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A decision support simulation model for bed management in healthcare

Raja A. Baru

A DECISION SUPPORT SIMULATION MODEL FOR BED MANAGEMENT IN HEALTHCARE

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RAJA ANVESH BARU

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Dr. Elizabeth A. Cudney, Advisor
Dr. Ivan G. Guardiola
Dr. Susan L. Murray

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ABSTRACT

In order to provide access to care in a timely manner, it is necessary to effectively manage the allocation of limited resources such as beds. Bed management is key to the effective delivery of high-quality and low-cost healthcare. An efficient utilization of beds requires a detailed understanding of the hospital's operational behavior. It is necessary to understand the behavior of a hospital in order to make necessary adjustments to its resources, and policies, which can improve patient's access to care. The aim of this research was to develop a discrete event simulation to assist in planning and staff scheduling decisions. Each department's performance measures were taken into consideration separately to understand and quantify the behavior of individual departments, and the hospital system as a whole. Several scenarios were analyzed to determine the impact on reducing the number of patients waiting in queue, waiting time for patients, and length of stay of patients. From the results, the departments that have long queues of patients, waiting times, and lengths of stay are detailed to predict how the hospital reacts to patient flow.

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NOMENCLATURE

Symbol	Description
LOS	length of stay
ICU	intensive care unit
3 TCU	transitional care unit on third floor
3 MSU	medical surgery unit on third floor
4 MSU	medical surgery units on fourth floor
ED	emergency department
TCU	transitional care unit
MSU	medical surgery unit
OR	operating room
M/ PH/ c	poisson arrivals/ phase type/ number of servers
MAU	medical assessment unit
VAMC	veterans administration medical center
BMS	bed management system
EDIS	emergency department integration software
FIFO	first in first out
ANOVA	analysis of variance

1. INTRODUCTION

The demand for hospitals has been increasing with the increase in population, but the resources are not increasing accordingly. Bed management has become an important criterion in delivering quality and cost effective health care. An efficient utilization of beds requires a detailed understanding of the hospital's operational behavior. It is necessary to understand the behavior of a hospital in order to make necessary adjustments to its resources, and policies, which can improve patient's access to care.

In order to learn what has already been researched in the field of bed management, Paper I provides a current literature review in bed management. It investigates the utilization of various operations and simulation methods to analyze and design hospital facilities. It also details the problems faced during capacity planning and in the process of developing models for bed management.

This research focuses on developing a simulation model for decision support for bed management. Most hospitals have a restriction on beds, and large amounts of money are needed to increase the capacity. Hospitals need to have a model for how they would behave if they were to increase the resources in any department or decrease the bed turnover time or reduce the length of stay for patients. All of these activities are difficult to implement in the real world but it is easier to implement these decisions in a simulation model. Paper II covers the simulation model for a hospital to understand the hospital's behavior. The model developed in this paper was meant to assist in planning and staff scheduling decisions. It is provided along with several scenarios to reduce the patient waiting times and length of queue of patients.

PAPER

I. SYSTEMATIC REVIEW OF OPERATIONS RESEARCH AND SIMULATION METHODS FOR BED MANAGEMENT

Raja A. Baru, Elizabeth A. Cudney, and Ivan G. Guardiola
Engineering Management and Systems Engineering
Missouri University of Science and Technology
Rolla, MO 65401, USA

Debra L. Warner and Raymond E. Phillips
Veterans Health Administration

Abstract

Efficient functioning of a hospital depends on how it allocates its resources, particularly allocating beds to patients, a problem fraught with complexities and uncertainties. Prolonged waiting induces patients leaving the hospital without being seen and causing losses to the hospital. To improve hospital efficiency and level of service, decision support systems are proposed to enable better decisions. There is substantial published research evaluating the use of decision support systems applied to analyze and design hospital facilities. The approaches identified in the literature include operations research techniques such as integer programming, goal programming, stochastic process, and queuing theory; simulation; and, in some cases, both approaches are used. These techniques enable a hospital to treat its patients more efficiently, meet performance targets, and manage costs. This paper aims to review and categorize this literature to motivate further research in bed management. In addition, various practices in different specialization units, problems faced while capacity planning, and methods developed for bed management in hospitals are provided.

Keywords

Bed Management, Healthcare, Literature Review

1. INTRODUCTION

Bed management has been an issue from the evolution of hospitals, but due to the increasing demand it has become more critical. In addition, bed management has become an important criterion in delivering quality and cost effective health service. Now it has grown to such a level that most hospitals have a bed management team for capacity planning.

Bed management is the allocation and provision of beds especially in a hospital where beds in specialist wards are a scarce resource [1]. It is focused on facility performance and reduction in costs to both the hospital and patients through optimization of the various processes involved. Bed management involves goal oriented tasks. The goals of bed management involve access to an appropriate bed to each patient in a timely way and reduction in number of patients that are turned away and directed to another facility due to lack of an available bed. There are numerous benefits of bed management including customer satisfaction, increased profits, forecasting capacity, and increased level of care. Hospitals must focus on reliability, accuracy, and customer level of care to be competitive and profitable, a key method to accomplish this is by continuously improving their bed management system. Complexity in planning is rising due to the increased day-to-day variations in demand and insufficient resources.

A convenient model for planning needs to involve the best techniques, objectives, adaptability, and usability by staff. To develop a model it involves analyzing different approaches, identifying drawbacks and system constraints, testing these approaches, and implementing and validating the solutions. Hospital administrators can choose these techniques for planning (e.g., operations, simulation). These techniques are used to monitor, analyze, and improve flow processes, which can aid in increasing inpatient number and quality. Through the use of these techniques hospital staff are able to manage and develop an understanding of the critical situations and develop solutions through the use of collective knowledge [2].

Further improvement in practices is necessary to meet the requirements due to the increased demand and constantly changing scenarios. There are more complexities day-by-day, and often hour-by-hour, and improving bed management systems will increase efficiency, improve prediction of inpatients, enable better health care, and reduced risks. Several decision support systems are currently used to route the patient flow into respective hospitalization units. These decision support systems include operations research techniques such as integer programming, goal programming, stochastic process, queuing theory; simulation; and, in some cases, both approaches are used.

Out of the many subsystems in a healthcare system, hospitals are highly integrated service units attending to the needs of the patients under treatment. A hospital system consists of a number of sub-units which can include the emergency department (ED), intensive care unit (ICU), transitional care unit (TCU), medical surgical unit (MSU), operating room (OR), and diagnostic services, such as pathology and radiology, etc. Healthcare systems deal with different aspects of healthcare and its problems are due to several combinations of patient status, service types, and varieties of constraints. Therefore, it is necessary to design the system with respect to the various constraints and conditions [3-6].

The purpose of these techniques is to identify the factors that are causing bed blockage, occupancy level, length of stay (LOS), number of inpatient admissions, and patient tracking. The increasing cost of operations and maintenance, and healthcare cost to the patients due to the use of newer technologies, resources, and methods have added newer dimensions as constraints to the problems of healthcare system [7-9].

2. RESEARCH METHODOLOGY

This study aimed to review the existing literature regarding bed management practices, use of bed management, and provide findings and trends. The research was carried out using the Google Scholar database. With the research goals in mind, the terms operations research, simulation, and bed management were used to search for articles. Since bed management has been a research topic for many years, no data ranges were used to limit the search. There are many sources that outline these various topics of bed management. A thorough search of peer-reviewed literature was conducted and the findings compiled. Through the systematic literature review, several main themes for research practices were identified. These included the use of operations research, simulation, and combined operations research and simulation models. The following section provides the literature review based on these categories [2].

3. BED MANAGEMENT LITERATURE REVIEW

The required number of beds to meet the demand is a recurrent problem in bed management. Therefore, hospital capacity planning is a well-researched problem in healthcare [10, 11]. There are several practices followed to solve this problem based on different concepts. Oliveira et al. utilized a data mining tool to identify data about patient's management to provide decision makers with critical information to aid their decisions [12].

Most recently, Tortorella et al. investigated bed management in detail by employing a different approach that increased the patient's bed turn over time through coordination and communication. Through the development of a bed management system, communication was improved among the various disciplines in the system. This led to an increase inpatient flow [13].

Lovett et al. reported an innovative approach that integrates multiple services into a single patient flow management center to manage the supply and demand for inpatient services across the system [14]. This process aids in improving communication, coordination, and accountability. It is important to note that while researchers are investigating various practices in bed management, there are many other models that warrant discussion [2].

3.1 BED MANAGEMENT USING OPERATIONS RESEARCH

Several researchers looked at the effectiveness of practicing operation research techniques for bed management. To that point, Cochran et al. approximated the hospital inpatient demand by employing a queuing technique for decision-making. They identified, in general, that patients' data is collected at midnight, but this data cannot be taken into consideration since it does not indicate any variations in demand during the day. The month of March was selected for analysis because it is considered to be the busiest month by hospital management. They deduced that financial data plays a vital role and for inpatient bed capacity planning; therefore, this data should be utilized in any analysis [15].

