the results obtained from the fixed seed experiments as well as the random seed experiments with the data collected from Mamelodi Hospital.

Source	Number of admissions	Number of deaths	Bed Occupancy rate %	ALOS	Number shown away
Mamelodi Hospital	1176	76	68.02	4.97	Data not available
Rule set 1: Fixed	1418	72	88.98	5.59	0
Rule set 1: Random	1433.65	75.65	89.97	5.52	0
Rule set 2: Fixed	1403	83	88.04	5.65	7
Rule set 2: Random	1428.85	74.65	88.32	5.63	21.4
Rule set 3: Fixed	1265	70	79.38	6.26	128
Rule set 3: Random	1327	73.4	83.27	5.97	133.1

Table 4.10: Comparison of results with data obtained from Mamelodi Hospital

All Rule sets perform better than the current system. The models are built using data obtained from Mamelodi Hospital with regards to the number of arrivals of patients, LoS in the wards and probability of deaths in order to be able to accurately compare the results.

4.7 Conclusion

The results in table 4.9 indicates that the results are not influenced by randomness to a large extent. The closeness between the results of the fixed seed and random seed in table 4.10 affirms this.

Table 4.10 shows that all the Rule sets perform better than the current system that is used within Mamelodi Hospital. This is partially due to the models tracking which beds are open and which are occupied. Currently, open beds are not always tracked in the units and wards of the hospital. The models can find an open bed faster than the current system.

Figure 4.13 and table 4.10 show that Rule set 1 performs the best of all the sets by admitting all the patients that arrive at the hospital for both the fixed seed and random seed models. Regardless of the performance of the first come, first served model it will not be practical to implement this Rule set in the hospital. This model assumes that a patient can occupy any bed which is not true. Different types of beds exist and an adult can not occupy a crib or incubator. Further it will endanger and unsettle patients if no rules are followed when allocations are made. Children cannot share rooms with adults, unless it is a baby who is placed in the same room as the mother. Female and male patients cannot share rooms. Pathology of patient and infectiousness must be considered in order to lower the hospitals risk of spreading disease and infections.

Rule set 2 performs very well in comparison to Rule set 3. This Rule set 2 is plausible to implement but allocating adults by pathology or needs should still be considered to reduce the risk of infections. It will place unnecessary strain on the doctors because the patients are allocated across the whole hospital and not in one focussed ward. It can also occur that a patient does not obtain the specialised care that is required.

Rule set 3 performs the worst of the three Rule sets, but still outperforms the current system. This model takes into consideration the most important rules and creates focussed units within the hospital. Male and female adult patients are allocated to wards according to their needs. Children and babies are assigned to the correct wards to receive specialised care. This rule set gives preference to emergency patients and beds can be reserved for elective patients. Rooms can be used for isolation purposes to protect other patients from infections or diseases. This model allows patients to be transferred between wards.

Of all the rule sets, Rule set 3 takes into consideration the most important rules. Rule set 3 is therefore the best rule set.

Chapter 5

Conclusion and Recommendations

5.1 Conclusion and recommendation

South African public hospitals have a shortage of hospital beds and struggle to allocate patients to beds and keep track thereof. This contributes to the inefficient utilisation of limited hospital capacity. In literature, this problem is called the *bed management problem with specific focus on bed allocation*.

This report addresses this problem by creating a generic bed management model that will better match patients to beds and therefore maximise the capacity utilisation of a South African Public Hospital.

Different techniques have been studied in literature in an attempt to solve this problem. A comparison between these techniques show that agent based simulation modelling is the best suited for this specific problem.

Agent based simulation allows each patients characteristics and needs to be taken into account and match it to a bed that will fulfil the patients needs. This simulation method lends the required flexibility to the model to be able to test individual as well as combined allocation rules.

In order to match a patient with specific characteristics and needs to a bed which can fulfil these needs, certain bed allocation rules should be adhered to. These allocation rules are studied by using conceptual models. In Chapter 3 test seven individual allocation rules are tested. These rules include allocation according to patient characteristics, reservation of beds for elective patients, and allocating more than one patient to a bed.

