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Abstract

The report underhand is a combination of phase 1 & 2 of a study aiming to develop an understanding about bed assignment problems and analyzing the performance of the bed allocation process currently adopted at LAU Medical Center – Rizk. Bed assignment problems (BAP) have been a huge area of interest due to its implications on a hospital's operations and costs. Also, assigning beds to patients at hospitals could highly affect key performance indicators. Several researchers have adopted numerous mathematical models and other techniques to try and tackle this problem. Linear programming and simulation modeling are the methodologies used in this research. A literature survey was conducted on bed management while focusing on Linear Programming and Simulation Modeling as optimal methodologies. The latter is followed by an application of linear programming and simulation modeling at LAUMC Rizk. The aim of both methodologies is to develop an optimal bed assignment strategy. The objective function of the Linear Programming Model suggested is to maximize the admission of patients in the system based on criticality. The simulation model was constructed using ARENA which aided in the data analysis step. After validating the simulation model, alternative bed allocation scenarios were developed and the optimal scenario was selected as an improvement for the hospital. Also, this research suggests general improvements to improve bed utilization at the hospital. Finally, in light of the current COVID 19 pandemic this research suggests an optimal strategy for the admission of infected patients.

Chapter 1: Introduction

1.1. Problem Statement

There are a lot of factors that play a role in ensuring that patients get the most efficient and effective healthcare service. Research related to the latter have always aimed at optimizing hospital resources in order to increase patient safety, improve quality of service and minimize any errors that can rise throughout the patients stay at the hospital. It would be logical to state that hospitals want to avoid adding their resources capacities which would have detrimental financial impacts. Instead hospitals want to enhance operational efficiency, optimize the utilization of resources and also minimize cost. Research and methodologies to improve patient healthcare at a reduced cost have been a main concern for the health industry worldwide. Noting that in the Middle East region it has been a major dilemma to deliver high quality healthcare due to the increase in costs, rise in demand and patient's expectations (Deloitte Middle East, 2015; Mourshed, Hediger, & Lambert, 2006).

The correct allocation of resources at a hospital determines whether patients are going to meet their expectations or not. There is no doubt that the most significant resources at hospitals are beds. According to a study developed by Bayram et al. (2013), which aimed at identifying critical hospital resources necessary for four specific admitted-patient's scenarios, they found that hospital beds are most critical. Unfortunately, in Lebanon it has been determined that the average occupancy rate for hospitals is 90% (Ghanem, 2019). Also, Sleiman Haroun, Chairman of the Syndicate of Private Hospitals, stated "Hospitals are sometimes unable to accept all the patients due to a shortage in the number of beds" (Ghanem, 2019). To further emphasize on the shortage of beds in Lebanon, a survey conducted by El-Jardali et al. (2010) found that 61.8% of Lebanese hospitals have 20-100 beds, 19.7% have 101-200 beds and 9.3% have more than 200 beds. Hospital beds are a very critical resource to serving patients; however, they also create an area where patients would queue for being treated.

In this paper we focus on the necessity of adopting an optimal bed assignment model to ensure efficient and nimble hospitals in Lebanon. The latter has been proven to affect all of patient care, patient flow, patient and staff satisfaction and the hospital's operating margin.

1.2. Purpose of Study

Without a doubt, we can say that the hospital's most important asset is their patients (M. Yaghoubi et al., 2017). Therefore, targeting patient's needs and inclinations has turned into a significant supporter for improving consideration conveyance, improving patient fulfillment, and accomplishing better clinical results. Haj-Ali et al. conducted a cross-sectional study of six hospitals in Lebanon (2014) to measure patient satisfaction using the SERVQUAL model (Parasuraman et al., 1988). The model assesses five dimensions of quality: reliability, assurance, tangibility, empathy and responsiveness. As a result, 76.34% of the patients were unsatisfied with the quality of services. In addition, according to Ibrahim et al. (2019), health expenditure (total % of GDP), also has significant impact on the efficiency of the healthcare system. The Institute for Health Metrics and Evaluation (IHME) reports that in 2016 the Government's health spending per person in Lebanon is $250. Comparing that number to a developed country, like France, for example, the government's healthcare spending per person is $3985.This big gap in the investment for the health sector calls for a need of an efficient model to optimize resource allocation with an acceptable service quality. The drive to reform health care is highly correlated to enhancing the methodology in which care is delivered.

1.3. Description of Methodologies

1.3.1 Linear Programming

Linear programming (LP) seeks an optimal allocation of resources subject to constraints and requirements in order to minimize or maximize a factor of interest. It translates a real life decision problem into a mathematical model characterized by its decision variables that the linear program aims to determine by optimizing the objective function (Vanderbei, 2014). LP is also defined by constraints that link the decision variables to known limitations and requirements. It is widely used in diverse areas such as airlines, agriculture, energy planning, hospitals, etc.

All those attributes make LP an ideal candidate for the bed assignment problem. In fact, the latter searches for an optimal allocation of beds that either maximizes utilization/profit, minimizes cost of misallocation or both. This problem is also subject to constraints such as capacity, nurse availability, isolation, preferences, etc. By converting the numerical information and verbal descriptions of the problem at hand into a mathematical formulation that defines the relationships that join the various decision factors, LP can evaluate the many alternatives based on the constraints and return an optimal bed allocation solution. This technique also guarantees objective decision making.

1.3.2 Simulation Modeling

Simulation modeling aims to meticulously translate the actual system to a digital prototype in order to analyze its performance under varying conditions. It is used in many fields such as manufacturing to reveal bottlenecks or even in-service industries to evaluate queues.

A simulation model can replicate the logic of a system based on descriptive and statistical data that define the flow of entities in the model's processes and stations (Snow, 2002). Each activity in the prototype is characterized by its resources and its completion rate calculated from a sample distribution function. Many logical rules can dictate the motion of entities in the system such as decision nodes that distinguish between different entities attributes.

A simulation model is very useful in the bed allocation problem since it is based on the actual hospital data and thus depicts the system as it is. It also clearly shows the patients' flow in the system and eventually the capacity problems. By highlighting the issues that the allocation problem faces, it is easy to create tangible and effective solutions. Simulation is an effective tool that compares the system before and after the improvements thus quantifying the added value of the enhanced model.

1.4. Project Plan

Different engineering tools and methods were used in order to properly develop a strategy and plan to achieve the problematic set for this project. The aim and importance of a refined project plan is to properly guide the team in identifying goals, setting deadlines and defining roles. The tools used for this plan are provided in the appendix of the report. Primarily, the team created a Google Drive folder which acted as the main platform of communication and sharing progress. The folder was also shared with the team's advisor for constant follow up. Second, a Mind Map was developed in order to organize the team's thoughts. It was a creative tool used to decide on the main ideas related to the project. After developing the mind map, a Work Breakdown Structure was established to arrange and systemize the project tasks in different levels. These levels vary from general ones moving into more detailed sublevels. Fourth, the team used a Gantt chart to monitor progress, follow up on deadlines and visualize the timeline for each task. Through the Gantt chart the team was able to see the percentage completed of each task and followed up on whose responsibility it is to reach a 100% with the Linear Responsibility Chart. The latter was used as a tool to divide the tasks among each team member and equally assign a level of responsibility on each one. Finally, the Critical Path Method helped the team in determining the critical activities and the critical path. Accordingly, it showed the team the approximate total project duration based on the durations put in the Gantt chart.