Similarly, Cote developed an advanced forecasting model using census data. This model determined the frequency distribution using hourly census information to interpret bed demand. Cote developed an analytical model, compared the results with the simulation results, and concluded that both results were almost similar. It was determined that the analytical model avoids the computational effort necessary in simulation models [16].

Gorunescu et al. took a broader approach by using queuing theory to illustrate patient flow to develop an approach for advancing the utilization of hospital resources in order to enhance care. They utilized the M/PH/c queue, where M is for Poisson arrivals, PH is the service distribution (i.e. phase type), and c denotes the number of beds. The research provided a method for determining the optimum number of beds by giving an adequate level of patient dismissal. The finding suggested that a level of 10-15% bed vacancy is important to maintain administration productivity [17].

Utley et al. proposed the creation of an intermediate care unit in the process from emergency to specialized wards. The optimal number of beds in the care unit is determined using a mathematical sizing model. This model calculates the patient flows, waiting times, length of stay, and service time until they discharge from care unit. This approach reduces the excess flow of patients into acute care and reduces the losses due to admission cancellations [18].

Nguyen et al. proposed a straightforward model to hone the bed capacity of a hospital. The proposed model took into account a score model with three elements as parameters, which included the number of beds, number of unscheduled affirmations, and number of vacant beds. The optimum number of beds is the number for which both the mean and the standard deviation of the score are the least. The algorithm of the model is focused around the increase of one virtual bed at each stage and the count of the score for every saturation limit for each empty bed [19].

With a different view, Akcali et al. developed a network model that simultaneously determines the timing and extent of changes in bed limit that minimizes the limit expense while maintaining the desired level of quality operation. The research transformed the capacity planning model into a shortest path model, where the target is to minimize the expense. This model fuses the sensible concerns connected with deciding the size of the hospital, for example, finite planning horizon, an upper limit on the normal holding up time, and budget constraint. It accommodates capacity change through shuttering. One limitation of this model is that it is focused around a broad view in the assumption that the requirement and service are equal [20].

Recently, Bachouch et al. proposed a model that involves bed planning for both elective and acute patients. Several constraints such as single rooms, no mixed-sex rooms, incompatibility between pathologies, and contagious patients are taken into account while planning. Each time the same patient is hospitalized, the patient is allocated to the same bed and an availability time period is defined. An integer linear program is constructed based on these constraints. The objective function is to minimize the associated costs due to readmission of the patient and refused admissions [21].

Ataollahi et al. proposed the use of goal programming for bed management. Goal programming is a technique used for multiple objective optimization. Goal programming is different from linear programming, in that instead of maximizing or minimizing the objective function, the deviations between objectives are minimized in light of the constraints. The three steps of goal programming model include defining the decision variables, defining the goals, and defining the deviation variables. This model is solved using General Algebraic Modeling System (GAMS**)** [22]**.** Table 1 provides a summary of the various operations research methods for bed management.

Table 3.1. Comparison of Operations Research Methods

Author	Method	Findings
Cochran	Queuing Technique	• March is busiest month. • Midnight data cannot be taken into consideration. • Financial data plays a vital role.
Cote	Forecasting Model	• Frequency distribution of data helps to interpret bed demand.

Table 3.1. Comparison of Operations Research Methods (cont.)

Gorunescu	M/PH/c queue	• 10-15% bed vacancy helps to improve productivity.
Utley	Mathematical sizing model	• The creation of intermediate care regulates excess patient flow.
Nguyen	Score model	• The optimum number of patients is for which mean and SD are least.
Akcali	Network model	• This model reduces the timing and extent of changes in bed limit that reduces expense.
Bachouch	Integer linear model	• Expenses due to readmission of patient and refused admissions can be reduced.
Ataollahi	Goal programming	• Minimum deviations between objectives helps to identify optimal number of beds required.

3.2 BED MANAGEMENT USING SIMULATION

Researchers have also proposed several models using a different approach based on simulation to solve the bed management problem because of its ability to analyze dynamic situations.

In order to optimize bed management, El-Darzi et al. analyzed a geriatric department in a hospital to study the effect of length of stay, occupancy, and bed blocking on patient flow. Discrete event simulation was used to identify the distribution, flow in each state, and key factors affecting the flow. With the help of a queuing system, the model estimated the bed blockage quantities among different units. Several constraints were placed on the queue list and the amount of emptiness needed for each state. The limitation in this approach is the model assumed that both the arrival and admission number were the same [23].

The research of Huang mainly focused on reducing the medical emergency admissions by 15% through the medical assessment unit (MAU) and reducing the patient's average length-of-stay by one day. The decision making support provided includes the determination of size of the MAU (i.e., number of beds), which helps in allocating beds to different units. The research evaluated the number of beds required for the MAU to handle the expected load by taking the results from the data collected in the month of March as it is the believed to be the busiest month of a year. A computer simulation model using the AT&T Witness simulation package was developed with the available data to estimate how many beds were required by the MAU and to represent the mid-day bed occupancies of each specialty. The average bed occupancy rate of a specialty by its own patients was increased if the emergency patients are sent to the MAU and they deliberately ignored the effect of bed overflows, and then checked the effect of bed overflows. The objective was to minimize the number of bed days with overflow. The model was used to simulate and obtain an optimal bed allocation only in the sense to achieve the objective [24].

Standridge et al. proposed that simulation can be applied to various public related problems within the hospital. A description of how simulation is useful in each of these areas with examples was provided. Standridge et al. explained that simulation was better in analyzing various cases and barriers to the acceptance of simulation. The main limitation is that the use of simulation is complex; therefore, a simpler and faster foundation should be taken [25].

In another application, Bagust et al. determined the effect of emergency department admissions on hospital bed management. The research examined the effect of emergency admissions on hospital bed demand on a daily basis to identify the bottlenecks of inpatient flow. Discrete event simulation modeling was used due to randomness in the demand. The proposed model defines the relationship between fluctuating demand and available bed capacity. The results of the model indicate that a hospital can have regular shortages if the average bed occupancy of the unit rises to 90% or more. The limitation to the proposed model is the length of the time required to run the model [15, 26].

Elbeyli et al. examined inpatient flow to identify bottlenecks and assess the impact of bed availability on the waiting time of the admitted patients in ED before being transferred to other units of the hospital. Bottlenecks are the sources of long waiting times. The simulation software ProModel was used for this research. First, data related to the daily volume of the ED and other units was collected and analysis was performed. Several what-if scenarios such as adding beds were introduced into the model and results were compared [27].

Harper et al. created a simulation model using a three-phase simulation shell, which is flexible and fast. The research identified that the deterministic way of calculating length of stay, which uses a constant daily arrival rate that is independent of time for emergency and elective patients, would lead to erroneousness results. Therefore, the determination of LOS for each individual department would be a more representative indicator in the estimation of beds. The priority of relationship between bed occupancy and refusal rate, forecasting future bed requirements, and patient categorization could be illustrated by this model [28].

A simulation model that focused on the plausibility of elective surgery quotas in conjunction with a planning window to enhance the booking of elective surgeries for an ICU (consisting of 14 beds) was the focus of the research of Kim et al. The steps for this model include establishing a scheduling window and a specific form of quota system. The research was performed using a simulation of one surgery per day quota system, two surgeries per day quota system on a horizon of a one week and two week window. From the results obtained it was recommended one elective surgery per day quota system over a week or 2 week scheduling window reduces the number of cancellations in surgeries. However, there is an effect from the quota system on upstream patient sources and the downstream ICU server. Therefore, the research determined that linking the controllable process, the scheduling of elective surgeries, and the ICU admission process would improve the performance of the ICU [29].

A simulation model approach was proposed by Eldabi et al. called the Modelling Approach that is Participative Iterative for Understanding (MAPIU). The main objective was to improve the understanding of the system by stakeholders. Eldabi et al. explained how the steps in a simulation model varied by different authors in the construction of a simulation model. The research proposed an alternative model to all the existing simulation models that includes the participation of stakeholders in the model [30].

More recently, Troy et al. explained a simulation model based on the Monte Carlo technique. Monte Carlo simulation, a statistical experimental technique, is used to run pseudo random data to analyze the data. This simulation model is built to identify admission requests, model entities, and find start and end times belonging to ICU bed usage. The model calculated the confidence intervals of the wait times based on the cardiac patients since they are the patients who most admit into the ICU. The limitation for this model is that it requires a warm up period of three months to run and it is limited only to the ICU department of a hospital [31]. Table 2 provides a comparison of the various simulation methods in the literature.

