DISCRETE EVENT SIMULATION APPROACH TO BED CAPACITY OPTIMIZATION AT THE MATER HOSPITAL'S EMERGENCY UNIT

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A RESEARCH PROJECT SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENT FOR THE AWARD OF THE DEGREE OF MASTER OF BUSINESS ADMINISTRATION

2016

DECLARATION

This research Project report is my original work and has not been submitted for a degree in any other University or Institution.

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Declaration by Supervisor

This Project report has been submitted for Examination with my approval as the University Supervisor.

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ACKNOWLEDGEMENT

I wish to express my deepest gratitude to my Supervisor Mr. Ernest O. Akelo for his painstaking guidance that saw the success of this research project. It is upon your knowledge and willingness to share it that this work was anchored.

This research work did not get to fruition without the contribution of my Moderator Dr. Magutu P. Obara who even as I moved forward ensured that everything was happening in tandem with set academic guidelines of the University.

The Mater Hospital was very instrumental in the entire research process by allowing the data collection both primary and secondary on the precincts of the hospital. I convey my most high appreciation to the administration that recognized the value of this study on the problem phenomenon and allowed it to proceed with a view to getting it solved.

DEDICATION

To Margret my love, I say thank you for the support and constant impetus that kept me going. Despite the time it took away from my children; Travis and Kate, I really appreciate your understanding.

As for my dear parents Japheth Omung'a and Taphroza Mideva, thank you so much for your sacrifices that saw me get an education. It is only because of you that I am who I am.

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LIST OF ACRONYMS AND ABBREVIATIONS

A.E.D-Accident & Emergency Department

C.I.H.I-Canadian Institute for Health Information

D.E.S- Discrete Event Simulation

E.D- Emergency Department

I.C.U- Intensive Care Unit

K.E.M.R.I-Kenya Medical Research Institute

K.M.T.C- Kenya Medical Training College

M.H-Mater Hospital

L.O.S-Length of Stay

M.O.H-Ministry of Health

N.L.S- National Laboratory Service

P.D.S.A-Plan Do Study Act

U.S.A-United States of America

U.O.N- University of Nairobi

ABSTRACT

Ambulance diversion and long patient waiting time are two undesirable effects of emergency department constricted patient flow and indicate a lack of capacity optimization. On the other hand, capacity optimization for an Emergency Department (ED) is elusive due to the stochastic nature of patient arrivals, length of stay, service rate and discharge patterns. The study's main purpose was to design a Discrete Event Simulation model that would enhance emergency patients' bed capacity optimization and ED throughput management by incorporating the concept of uncertainty in its predictions. The study pursued the following three specific objectives; to establish emergency patient arrival and exit patterns at Mater Hospital, to determine the relationship between emergency patient arrival rate (μ) and the exit rate (ƛ), and to establish the optimum emergency patient bed capacity for Mater Hospital's emergency unit. This was a case study that relied on historical data kept by the hospital to build probability distributions for patient arrivals, waiting times, service rates and exit rates for the Emergency unit. The processed probability distributions formed the input data for the Discrete Event Simulation (DES) model. The DES model was iterated many times (1000) in order to increase the accuracy of the model output information necessary for decision making. The model performance accuracy was also measured through the process of Validation which compared actual data with data from the simulation model using the student t-test procedure at 95 percent confidence level assuming equal variance. The study established that patient arrival and exit patterns at the Mater Hospital were highly random with the arrival rate (μ=3) hovering above the discharge rate (ƛ=2). The mean patient waiting time dropped from approximately 32 minutes currently to 12 minutes after introducing efficiency improvements of an additional two patient beds during simulation.This represents a 60% drop in waiting time. The model was a reasonably accurate representation of emergency patient flow at the Hospital due to the higher calculated p-value (p=0.97, d.f=238) than the 0.05 critical value implying the lack of a significant statistical difference between the actual data and the corresponding simulated data. Employing Discrete Event Simulation in an Emergency Department of a Hospital can solve capacity management and flow problems significantly.

CHAPTER ONE

INTRODUCTION

1.1 Background

There is evidence in operations management and health service literature of a direct link between capacity management and service quality. Being patient-oriented the healthcare industry needs constant interaction with those they serve. Their use of nursing care, facility and equipment means that hospital services are highly driven by capacity. Good management of capacity resources therefore determines the cost and quality of service and eventually the customer satisfaction. Hospitals that offer high quality healthcare services have discovered a better way of managing their capacity resources and facilities (Li & Benton, 2003). Overcrowded emergency departments afflict patients, policy makers and staff in hospitals worldwide yet patient demands on these services has been increasing despite the shrinking budgets. As a result, administrators are seeking practical and optimum solutions on resources management to alleviate the challenges presented by managing healthcare organizations, (Morgan, Andrew, Ron & Jean-Éric, 2013).

The study and analysis of healthcare systems has become necessary in order to realize improvement in service quality. The healthcare industry like any other industry has to meet its goals like optimizing the use of facilities and manpower, high service quality, low cost and overall performance in the context of limited resources of finances and time, (Bhattacharjee & Ray, 2014). Intensive care units which are an important component in hospitals are responsible for the care of critically ill patients in need of immediate attention such as emergency cases and surgery recovery. Due to these critical patient conditions, requests for the emergency beds must be processed and allocated with no waiting time (Zhu, Hoon, &Liang, 2012). Any amount of delay could pose a significant threat to the patients' safety and often times ends in fatality.

According to Zhu et al. (2012), lack of the emergency beds may cause service level deteriorations including surgery cancellations and ambulance diversions. Excessive patient beds on the other hand will unnecessarily take up hospital budget, space and other valuable resources. Thus a balance between patient bed capacity, service level and cost effectiveness is paramount in any hospital. In addition to the complexity of emergency services in a hospital, service demand is also growing due to the increasing number of road accidents, incidences of terror attacks and other natural disasters like fire. All these factors and the stochastic nature of emergency cases add considerable variability to the service demand and thus a more challenging task of capacity management, (Zhu et al. 2012).

1.1.1 Discrete Event Simulation

Simulation is the process of trying to create a replica of a real system's appearance, features and operation (Render Stair and Hanna 2006). Actually, Simulation involves modeling processes. Render et al. (2006) further clarifies that simulation makes it possible to evaluate a system's response to changes that may not be possible to study in a real case scenario. Simulation models also help to foresee the change in working of a real system when changes are made to its constituent parts.

Albrecht and Az (2010) define Discrete Event Simulation as a mathematical and logical representation of a real system whose changes occur at certain time intervals during simulation like the case of patients waiting for treatment in a hospital or customers waiting to be served in a bank. Simulation has been argued to be the most realistic approach to study the impact of different decisions in complex systems that exhibit stochastic behavior like arrivals, service rates, demand and so on. Simulation is a non intrusive, cheap and convenient way to evaluate diverse situations without necessarily introducing any changes in the physical system, which would otherwise be costly (Romero, Dellaert, Van der Geer, Frunt, Jansen-Vullers, & Krekels, 2013).

Hamrock, Parks, Scheulen and Bradbury, (2013) describe Discrete Event Simulation as a type of computer simulation that imitates the Operation of a real-world system. Simulation in healthcare commonly deals with bed capacity management, manpower scheduling, improving patient flow, patient admission management, scheduling of procedures and using auxiliary resources like pharmacies and labs. Simulation modeling has been shown to be effective in many healthcare settings. Some models aim to improve patient flow, reduce wait times, maximize staff utilization, and accomplish other gains in efficiency. The Standard inputs to the DES model of this study included emergency patients flowing through the Emergency department, resources like hospital beds, patient arrival rates, time taken to serve the patients and the queue discipline (Hamrock et al., 2013).