1.5. Hospital Information

This research presented was developed in collaboration with LAU Medical Center-Rizk Hospital. Rizk Hospital is a private hospital with approximately 160 beds and a high occupancy rate. It has been operating in Lebanon since 1925 and has been working on advancing the healthcare system. The hospital is divided into five buildings (A,B,C,D and E), where the different hospital units are located in 3 buildings (A, B and D). The clinics are found in building C whereas the offices are in Building E. Moreover, Rizk has an emergency unit with 35 beds which are allocated for daily surgeries. Currently, the bed assignment process at Rizk is as follows: during the morning shift, the case manager checks the updates that occurred during the night shift on the hospital database. The manager double checks on the discharge cases for the day to forecast potential empty beds. Accordingly, the manager works on accelerating the discharge process in order to admit more patients during the day. All throughout the shift, the manager receives updates on discharged patients, potential discharge cases, recently admitted patients, potential patients, emergency and transfer patients and surgery patients in order to advise on available beds. Constant coordination takes place between the nurses, case manager, ABC (Admission, Billing & Collection) manager, medical director and admission officer for the information in the hospital to flow smoothly and enhance the admission and bed assignment process. Detailed information of the hospital's operating system will be explained in Chapter 4.

1.6. Paper Division

The remainder of this paper includes the following: Chapter 2 presents a literature review on bed assignment problems and solutions adopted by hospitals to tackle the latter. Also, it will discuss the history and development of the methodologies used in the research which are Linear Programming and Simulation Modeling. Next, in Chapter 3, several Linear Programming applications in hospitals, which were used as a solution technique for bed assignment problems, will be discussed in detail. Finally, a conclusion will wrap up the work established and a detailed plan of future work.

Chapter 2: Bed Management Literature Survey

This section tackles two main concepts. First, it will tackle the history and development of the methodologies that will be used in this research. Noting that the tools used in this research to develop an optimal strategy for bed assignment problems are Simulation Modeling (SM) and Linear Programming (LP). Second, it will be highlighting Bed Assignment Problems (BAP) and how the issue was raised in the first place. That latter will discuss when how Bed Assignment Problems evolved by mentioning the engineers that sought to find a solution to such complex problems in hospitals.

2.1. Methodology

The use of Simulation Models and Linear Programming Methods for scheduling bed assignments is not new. In fact, both methodologies have been used to schedule other medical processes. When it comes to Simulation Models, it has been used to create a realistic representation of numerous healthcare processes. The latter mainly focuses on simplifying the understanding of different situations that could arise, the logistics involved and the decision making process involved in the healthcare system. For instance, a research developed by Zhang et al. (2018) identified the following types of simulation models used for non-technical skills training in healthcare logistics: (1) Discrete-event simulation in single category and single unit scenarios, (2) Discrete-event simulation in cross-departmental and cross-institutional and (3) Agent- based simulations & participatory simulations. When it comes to Linear Programming, it has led to revolutionary solutions for several problems in the healthcare industry. For example, linear programming has been used as a method to develop balanced diets at lesser costs and it has been identified as a replacement to planning critical medical aspects (Zhang et al., 2018).

Sections 2.1.1 and 2.1.2 will explore in detail the history and development of both LP and SM.

2.1.1. Linear Programming

In order to better understand the history and the elements that triggered the creation of linear programming, a dive into the decision-making of military institutions is a prerequisite. Hillier and Lieberman (2010) pinpointed that military establishments had been witnessing a high increase in the complexity of their operations which called for a change in computational strategy. According to Dantzig (1963), before 1860, a Supreme Commander was solely responsible for the planning of operations. The need of General Staff of experts to assist him soon became a necessity to plan the military and economic activities in a way that complies with all the plans and constraints of all the departments. The military planning operation was further divided among staff agencies in 1917. During World War 2, military staff planning became so time consuming and complex that "program monitoring function" was developed in 1943 to coordinate the work better (Dantzig, 1963). Hillier and Lieberman (2010) noted that the methods used to assist the planning process eventually led to the creation of a scientific programming technique after the war. The need to efficiently coordinate and plan military resources and staff has long been examined, but two major elements triggered its solution: the creation of powerful electronic computers and the inter-industry model (Dantzig, 1963). In 1947, the "Project Scientific Computation of Optimum Programs" intensively worked on the generalization of the inter industry approach to overcome its limitations which lead to the creation of linear programming and the simplex computational method in 1947 (Dantzig, 1963). As stated by Todd (2002), LP was adopted and experimented on widely in the decades to follow. Indeed, in the 1950s, the theoretical basis of LP was developed and it was applied to industrial settings. The 1960s witnessed the beginning of large scale LP and the 1970s gave rise to the theory of computational complexity (Todd, 2002). Nevertheless, LP was widely studied by professionals of diverse fields and applied in many classical theories such as game theory and linear inequality theory (Dantzig, 1963). It is important to note that many economical applications such as the Leontief input-output model and mathematical theories such as the Hitchcock transportation problem also indirectly influenced the creation and development of the LP method (Dantzig, 1963). This OR tool's scope widened throughout the years to reach countless other industries such as aerospace, healthcare, logistics and supply chains (Hillier and Lieberman, 2010).

2.1.2. Simulation Modeling

The history of Simulation goes back to 60 years and ever since it has been developed as a tool of choice for operational systems analysis. Research by Roberts and Pedgen (2017) states that the four distinct worldviews of simulation dominant are: events, activities, processes and objects. These worldviews were developed in the 1960's by the pioneers of simulation: Tocher, Markowitz, Gordon, Dahl and Nygaard. Keith Douglas Tocher, a simulation pioneer, was mainly involved in the manufacturing industry. When he was working with United Steel Companies he developed the General Simulation Program and Activity Cycle Diagrams (Goldsman et al., 2010). The General Simulation Program

(GSP) was the first simulator to be developed, it was a tool mainly used to systematically construct an industrial plant. Tocher, describes the GSP as a set of routines necessary for all simulation programs as follows: Initialization, Time and State Advance, and Report Generation. Moreover, Tocher defined time and state control variables in an industrial plant. Machines cycle through states such as: busy, idle, unavailable and failed. Also, state progression could be either time-based or state-based (as cited in Goldsman et al., 2010). The GPS later evolved to General Purpose Simulation System (GPSS) by Geofferey Gordon, it was mainly designed to facilitate faster simulation modeling for complex teleprocessing systems. Roberts (2017) found that Process Modeling comes in the form of GPSS and it views the world as transactions that move through a model composed of blocks with a certain functionality. The second milestone Tocher achieved in simulation was the Three-Phase Activity-Scanning method for time control. The method involves advancing time to the next scheduled event which is time-dependent, the processing associated with the one or more time dependent events and the processing of other conditional events which are conditional on the occurrence of B-Event's (Roberts & Pegden, 2017). The second pioneer of Simulation is Harry Markowitz, who worked with RAND Corporation which is involved in providing military services for the United States Armed Forces. Markowitz is known for the creation of SIMSCRIPT, a general language with simulation capabilities. Luanne Johnson conducted an interview with Markowitz where he discussed how SimScript came about, and he claimed that two theories of his own allowed the birth of Simscript. His first theory rooted from the struggle of integrating the core processes of an Air Force and essential operations of a manufacturing facility in computers. Therefore, he concluded "What needed were reusable subroutine packages that you could put together in different applications" (Johnson, 1986). After that, Markowitz applied this theory on job shops at General Electric with a method titled "Electric Manufacturing Simulator, GEMS" which would allow flexibility in packaging through reusable subroutines. However, he later realized that the reusable subroutine was not totally reusable and flexible. The latter, lead to the emergence of his second theory behind Simscript and he states the following, "My theory was that what we needed a language that would allow you to create, destroy, file, remove, cause events and so on" (Johnson, 1986). Finally, Ole-Johan Dahl and Kristen Nygaard are the pioneers of object-oriented programming through their development of both programming languages SIMULA 1 and SIMULA 67 (Goldsman et al., 2010). The latter contribute to the description, interaction, reactivation and suspension of processes. Goldsman (2010) also mentioned that

SIMULA added flexibility in class declaration in terms of process description and is known as one of the most influential simulation languages.