Table 3.2. Comparison of Simulation Methods

Author	Software	Findings
El-Darzi	Bed Occupancy Modelling and Planning System package	• Bed blockage, occupancy, and emptiness impact patient flow.
Huang	AT&T Witness simulation package	• Reducing medical emergency admissions through a new medical assessment unit.
Standridge	Fortran	• Application of simulation in different areas is useful with less costs.
Bagust	Microsoft Excel .	• Risks are high when occupancy rates are above 85% and it reaches bed shortages. • Spare bed capacity is required.
Elbeyli	ProModel™ simulation software	• Adding beds to step down units increases patient flow by reducing the average waiting time. • Addition of beds to other units and the change in patient flow was observed.
Harper	STOCHISM	• The effects due to occupancy rates and refusal rates are determined. • Change in demand over time is predicted.

Table 3.2. Comparison of Simulation Methods (cont.)

Kim	Slam II simulation language	• Linking the scheduling of elective surgeries through a quota system to admission process can improve the performance of ICU.
Troy	Monte Carlo Simulation	• Functional capacity has the strongest impact on performance than actual capacity.

3.3 BED MANAGEMENT USING SIMULATION AND OPERATIONS RESEARCH

A hybrid approach where researchers took advantage of both operations research and simulation to reduce the complexities involved and to improve the patient flow has also been applied in the literature. This combined approach helps in identifying several key factors that influence patient flow in hospitals [31].

With this view, Costa et al. proposed a model to calculate the number of beds in a critical care unit. This model takes the distribution of data of different categories to determine the number of patients expected in a year, length of stay, and a target occupancy level. The research defined the steps of model as 1) rules are required to explain the patients flow; 2) statistical information about the current patient case mix, arrival patterns, length of stay, and number of beds is needed; and 3) the model is run repetitively with the current rules dictating patients' flow, to simulate the working unit with patients' arriving and leaving over long periods. In the last step, the results are compared with the actual data to verify the model. The model is based on queuing theory and computer simulation is used to solve the complex mathematical equations [32].

Marshall et al. proposed a model for patient flow based on the length of stay. The research focused on bringing together recent developments for inpatient flow modelling. For modelling LOS, probabilistic solutions are used to quantify their impact and sustainability in supporting hospital management service. Markov models, phase-type distributions, and conditional phase distributions are used in the proposed model. In addition, this approach suggested a mixed exponential model for the compartmental model of stream which can be converted to a discrete event simulation model [33].

Cochran et al. proposed a model to balance bed utilization by reducing bed blocking. Queuing networks are first used to analyze the flow patterns, then discrete event simulation is performed to maximize the flow. Queuing network analysis can be then used to test the bed reallocation. In order to maximize the flow and determine the waiting times the model used simulation; in particular, this research used the ARENA simulation package. The limitation is a large simulation model must be tested in order to validate the model with actual data. This can take a large warm-up time period, which is time consuming [34].

In another application, Oddoye et al. described the importance of a medical assessment unit to reduce the bottlenecks in acute patient flow in a general hospital. Simulation with the help of goal programming was performed to set the objectives to aid in decision-making. A visual interactive modelling system, developed in Micro Saint, was designed for patient flow in the hospital. The advantage of this simulation model is it takes less time to run and the results obtained are consistent with the different scenarios tested. Changes in the resources were also verified to determine these effects on the system [35].

Kokangul proposed a nonlinear mathematical model to determine the optimum number of beds. First, a simulation model was constructed, then the relationship between control parameters was determined. Finally, nonlinear mathematical models were used. Statistical modeling packages are used to determine the distributions for the daily accepted, rejected, transferred arrivals, discharges, and length of stay. The mathematical relationship between the control parameters and size of bed capacity is unknown; therefore, a fitting capacity function containing unknown parameters had to be chosen, and these parameters are estimated from the simulation models. Subsequently, this was performed for each of the control parameters suitable mathematical relationships; for example, linear or quadratic relationships should be obtained. Then these can be utilized as objective functions or constraints in nonlinear numerical models. These nonlinear models were solved using LINGO or MATLAB [36]. Table 3 provides a summary of the research literature in which both operations research and simulation models were applied.

Table 3.3. Comparison of Operations Research and Simulation Models

Author	Method and Software	Findings
Costa	Queuing theory and classification and regression tree (CART) analysis	• Developed a simulation model which predicts the arrival of patients in the Intensive Care Unit. • A model based on the average values leads to false results.
Marshall	Queuing and Bed Occupancy Management and Planning System (BOMPS)	• A different way in determining length of stay using Markov models, phase type distributions, and conditional phase type distributions is performed rather than calculating averages for length of stay parameter.
Cochran	Jackson Queuing networks and ARENA simulation package	• Queuing network was used to find out the bottlenecks in different units. • Simulation is done to balance the demand for beds.
Oddoye	Goal Programming and Micro Saint	• Importance of a medical assessment unit in an acute hospital and the way it helps to manage patient flow. • Simulation is developed to reduce the bed blockage.
Kokangul	LINGO or MATLAB	• Simulation was used to find the mathematical relationship between control parameters and size of bed capacity. • Cost analysis of additional bed capacity is performed

4. CONCLUSION

Bed management is a complex issue in healthcare system. However, the current literature has tackled the issue from multiple perspectives. Here, we have investigated several ways to solve bed management using operations research, simulation, and both techniques.

While this review limits itself to bed management, operations research, and simulation, there are many more documented examples of solving bed management using different techniques. Therefore, much research exists. It is relevant to mention that a successful bed management strategy is complex and should be handled with care. Administrators and staff need to be educated more and awareness is necessary to use different software for bed management. Moreover, research has to be continuous in this area to determine the best practices for bed management.

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II. A DECISION SUPPORT SIMULATION MODEL FOR BED MANAGEMENT IN HEALTHCARE

Raja A. Baru, Elizabeth A. Cudney, and Ivan G. Guardiola
Missouri University of Science and Technology

William T. Cahill, Raymond E. Phillips, Bruce L. Mutter, Debra L. Warner, and Christopher M. Masek
Veterans Health Administration

Abstract

In order to provide access to care in a timely manner, it is necessary to effectively manage the allocation of limited resources such as beds. Bed management is key to the effective delivery of high quality and low cost healthcare. The aim of this research was to develop a discrete event simulation to assist in planning and staff scheduling decisions. Each department's performance measures were taken into consideration separately to understand and quantify the behavior of departments individually, and the hospital system as a whole. Several scenarios were analyzed to determine the impact on reducing the number of patients waiting in queue, waiting time, and length of stay of patients. From the results, the departments that have high waiting times for patients, waiting times and length of stay are detailed to predict how the hospital reacts to patient flow.

Keywords: Discrete event simulation, capacity planning, hospital behavior, waiting times, scenarios.

INTRODUCTION AND MOTIVATION

The proper and effective allocation of limited resources is a ubiquitous problem across all hospitals and healthcare delivery systems. The most common of these limited resources being the finite number of beds. Hospitals frequently have more patients than they can handle resulting in significant scheduling delays and increasing queue length [1]. To address these problems hospital management requires an understanding of the hospital's internal functions, operations, and level of care to effectively plan and staff operations. Furthermore, hospital administrators should know each department's or unit's operational behavior and interdepartmental relationships to decrease waiting times and increase timely delivery of care to patients [2]. Allocation of a bed to a patient with minimum waiting time and reduction of the number of patients waiting for beds are the basis for the research. To address this common problem in hospitals a detailed understanding of each department's average length of stay (LOS) of patients, waiting times, bed turnover time, and queue length should be analyzed to enable a complete understanding of the functioning of a hospital.

The healthcare industry comprised 15% of the United States' Gross Domestic Product (GDP) in 2006, of which 45% of the cost was funded publically [3]. This grew to 17.1% in 2013 [4]. Due to this growth there is a need to increase the efficiency of processes and procedures used in healthcare. Perhaps no issue is more prevalent than increasing access to care. Access to care is concerned with helping people receive appropriate and timely health care resources in order to preserve or improve their health.

Access to health care services is very important for any hospital to provide quality service to patients. Moreover, timely access to healthcare can reduce preventable death, increase quality of life, increase life expectancy, and prevent the spread of diseases. Barriers in providing services include the lack of available beds and increased waiting times which lead to patient dissatisfaction, increased number of patients who leave without being seen, and prolonged delays in care [5].

There are a variety of measures that dictate the access of care; however, the most common is the reduction of waiting times and effective use of bed management policies. Wait times increase risk and affects the quality of care [6]. A patient waiting also leads to increased costs, complications, suffering, and reduced efficiency. Healthcare processes can be improved by determining the bottlenecks in the system and facilitating patient flow within the hospital units at all acute levels. The flow of patients can be addressed using discrete event simulation to model the individual departments and relationships between departments in a hospital. Discrete event simulation was utilized in this research due to its ability to model what-if scenarios and make predictions of outcomes, particularly for situations such as those in healthcare that are very expensive to perform in reality.