1.1.2 Hospital Bed Capacity Optimization

Yi, George, Paul and Lin (2010) define a hospital's Capacity as the total number of patients a hospital is able to treat within tolerable amount of waiting time. Yi et al. (2010) further explains a hospital's emergency capacity as the emergency number of patients the hospital is able to admit and treat efficiently within a certain time period without life-threatening waiting times. Capacity planning are the strategic decisions which determine the capacity of the hospital. This study adopted number of inpatient beds which is the most fundamental measure of a hospital's capacity (Green, 2002).

There are other different measures that determine a hospital's capacity although the most important is the number of inpatient beds (Green, 2005). The other major components of capacity are; personnel particularly nurses who act as the chief caregivers as well as managers of the clinical units in a hospital. Operating rooms also form a significant component of capacity whereby their efficient utilization is central to the smooth functioning of the hospital as a whole and not just the emergency unit. Major diagnostic equipment, such as magnetic resonance imaging devices (MRIs), is also considered another important category of capacity. These machines are extremely expensive, so operating policies are usually oriented towards achieving 100% utilization, (Green, 2005). This is where the concept of optimization is ideal to solve the challenge of optimal bed allocation.

Schmidt, Geisler and Spreckelsen (2013) define hospital bed capacity optimization as the kind of allocation of beds in a hospital that involves short admission waiting periods for the patients and which also aims for a low rate of canceled admissions, yet with a high occupancy rate. Optimal bed allocation on the other hand is constrained by the patients' actual length of stay which in most cases is uncertain (Schmidt et al., 2013).

1.1.3 The Mater Hospital Emergency Unit

The Mater Hospital opened its doors for the first time to its patients in the Year 1962 by the Sisters of Mercy, a Catholic Order of Nuns from Ireland. The Hospital was registered as a Trustee after Kenya gained its independence from the colonial rule. Mater started as a general hospital with 60 beds mainly for the poor native Kenyans. About 12 acres of land were allocated by the colonial government in the former swampy, mosquito-infested area that is currently the Industrial. The 60 bed maternity ward was added in 1970 with, postnatal, antenatal and immunization clinics aimed at upgrading maternity healthcare quality.

In recognition of their contribution to training midwives, Mater was chartered as a school of Midwifery in 1972. In 1975, a consultant's block of 6 offices was opened enabling specialized consultants to practice on site and deliver significantly better medical services to the patients. In 1986, the hospital opened its own pharmacy, physiotherapy and laboratory services and, in 1990, opened its counseling centre for inpatients, outpatients and staff who needed advice and guidance on family planning, HIV, and other concerns of a psychological and/or physical nature. A larger and more efficient Accident and Emergency Department was opened in 1995 together with a Cardiac Unit and an Intensive Care Unit. The modern, Accident & Emergency Unit is now reputed to be among the leading in East Africa. The emergency unit prides itself in high experience for the treatment of tropical diseases, gunshots, industrial accidents, disaster management, poisons and many other cases of emergency.

1.2 Research Problem

Hospital administration is usually faced with optimization problems such as prediction of required size of bed capacity, equipment or staff capacities or determination of the optimum inventory policy. These kinds of problems depend on the number of patients in the unit. The random arrival rate and random length of stay (LOS) of patients make the number of patients in the unit behave as a stochastic process. This stochastic behaviour makes prediction of the optimal size of the required bed capacity more intricate. The most recent predictions of the required bed capacity have tended to use stochastic approaches (Kokangul, 2008).

Ridge, Jones, Nielsen and Shahani (1998) undertook seven patient flow studies at a Los Angeles County Hospital's Emergency Department in the United States of America for a period of five years. These researchers estimated several factors in the emergency treatment process including triage, registration, placement in the emergency bed, preliminary medical assessment, disposition order and the final patient discharge. In their conclusion, they argued that the lack of inpatient beds was responsible for substantial patient delays at the hospital. In Kenya for example the Auditor general's report of 2012 found that one of the reasons for the extraordinarily long patient waiting times at Kenyatta Hospital is that key operational systems of the Hospital are not optimally used as they should be. Others were excessive demand and insufficient resources both facilities and personnel. In an extreme case of inefficiency for instance, an accident victim who was bleeding in the brain and for whom every second was crucial for his survival spent 18 hours in a waiting ambulance in Kenyatta hospital's compound because the Hospital claimed it did not have an emergency bed available since the 21 beds were all occupied and this led to the eventual demise of the patient (Kilonzo, 2015).

Hospital emergency wards suffer overcrowding as a result of excessive waiting time and low service rates. This overcrowding in turn cause patient bed shortages and the eventual admission delays or worse still admission cancellations. In desperate cases patients maybe admitted into wards unsuited to their pathologies hence risking inappropriate service quality Bachouch, Guinet and Hajri-Gabouj (2012). In the context of the need to strike a balance between service quality and the limited resources available, this study took a predictive approach to create case scenarios well in advance so that the right capacity for critically ill patients is availed at the optimum level.

Simulation was the ideal approach to solve this problem since it is able to deal with complex analyses like situations in hospital waiting times that cannot be presented by standard mathematical formulae. Standard mathematical formulae are unsuitable owing to the stochastic nature of the problem, the complexity involved in formulating the problem and the inherent complexity of interactions in the problem (Julie, Malcolm, Claire and Terry 2011). Assumptions for deriving queuing formulae are not always valid for many healthcare processes. Several patients for instance from the same terrorist attack may be brought to the Emergency Department at the same time and or the probability of new patient arrivals could be dependent on the previous arrivals when Emergency Department is close to its capacity (Julie et al., 2011). As is the case often times, most emergency departments handle unpredictable demand and simulation has always been the prime analytical tool (Bowers, 2013).

In this study DES was intended to provide a powerful data-driven decision making tool for the problem of hospital bed capacity optimization in the emergency department. Through replicating the behavior of emergency patient arrivals and exit at the hospital, DES helped to predict future patient numbers and therefore allowed advance planning of the optimum bed capacity that satisfies service delivery in terms of reduced patient rejection rates. DES can help to avoid wrong decisions such as adding bed capacity in the ED yet what is available has not been fully utilized which can lead to idle capacity (Hamrock et al., 2013).

By using Discrete Event Simulation approach to match the stochastic patient arrival rate to the ICU bed capacity; this study undertook to minimize the problem of patient waiting time as a solution to the perennial problem of inefficiency and poor quality of service at Mater Hospital’s emergency unit. The specific research questions addressed were as follows; what is the emergency patient arrival and exit pattern at Mater Hospital? What is the comparison between emergency patients' arrival rate (µ) and the exit rate (ƛ) at the Mater Hospital's Emergency unit? What is the optimum bed capacity for Mater Hospital's emergency unit?

1.3 Research Objectives

The main purpose of this research was to develop a Discrete Event Simulation (DES) model to aid in bed capacity optimization decisions at the Mater Hospital's Emergency unit and elsewhere in the healthcare industry.

1.3.1 Specific objectives

i. To establish emergency patient arrival and exit patterns at Mater Hospital.
ii. To determine the relationship between emergency patients arrival rate (µ) and the exit rate (ƛ) at Mater Hospital's Emergency unit.
iii. To determine the optimum hospital bed capacity for Mater Hospital's emergency unit.

1.4 Value of the Study

The value of this study is threefold. This research was designed to solve a practical problem that exists in the healthcare industry which is planning for bed capacity in emergency departments of hospitals with a specific focus on Mater Hospital. The simulation model used in studying the hospital's emergency department is an important tool that can form the basis of informed decision making for the management and professionals in the healthcare industry. The world of academia also stands to benefit immensely by virtue of this study creating new knowledge for reference by other scholars in teaching and also as a basis for research by those who will be interested in pursuing the subject further.