2.2. Bed Assignment Problem

When approaching the history of the field, it all started when Monge (1784) who investigated one of the first combinatorial optimization problems called the assignment problem by tackling it as a transportation problem (Alexander Schrijver, 2005). Then, the first published algorithm for the assignment problem was written by Easterfield in 1946. However, it was until 1951 that Dantzig formulated the assignment problem as a linear programming problem that converges into an integer optimum solution. With the development of statistical methods and simulation modeling in the 20th century, the first clinical trial was recorded after World War II (Olsen et al., 2010). Many methods have been developed over time to approach the BAP; the following are a few examples:

2.2.1. Linear Programing and BAP

The BAP's structure makes it an ideal LP candidate. Indeed, it aims to assign each patient an appropriate bed while respecting a set of constraints such as medical needs, clinical conditions and personal preferences (Guido, Groccia, & Conforti, 2018). One of the first models that tackled the decision process followed by hospital experts was the computer-based decision-making system developed by Clerkin et al. (1995). But Schäfer et al. attribute the focus the BAP has been getting to the formulation Demesteer et al. have provided in 2010 despite it not accounting for many real world constraints. For instance, the model disregards the difference between emergency and elective patients. It also ignores the doctor and nurse's specific objectives. Another one of its flaws is its static offline planning operation that highly defies the dynamic nature of hospitals (Schäfer et al., 2019). But despite its shortfalls, many researchers took this model as a foundation for their formulations. In fact, based on that first LP model, Bilgin et al. (2012) and Range et al. (2014) worked on the computational efficiency of the problem. Others contributed to the formulation by incorporating upstream planning problems like surgery (Ceschia and Schaerf, 2016). Each model developed added value to the BAP by introducing a new constraint or accounting for uncertainty using a new method. For instance, Lei, Na, Xin, and Fan (2014) presented a mixed ILP formulation that includes the effects of the deterministic and stochastic length of stay of patients and added constraints on surgery capacity. LP has proved to be an essential part of the BAP solution. Real life applications, such as the case study conducted by Schäfer et al. (2019) in a large German hospital prove its importance through key performance indicators like the overflow or the utilization of the resources. As for the solving methods used, Bilgin et al. (2012) developed a hyper-heuristic approach to solve the BAP by working on finding the best level of trade-off between the solution's quality and the problem run time. Range et al. (2014) used the column generation approach to generate a solution fast. Moreover, linear Programming (LP) has been seen as an opportunity to solve complex hospital problems. Numerous factors need to be considered when developing such a model and thus several models exist with different objectives, parameters and constraints depending on the system of the hospital. For instance, models could differ based on the capacity of the hospital, the policies it adopts and its performance metrics. Here comes the role of one of the primary steps in developing an LP model which understands the problem at hand in order to describe the respective objective. The linear program should be modeled in a way that reflects the hospital goal. Thus, objective functions related to bed assignment problems vary greatly from minimizing total assignment cost to maximizing nurse staff usage and even minimizing the maximum number of clinical departments in one cluster. Moreover, according to He et al. (2018), performance metrics differ based on the problem defined by the researcher and categorized the measurements used in modeling bed management strategies as follows: (1) Emergency department related, (2) Inpatients units related, (3) Patients related and (4) Inpatients units related. Another significant step in LP modeling is stating the respective constraint. Constraints related to bed assignment models can be based on patient's perspectives and resources perspectives. Patient's perspective constraints can be patient types, disease type, patient priority level, isolation requirements and patient's preference whereas resource perspective constraints can be found in the capacity of the hospital as in number of beds and staff (He et al., 2018).

To better understand how LP was used to solve BAP problems, 7 articles were studied thoroughly in the following parts. This section will highlight the major steps involved in developing an LP model as follows: (1) Understanding the problem at hand, (2) Define the objective function, (3) Define the decision variables and (4) Define the constraints.

2.2.1.1 Maximizing Benefits Obtained from Bed Assignment While Minimizing the Penalties of Deviating from Hospital Goals

<u>Article Title:</u> *Automated bed Assignment in a Complex and Dynamic Hospital Environment*

Understand the problem at hand:

Thomas et al. (2013) tackled the bed assignment problem as a complex model that integrates several factors of the hospital together. To achieve efficient bed assignment, clinical information, hospital operations information, interactions between different hospital units, and updated information on patients, resources and workflows are required. Thomas et al. saw that the integration of patient flow, patient care and resource utilization in assigning beds to patients was neglected in previous literature and focused their model on this interrelation between all hospital units. The complexity of all hospital operations appears from the dynamically evolving nature of patient care service and the unpredictable and unplanned interactions of the scarce hospital resources. Several sets were defined and the most significant ones that stand out compared to other models are (S) Set of service lines, (C) set of clinical specialties, (Hc) Set of tier levels for clinical specialties, (Q) Set of request types. Service lines are categories of service care offered by the hospital. Clinical specialties are defined as the branch of medical care that is specialized in treating a specific disease. Tier levels are a multilevel ranking and ordering of units in decreasing order of preference. According to Thomas et al.'s model a service line may provide services to patients from multiple clinical specialties. Although a unit of a particular clinical specialty may be best suited for a given patient, other units are also able to accommodate that patient if beds in a unit for given clinical specialty are not available. This is why each unit is assigned a tier level to treat patients of a particular specialty.

Define objective function:

The objective function of this model seeks to maximize the benefits obtained from assigning patients to beds and minimize the penalties incurred in not meeting the hospital's requirements and goals. The model measures benefits when a bed request is fulfilled. The amount of this benefit depends on a number of factors, which include request type, patient type, unit originating the request, the number of patients waiting for admission to units, and waiting time of each request to be fulfilled. The model takes into account the relative importance of these factors from the weights of benefit parameters defined. These weights are based on user (hospital) preferences.

Define the decision variable:

Similar to different studies, the decision variable in this model is binary, it equals to one if request "i" is assigned to bed "j" and zero otherwise. What is significant in this variable is that the model is not only taking into account the patient, but is taking the "request" of the patient or even the request that comes from departments within the hospital itself. Requests, defined previously as a set, are bed requests of different types; either emergency admit, transfer from another hospital or scheduled surgery.