The purpose of this research was to develop a comprehensive simulation model for a hospital system to characterize the behavior and information for each department statistically. During the analysis of each department, several opportunities for improving patient access to care were identified. Through the use of discrete event simulation, these scenarios for improvement were tested to determine the factors influencing patient waiting times. The hypotheses and resulting analyses are also provided.

This paper is organized as follows. First, a review current relevant literature is provided. The research methodology is then presented, which gives insight to patient flow in a hospital and its related parameters. The different scenarios for the simulation model are then discussed. The paper concludes with key findings, study limitations, and future research.

LITERATURE REVIEW

Patient flow, bed allocation, and resource utilization in hospitals through the application of queuing and simulation models have been extensively studied [7-9]. Harper and Shahani [10] argue that a hospital system is complex and reducing its complexity does not result in an ideal model.

Several key studies on bed allocation and hospital flow utilize queuing theory. Cochran et al. [11] approximated the hospital inpatient demand by employing a queuing technique for decision-making. They identified that, in general, patients' data collected at midnight was not sufficient due to the variance that occurs during the day. The month of March was selected for analysis because it was considered to be the busiest month by hospital management. The research found that financial data plays a vital role for inpatient bed capacity planning; therefore, this data should be utilized for any analysis. Cote [12] developed an advanced forecasting model using census data. This model determined the frequency distribution using hourly census information to interpret bed demand. Gorunescu et al. [13] took a broader approach by using queuing theory to illustrate patient flow to develop an approach for advancing the utilization of hospital resources in order to enhance care. The findings suggested that a level of 10-15% bed vacancy is important to maintain administration productivity. Utley et al. [14] proposed the creation of an intermediate care unit in the process from emergency to specialized wards. This approach reduces the excess flow of patients into acute care and reduces the losses due to admission cancellations.

The model proposed by Nguyen et al. [15] took into account a score model with three elements as parameters, which included the number of beds, unscheduled affirmations, and vacant beds. The algorithm for the model focused around the increase of one virtual bed at each stage and the count score for every saturation limit for each empty bed. Akcali et al. [16] developed a network model that simultaneously determined the timing and extent of changes in the bed limit that minimizes the limit expense while maintaining the desired level of quality operations. One limitation of this model is that it is focused around a broad view in the assumption that the requirement and service are equal.

The use of simulation in the health care industry has grown considerably since it can be used to model a wide range of topics and answer a variety of research questions [17, 18]. From the literature, it is recommended to use simulation over analytical and deterministic approaches due to its ability to model complex systems. Uncertainty, accuracy, variability, and reliability are the key reasons to use simulation in healthcare modeling. Analytical models use formulas or mathematical equations to solve problems, and the variable demand patterns in a hospital are very difficult to model. Stochastic models have the advantage of probabilistic components while deterministic models do not [19]. Jun et al. [20] provided an extensive taxonomy on the literature of patient flow and allocation of resources using discrete event simulation in healthcare.

Simulation models have been utilized in health care operations broadly because of their ability to model dynamic systems. Lagergren [21] proposed the utilizing simulation to model scenarios that do not exist, which makes it possible to make predictions of outcomes. It also has the capacity to model unexpected situations which are very expensive to perform in reality. Standridge [22] proposed that simulation can be applied to various public related problems within the hospital and explained that simulation was better in analyzing various cases. The main limitation is that the use of simulation is complex; therefore, a simpler and faster foundation should be taken. Jacobson et al. [23] described the benefits of using optimization and simulation tools in health care decision-making. They proposed that with simulation models, many performance measures could be analyzed, which also helps in understanding relationship between various inputs.

Harper and Shahani [10] used simulation for general surgery to alter queue policies and day-to-day scheduling. Results have shown the throughput of patients can be increased without additional resources. Harper and Gamblin [24] addressed wait list issues by using a visual interactive simulation within a structured environment, which also helped to build acceptance of simulation results amongst managers. Duguay and Chetonane [25] modeled emergency departments (ED) using discrete event simulation and found it to be an effective tool due to the complexity of healthcare systems. A regional hospital was studied to improve the current process through data collection and change of control variables. Several 'what if' scenarios such adding staff and exam rooms were performed. Kumar and Mo [26] also used discrete event simulation to develop bed prediction models. They modeled bed occupancy for three different wards and three different types of patients. Data regarding the number of admissions, average length of stay over one year, and number of beds in each ward was collected. The simulation results showed that simulation was a useful tool in predicting bed occupancy.

In order to optimize bed management, El-Darzi et al. [27] analyzed a geriatric department in a hospital using discrete event simulation to study the effect of length of stay, occupancy, and bed blocking on patient flow. The limitation in this approach is the model assumed that both the arrival and admission number were the same. Bagust et al. [28] determined the effect of emergency department admissions on hospital bed management.

Discrete event simulation modeling was used due to the randomness in the demand. The results of the model indicated that a hospital could have regular shortages if the average bed occupancy of the unit rises to 90% or more. The limitation to the proposed model is the length of the time required to run the model.

More recently, Troy and Rosenberg [29] explained a simulation model based on the Monte Carlo technique. The simulation model was built to identify admission requests, model entities, and find start and end times belonging to the intensive care unit (ICU) bed usage. The model calculated the confidence intervals of the wait times based on the cardiac patients since they are the patients who are admitted the most into the ICU. Costa et al. [30] proposed a model to calculate the number of beds in a critical care unit. This model uses the distribution of the data from different categories to determine the number of patients expected in a year, length of stay, and a target occupancy level. The model was based on queuing theory and computer simulation was used to solve the complex mathematical equations. Cochran et al. [31] proposed a model to balance bed utilization by reducing bed blocking. Queuing networks were first used to analyze the flow patterns, and then discrete event simulation was performed to maximize the flow.

Elbeyli and Krishnan [32] examined inpatient flow to identify bottlenecks and assess the impact of bed availability on the waiting time of the admitted patients in the ED before being transferred to other units of the hospital. Bottlenecks are the sources of long waiting times. Eldabi et al. [33] proposed a simulation model approach called the Modelling Approach that is Participative Iterative for Understanding (MAPIU). The main objective was to improve the understanding of the system by stakeholders. The research illustrated how the steps in a simulation model varied by different authors in the construction of a simulation model. The research proposed an alternative model to the existing simulation models that includes the participation of stakeholders in the model. Marshall et al. [34] proposed a model for patient flow based on the length of stay. The research focused on bringing together recent developments for inpatient flow modeling. For modeling the LOS, probabilistic solutions were used to quantify their impact and sustainability in supporting hospital management services.

Oddoye et al. [35] described the importance of a medical assessment unit to reduce the bottlenecks in acute patient flow in a general hospital. Simulation, with the help of goal programming, was performed to set the objectives and aid in decision-making. A visual interactive modeling system was designed for patient flow in the hospital. The advantage of this simulation model is it takes less time to run and the results obtained are consistent with the different scenarios tested. Changes in the resources were also verified to determine these effects on the system.

Many public health systems have been modeled with the use of simulation to analyze wait times. Managers have used simulation as a tool by managers to experiment with different resources to quantify how the hospital system reacts if they were implemented [36]. Davies [37] proposed a simulation model to determine the bottlenecks and identify the main cause as bed shortages for the situation.

Jun et al. [20] also reviewed literature on the application of discrete event simulation to hospital systems and determined that distributing patient demand over horizon improved patient flow by decreasing waiting time in outpatient clinics. Rohleder et al. [38] used simulation modeling to redesign phlebotomy and specimen collection centers. The main focus was to reduce average waiting times as well as their variability. Simulation was used to predict implementation problems and to improve results. In addition, an orthopedic outpatient clinic was modeled to improve process flow and patient scheduling and optimize staffing levels.

Simulation models have been extensively utilized in surgical suites to improve efficiency and reduce wait times. Blake et al. [39] used operation research techniques to analyze wait times in a surgery department. Capacity planning decisions were developed and performance was analyzed using discrete event simulation. The research examined various scenarios and studied the consequences of reallocating resources, maintaining standard length of stays, and various options for reducing wait times. Bowers and Mould [40] designed a simulation model to increase operating room (OR) utilization by scheduling deferrable patients into planned orthopedics blocks.

McLay et al. [41] performed a study on screening strategies for cervical cancer patients. They developed a simulation optimization model to determine the ages at which screening should be performed, which resulted in dynamic, age based screening policies. Simulation was used to predict the number of vaccines, and also provide information on screening policies that offered substantial economic savings.

Harper [42] proposed a framework for larger, robust models that highlights the significance of developing patient groups that are statistically and meaningfully correct. The research also suggests that outputs must provide detailed information to end-users. Everett [36] suggested that a simulation model must be understandable to health administrators and should involve them in the development process rather than just providing detailed information.