Policy makers will find the results and recommendations of this research valuable as a guideline for enforcing quality and efficiency in the healthcare industry since the study laid bare what is possible as to how hospitals can be managed better using scientific approaches as opposed to the traditional approach to management.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

The majority of health care managers apply relatively simple approaches to the complex and uncertain problem of bed capacity optimization. An example is the use of target occupancy level coupled with average length of stay of patients to predict bed capacity required for a hospital or emergency units in hospitals. The failure to adequately consider the uncertainties associated with patient arrivals and time needed to treat them by using such simple approaches has resulted in bed capacity constraints where a huge proportion of patients in need of treatment are turned away (Green and Nguyen, 2001). This chapter looks at various past studies in the area of Simulation of queuing lines in hospitals and the characteristics associated with the phenomenon of bed capacity planning and optimization.

2.2 Queuing Theory

The queuing theory was established in the initial stages in the early 1900 by A.K Erlang. His work on the queuing theory began as a study of the clogging and long waiting times that were inflicting telephone calls. The theory grew more sophisticated and gained widespread application in a variety of waiting line situations. The characteristics that describe a queuing system are as follows: probability of an empty system, waiting line average size, total average units in the whole system, the average waiting time, the average service time of the whole system and the probability that a new arrival has to wait for service (Anderson et al. 2001). The above characteristics of a queuing model are given a Kendal notation which denotes a general queuing system by (a/b/c): d/e, where;

a= probability distribution of the inter-arrival time.

b = probability distribution of the service time.

c = number of servers in the system,

d = maximum number of customers allowed in the system,

e = queue discipline.

Thus M/M/l: (oo/FIFO) describes a simplified queuing system assuming inter-arrival times and service times are governed by exponential type of distribution. The second assumption is that there is only one server and that the queue discipline is first in first out. The number of units in need of service from the system infinite, (Tulsian and Vishal, 2002).

2.2.1 Waiting Lines (Queuing)

Roberta and Bernard (2000) define Queuing as waiting to be served. They further explain that waiting lines form when the arrival rate is faster than the service rate. The stochastic nature of arrivals and service time makes it difficult to plan capacity which in turn leads to waiting lines. Waiting to be served is undesirable. Scholars have developed Models that aim to help managers understand and make better decisions concerning the operation of waiting lines (Roberta & Bernard (2000). Waiting time is a critical measure of efficiency and effectiveness in hospitals (Clague, Reed, Barlow, Rada, Clarke & Edwards, 1997).

In a study on patient delays in Dublin, inappropriate staffing levels of nurses and physicians, confusing medical staff role definitions, long distances to adjacent facilities and inappropriate Accident and Emergency layout structures were identified as the primary causes for patient delays, (Regan, 2000). Even though long waiting time is a problem in Kenyan hospitals, the phenomenon is global. In their hospital survey for example, Blendon, Schoen, DesRoches, Osborn, Zapert, & Raleigh (2004) found that Canada, Britain and the USA reported average waiting times of about two hours or more. In Hong Kong’s public hospitals, Aharonson, Paul and Hedley (1996) found that patients spent a huge proportion (82%) of their visit time in the waiting room.

2.2.2 Arrival Rate

The speed at which customers arrive at the service facility in a given period of time is referred to as arrival rate. The arrival rate can be estimated from historical data of the system that has been in operation, (Heckerling, 1984). When patients arrive at a rate that exceeds the service rate, a queue will form. Arrivals may come in singly or in batches;

they may come in consistently spaced or in a completely random manner (Heckerling, 1984). When patients arrive at the hospital, they are put in different queues based on need such that those with more critical requirements can then be managed separately and reduce the risk of delaying other patients unnecessarily which can impact service experience negatively. In this case, Mater Hospital has a special queue for ICU bound patients only which is the emergency department.

2.2.3 Service rate

The arrivals in queuing theory are measured in terms of rate of arrival while service in terms of the amount of time. The service times are assumed to be independent and distributed in an identical manner in addition to being independent between unit arrivals. Service time maybe deterministic or exponentially distributed. It may also dependent on the length of the waiting line. The distribution commonly assumed for service times is the negative exponential distribution although empirical research has proved the assumption to be invalid just like the assumption of Poisson distribution for arrivals. The service mechanism defines how units in the system are processed for example the treatment of patients in a hospital. The service mechanism is composed of servers' number and the service time, both of which can randomly vary over time, (Heckerling, 1984).

2.3 Discrete Event Simulation of MH's Emergency Unit

The random number of patient arrivals and random length of stays make the number of patients in a hospital unit behave as a stochastic process. This makes the determination of the optimum size of the bed capacity more difficult (Kokangul, 2008). The number of arrivals per day, service level and occupancy level directly affect the optimal bed capacity (Kokangul, 2008). The determination of the best principle for setting the optimum size of bed capacity is an interesting exercise and is useful in practice. The number of patients in the emergency unit display randomness which creates difficulty in predicting hospital bed capacity demand. This can be likened to the random arrival of Accident and Emergency patients at the ED department of MH whereby the next patient arrival is independent of all previous patient arrivals, (Kokangul, 2008).

2.4 Empirical Review

The study of ED performance in hospitals has been an undertaking of many scholars aiming to improve on efficiency. To achieve efficiency of emergency departments, it is critical to aim at reduction of patient service time. Quite a number of past studies have tried to investigate time intervals in the ED patient treatment process. Researchers from Ontario in Canada used primary hospital data to calculate a median length of patient stay in Canadian hospitals in the city of Ontario and they found it to be 128 minutes. About (10%) of the patients studied had spent the longest time of up to six hours in the ED, (Canadian Institute for Health Information, 2005).

Arkun et al. (2010) undertook a three-month period study that employed observational methodology on adult patients that were on the queue in an Emergency Department at a specified time of every day covered by the study. In their conclusion, they were convinced the factors that greatly contributed to sluggish patient flow were day of the week and ED's bed occupancy rate. Indeed, occupied beds meant that no more patients could be admitted into the emergency unit for treatment.

Although many scholars have continued to investigate factors contributing to ED congestion, a lot of scholarly disagreements have emerged. Some think that the lack of patient beds add to the problem of ED congestion. In fact in a survey of Canadian Emergency Department directors, the vast majority (85%) indicated that lack of patient beds greatly caused ED overcrowding (Canadian Agency for Drugs and Technologies in Health, 2006). Several studies emphasize ED patient flow problems as being the result of patients who overstay in the hospital wards, (Espinosa et al. 2002; Schull et al. 2003; Asplin et al. 2003; Schull, 2005).

A number of studies have come up with possible solutions to curb this problem of ED overcrowding. Ng (2006) for example proposes certain improvements like clear labeling of supplies and stationing equipment in the most easily accessible locations to reduce time wastage trying to locate them, creating standardized layouts and the use of treat and release area nurses to quickly move the patients immediately a bed is available. Jacobsen and Resar (2006) propose that an inpatient's discharge is arranged earlier in the whole process to help reduce the time taken in admitting an ED patient to a hospital bed. Haraden and Resar (2006) on the other hand advocate for inpatient bed discharge slots such that less time is spend waiting in the ED for a bed.

Blake et al. (1996) successfully demonstrated with a computer simulation model that increasing physician working hours during specific periods reduced patient wait times in the ED. In the same way Duguay and Chetouane (2007) used discrete event simulation analysis to show that patient waiting time reduced by just adding one physician and one nurse in the ED. In an effort to reduce patient length-of-stay, Dickson et al. (2009) demonstrated how ordering laboratory tests and X-rays earlier in a patient's treatment process reduced service time significantly. Macias and Patel (2009) approached the problem using PDSA (Plan Do Study Act) cycles to enhance service quality for asthma patients and resulted in significant improvements.