Define the constraints:

Thomas et al. defined the models constraints into two types: soft and hard constraints. A corresponding constraints parameter is also defined in the model to define whether the constraint is considered soft or hard. "C_t^H" is set to 1 if the user considers the constraint "t" as hard and 0 otherwise. The different constraints defined include the following: Tier constraints ensure that patient is placed below the specified tier level. Target unit constraints, service-line constraints, room-type constraints, discharge constraints, attributes constraints, gender-mismatch constraint which ensures that all patients in the room have the same gender, nurse-patient ratio constraints which make sure that adequate staffing is present to take care of all patients in open units and a bed-utilization constraint. What is unique about this model is that it also defines a solution-stability constraint which ensures that only a specified fraction of assignments from previous runs can change. The model imposes three hard constraints on the users which are: patient-assignment, bed-assignment and isolation constraints.

2.2.1.2 Minimizing the assignment delay, affinity, ward occupancy and change of ward occupancy costs.

Article Title: *Decision Support for Hospital Bed Management Using Adaptable Individual Length of Stay Estimations and Shared resources*

Understand the problem at hand:

The model presented by Schmidt et al. (2013) introduces two notions previously neglected in the literature: adaptable patient length of stay estimations and aggregate bed capacities. In order to mathematically represent the uncertainty of patients' recovery rates, Bernoulli distributed random variables and approximate probability densities were used to calculate the expected free room capacity from individual length of stay estimates. The model was solved using an exact approach and three heuristics which all resulted in a reduced dismissal rate and an improved assignment. Four sets were defined: set of patients, set of patient preference, set of wards, and set of allowed admission days. The latter introduces the notion of a time planning horizon into the model which confirms its objective to account for the uncertainty of length of stay.

Define objective function:

To determine the suitability of an assignment, the affinity of a room with respect to a clinic is represented by a mapping that assigns a binary value to each ward/clinic pair. Five mappings are used: mapping of the affinity between wards and clinics, mapping of the patients that request a certain preference, mapping of wards that satisfy a certain preference, mapping of the maximum length of stay of a patient within his set and mapping of patients to their treatment priority.

Based on the above, the objective function seeks to minimize the affinity cost, the ward occupancy cost, the change of ward occupancy cost and assignment delay cost that is based on the treatment urgency.

In brief, the authors seek to find the best affinity between wards and clinics, maximize ward's rate of use, minimize transportation of patients between wards and reduce waiting time in function of patient criticality.

Define the decision variable:

The decision variable defined in this model is binary and equals one if patient i is admitted to ward j at time t and equals zero otherwise.

Define the constraints:

The first constraint ensures that every patient is assigned an admission date and a ward. To ensure a solution is eventually reached, a dummy ward with a high capacity is created and assignments to that ward incur a very high penalty cost and are considered dismissals. Another constraint makes sure no patient is assigned more than one admission date or one ward. Another constraint prevents exceeding a ward's capacity.

2.2.1.3 Minimizing cost considering stochastic/deterministic length of stay

Article Title: *A Mixed Integer Programming Model for Bed planning considering stochastic length of stay*

Understand the problem at hand

Unlike the other models discussed in this section, the bed assignment problem understudy is only for a gynecological ward and not the hospital as a whole. The problem at hand focuses on the length of stay (LOS) of patients at the gynecological ward which contains 40 beds and more than 20 staff members. Two models were developed to study the BAP at hand. Lei et al. (2014) first developed a mixed integer programming model to assign patients to available beds while considering the deterministic length of stay. The second is a mixed integer programming model taking into account stochastic length of stay. The latter arose from the fact that the variance of a patient's length of stay was calculated to be significant. Moreover, Lei et al. (2014) states that the currently adopted strategy in hospitals in China is to assign patients to beds based on a first come first serve rule which could cause unbalanced workload and long waiting time for admissions. Lei et al. (2014) classified patients into three categories, noting that each category has its sub-categories, as follows: (1) Emergency, (2) Surgical and (3) Non-surgical. It is important to note that the previous classification is based on the 13 gynecological pathologies that the ward covers. Also, for both models developed the distribution of LOS by pathology is determined.

It is important to point out that the deterministic LOS model was based on the fact that each patient's length of stay is treated as determined while in the stochastic LOS model, probability distributions were introduced which described the respective LOS (Lei et al., 2014). Noting, the distributions were gathered through statistical analysis of data gathered from the ward under study.

Define Objective Function

The objective behind both the model with the deterministic length of stay and the model with the stochastic length of stay are different. When it comes to the MIP considering a deterministic length of stay the objective function is to minimize two parts of cost, the first being the patient's hospitalization delay cost and the second is the cost of refused patient admissions caused by the unavailability of bed resources (Lei et al., 2014). The first cost is denoted by the multiplication of the number of delay days with the unit delay cost. On the other hand, the objective function of the MIP considering a stochastic length of stay is minimizing the cost of idle beds which is caused by overbooking, the cost of bed overlap that is due to inadequate reservation and the other two costs that are mentioned in the first model. To explain this further, the bed idle cost is generated when the patient's actual LOS is shorter than what the researchers have anticipated which leads to an idle bed once a patient is released early. The bed overlap cost is generated when the patient's actual LOS is longer than what was anticipated. This leads to the next patient not being assigned to that specific bed and thus the ward will need to increase bed resources to fulfill the admission of all patients.

Define decision variables

Lei et al. (2014) mentioned that the deterministic LOS model is based on an existing study and the researchers added the constraint of surgery capacity. Accordingly, a surgery variable was added as "Su" which is equal to 1 if patient i would take surgery and 0 otherwise. In addition to that, there is a decision variable that shows the refuse variable REF_i **which** is 0 if patient i could be assigned to a bed and 1 otherwise. Due to the focus on LOS, two integer variables that refer to the first and last hospitalization days of a patient are introduced. In the stochastic LOS bed planning model, researchers defined a decision variable which signifies the bed status in respect to the actual LOS where the variable is 1 if the patient will stay in the allocated bed according to their respective actual LOS and 0 otherwise. The full variables of both models are shown in Appendix H.

Define the constraints

Constraints in this study differ between the stochastic LOS model and deterministic LOS model. In the deterministic LOS model, constraints exist to ensure that a patient could be assigned to one bed, in idle status, in each day. Also, other constraints state that a patient would be allocated a bed according to their LOS. Other constraints are there to guarantee that patients are assigned a bed during their appropriate hospitalization time which is defined as [EAR, LAT]; with EAR standing for earliest hospitalization admission day and LAT stands for latest hospitalization admission day. As mentioned in the decision variables, Lei et al. (2014) introduced a surgery variable and accordingly introduced a constraint which makes sure that on a specific day 't' the total number of surgeries does not exceed the maximum workload (SUR_t). Now when it comes to the stochastic LOS model other constraints are depicted based on the introduced costs which are not in the deterministic LOS model; Bed overlap and bed idle cost. For instance, for the bed overlap cost consists of two parts and thus two constraints exist to show the overlap with new arrangements (part 1) and overlap with previous arrangements (part 2).

Relevant Conclusion

What is interesting about both models discussed previously is that they give distinct results. After conducting numerical experiments to compare between the models, the researchers concluded that a stochastic LOS model guarantees a better solution when studying bed planning due to the potential bed conflict cost (Lei et al., 2014).