The proposed research analyzes the hospital beds in all departments rather than just in one department. This is a contribution to the literature because it takes into account the dependencies between departments. A critical consideration for hospital beds is the transfer of patients between departments and how this impacts the overall length of stay of patients. Therefore, the simulation model enables a unique set of scenarios to efficiently model the hospital units, patient's admissions, and wait times to improve bed management and quantify the impact on the overall system.

HOSPITAL BACKGROUND

For this research, the Sacramento Veterans Administration Medical Center (VAMC) was used to develop the simulation model. The Sacramento VAMC provides comprehensive health care services and has all acute beds, in which patients are treated for brief stays related to surgery recovery, disease, trauma, or illness. It consists of 50 beds distributed in the intensive care unit, transitional care unit (TCU), and medical surgical unit (MSU). Patients admitted to the hospital are assigned to the ICU, TCU, and MSU departments based on their level of acuity. The ICU consists of 10 beds, TCU consists of 16 beds, and MSU consists of 19 beds on the third floor and five beds on the fourth floor.

RESEARCH METHODOLOGY

In order to develop simulation model, data was collected from the Sacramento VAMC on patient movement throughout the hospital. The data was comprised of multiple large sets of data and spans across all major units within the hospital. Specifically, the data contained all departments and units within the hospital with the exception of behavioral health unit. Hence, the data is comprised of high fidelity information for each patient, which included admission time and date, discharge time and date, ward/unit of admission, ward/unit of discharge, and spanned from January 1, 2009 through December 31, 2014. The data set contained information on 23,019 patients. From the total data, the records from January 1, 2009 through December 31, 2013 were used for the analysis. Initially data was filtered in Excel to determine the details for each department individually. Therefore, the details for direct admission to a department for each patient and their length of stay were determined. In a similar manner the transfer data contained details of how patients moved throughout the hospital. In these transfers individual patients are tracked from admission to discharge with transfer information regarding the unit of care. However, it is important to note that these transfers may in many cases not directly correspond to a physical movement of the patient's location, but rather correspond to a lower or elevated level of care. Also, in some cases patients were elevated to levels that required a physical movement of the patient. The data on patient transfers spans from April 2014 to March 2015 and consists information for 1,129 patients. The data is used to calculate the length of stay of patients transferred from one department to another department. The data was filtered initially in Excel to separate transfer patients records individually by department. From the data, transferred patient's length of stay in ICU, 3 TCU, 3 MSU, and 4 MSU were calculated. The length and detailed information facilitated the statistical analysis associated with all patient flow within the hospital across the various units within the hospital.

The required data for the simulation model was based on the arrival times of patients, admission department, length of stay of each patient, discharge department, and department transfer data. The data was collected from patient's records and the Bed Management System (BMS) for five years. With the details of LOS of direct admission and transferred patients to ICU, 3 TCU, 3 MSU, and 4 MSU, the length of stay distributions were calculated using the input analyzer in ARENA and graphical evaluation (confirming the histogram with the distribution function). The input analyzer fits the best distribution to the provided data for each department. The Input Analyzer assures that these distributions are fitted to non-negative data using the in built feature auto data translation. Since the 3 TCU and 3 MSU data does not fit to any distribution in the Input Analyzer, so a user defined continuous distribution based on the probabilities are used as input distributions. Table 1 and Figure 1 show the graphical evaluation. All distributions were determined using actual patient data provided by the VA Hospital.

Table 1. Distributions for all departments

Department	Sample Size	Distribution Choice	Chi Square Value
ICU	1365	LOGN(63.1,68.5)	0.02
4 MSU	232	LOGN(37.3,30.3)+2	0.24
ICU Transfer	169	-0.5+WEIB(4.12,1.15)	0.75
3 TCU Transfer	279	-0.5+LOGN(3.63,3.26)	0.74
3 MSU Transfer	1397	-0.5+LOGN(3.71,3.8)	0.71
4 MSU Transfer	213	-0.5+LOGN(2.69,2.09)	0.33

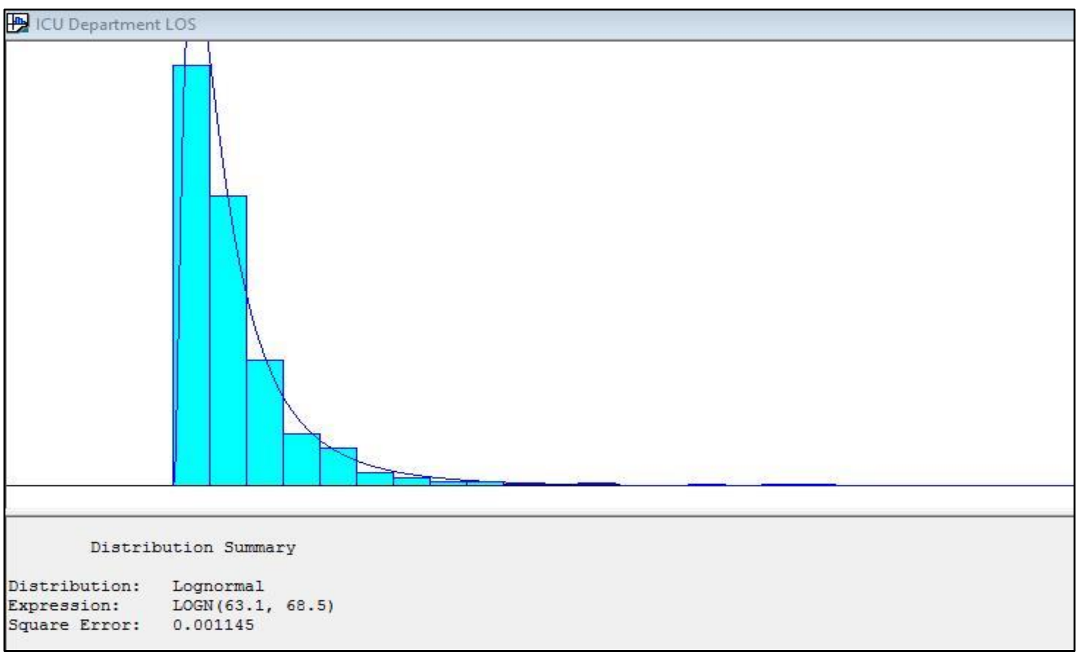

Figure 1. Graphical Distribution of LOS for the ICU Department.

For the simulation, patients admitted to the hospital move directly to their respective departments, such as ICU, 3 TCU, 3 MSU, and 4 MSU, if a bed is available. Otherwise, patients wait in queue in the emergency department. If a patient has a scheduled surgery, the surgery does not start until a bed is assigned to that patient, effectively guaranteeing the patient will have a bed after surgery. After the completion of a patient's derived LOS, the patient is transferred or discharged. Transfers and discharges were modeled based on the proportions obtained by analyzing the data provided, which indicated that 57.2% of patients are transferred out of ICU, 14.1% from 3 TCU, 11.6% from 3 MSU, and 49.3% from 4 MSU to another department. The remaining patients are discharged directly from that ward. Table 2 below summarizes the proportions for patient transfers between departments within the hospital.

Table 2. Proportions of Transfers by Department

Department Patient was Transferred from	**Department Patient was Transferred to**	**Percentage Transferred**
ICU	3 TCU	28.1%
ICU	3 MSU	26.7%
ICU	4 MSU	1.8%
ICU	Discharged	42.8%
3 TCU	ICU	2.2%
3 TCU	3 MSU	10.7%
3 TCU	4 MSU	1.2%
3 TCU	Discharged	85.9%
3 MSU	ICU	1.4%
3 MSU	3 TCU	4.3%
3 MSU	4 MSU	5.9%
3 MSU	Discharged	88.4%
4 MSU	ICU	1.1%
4 MSU	3 TCU	5.5%
4 MSU	3 MSU	42.7%
4 MSU	Discharged	50.7%

MODELING AND SIMULATION METHODOLOGY

The simulation model was developed using the ARENA© software package, which uses an entity-based, flowcharting for modeling dynamic processes. Entities in the simulation model proceed through a flow chart of the process and seize control of resources as they are processed. Resource units can be changed according to the patient flow requirements and results can be used to understand the changes in system behavior.