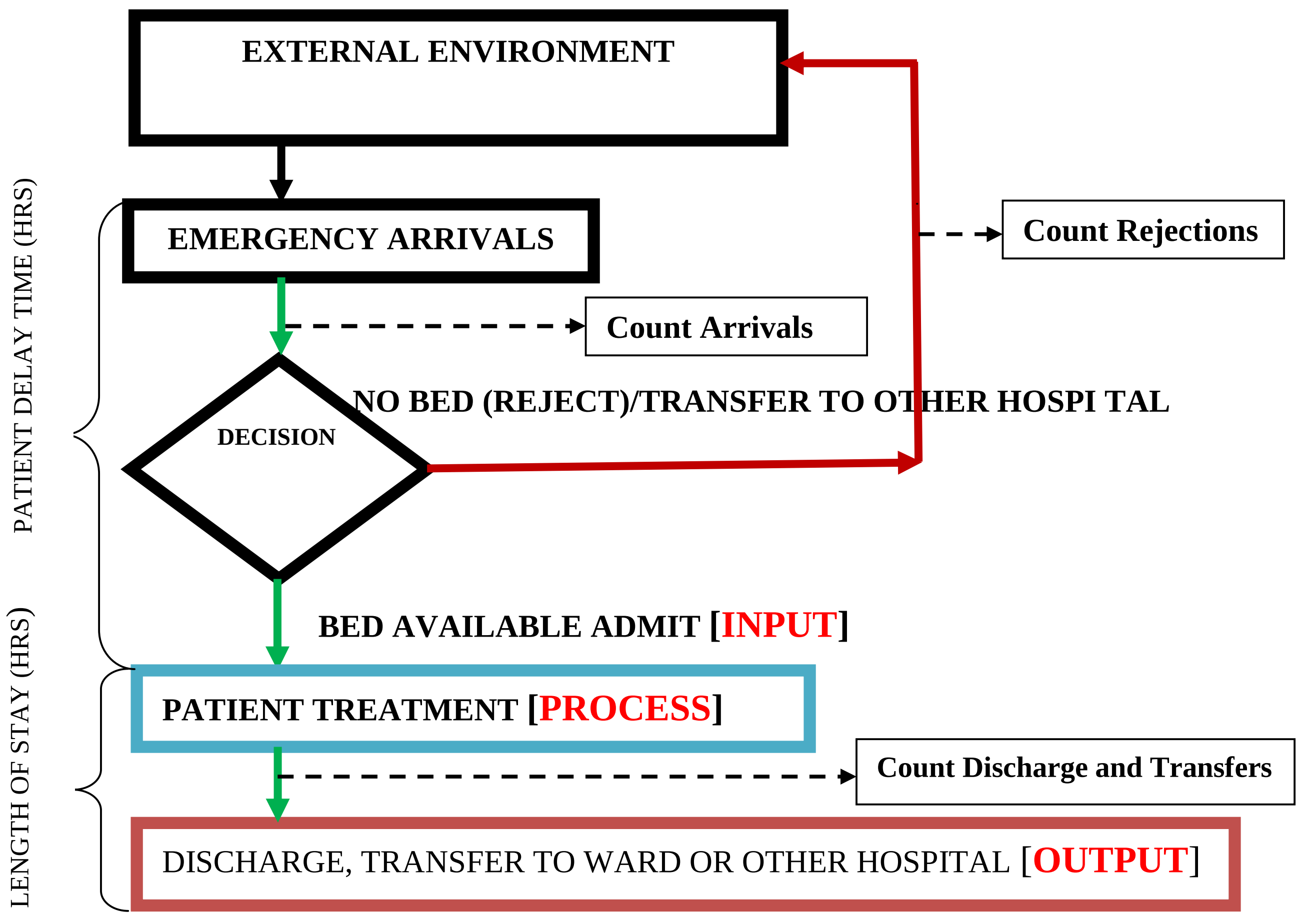
Although adding capacity may to certain extend alleviate ED flow problems Haraden and Resar (2004) argue that this may not always be the case. Adding ED beds without addressing underlying ED crowding is comparable to enlarging the already big end of a funnel. Variation in capacity levels (Silvester et al., 2004) and length of stay Gallivan, Utley, Treasure and Valencia (2002) are the two key factors that must be addressed to prevent constricted patient flow in the hospitals' EDs. Eitel, Rudkin, Malvehy, Killeen and Pines (2010) propose a detailed approach to addressing ED flow problems through managing service demand, process mapping, lean thinking and simulation.

2.5 Summary of Literature review

Reviewed literature on emergency department overcrowding and patient waiting time alludes to a problem that inflicts hospitals not just in Kenya but those in developed countries too. Long waiting time is highly undesirable and the source of dissatisfaction if not tragic for patients in critical conditions who need care without delay. In an attempt to solve the problem of waiting time, several studies consider computerized simulation as a very versatile analytical tool for queue management and capacity planning in hospitals.

Evidence on the use of Computer simulation in Kenyan hospitals is rare and this study aims to fill that gap and make hospital managers alive to the fact that simulations can be very handy in managing the challenging operations of a hospital.

2.6 The Hospital Conceptual Framework

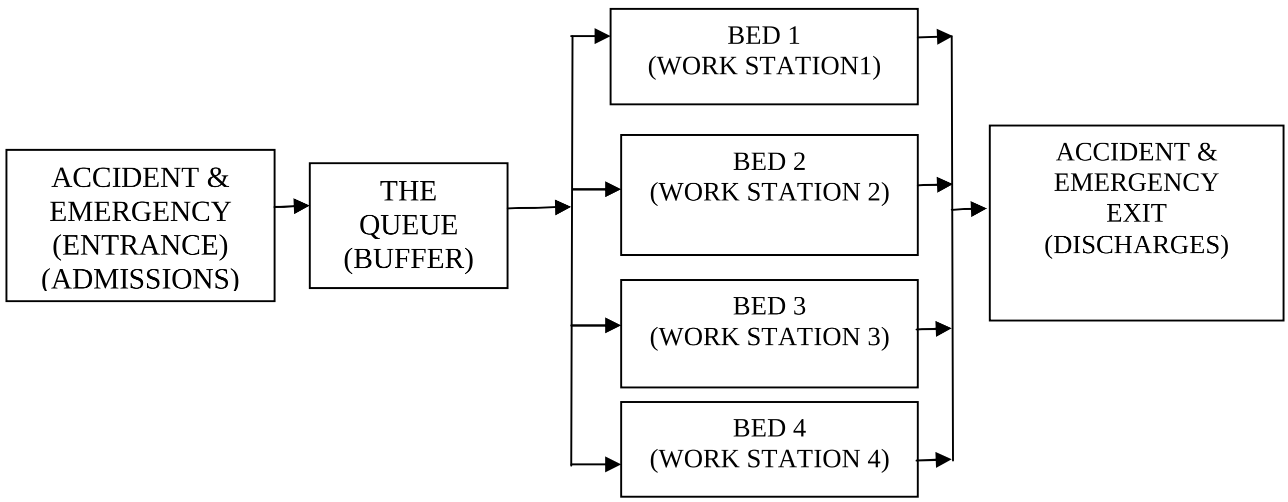


Source: Researcher 2016

Figure 2.1: Mater Hospital's Conceptual Framework

The Framework in figure 2.1 illustrates the arrival of Emergency patients at the Mater Hospital's emergency unit as an input-process-output analysis setup. Patients arrive randomly from the environment around the hospital either by ambulance or any other means and each is immediately placed in an ICU bed depending on availability and this represents the input phase. If the ICU bed in unavailable, the patient is rejected and subsequently rerouted to another alternative hospital immediately. In the process phase, the patient (s) undergo treatment for a particular period after which they are either discharged, transferred to the general ward or even referred to another hospital. The discharge from the emergency unit refers to the output phase. The Key emphasis of this study is to minimize patient waiting time to an acceptable level and also ensure very low patient rejection rates.