2.2.1.4. Maximizing Patient Admission and Minimizing Internal Movements of Patients

Article Title: *Multi-objective Optimization of Hospital Inpatient Bed Assignment*

Understand the problem at hand

What is significant about the problem at hand is that it is divided into two stages followed by two objectives. The latter rises from the fact that numerous factors are taken into consideration when assigning patients to beds and each time a new patient is admitted this could lead to the rearrangement of already admitted patients. Such movements lead to the increase in the workload of staff and the risk of patients being affected with nosocomial infections. The mathematical formulation aims at finding the strategy hospitals should follow when assigning patients to rooms by focusing on isolation constraints while minimizing the internal movement of previously admitted patients. In other words, the model at hand seeks to reduce infectious disease spread in a hospital while taking into account bed assignment policies in order to then suggest optimal bed assignment policies.

The sets defined in this model came at a lot of instances as form of unions between one another. For instance, Hoff defined a set of patients (P) which is the union of each of the set of patients currently admitted (PA) and patients seeking admission (PN). Moreover, a set of all hospital rooms (R) was defined which is the union of set of rooms for a specific unit (RU) and set of special triage/discharge rooms (R_s). Noting, the set (R_s) is the union of triage rooms (T) and set of discharge rooms (D). In addition to the aforementioned sets, set of genders (G), set of isolation conditions (I) and set of units in the hospital (U) were defined.

Define Objective Function

Hoff (2017) defined the model as a multi-objective problem which involves maximizing patient admission and minimizing the internal movement of patients. It solves two stages to achieve both objectives. The first stage is deciding which patients to admit based on their criticality. The second stage assigns beds to patients in order to minimize patient movements in the hospital. Hoff (2017) accommodated his model to the fact that there is a penalty involved when a patient is not placed in a unit of preference which thus increases the cost of the movement. It is important to point out the significant parameters in this model that aim at minimizing the internal movement of patients which are the previous location of the patient, the movement restriction of a patient signifying if he/she can be moved or not, the transfer penalty for movement if the patient was moved from one room to the other and the cost of assigning the patient to a certain unit.

Define decision variables

Hoff (2017) defined three distinct variables in this problem as follows: (1) x_{ij} = 0 if a patient i is not assigned to room j and 1 otherwise, (2) δ_{hj} = 0 if gender h is not present in room j and 1 otherwise, (3) γ_{ij}= 0 if isolation condition i is not present in room j and 1 otherwise, and finally (4) $\beta_{ij'j}$ which signifies the movement penalty for patient i from room j' to j.

Define the constraints

Hoff (2017) defined common constraints for both objective functions as well as other different ones. When it comes to the common constraints they are to ensure that any patient previously admitted to the hospital occupies a bed and to ensure that patients who are seeking admission are either assigned a bed or wait for a bed. Additional common constraints would be to ensure that a patient is assigned a room only if there is a common gender or if it is empty. Also, another common constraint is to ensure that a patient is allocated in a room that is empty or their respective isolation requirement is present in the room. In addition to constraints that make sure all previously admitted patients are not assigned back to the triage room and that current patient are not reassigned to a different room. The final common constraint is to ensure that patients are assigned to rooms within their current unit. On the other hand, other constraints are unique for each objective. For instance, when it comes to the objective of step 1, there is a constraint which ensures that the total number of patients in a room does not exceed the total number of beds available in the room. In the objective related to step 2, there are constraints that define the penalty for moving previously admitted patients to a new room and the penalty of admitting a patient to a non-preferred unit. Another interesting constraint Hoff (2017) added was in the objective of step 2 which is to ensure that any patient admitted in the first step is assigned a room.

2.2.1.5 Minimizing the penalty costs of lack of specialty, age and gender compatibility, equipment availability in room, department compatibility and patient preferences and transfers.

<u>**Article Title:**</u> *An efficient matheuristic for offline patient-to-bed assignment problems*

Understand the problem at hand:

The problem is solved in two consecutive steps: patients are first assigned to rooms and then to beds in that room. The patient-room assignment solves hard constraints on age policies, gender policies and mandatory equipment availability. In case of infeasibility, some of those constraints are relaxed. The second step assigns patients with comorbidity based on their length of stay.

Sets are divided into two categories: hospital resources and patients. The first category includes set of departments, set of specialties in each department and set of level of expertise in treating a disease in each department. It also contains the set of rooms with their corresponding capacities and equipment which defines their suitability for an assignment. Apart from the set of types of bed equipment, rooms are also defined by their set of gender policies and set of age policies. The second category, the patients set, is branched into set of female patients and set of male patients. There is also a set of patients that requires at least one mandatory bed and another set of those who do not. In addition to the attributes mentioned above, patients are also identified by their preferences and length of stay.

Define objective function:

The objective function seeks to determine an optimal assignment of patients to rooms by optimizing patient care and meeting patient preferences. Thus it seeks to minimize the overall penalty by night multiplied by the length of stay for the patient. The total penalty is the result of the sum of 4 penalty values: specialty compatibility, equipment availability in room, department compatibility and patient preferences.

The objective function of the relaxed PBAP adds to the original one three new violation values: total penalty due to violations of mandatory equipment, on age policies and on gender policies.

In the second step, a new term is to be minimized in the objective function: transfer penalties. Indeed, if a patient has to be treated by more than one specialty, he will change rooms during his stay and will have more than one admission and discharge dates and distinct and consecutive length of stays.

Define the decision variable:

The decision variables are binary and take on the value one if the patient p of the set of patients is assigned to the room r of the set of rooms and zero otherwise.

In the relaxed PBAP, new binary decision variables are introduced and take the value one when the corresponding hard constraint is violated and zero otherwise. Note that the three hard constraints refer to age and gender policies and equipment availability.

Define the constraints:

The model lists hard constraints such as each patient is assigned one room and one bed only, the room capacity is not exceeded, each patient that needs a specific equipment has access to it, a patient satisfying a gender policy is assigned to a room with that same gender policy and a patient satisfying an age policy is only assigned to a room with that age policy. Penalty values are also introduced to limit violations of constraints. For instance, penalties are applied to patients that are assigned to a department without the right speciality. In the relaxed PBAP, further violation values are introduced, namely on gender, age and equipment availability. Furthermore, patient motion is discouraged unless for comorbidity reasons and even then transfers are minimized. Indeed, the third optimization model also adds restrictions on patient movements in order to reduce room transfer by penalizing them.

2.2.1.6 Maximizing Weighted Objective Function to Assign Patients to Beds

Article Title: *Operational patient-bed assignment problem in large hospital settings including overflow and uncertainty management*

Understand the problem at hand:

The model recently presented by Schafer et al. (2019) presents a decision support model PBA considering trade-off situations between three main stakeholders (patients, nurses and doctors), and capable of handling overflow situations. They investigated the model on two departments having 55 rooms with a total of 120 beds spread over 5 wards. In addition, emergency patient arrivals are forecasted using historical probability distributions while accounting for uncertainty. Furthermore, the model presents six sets: beds, departments, patients, rooms, days, and wards.

Define objective function:

The objective function is to maximize weighted functions to assign beds to elective and emergency patients. These weights are denoted by alpha, beta, ceta and omega and variate from one function to another. The first function is patient-specific and used to assign a bed to the patient. The second function is also patient specific and used to model the preferences of the patients (for example, patients in a certain age range are roomed together). The third function is doctor-specific and rewards for assigning patients of same department the same room, since it is easier for doctors to handle several patients that they are responsible for in the same room. The fourth function is nurse-specific and used to balance workload for nursing staff.