In the simulation model, patient flow is used to model the processes within hospital for the ICU, TCU, and MSU. The dynamic nature of patient arrivals to hospitals is embedded into the system. When the patients are admitted to MSU on the third floor, if the queue length is greater than three then they are shifted to the fourth floor. In the case of the ICU, if the queue length is greater than two then patients are diverted to another nearby hospital for treatment. Patients arrive into the system according to the real arrival times obtained for the four years of data (2009-2013). That is, the hospital's historical data is directly embedded in the model. In implementing the historical information of patient behavior into the simulation removes the need to estimate parametric statistical models to describe arrivals and discharges, as well as LOS stochasticity. Patient flow was simulated to develop a prediction model of hospital bed occupancy. Figure 2 provides the conceptual model for the simulation. The conceptual model for the simulation takes into account patient movement (transfers) between departments and was modeled using data from the BMS. The assignment and movement to beds were modeled using data directly from the Emergency Department Integration Software (EDIS) and BMS; therefore, it indirectly takes into account surgery cancellations and nursing shortages that are captured in the normal variability within the historical data. Anomalies or extreme conditions were captured in the data but were not considered in the model development. However, these conditions could be easily modeled with minor changes to the simulation model for "what if" scenarios.

The appropriate application of discrete-event simulations as an effective model is due in part to the temporally dynamic and stochastic behavior associated to the mixture of patient care needs. In that, patient mixture can vary from day to day; moreover, the healthcare needs of the patient can vary as well and have unforeseen characteristics or complications that impact the most common measures of performance such as, but not limited to, LOS, daily admissions distributions, daily discharge distributions, and other major factors that impact effective decision-making and process improvements methodologies. To this end, discrete event simulation has been widely accepted as a viable and effective modeling tool for hospital dynamics and stochasticity where the development of deterministic or stochastic models is not tractable.

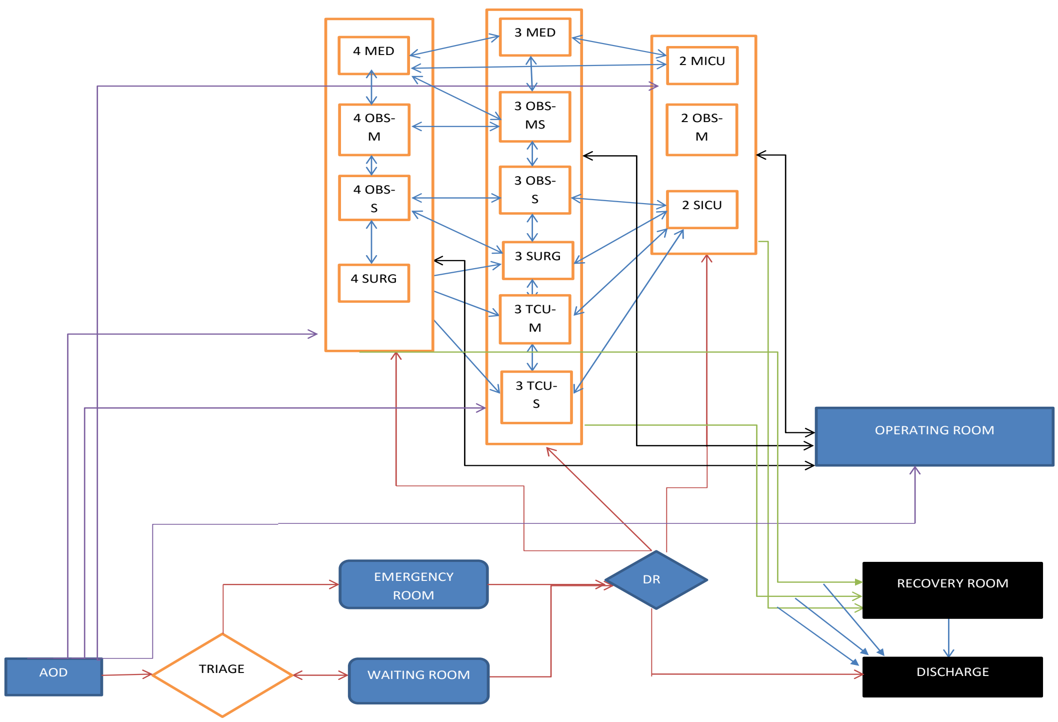

Figure 2. Conceptual Model for Simulation

Patients enter into the system according to the original arrival records of patients. A ReadWrite module is used to import the data from an Excel file. Since different kinds of patients admit to a hospital they must be routed to respective departments for care. Using the ReadWrite module each patient is assigned an attribute called type, which assigns each patient to his or her respective ward according to the data. After the patient is checked at the triage, patients move to their departments. A decide module is used to route patients based on conditions or proportions calculated from the historical data. When a patient is routed to a different department, the patient's attributes are changed with respect to that department, such as an ICU patient. A bed is allocated to the patient if there are available beds. If a bed is not available, the patient waits in queue until a bed is available. After a patient is assigned to a bed, the patient stays there for their treatment. This is simulated using the process module and seize delay logic, which seizes a bed for a patient whenever it is available for a specified amount of time. The release module is then used to release the seized resources after the patient LOS is completed. The length of stay for the patient is expressed in terms of a distribution. After the patient LOS is completed, the patient is moved from that bed and transferred to another department or discharged from the hospital. Bed cleaning occurs before another patient occupies the bed. Only after cleaning, the bed is available for another patient. The bed resource is set into a failure state for two hours after the patient vacates the bed, which then enables the bed to be available to another patient after cleaning. The patient is discharged or transferred to another department depending on the level of the care required using the decide module. The number of patients transferred or discharged is calculated in terms of the proportions from the actual data. After the patient is transferred, the attributes are changed accordingly; for example, an ICU patient may be transferred to 3 MSU.

The rule for patients waiting in queue is first in first out (FIFO), even though this is not followed clinically because many factors influence this decision. For example, a patient with complications that needs a higher level of care is given a higher priority for seizing a resource. However, the FIFO principle is used to reduce the complexity for the purpose of this model.

From the simulation model three hypotheses were developed to validate the model and test “what if scenarios”:

$H1_0$: There is no statistical difference between the simulated LOS and actual LOS values.

$H1_A$: There is a statistical difference between simulated LOS and actual LOS values.

$H2_0$: A change in bed turnover time does not reduce the number of people waiting in queue.

$H2_A$: A change in bed turnover time reduces the number of people waiting in queue.

$H3_0$: A reduction in LOS does not reduce the number of patients waiting in queue.

$H3_1$: A reduction in LOS reduces the number of patients waiting in queue.

With the large dataset provided, the inputs for the simulation model were calculated. The main inputs for the model were arrival times of patients, LOS, and department assigned to at admission. The arrival times of patients were calculated from the dataset and imported into the simulation model where each patient is admitted to their respective department.

The LOS data was calculated for each department and analyzed to determine the appropriate distribution. The data from the simulation was compared to the original data statistically. The simulation model provides in-depth details on waiting times, queues, average LOS by department, and total number of patients discharged by department.

In addition to comparing output performance measures, an animated version of the hospital bed usage was developed using the ARENA simulation package as shown in Figure 3. The simulation animation was to hospital administration to confirm patient flow and validate the expected output. In the animation, whenever a bed is occupied by a patient, the bed color changes to blue.

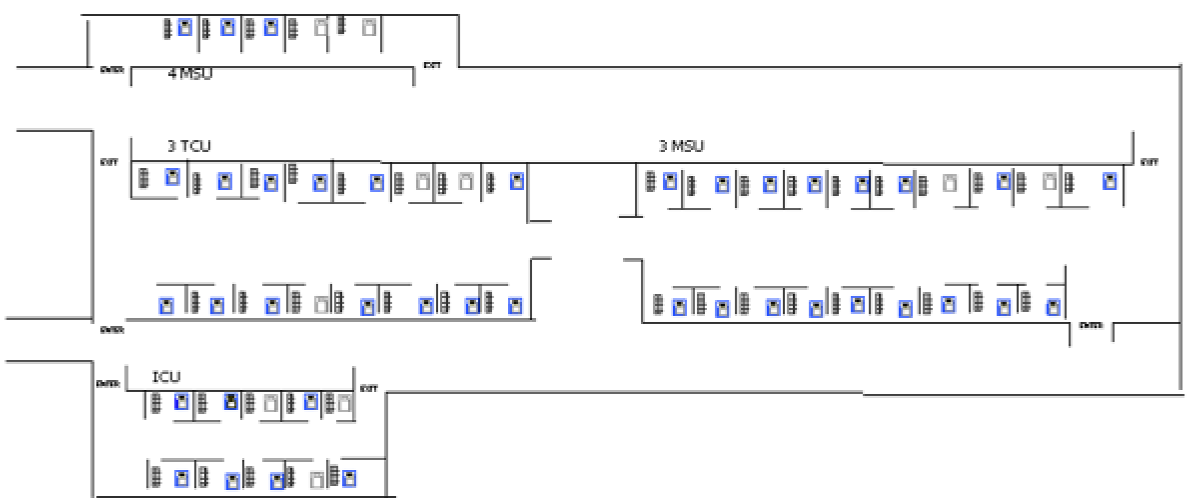

Figure 3. Bed Layout in the Arena Simulation

MODEL VERIFICATION AND VALIDATION

Verification of the model was performed in three stages. First, the arrival of patients were examined to confirm they were embedded into the simulation appropriately by exporting the arrival time information for each patient to an excel file using the ReadWrite module.