2.7 Emergency Process Flow Simulation Map



Source: Researcher 2016

Figure 2.2: Emergency Process Flow Simulation Map

The process flow map above assumes a First in First out (FIFO) queue discipline such that service (admission and subsequent treatment) for patients is based on first come first served basis. There is also the assumption that patient arrivals follow a Poisson distribution with no major catastrophic events like terrorist attacks which may interrupt the statistical distributions.

CHAPTER THREE

RESEARCH METHODOLOGY

3.1 Research design

This research was a case study of the Emergency department at the Mater hospital. The study used historical data provided by the hospital to simulate the emergency care process and specifically the random process of patient arrivals. A case study has been defined by Yin (1994) as an empirical inquiry which investigates a contemporary phenomenon within its real-life context, especially when the boundaries between phenomenon and context are not clearly evident. Research design constitutes the blueprint for the collection, measurement, and analysis of data. The study used a descriptive research design. Descriptive research determines and reports the way things are (Mugenda and Mugenda, 2003).

3.2 Population

The population of this study varied over the period of the research and was categorized into all patient arrivals at Mater hospital per day. The Mater Hospital was found to be an ideal case study since it serves a huge population in the East and central African region and therefore representative of a wide geographical area.

3.3 Sample design

The sample design for secondary data of this study entailed hourly patient arrivals at Mater Hospital for a period of 5 years from 2010-2015. The study employed a systematic sampling technique which Kothari (2004) defines as the kind of sampling whereby members of a larger population are drawn according to a random starting point and a fixed periodic interval. In this case, the fixed interval is one year and the random starting point was the year 2010.

3.4 Data collection

The study utilized both secondary data from records kept by the Hospital's Information management system and primary data collected by the interview schedule. The data of interest was average hourly patient arrivals.

3.5 Data Analysis

Once the historical data was collected from the hospital, it was used to build probability distributions for patient arrivals, waiting times, service rates and exit rates for the ICU unit. The processed probability distributions formed the input data for the Discrete Event Simulation model. The DES model was run as many times as possible in order to increase the accuracy of the model output information necessary for decision making. The model performance accuracy was measured through the process of Validation which determines whether the simulation model is a useful or reasonable representation of the real system (Shim and Kumar, 2010). The best way to achieve this was through comparison of the output data from the simulation model with the actual data from the hospital using the student t-test procedure at 95 percent confidence level assuming equal variance. A trend line graph for both simulated and actual hospital data was also drawn for a clearer visual comparison.

CHAPTER FOUR

DATA ANALYSIS, RESULTS AND DISCUSSION

4.1 Introduction

The emergency unit at Mater hospital is strategically located directly towards the entrance to the hospital and well labeled allowing for easy and quick access for both walk in and ambulance delivered patients. There are nine critical patient beds allocated to the emergency unit (EU) with standby doctors on four who also serve other patients at the hospital. The EU has got the main entrance for patients from outside the hospital and another inlet from within the hospital. There is a desk for enquiries adjacent to the main entrance manned by two receptionists on a 24 hour schedule. In addition to the reception, there is a registration counter for records purposes and registers patients. On a patient's arrival, the fee clerk receives the hospital charges in a cabin adjoining to the registration desk. The fee counter operates between 8:00 to 20:00 hours. The emergency unit depends on a number of other facilities that include a radiology room; attendant's waiting hall, laboratories, the chemist, a blood bank and toilets.

4.2 Emergency patient distribution characteristics

4.2.1 Daily Average Patient arrivals

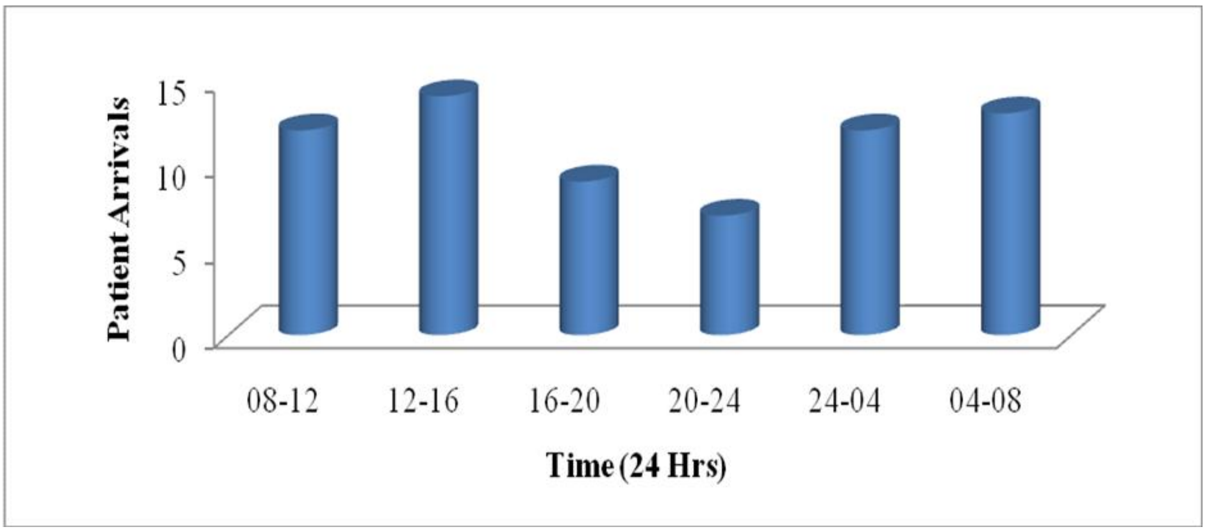
Table 4.1: Daily Average Patient arrival Distribution

Table 4.1illustrates the probability of different rates of patient arrivals per hour at the Mater Hospital's emergency department. The arrivals were counted on an hourly basis for twenty four hours of each day for five consecutive days beginning from Monday to Friday. The probabilities were estimated by counting the number of patients between the different time intervals in the 24 hour period every day. By dividing the total arrivals for each time category by the grand total arrivals for 24 hours the various probabilities of arrivals were estimated.

Time (24Hrs)	Patient arrivals	Probability (%)
08-12	12	18
12-16	14	21
16-20	9	13
20-24	7	11
24-04	12	18
04-08	13	19
TOTAL	**67**	**100**

Source: Secondary data 2016

The illustration of the details contained in the table 4.1 above is as shown in chart 4.1 below;



Source: Secondary data 2016

Figure 4.1: Daily average patient arrival distribution

The highest number (21%) of Emergency patients at the hospital is received between 12:00 to 16:00 hours on any given day that was covered during the study period. The least number (11%) of emergency patients on the other hand arrive at the hospital between 20:00 and 00:00 hours. The mean emergency number of patients was found to be 5 per hour with a standard deviation of 2 and a median of 3 during the period covered by the study. This therefore means that 12:00-16:00 is the time at which the hospital must prepare to handle more emergency patients than any other time of the day on average.

4.2.2 Daily average Patient exits

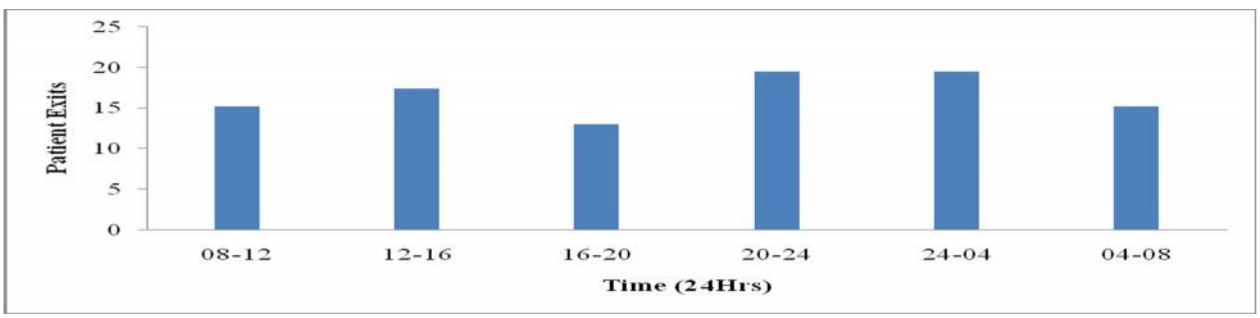
Table 4.2: Daily average Patient exit Distribution

Table 4.2 contains information on the average number of patients that were being discharged from the hospital's emergency department on an hourly interval in the entire 24 hours during the study period. This data was gathered directly by means of a head count of all patients that exited the emergency department after treatment in 24 hours. The probability of arrivals was computed by dividing the average total arrival of a time interval e.g. between 08:00 to 12:00 and the average total daily arrival.