Define the decision variable:

The decision variable is binary which equals to one if patient *p* is allocated to bed *b*, zero otherwise.

Define the constraints:

The model lists the following hard constraints: male and female inpatients in non-ICU are not allowed to share the same room; some patients have to be allocated to a specific room with the required medical equipment; some patients need to be isolated due to their medical conditions; patients who already have been allocated a room in the designated department remain in the same room to avoid patient's discomfort and additional work for the staff.

2.2.1.7 Minimizing the Sum of Unsatisfied Constraints

Article Title: *The patient bed assignment problem solved by autonomous bat algorithm*

Understand the problem at hand:

The uniqueness of this model developed by Taramasco et al. (2019) is the fact that its objective is to minimize the sum of unsatisfied constraints, and that the "bat algorithm" is used in finding the optimal solution of the model. In previous literature, most bed assignment problems were based on constraint programming (CP) paradigm. The latter model is a mathematical formulation based on three different components, set of decision variables and their respective domains, a linear or nonlinear function - cost function or objective function - and constraints. The constraints would be considered either soft or hard constraints and the model would work on solving the objective function while satisfying all hard constraints. The model in this literature designs a model for BAP based on the constraint optimization problem (COP). This method allows the user to relax a strict constraint satisfaction problem (CSP) model. Hard constraints are modeled as normal constraints and the soft constraints are taken into consideration in the cost function. The COP, in other words, is a constraint network extended with a cost function. This literature introduces the min-CSP patient bed assignment problem model which maximizes the usage of beds and considered the possibility that constraints can be violated. The model is based on two different stages; the first allows the user to find the best bed in the hospital itself. If the algorithm does not find the best match internally, the second stage searches for the best solution in the entire public health network (external to the hospital itself). Taramasco et al. defined two different sets (Health Service, Patients) and many parameters within the sets. Under health services for example, they defined “Dh” which is the Distances between hospitals, where {d1. . . dh} represent the directional distances between the j^{th} hospital and the k^{th} hospital. That parameter is used in the second stage of the algorithm.

Define objective function:

To form the objective function, a weighted sum of violated constraints is calculated. The sum is used to penalize solutions that do not satisfy all constraints in the problem. The objective function becomes a minimization one and aims at minimizing the number of unsatisfied constraints in the model.

Define the decision variable:

The decision variable “b^{t}_{pr}” is a binary variable which equals 1 if bed of type “t” (1=critical, 2=normal) in room “r” is assigned to patient “p” and 0 otherwise. What is significant about this decision variable is the fact that the criticality of the patient is modeled as a type of bed.

Define the constraints:

The model’s constraints are divided into seven. These constraints are the ones that realistically should be satisfied but can be violated. The model includes exclusivity, risk and dependence, isolation, unit policies, gender policy, age policy and distance as constraints. Risk and dependence refers to the severity of the patient's condition and is divided into three levels: Maximum, medium and minimum risk. Moreover, the distance constraint ensures that the distance between the current hospital and the nearest one with availability is best fit to the patient’s needs and requirements and this is why it can be violated.

2.2.2. Simulation and BAP

He et al. (2014) stated that “simulation modeling is the dominant technique being used in studying inpatient bed management”. It was in fact due to the increase of health costs over the past 40 years, Discrete-Event Simulation (DES) has become a tool for health care such as BAP to improve the efficiency of health care operations by evaluating the efficiency of the existing system (Jacobson et al., 2006). It can serve as a forecasting tool to examine complex relationships between variables (such as patient length of stay, arrival rate of patients), and to assess the potential impact of modifications to the system. Due to the numerous and successful DES health care studies, it has become progressively recognized by health care facilities. Fetter and Thompson (1965) conducted one of the first DES for outpatient clinics. By analyzing physician utilization rates with respect to patient waiting time, they found that increasing the physician's appointment load (capacity) from 60% to 90% will decrease physicians' idle time by 160 hours and increase patient waiting time by 1600 hours (within a period of fifty days).

Cardona et al. (2017) applied DES to the Veteran Affairs (VA) Sacramento Medical Center to optimize number of beds to add to the specified units within the hospital by successfully simulating validated data for arrival times and Length of Stay (LOS). However, they kept waiting times unconstrained where in reality there is a limit to the patient's queuing time. Clissold et al. (2015) conducted a study with a DES model to test the impact of increasing emergency units in Flemings Medical Center. The DES parameters included arrival times, admission rates, treatment times, triage types and resource capacities. The data were analyzed before constructing the model and then verified. The results showed that augmenting the demand from one to four patients per hour expanded into a nonlinear increase in LOS. Having an animated visual representation helps in better understanding the system in hand. In another application, Harper and Shahani (2002) created a three-phase simulation shell to create their model. They found that determining LOS for each department provides a more accurate representation for estimating the capacity (number of beds) than calculating LOS for emergency and elective patients. This model highlights the relationship between bed refusal rate, bed occupancy and forecasting bed requirements.

DES models examine the interactions between multiple sub-systems and presents insights on complex variables such as patient and inpatient flow from admission to discharge. Sensitivity analysis can also be conducted to predict outcomes of a decision and gain the ability to forecast required capacity and allocate bed strategies.

Simulation models can be combined with mathematical programming models to provide optimal solutions for the desired objective functions. The following literature studies related to simulation and BAP aided in the understanding and development of the simulation study in Chapter 4.

2.2.2.1 A Conceptual Framework for Improving Critical Care Patient Flow and Bed Use.

A recent study on modeling of ICU (Intensive Critical Unit) was conducted by Mathews and Long in 2019. Their main objective is to maximize bed use and minimizing admission wait time for critical patients by balancing the ICU and step-down unit (SDU, which is referred to patients with intermediate care level needed) with patients with different acuity levels. Five essential inputs were used in the model: number of beds in each unit, patient type and priority level, timing of patient arrival, patient prioritization for admission, and unit length of stay. The study's chosen hospital owns 51 beds from which 36 are ICU beds and 15 are SDU beds. Furthermore, patient type is categorized into four priority classes based on the hospital's policies: acute non-ED (highest level), acute ED, subacute non-ED, subacute ED (lowest level). The timing of patient arrivals is calculated using the hospital's historical data and fitted into an exponential distribution. The triage policy in the ICU is to allow acute or subacute patients with a cut-off policy that accounts the last bed for acute patients only; and the triage policy in the SDU is to permit only subacute patients. Finally, length of stay is classified as "long stay" or "short stay" , and vary between acute and subacute patients: acute patient has either a service time less than 2 weeks (short) following a Lognormal distribution or longer than 2 weeks following an Exponential distribution (long stay), and subacute patient has either a service time less than 24 hours following a Uniform distribution (short) or greater than 24 hours following an Exponential distribution. In addition, they take into consideration the time to transfer (TTT) the patient after the service ends by modeling it through the use of multivariate regression analysis to examine the relationship between the ICU/SDU and TTT. The simulation bed allocations scenarios were described by four alternate policies. The first scenario describes "unit composition" where different bed capacities in ICU and SDU are simulated and shows a reduction in wait time for acute patients. The second scenario describes "reserved acute beds" for the cut-off policy and also shows a reduction in waiting time. The third scenario describes ICU expansion where additional beds are added to ICU while keeping SDU at 15 bed capacity and demonstrated major improvements in average wait times for all patients. The fourth scenario describes a reduction in TTT to a target of 1 hour that led to 46% improvement in wait times for bed assignment.