The conceptual models found that the decision between allocations rules cannot solely be based on the impact on bed utilisation but that the patient's comfort and protection also plays a critical role. Patients should be allocated to beds according to age and gender. The gender-based rules are usually more applicable to adult patients. In the wards, different rooms exist and each room is allocated to a specific gender. This helps in allocating the patients based on gender. Children are not as sensitive to this rule. But it is imperative that children and adults be separated for the protection of the children. In order to provide the best care for the patients that need it the most all allocation rules should be subordinate to the patient criticality.

Combinations of the rules tested in Chapter 3 were further tested in Chapter 4 in a case study done at Mamelodi Hospital. Three rule sets were created. The results show that all three rules sets perform better than the current system that Mamelodi Hospital uses. This is partially due to the models tracking which beds are open and which are occupied. Currently open beds are not always tracked in the units and wards of the hospital. The models can find an open bed faster than the current system.

Of the three rule sets tested in Chapter 4, Rule set 3 provides the most satisfactory results. This model takes into consideration all of the most important rules and creates focussed units within the hospital. Male and female adult patients are allocated to wards according to their needs and children and babies are also assigned to the correct wards to receive specialised care. This rule set also gives preference to emergency patients and beds can be reserved for elective patients. Rooms can be used for isolation purposes to protect other patients from infections or diseases. This model also allows patients to be transferred between wards.

In conclusion different allocations rules are applicable to different patients. Implementing the right combinations of rules, similar to those used in Rule set three, will improve bed utilisation whilst still adhering to all allocation rules. Better tracking of beds and when beds will become available will also improve bed utilisation and the patients hospital experience.

5.2 Suggestions for future projects

The work done in this project creates the opportunity for the following future projects.

1. Study of how the backlog in the Emergency Department can further be reduced through improvements of the Emergency Department processes and patient flow in conjunction with the findings of this project. Currently Mamelodi Hospital sends all patients waiting to be admitted to the Hospital to the Emergency Department to wait for an open bed. This creates a major back log of patients waiting to be admitted. In some cases patient wait for up to 5 days before a bed becomes available.

2. This project can be expanded by using Diagnosis Related Groups (DRG) to create a data base of treatments that each group commonly require, ALOS per group and cost related to the patients care. This data base can be used to more accurately forecast when beds will become available. This forecast can be used to improve reservations of elective patients and reduce the number of cancelled admissions.

   The data base will also assist in improving the accuracy of the cost of a patient's stay and the resources that the patient uses. This knowledge can be combined with historical data of commonly occurring DRG in the particular Hospital in order to improve the amount of funds as well as the resource that a hospital requires.

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Appendices

Appendix A

Project sponsor form

Identification and Responsibility of Project Sponsors

All Final Year Projects are published by the University of Pretoria on *UPSpace* and thus freely available on the Internet. These publications portray the quality of education at the University and have the potential of exposing sensitive company information. It is important that both students and company representatives or sponsors are aware of such implications.

Key responsibilities of Project Sponsors:

A project sponsor is the key contact person within the company. This person should thus be able to provide the best guidance to the student on the project. The sponsor is also very likely to gain from the success of the project. The project sponsor has the following important responsibilities:

1. Confirm his/her role as project sponsor, duly authorised by the company. Multiple sponsors can be appointed, but this is not advised. The duly completed form will considered as acceptance of sponsor role.
2. Review and approve the Project Proposal, ensuring that it clearly defines the problem to be investigated by the student and that the project aim, scope, deliverables and approach is acceptable from the company's perspective.
3. Review the Final Project Report (delivered during the second semester), ensuring that information is accurate and that the solution addresses the problems and/or design requirements of the defined project.
4. Acknowledges the intended publication of the Project Report on UP Space.
5. Ensures that any sensitive, confidential information or intellectual property of the company is not disclosed in the Final Project Report.

Project Sponsor Details:

Company:	Mamelodi Hospital
Project Description:	Improving Hospital bed utilisation through simulation and optimisation in a South African Public Hospital
Student Name:	Connie Bleeun
Student number:	11026082
Student Signature:	
Sponsor Name:	DR M. THOABALA MOTJOPE.
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