Time (24Hrs)	Patient arrivals	Probability (%)
08-12	7	15
12-16	8	17
16-20	6	13
20-00	9	20
24-04	9	20
04-08	7	15
		100

Source: Secondary data 2016

The average daily patient discharge pattern is also illustrated by figure 4.2 below;



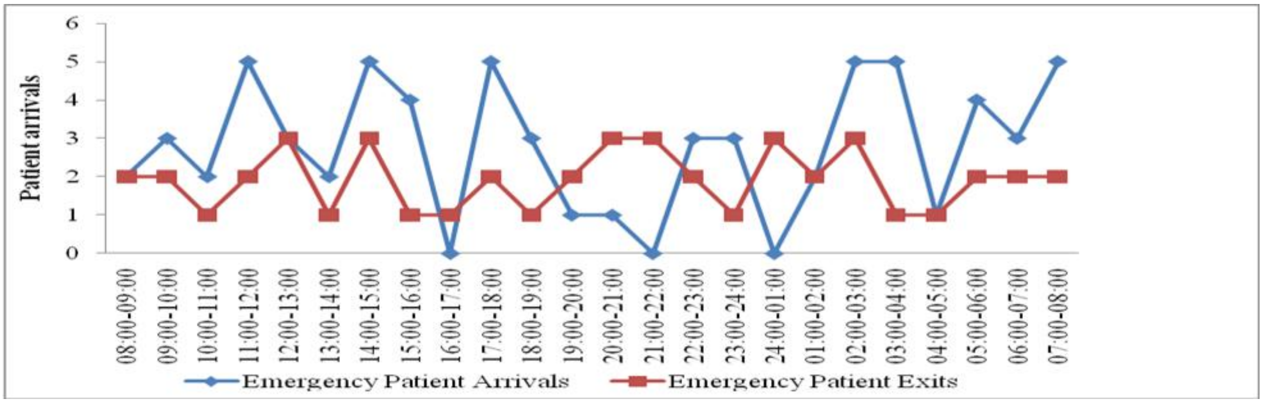
Source: Secondary data 2016

Figure 4.2 Daily average Patient exit Distribution

The majority (40%) of emergency patients exit the hospital's emergency unit between 20:00-04:00 hours. On the other hand the least number of patients (13%) exited the emergency department between 16:00 to 20:00 hours. The average emergency patient discharge at the hospital's emergency unit was found to be 2 patients with a single unit standard deviation and a median of 2 patients.

4.3 Average Patient Arrival rate (µ) versus Exit rate (ƛ) at the Emergency unit

This figure is an illustration of the average daily rate at which patients arrive and get discharged from the hospital's emergency department per day (24hours). Data on both arrival and exit of patients was gathered by head count.



Source: Secondary data 2016

Figure 4.3: Arrival rate vs. Exit rate

The average daily emergency patient arrivals and exits were found to be very erratic and this stochasticity makes it very difficult to predict the emergency service demand of the hospital. This is in concurrence with Zhu et al., (2012) who argue that deterministic models are not suited well enough at representation of random processes and results of this study of the emergency department in terms of patient arrivals and discharge yielded a characteristic random process such that the next arrival is not determined by a previous arrival. Similarly the next patient to be discharged is independent of the previously discharged one. There was always an emergency patient in the queue at the hospital which Schmidt et al., (2013) attribute to the random behavior of patients length of stay such that allocating the optimum bed capacity is nearly impossible. When the patient length of stay is unpredictable it renders predicting patient discharge unpredictable as well which in effect brings about constricted patient flow in the emergency unit because management cannot conclusively tell when the next bed will be empty to accommodate a new occupant.

Several studies (Espinosa et al. 2002; Schull et al. 2003; Asplin et al. 2003; Schull, 2005) also agree with this study results that indeed patients who are already admitted lead to substantial congestion of the emergency department in hospitals. The mean emergency arrival number (µ =3) was found to be higher that the emergency patient exit/discharge number (ƛ=2). This consequently means that a queue will always form when patient exit rate is lower than patient arrival rate a problem that leads to lack of bed availability. Ridge et al., (1998) in their paper on Capacity planning for intensive care units also encountered a similar problem which led them to conclude that lack of inpatient beds for new patients in hospitals caused significant patient delays and consequently service quality deterioration.

4.4 Emergency bed capacity Optimization

The study first established the operational efficiency and bed capacity of the hospital before any adjustments were made followed by efficiency once improvements were added to the hospital's capacity.

4.4.1 Simulation of the emergency workflow process before efficiency adjustments

The simulated overall Mean Cycle time for the Hospital's emergency department Queue before making adjustment was found to be 0.52 hours which is approximately 31 minutes of patient waiting time before admission into an ED bed. For critically ill ICU bound patients, this is very long and unacceptable waiting time and can lead to lose of lives. The Overall mean service level before adjustment was found to be 0.94 which translates to 94%. This is quite high and measures the hospital's emergency department performance. In this case the hospital is able to serve 94% of its total emergency service demand.

The overall mean inventory for the hospitals queue was found to be 2 patients implying that, at the current operational set up, there were always 2 patients in the queue waiting for admission into the emergency unit. This is true considering that mean patient arrivals (µ=3) were found to be higher than mean patient exits (ƛ=2) for the emergency department. The implication when arrivals are more than exits/discharge is that a queue will always form.The final inventory of the emergency unit's queue at the hospital was found to be 5 patients. This represents the throughput of the whole emergency process at the hospital in the simulated time.

4.4.2 Simulation of the emergency workflow process after efficiency adjustments

In consideration of the unacceptable waiting time for emergency patients at the hospital, there was need to introduce adjustments that could reduce the waiting time and thus improve service quality. As a result, two more beds were added to the workstations in order to simulate the gain in emergency service quality characteristics. The most striking improvement on addition of two beds was the drop in Mean Cycle time for the emergency unit queue from approximately 31 minutes to 12 minutes which represents a 61% drop in waiting time for the emergency patients. In their study, Duguay and Chetouane (2007) achieved a similar efficiency gain by demonstrating that indeed by adding extra capacity of one physician and one nurse waiting time for patients was greatly reduced in their Discrete Event Simulation analysis model.

Although the study established the importance of sufficient emergency patient bed capacity in alleviating patient flow problems, it should be noted that addressing capacity alone may not be enough a solution in tackling emergency department overcrowding. Eitel et al., (2010) emphasize the need to address fully emergency patient flow issues as the only way to solve the issue of service deterioration in the emergency departments of hospitals. They offer solutions such as managing the demand behavior of the hospital, complete mapping of hospital processes, lean thinking methods and discrete event simulation.

Another improvement was also recorded in overall mean service level from 94% before adjustments to 95% after addition of the extra beds. This represents the ability to serve more patients who are in demand of the emergency service from the hospital. The overall mean inventory for the hospitals queue dropped by 50% from 2 patients at the current operational set up to 1 patient after the addition of two beds. Considering that mean patient Arrivals (μ=3) were found to be higher than mean patient exits/discharges (λ=2) for the emergency department the drop in the size of the waiting line invenotry will greatly reduce queue buildup. The optimum bed capacity that improves service quality characteristics like overall mean inventory (number of patients waiting in the queue), Overall mean service level (size of the service demand satisfied by the emergency unit or its performance) and overall Mean Cycle time (patient waiting time) was found to be 6 emergency patient beds.