Concerning data validation, they simulated 2,000 patients for a period of six months. This process was repeated for 10,000 iterations.

2.2.2.2 A decision support simulation model for bed management in healthcare.

The research under study aimed to utilize discrete event simulation in order to optimally plan and staff scheduling decisions at Sacramento Veterans Administration Medical Center. The hospital provides comprehensive health care services and has all acute beds. Moreover, it has 50 beds distributed in 3 units; Intensive care unit (ICU) with 10 beds, Transitional care unit (TCU) with 16 beds and Medical surgical unit (MSU) with 19 beds. Any patient admitted to the hospital is assigned to the departments based on their level of acuity. In order to understand both individual departments and the hospital system as a whole, each department's performance measures were taken into consideration (Baru, 2015). Baru (2015) developed several alternative scenarios in order to determine impacts on reducing the number of patients waiting in queue, the waiting time and length of stay of patients.

Baru (2015) focused on gathering data about all departments and units within the hospital and so it consisted of the following: (1) Admission time and date, (2) Discharge time and date, (3) Ward unit of admission and (4) Ward/unit of discharge.

The data collected for the simulation model is based on the arrival time of patients, admission department, length of stay (LOS) of each patient, discharge department and department transfer data (Baru, 2015). The latter were collected from patient's records and the Bed Management System of the hospital. The data sample size in this study is 23,019 patients. Also, it is important to note that the data was filtered in order to get accurate data about each department. Accordingly, Baru (2015) stated that the details for direct admission to a department for each patient and their LOS was determined. In addition to the transfer data which contained how patients moved in the hospital and these transfer patients were tracked from admission to discharge. The LOS distributions were calculated based on details of LOS of direct admission and transfer patients to ICU, TCU and MSU. Input analyzer was used to generate the required distributions and the table below shows the distributions generated. Noting that 3 MSU refers to the third level of that unit and 4 MSU refers to the fourth level of that unit. TCU and MSU data did not fit in any distribution when added to input analyzer and so a user defined continuous distribution based on the probabilities was used as input distribution (Baru, 2015).

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: LOS Distribution

The following conditions are present in this Simulation: (1) Patients admitted move directly to their respective department if a bed is available otherwise wait in queue in ER, (2) If patient has a scheduled surgery, surgery starts only when the patient is assigned a bed, (3) After the completion of a patient's derived LOS, he/she is either transferred or discharged, and (4) 57.2% of patients are transferred out of ICU, 1.1% from 3TCU, 11.6% from 3 MSU and 49.3% from 4MSU to another.

Baru (2015), developed three hypotheses from the simulation model to validate the model and to test alternative scenarios:

- H10: There is no statistical difference between the simulated LOS and actual LOS values.

  H1A: There is a statistical difference between simulated LOS and actual LOS values.

  This hypothesis is to determine if there was a statistical difference between the simulated and actual LOS.
- H20: A change in bed turnover time does not reduce the number of people waiting in queue.

  H2A: A change in bed turnover time reduces the number of people waiting in queue.
- H30: A reduction in LOS does not reduce the number of patients waiting in queue.

  H31: A reduction in LOS reduces the number of patients waiting in queue

To verify his model, Baru (2015) adopted three stages:

1. The arrival of patients was examined to confirm they were embedded into the simulation appropriately
2. The model was verified using the check model function in Arena
3. The information logic was verified with the staff and administration of the hospital

Parametric and nonparametric tests were conducted to determine if the actual LOS and the simulated LOS values are different from each other

LOS data were verified to ensure that the model is an accurate representation of the hospital system. (Wilcoxon test)

Hypothesis Testing

Hypothesis 1: A one-way analysis was performed to characterize how the distribution of the actual and simulated LOS differ. Through the Wilcoxon Test, the result showed to reject the null hypothesis since the p-value is greater than 0.05 and thus there is no statistical difference between the simulated and actual LOS.

Baru (2015) developed and analyzed three alternative scenarios to determine performance measures:

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

   To compare means of the number of patients in the queue by changing the bed turnover time, a one-way ANOVA technique. Wilcoxon test was performed on Hypothesis 2 and the results showed no statistical difference since p value is less than 0.001. Also, the average waiting time for patients and the average number of patients waiting in the queue reduced in this scenario.
2. **Scenario 2:** Reduce the number of people waiting in queue and waiting time through reducing LOS

   To compare the means of the number of patients in the queue by changing the LOS values, a one-way ANOVA technique was used. The LOS values were reduced by 10 hours for direct admission departments and by one day for transfer. The results showed a statistical difference in Hypothesis 3 since p value is less than 0.001 and we reject the null hypothesis. As in Scenario 1, the average waiting time for patients and the average number of patients waiting in the queue reduced in this scenario.
3. **Scenario 3:** Addition of two beds to 3TCU and 4MSU

   This scenario was developed due to the fact that 3TCU and 4 MSU have large waiting time for patients and this could be due to the lack of beds. Baru (2015), conducted a comparative analysis and it was shown that the addition of beds actually reduced the waiting times, number of patients in the queue and LOS.

2.2.2.3 Case Study of Lean in Hospital Admissions to Inspire Culture Change.

This study conducted by Haddad et al. (2016) aimed at improving patient flow and reducing unnecessary waiting and handling by patients and staff by utilizing lean thinking and discrete event simulation. The research was conducted over a six-month period at the University Medical Center - Rizk Hospital with 250 beds. Arena was used for the simulation model of the process at hand.

Stage 1: Registration			
Arrivals	Open patient file	Get Insurance approval	Submit insurance approval
EXP(19)	8.5+ 15*BETA(1.01,0.928)	24.5+11*BETA(0.954,1.03)	TRI(2,5,6)

stage 2: Pre-op Tests			
Arrivals	Retrieve admission form & Pre-op tests clearances	Submit Pre-Op Form and test clearances	Perform pre-Op examination
EXP(39)	3.5+16*BETA(1.08,1.16)	UNIF(4.5,8.5)	39.5+41*BETA(0.961,0.84)

Stage 3: Surgery Day		
Arrivals	Prepare for operation (administrative procedures)	Prepare for operation (medical procedure)
EXP(40)	7.5+16*BETA(0.875,0.83)	14.5+16*BETA(0.948,0.991)

Figure 2: Data Extracted from Research

2.2.2.4 Improving hospital bed utilization through simulation and optimization.

Holm et al. (2013) conducted a research encompassing a discrete event simulation model that follows two steps: the first phase seeks to develop a matrix that displays the statistics of the bed utilization of each ward and in the second phase the data found is fed into an allocation algorithm that allocates the available beds to the wards optimally. Each ward has two defining characteristics: its specific arrival times and length of stay.

The research studies the Akershus University Hospital (Ahus) that has 718 regular beds. The data used was based on empirical historic data as well as subject matter experts' evaluations. Note that the arrival rates were increased by 40% due to population increase and restructuring measures, so the number of crowding beds was also tracked (crowding refers to the beds placed in the corridor of the ward or in a ward already at full capacity).