In the second stage, the model was verified using the check model function in Arena. Finally, the information logic was verified with the staff and administration of the hospital.

To determine if the actual LOS and simulated LOS values are different from each other both parametric and non-parametric tests were performed. Parametric tests are used to compare two samples that are normally distributed. However, non-parametric tests are used to compare two samples whose underlying statistical distribution are unknown or for samples for which the assumption of normality exists. A two-sample t-test is used in parametric tests and a Wilcoxon Rank Sum Test is used for non-parametric tests. It is the non-parametric equivalent to the two-sample t-test and is sometimes called as Mann–Whitney U test. The only assumption for this test is that the observations are independent. As these samples are not normally distributed and independent, a non-parametric test was used for the statistical analysis.

To ensure that the model is an accurate representation of the hospital system, initially the LOS data elements were verified. This included comparing the LOS predicted values from the simulation model to the actual data for year 2014. A Wilcoxon test was performed since the data were non-normally distributed.

The first hypothesis was developed to determine if there was a statistical difference between the simulated (predicted) and actual LOS. The purpose of this hypothesis was to validate the simulation model.

> $H1_0$: There is no statistical difference between the simulated LOS and actual LOS values.

> $H1_A$: There is a statistical difference between simulated LOS and actual LOS values.

A one-way analysis was performed initially to characterize how the distribution of LOS values differs between the actual LOS and simulated LOS for each department. The ANOVA tests the null hypothesis that samples in two or more groups are drawn from populations with the same mean values. The variable of interest and the factor examined is LOS values. There are classified in two groups as Simulated LOS values and Actual LOS values.

Table 3. P-values of LOS simulated and actual values

Test	Hypothesis	P-value
Wilcoxon test	There is no statistical difference between the ICU simulated LOS and actual LOS values.	0.64
Wilcoxon test	There is no statistical difference between the 3 TCU simulated LOS and actual LOS values.	0.15
Wilcoxon test	There is no statistical difference between the 3 MSU simulated LOS and actual LOS values.	0.09
Wilcoxon test	There is no statistical difference between the 4 MSU simulated LOS and actual LOS values.	0.40
Wilcoxon test	There is no statistical difference between the transfers to ICU simulated LOS and actual LOS values.	0.87
Wilcoxon test	There is no statistical difference between the transfers to 3 TCU simulated LOS and actual LOS values.	0.25
Wilcoxon test	There is no statistical difference between the transfers to 3 MSU simulated LOS and actual LOS values.	0.06
Wilcoxon test	There is no statistical difference between the transfers to 4 MSU simulated LOS and actual LOS values.	0.10

The one-way ANOVA technique was used to compare means of simulated LOS values and actual LOS values. The results showed no statistical difference at a significance level of 0.05. Since the P-value statistic was greater than 0.05, we fail to reject the null hypothesis; therefore, there is no statistical difference between the simulated and actual LOS. The P-value was greater than 0.05 indicates that the model was performing correctly. Table 3 shows the Wilcoxon tests for 3 MSU, 3 TCU, 4 MSU, and ICU, Transfer to ICU, Transfer to 3 TCU, Transfers to 3 MSU, Transfers to 4 MSU. Therefore, it was concluded that the model performed as designed and the design was an accurate depiction of the actual hospital system.

ANALYSIS OF SIMULATION RESULTS

Arena generates output reports which give details about the patient waiting times, average length of stay of patients of each department, average queue length of patients, average waiting times, statistics of each department admissions, and records of patients transferred to another hospital because of restricted queue length at ICU department. After validating the proposed simulation model, several what if scenarios were analyzed to determine performance measures and quantify how these impact the waiting time and waiting queues of patients. Three scenarios where tested, including:

1. Scenario 1: Reduce the number of people waiting in queue and waiting time by decreasing the bed turnover time.

2. Scenario 2: Reduce the number of people waiting in queue and waiting time through reducing LOS.

3. Scenario 3: Addition of two beds to 3 TCU and 4 MSU.

SCENARIO 1: REDUCE THE NUMBER OF PEOPLE WAITING IN QUEUE AND WAITING TIME BY DECREASING THE BED TURNOVER TIME

Bed turnover time indicates the time elapsed between a discharged patient and another admission. Bed cleaning time is also included in this time. In the first scenario, the purpose was to determine if reducing the bed turnover time from two hours to one hour affected the number of patients waiting in queue. A reduction in the cleaning time can be achieved through adding additional housekeeping staff. The data for the number of patients waiting in queue with and without reduced bed turnover time was analyzed using the simulation model. The data was compared statistically to determine if there was any change in the number of patients waiting due to a reduction in the bed turnover time.

The scenario relates to the second hypothesis, which was developed to determine if there was a statistical difference in the number of people waiting in queue when the bed turnover time was reduced. This "what if" scenario was developed to determine the impact of bed turnover time on the number of patients in queue. The bed turnover time was reduced from a two hour to one hour time process in all departments. The number of people waiting in queue was collected for both time periods from the simulation model using the statistic module.

$H2_0$: A change in bed turnover time does not reduce the number of people waiting in queue.

$H2_A$: A change in bed turnover time reduces the number of people waiting in queue.

A one-way ANOVA technique was used to compare means of the number of patients in queue by changing the bed turnover time. This data was collected using the statistic module in ARENA. Since these samples were not normally distributed and independent, a non-parametric Wilcoxon test was performed.

Table 4. P value for reduced bed turnover time

Test	Hypothesis	P value
Wilcoxon test	A change in bed turnover time does not reduce the number of people waiting in queue	<0.001

The results showed no statistical difference at a significance level of 0.05. Since the P-value was less than 0.05, we reject the null hypothesis; therefore, there is a statistical difference between the number of patients in queue when the bed turnover time is reduced. Table 4 shows the Wilcoxon tests for the second hypothesis. Statistical results for reduced bed turnover time.

The average waiting time for patients and the average patients waiting in queue in hospital system were 7.95 hours and 2.93 patients, respectively. When the bed turnover time was reduced from 2 hours to 1.5 hours both measures were reduced to 7.18 hours and 2.55 patients. A further reduction to a 1 hour time period reduced the average waiting time to 6.10 hours and an average queue of 2.33 patients.

SCENARIO 2: REDUCE THE NUMBER OF PATIENTS WAITING IN QUEUE AND WAITING TIME THROUGH A REDUCTION IN LOS

Improper planning can lead to an increase in the patient's LOS, which directly affects the other patients. In particular in this hospital, the number of patients the ICU department can hold in queue is two. When there are more than two patients in queue for the ICU, they are transferred to another nearby hospital. The queue can be reduced by decreasing the patient LOS by proper planning, improving the rounds of doctor, and timely discharge of patients. For this analysis, the LOS for each direct admission department and transfer department was reduced by 10 hours to analyze its impact on the waiting queue. The patients LOS can be reduced by discharging the patients more effectively and decreasing the discharge time. Data for the patients waiting in queue was gathered through the simulation for before and after the change in the LOS. Statistical analysis was performed to determine if there was an impact on the waiting queue due to a reduction in the LOS. The third hypothesis was developed to determine if there was a statistical difference in the number of people waiting in queue when the LOS was reduced.

$H3_0$: A reduction in LOS does not reduce the number of patients waiting in queue.

$H3_1$: A reduction in LOS reduces the number of patients waiting in queue.

A one-way ANOVA technique was used to compare the means of the number of patients in queue by changing the LOS values. The LOS values were reduced by 10 hours for direct admission departments and by one day for transfer departments. This data was collected using the statistic module in ARENA.

Table 5. P value for reduced LOS.

Test	Hypothesis	P value
Wilcoxon test	A reduction in LOS does not reduce the number of patients waiting in queue	<0.001

The results showed a statistical difference at a significance level of 0.05. Since the P-value was less than 0.05, we reject the null hypothesis; therefore, there is statistical difference between the number of patients in queue when the bed turnover time is reduced. Table 5 shows the Wilcoxon tests for the third hypothesis.

With the reduction in LOS by 10 hours for each department, there is a change in the average patient wating times and average patient queues. Both measures were reduced in terms of waiting time from 7.95 hours to 2.07 hours and number in queue from 2.93 to 0.80 patients. From the simulation model, the number of people being transferred to another hosptial because of high queue length can also be estimated. In particular, at the VA Sacramento Hospital, the maximum number of patients allowed waiting in queue for admission into the ICU Department is two. If the waiting number is above two patients, these additional patients are routed to another hospital. Figure 4 provides the average number of patients waiting in queue based on the actual data. LOS values are reduced by

10 hours for direct admission departments and transfer departments. The reduction in LOS also reduces the number of patients waiting in queue as shown in Figure 4.