4.4.3 Model Validation

Table 4.3: t-Test: Two-Sample Assuming Equal Variances

Table 4.3 contains output of the t-test analysis that was used to check the simulation model fitness regarding its representation of the hospital under study. To measure how accurate the model is in simulating patient arrival data, a sample of patient head count of arrivals was compared to a similar but simulated data set using the Student's two sample t-test assuming equal variances.

	ACTUAL	***SIMULATED***
Mean	2.80	2.80
Variance	2.80	2.40
Observations	120	120
Pooled Variance	2.60	
Hypothesized Mean Difference	0.00	
Df	238	
t Stat	0.04	
P(T<=t) one-tail	0.48	
t Critical one-tail	1.65	
P(T<=t) two-tail	0.97	
t Critical two-tail	1.97	

Source: primary data 2016

The results in the table 4.3 are of the two sample t-Test procedure assuming Equal Variances such that both simulated and actual data collected from the hospital was hypothesized to come from the same population. This is only the case if the model is close enough to the study phenomena being modeled. Both actual and data from the simulation model had an equal mean of about 3 patient arrivals at the emergency unit. On the other hand the actual data had 2.8 while simulated data had 2.4 corresponding variances. According to the results in table 4.3, the model was an accurate representation of emergency patient flow at the Mater Hospital. This is due to the high calculated p-value (p=0.97, d.f=238) which is greater than the 0.05 critical value. When the calculated p-value is greater than the critical value (0.05) then there is no significant statistical difference between both the actual data and the corresponding simulated set.

CHAPTER FIVE

SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

5.1 Summary

The highest average number of Emergency patients at the hospital was received between 12:00 to 16:00 hours during the study period. The average emergency number of patient arrival was found to be 5 per hour with a standard deviation of 2 and a median of 3. The majority of emergency patients exit the hospital's emergency unit between 20:00-04:00 hours. The least number of patients were discharged from the emergency department between 16:00 to 20:00 hours. The average daily emergency patient arrivals and exits were found to be highly stochastic. The average emergency patient arrival number was found to be higher that the average emergency patient discharge number.The Hospital's emergency department queue before making adjustment was found to have a higher patient waiting time than after efficiency improvement. The hospital's emergency department performance was found to be lower at the current operational set up before efficiency improvement with longer queues. The throughput of the whole emergency process at the hospital in the simulated time was also found to be higher.

The improvement on addition of two beds was a drop in average patient waiting time for the emergency unit queue. Improvement was also recorded in overall mean service level after addition of the two extra beds. The overall mean inventory (queue size) for the hospital's queue dropped after the addition of two beds. The optimum bed capacity for the emergency department was found to be 6. The model was an accurate representation of emergency patient flow at the Mater Hospital since the difference between simulated and actual data was statistically insignificant.

5.2 Conclusions

The conclusions of this study are threefold according to the objectives pursued in the course of the research. The objectives include establishing emergency patient arrival and exit patterns at Mater Hospital, to determine the relationship between emergency patients arrival rate (μ) and the exit rate (ƛ) and finally to establish the optimum hospital bed capacity for Mater Hospital's emergency unit.

5.2.1 Relationship between Patient Arrival and Discharge Patterns

The mean emergency arrival was found to be 3 patients per hour with a standard deviation of 2 and a median of 3 during the study period. The mean emergency discharge at the hospital's emergency unit was found to be 2 patients with a unit standard deviation and a median of 2. The average daily emergency patient arrivals and exits were found to be highly stochastic and this stochasticity makes it very difficult to predict the service demand of the hospital. The mean emergency arrival number was also found to be higher than the mean emergency discharge number which leads to the inevitable buildup of the queue.

5.2.2 Emergency bed capacity Optimization and Model Validation

The simulated overall Mean Cycle time (patient waiting time before admission into an ED bed) for the Hospital's emergency department was found to be approximately 31 minutes before adjustments. The Overall mean service level before adjustment was found to be quite high and measures the hospital's emergency department performance. In this case the hospital is able to serve most of its total emergency service demand. The overall mean inventory for the hospital's emergency queue was found to be 2 patients implying that before improvements, there were always 2 patients in the queue waiting for admission into the emergency unit. When arrivals are more than exits/discharge a queue will always form. The final inventory of the emergency unit's queue at the hospital was found to be 5 patients. This represents the throughput of the whole emergency process at the hospital in the simulated time.

The most striking improvement on addition of two beds was the drop in patient waiting time. Another improvement was also recorded in overall mean service level after addition of the extra beds. With the adjustment, the hospital is able to meet more of its service demand. The overall queue size also dropped after the addition of two beds. Considering that mean patient Arrivals were found to be higher than mean patient exits/discharges for the emergency department, the drop in the size of the waiting line invenotry greatly reduces queue buildup.

The optimum bed capacity that improves service quality characteristics like overall mean inventory (number of patients waiting in the queue), overall mean service level (size of the service demand satisfied by the emergency unit or its performance) and overall Mean cycle time (patient waiting time) was found to be 6 emergency patient beds. The model was a reasonably accurate representation of emergency patient flow at the Mater Hospital since there was no significant statistical difference between both the actual data and the corresponding simulated dataset. The model therefore simulates data which shares the same distribution characteristics with the Hospital's actual data.

5.3 Recommendations

The hospital should try and match the human resources with temporal arrival pattern of emergency patients in order to tackle the challenge of randomness and avoid any delays or reduce waiting time to a bare minimum. The hospital should formulate service quality benchmarks for various characteristics (waiting time, service time, throughput, queue size) with corresponding annual audit mechanisms. This will serve to pinpoint areas in need of improvement and hence improve service quality. The optimum bed capacity the hospital should adopt to reduce on emergency patient waiting time is 6 with the accompanying resources like the doctors, nurses and treatment machines.

5.4 Limitations of the Study

This study was limited by a number of challenges first among them was the amount of time allocated to study the phenomena. In order to get as close to the modeled case as possible, there is need to devote a reasonable amount of time in order to incorporate as many resources consumed by the ED and also use large data sets spanning several years so that even the probability distributions are close if not equivalent to the actual distributions.

This study covered the entire 24 hours in any single day during data collection at the hospital and the researcher had to collect more data from patients after having been admitted. As a result, the possibility of incorrect data provided by patients due to recall bias or over exaggeration of waiting time cannot be ruled out and this may impact the overall accuracy of the study results. Access to hospital records proved to be a challenge to the researcher whereby certain data types were not kept by the hospital in their records and that getting access to records took too long due to security and confidentiality clearances.

5.5 Areas of Further Study

This study considered the emergency hospital beds as the only measure of capacity for designing the simulation model. Emergency departments in Hospitals depend on several resources in order to deliver their services effectively including, x-ray machines, MRI machines and surgical equipment. In addition, there are decision points in an emergency department which determine the next entry point for the treated patient. This study therefore suggests a more detailed case study that incorporates other resources utilized by the emergency unit and also a consideration of the concept of decision points.

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APPENDIX 1: DAILY DATA COLLECTION SHEET

	Time (Hrs)	Patient arrival time	Patient adm. time	Waiting time (Hrs)	Number of Patient arrivals	Number of patient exits	Length of stay (LOS)
1	08:00-09:00						
2	09:00-10:00						
3	10:00-11:00						
4	11:00-12:00						
5	12:00-13:00						
6	13:00-14:00						
7	14:00-15:00						
8	15:00-16:00						
9	16:00-17:00						
10	17:00-18:00						
11	18:00-19:00						
12	19:00-20:00						
13	20:00-21:00						
14	21:00-22:00						
15	22:00-23:00						
16	23:00-24:00						
17	24:00-01:00						
18	01:00-02:00						
19	02:00-03:00						
20	03:00-04:00						
21	04:00-05:00						
22	05:00-06:00						
23	06:00-07:00						
24	07:00-8:00						

Source: Researcher 2016

APPENDIX 2: INTERVIEW SCHEDULE

1) What is the size of MH's Emergency unit in terms of bed size?

2) What is the average number of patients treated in the Emergency Department per day?

3) What is the room capacity of the Emergency Department?

4) How long does each process take?

(a) Is the process time constant for all patients?

(b) If not, what do you think causes the variability?

5) How does the staffing remain the same or it changes throughout each day of the week?

(a) What is the physician-to-nurse ratio?

(b) What is the nurse to patient ratio?

6) How long does it take for a patient to go through the triage?

(a) Is the process time consistent from patient to patient? Does it differ depending on the acuity level? Does the time differ even among different types of patients within the same acuity? If there are any differences, what causes the differences?

(b) How many triage nurses are there? Does this number change (e.g. according to time of the day, day of the week, weekend vs. weekday

7) How many triage rooms are there?

(a) If there are multiple rooms, are all the rooms staffed?

(b) Are the rooms fully staffed during certain days/times but unstaffed at other times?

8) How do these factors affect the flow of emergency Patients at MH?

a) Weather

b) Days of the week

c) Time of the day

d) Time of the month

APPENDIX 3: SIMULATION OF THE EMERGENCY WORKFLOW PROCESS BEFORE EFFICIENCY ADJUSTMENTS

Simulation Results		**Number of iterations =1000**	
Element	**Element**	**Statistics**	**Overall**
types	**names**		**means**
Entrance(s)	A&E Entrance	Objects entering process	8.86
		Objects unable to enter	0.00
		Service level	0.94
Work Station(s)	DOCTOR 1	Final status	NA
		Final inventory (int. buff.)	0.01
		Mean inventory (int. buff.)	0.00
		Mean cycle time (int. buff.)	Infinite
		Work cycles started	0.94
		Fraction time working	0.68
		Fraction time blocked	0.00
	DOCTOR 2	Final status	NA
		Final inventory (int. buff.)	0.02
		Mean inventory (int. buff.)	0.01
		Mean cycle time (int. buff.)	Infinite
		Work cycles started	0.94
		Fraction time working	0.67
		Fraction time blocked	0.01
	DOCTOR 3	Final status	NA
		Final inventory (int. buff.)	0.01
		Mean inventory (int. buff.)	0.00
		Mean cycle time (int. buff.)	Infinite
		Work cycles started	0.94
		Fraction time working	0.67
		Fraction time blocked	0.00
	DOCTOR 4	Final status	NA
		Final inventory (int. buff.)	0.01
		Mean inventory (int. buff.)	0.00
		Mean cycle time (int. buff.)	Infinite
		Work cycles started	0.80
		Fraction time working	0.42
		Fraction time blocked	0.00
Buffer(s)	Emergency Queue	Objects leaving	3.62

		Final inventory	5.24
		Minimum inventory	0.00
		Maximum inventory	5.24
		Mean inventory	2.07
		Mean cycle time	0.52
Exit(s)	A&E Exit	Objects leaving process	0.00
		Object departures missed	0.22
		Service level	0.00
	Resource(s)		
	BED 1	Mean number in use	0.68
	BED 2	Mean number in use	0.67
	BED 3	Mean number in use	0.67
	BED 4	Mean number in use	0.42

Source: Researcher 2016

APPENDIX 4: SIMULATION OF THE EMERGENCY WORKFLOW PROCESS AFTER EFFICIENCY ADJUSTMENTS

Element	**Element**	**Statistics**	**Overall**
types	**names**		**means**
Entrance(s)	A&E Entrance	Objects entering process	8.98
		Objects unable to enter	0.00
		Service level	0.95
Work Station(s)	DOCTOR 1	Final status	NA
		Final inventory (int. buff.)	0.01
		Mean inventory (int. buff.)	0.00
		Mean cycle time (int. buff.)	Infinite
		Work cycles started	0.95
		Fraction time working	0.68
		Fraction time blocked	0.00
	DOCTOR 2	Final status	NA
		Final inventory (int. buff.)	0.01
		Mean inventory (int. buff.)	0.00
		Mean cycle time (int. buff.)	Infinite
		Work cycles started	0.95
		Fraction time working	0.68
		Fraction time blocked	0.00
	DOCTOR 3	Final status	NA
		Final inventory (int. buff.)	0.01
		Mean inventory (int. buff.)	0.00
		Mean cycle time (int. buff.)	Infinite
		Work cycles started	0.95
		Fraction time working	0.68
		Fraction time blocked	0.00
	DOCTOR 4	Final status	NA
		Final inventory (int. buff.)	0.00
		Mean inventory (int. buff.)	0.00
		Mean cycle time (int. buff.)	Infinite
		Work cycles started	0.80
		Fraction time working	0.41
		Fraction time blocked	0.00
	DOCTOR 5	Final status	NA
		Final inventory (int. buff.)	0.01
		Mean inventory (int. buff.)	0.00

		Mean cycle time (int. buff.)	Infinite
		Work cycles started	0.80
		Fraction time working	0.40
		Fraction time blocked	0.00
	DOCTOR 6	Final status	NA
		Final inventory (int. buff.)	0.01
		Mean inventory (int. buff.)	0.00
		Mean cycle time (int. buff.)	Infinite
		Work cycles started	0.80
		Fraction time working	0.40
		Fraction time blocked	0.00
Buffer(s)	Emergency Queue	Objects leaving	5.22
		Final inventory	3.76
		Minimum inventory	0.00
		Maximum inventory	3.76
		Mean inventory	1.20
		Mean cycle time	0.20
Exit(s)	A&E Exit	Objects leaving process	0.00
		Object departures missed	0.20
		Service level	0.00
	Resource(s)		
	BED 1	Mean number in use	0.68
	BED 2	Mean number in use	0.68
	BED 3	Mean number in use	0.68
	BED 4	Mean number in use	0.41
	BED 5	Mean number in use	0.40
	BED 6	Mean number in use	0.40

Source: Researcher 2016

APPENDIX 5: BUDGET

Budget Item	**Approximate Cost (KShs.)**
Transport and Accommodation	15,000
Printing and Spiral binding	4,835
Typesetting	1,530
Final Hard cover Binding	2,100
Internet costs	6000
Mobile Phone call costs	3000
Miscellaneous	3000
Total Cost	**35,465**

Source: Researcher 2016

APPENDIX 6: INTRODUCTION LETTER

UNIVERSITY OF NAIROBI
SCHOOL OF BUSINESS

Telephone: 020-2059162
Telegrams: "Varsity", Nairobi
Telex: 22095 Varsity

P.O. Box 30197
Nairobi, Kenya

DATE 12/10/2016

TO WHOM IT MAY CONCERN

The bearer of this letter HUDSON EBOSO OMUNGA

Registration No. D61/72429/2011

is a bona fide continuing student in the Master of Business Administration (MBA) degree program in this University.

He/she is required to submit as part of his/her coursework assessment a research project report on a management problem. We would like the students to do their projects on real problems affecting firms in Kenya. We would, therefore, appreciate your assistance to enable him/her collect data in your organization.

The results of the report will be used solely for academic purposes and a copy of the same will be availed to the interviewed organizations on request.

Thank you.

UNIVERSITY OF NAIROBI
SCHOOL OF BUSINESS
12 OCT 2016
P.O. Box 30197 – 00100, NAIROBI

PATRICK NYABUTO
SENIOR ADMINISTRATIVE ASSISTANT
SCHOOL OF BUSINESS