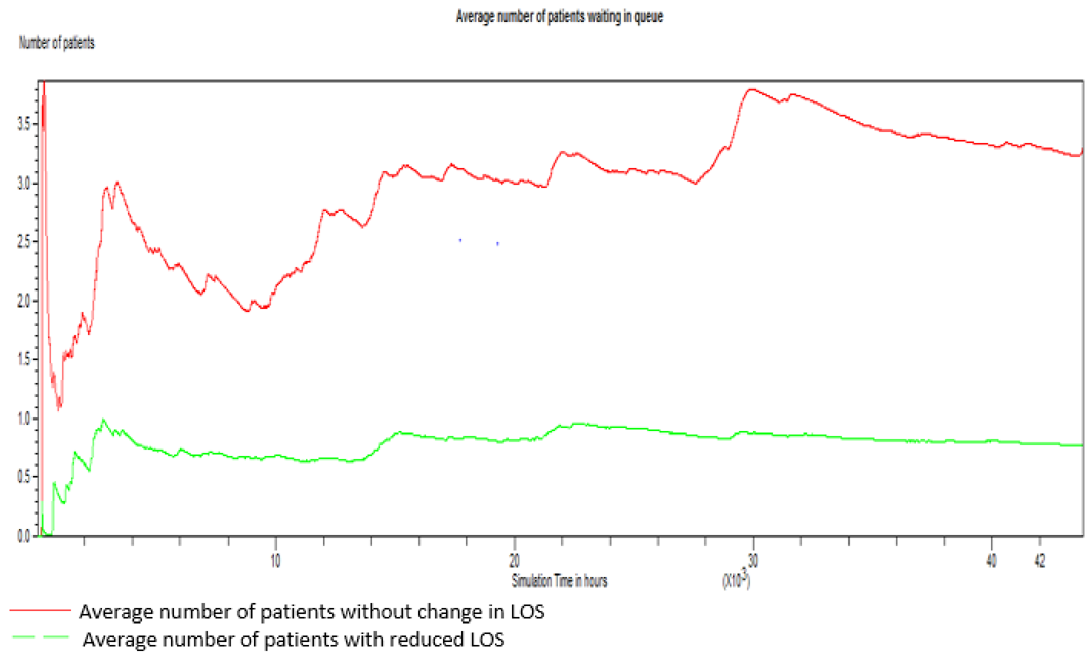

Figure 4. Average number of people waiting in queue with reduced LOS

SCENARIO 3: ADDITION OF FOUR BEDS TO 3 TCU AND TWO BEDS TO 4 MSU

From the results obtained, the data shows that the 3 TCU and 4 MSU have large waiting times for patients, 8.95 and 13.10 hours, respectively. The waiting times are due to the lack of available beds for patients. The addition of beds may reduce the waiting times, number of patients in queue, and length of stay. Tables 6 and 7 show the comparative analysis of the 3 TCU and 4 MSU with addition of four beds and two beds respectively to each department.

Table 6. Comparative analysis for 3 TCU with 16 and 20 private beds

3 TCU	Average Waiting Time (hours)	Average Number of Patients in Queue	Average Length of Stay (hours)
16 Beds	8.95	1.57	71.78
20 Beds	0.40	0.07	62.92

Table 7. Comparative analysis for 4 MSU with 5 and 7 private beds

4 MSU	Average Waiting Time (hours)	Average Number of Patients in Queue	Average Length of Stay (hours)
5 Beds	13.10	0.37	52.15
7 Beds	2.77	0.1	42.18

CONCLUSIONS AND IMPLICATIONS

A simulation model of the hospital system was constructed using ARENA to understand admission and transfer patients length of stay, waiting time, and queue lengths. Through the analysis of the historical data and the simulation model it was shown that the wait times are highest for the 3 TCU and 4 MSU and transfers to 3 TCU with an average waiting time of 8.95, 13.10, and 9.07 hours, respectively. With the current LOS and the bed turnover time, the patients wait in long queues before being admitted. If the following reccommendations are implemented there will be decrease in the patients waiting time.

Reducing the length of stay of patients and decreasing the bed turnover time allows resources to become available for another patient quickly, which improves patient access to care. The average wait times for 3 TCU and 4 MSU and transfers to 3 TCU will reduce to 1.74, 2.77, and 1.86 hours, respectively.

The number of people being transferred to another hospital because of high queue length at ICU can also been reduced with reduction in LOS. A reduction in 10 hours in LOS will result in a decrease of the average number of patients in queue from 11 to 4 patients. The statistics of patient waiting times and waiting queues for each department helped in determining the appropriate number of beds for each ward.

The departments with the highest waiting times and waiting number can be reduced by addition of beds. From the simulation results indicated that 3 TCU and 4 MSU have the highest waiting time and waiting queues. Therefore, an addition of 4 beds to 3 TCU and 2 beds to 4 MSU reduce the average waiting times of 3 TCU and 4 MSU from 8.95 to 0.4

hours in 3 TCU and from 13.10 to 3.49 hours in 4 MSU. In addition, the waiting queue was reduced from 1.57 to 0.07 in 3 TCU and from 0.37 to 0.10 in 4 MSU.

Through the use of simulation, the operational behavior of the hospital was determined. The simulation model was used to determine patient statistics, average waiting times, average length of stay of direct admitted, and transferred patients. This model can be applied to any hospital which demonstrates indepth details of its functionality. This model allows hospital administrators to model their hospital and quantify the behavior of the hospital with respect to changes in resources, LOS, and bed turnover times. This methodology helped to solve the problem faced in hospital in real terms patient waiting times due to a limitation of beds.

Based on the findings from the study the following additional recommendations are proposed to reduce waiting times, number of patients waiting, and number of patients transferrred to another hospital due to lack of beds. A clear and quick notification of the discharge of patients should be implemented to provide timely notification to the cleaning staff, which will reduce delays in the cleaning time. Patient status and level of care required should be examined frequently to reduce the length of stay of patients and reduce the need for patients to be transferred to another hospital due to long queues. Finally, the policies and practices of scheduling and discharge should be reviewed and updated as necessary.

LIMITATIONS AND FUTURE RESEARCH

Due to the limitations in the data, the current model only accounts for a maximum of one transfer between departments for each patient. Data was not available on multiple transfers. In reality, patients that require a high level of care or have frequent changes in their condition can be transferred more than once during their hospital stay.

After a patient is admitted to a department, they may be transferred to another department. In the current model, patients are transferred to other departments using proportions calculated from historical data. However, if this data was available it could be modeled more effectively. In addition, the bed cleaning time is a constant of two hours in the proposed model due to a lack of available data. Historical data of bed cleaning will enable the determination of the appropriate statistical distribution.

In the proposed model the resources are beds. However, a simulation model with resources using nurses, doctors, and beds could provide a more accurate and robust model. Finally, the development of a simulation model with optimization values to determine better usage of resources and estimates costs of each activity could be developed. There are many extensions to this work which are currently under research.

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SECTION

2. CONCLUSION

With the increase in population, the number of hospital's patients is also increasing. There is a large difference between the rate of patients arriving at the hospital and the rate of increase for a hospital's resources. Several of the studies that have been conducted based on this issue were grouped in this research study in order to determine various methods that have been already used.

The simulation model developed in this research provided solutions to reduce the long waiting times that patients face in hospitals. This model helps to understand the behavior of hospitals by providing estimates of waiting times, waiting numbers and lengths of stay for patients in individual department. This model also helps in planning and decision making in terms of increasing beds and staff. It allows a facility to run the hospital virtually with different possible and impossible cases and so that the results can be evaluated. The model has the capability to solve different scenarios and which help determine the optimal solution. Though the model may not give the accurate results, it gives the most appropriate results.

The research has filled some of the gaps in the current literature of bed management issues, as well as that of decision methods for bed management. Important extensions from this research, however, will bring more robust decision support simulation models for bed management in healthcare.

The research was limited to the case of bed management of four departments in the hospital. An immediate extension to this work would be to consider cases that include all departments in the hospital. In this research models were developed using the beds as resources, however it would be more effective if nurses, doctors and staff were incorporated in the model. This would help to analyze the entire working climate and patient movements in hospital system. An important area of future work from this research would be to consider integrating the data directly into the simulation from hospital data systems. Therefore, future work is needed to fill this gap.

VITA

Raja Anvesh Baru was born on 4th May 1993 in Khammam, India. He received his Bachelor of Science degree in Electrical and Electronics Engineering from University College of Engineering, Osmania University in Hyderabad, India.

In 2014, Raja began attending Missouri University of Science and Technology (Missouri S&T) in Rolla, USA. In December 2015, Raja received a Master of Science degree in Engineering Management.