Prevalence (the average number of crowding beds being used) and incidence (the number of patients being placed in crowding beds) were both used as optimization criteria. But prevalence was ultimately chosen as more adequate because incidence tends to sacrifice wards which have a long LOS and low patient turnover. The study resulted in a reduction of crowding patient nights from 6.5% to 4.2%.

Ideas to consider: elective patients' arrival rates are reduced to half during 13 low-season weeks. Acute arrivals have constant arrival intensity regardless of the hour and the day of the week. A fixed discharge time was decided based on historic data and a probability approach decided if the patient would be discharged the previous or current day in accordance with his LOS value.

Simulation model validation and verification:

- The model was run on two software programs: R® and FlexSim HealthCare® which both resulted in similar outputs.
- The model was run for a duration of a full year 1000 times. Furthermore, most patients stay less than seven days, which makes observations that occur a week apart close to independent. Which renders the total independent observations 50,000. The standard deviation of the fraction of time the bed is used is also less than 0.0025, which is suitable enough for estimating optimal assignments.
- Validation was not done by comparing the output with real data since the model is a forecasted representation of the consecutive year. Nevertheless, the arrival generator is based on the technique successfully implemented in an ED simulation in the same hospital in previous years.
- Acute arrivals are validated from through the electronic patient registry of previous years.
- Experts also evaluated and validated the output.

Data Used:

- Acute arrivals: Poisson distributions
- Elective arrivals: Specific numbers at specific times
- Length of stay: Beta distributions
- Inter-arrival rate is exponential depending on the hour.

2.2.2.5 Minimizing bed occupancy variance by scheduling patients under uncertainty.

This bed allocation problem done by D'obrenan et al. (2020) targets assignment of patients to surgery blocks by taking into account the bed occupancy and surgery blocks availability. Since the LOS in surgery wards fluctuate greatly, the stochastic problem is first solved by modeling an integer linear program. In the second phase, a Monte Carlo simulation is applied followed by a taboo search. The objective of the study is to minimize bed capacity variation, maximize the number of patients treated and minimize the maximum waiting time.

Note that the Monte Carlo simulation is applied to check for feasibility:

- After each newly adapted solution of the ILP that is obtained by decreasing the number of patients in the blocks that returned an infeasible solution.
- After each tabu search algorithm's new proposed schedule.

Scope of work: 152 surgery blocks.

The lognormal distribution was chosen repeatedly in the literature for surgery times so the relevant parameters were first estimated based on maximum likelihood by using a fitting function in MATLAB R2014a R.

- Trauma surgery, long stay patient group distributions: lognormal distributions
- Short stay patient group within general surgery: lognormal distributions

The chi-squared goodness of fit test was applied for both those patient categories to conclude if the lognormal, normal or exponential distributions fit the surgery durations best. In both cases, the lognormal distributions showed better graphical fit which resulted in its application in the study.

2.2.2.6 A discrete event simulation model to support bed management.

The study conducted by Landa et al. (2014) aimed to observe the effect of integrating bed management with operational strategies without increasing bed capacity. The study was conducted with the Local Health Government of Liguria - a region in Italy. Data was collected over a one-year interval period at a public hospital. Data revolved around the patient flow from the emergency department to the inpatient wards. A Discrete Event Simulation (DES) model was developed in order to represent the real system. The research was conducted due to the increase in Emergency Departments over crowdedness in Italy. This was mainly due to both a public budget unbalance and the reduction, in the same period, of the number of inpatient ward beds available, which has been reduced from 6.1 to 4.3 per thousand populations in ten years ranking below the European average (Istat, 2011).

The objective of the study underhand is to develop a DES model to study the interrelation of the flows of emergent and elective admissions into inpatient departments. Real data was collected as mentioned earlier on a yearlong basis since it was found insufficient to consider average distribution patterns and this is due to the fluctuation of data points at different time intervals. The DES adopted a patient-centered approach, meaning that all necessary patient characteristics are taken into account from the moment the patient enters the system until they exit. The DES model divided the patients into two sets, emergent and elective patients. Different attributes were given to each patient as follows:

Table 1: Attribute Distribution

Patient	Attribute	Description
Emergent Patient	"to_admit"	1 if ED patient needs to be admitted to a ward 0 if discharged
	"ward"	Gives the ward where the patient whose "to_admit=1" should be allocated
	"Time_in_ED"	Time spent by the patient in ED
Elective patients & "to_admit=1" patients	"Length_of_stay"	Length of stay in ward based on the type of patient

The model was applied in a large public hospital in Genova. Data concerning the number of beds is only given in the wards. The hospital is composed of **79** different **wards** with **1256** available **beds.** The wards are grouped as followed: Medicine, Surgery, Orthopedics and other wards. For each ward group the number of beds available, the average time spent in the ED and the average length of stay was collected.

Table 2: Results Extratced

# of ED admissions	84,781
% discharged without admissions	(75.3%)
% transferred to inpatient wards	(24.7%)
# of inpatient ward admission	45,638
Elective	24,696
coming from ED	20,942
Average time spent in ED (in hours)	
patients discharged without admission	2.92
patients transferred to inpatient wards	4.45
Average LOS (in days)	
Medicine	3.14
Surgery	6.87
Orthopedics	9.00
Other	8.73
# of ward beds	1,141
Medicine	332
Surgery	157
Orthopedics	80
Other	569

Based on their observations and data, the researchers realized that the inter-arrival and service rates for both emergent and elective patients are very different based on several time slots, hence they chose 42 different slots from Monday through Sunday and based their data accordingly. After creating the model, running it for 360 days in addition to the first 90 days to obtain steady state conditions, the researchers validated their model. Firstly, they conducted a face validation with the hospital managers which helped in adapting the model to a truer representation of the system. Moreover, the simulation outputs were compared to real data using a T-test statistical test. Finally, after validating their results, Randa et al. used their DES to analyze the effects on system behavior of different bed management rules and inpatient ward organization and verify their effectiveness to face the bed allocation problem. They studied 5 different scenarios and analyzed them based on the following factors:

1. # of patients misallocated
2. Average # of ED patients to be admitted
3. Average waiting time before admission
4. # of postponed elective admissions
5. Average bed utilization rate

The scenarios were compared to the baseline Scenario 0 which is when the bed manager verifies if there is a bed available in the specific ward, if there is a free bed available in the ward assigned to her/him, if not it checks the bed availability in the other wards and when it finds a free bed sends the patient to the first ward with a free bed available even if misallocated. Scenario 1 for example, gives the bed manager the ability to postpone at most 4 times the assignment of a patient to a "wrong" ward in order to verify if after a short time (usually half an hour) some beds will be available. Moving from scenario 0 to scenario 1 reduced the number of misallocated patients by 61%.

2.2.2.7 A discrete event simulation model of patient flow in a general hospital incorporating infection control policy for methicillin-resistant staphylococcus aureus (MRSA) and vancomycin-resistant enterococcus (VRE).

The research understudy focuses on the proper allocation of patients with MRSA and VRE infections on hospital beds. Hospitals with double-occupancy rooms must take into consideration not only the gender constraint but also MRSA/VRE flags. Patients who are not infected by these bacteria should not under any circumstances be paired in a room with an infected patient. A DES model was developed in an acute care hospital - a hospital which has the goal of discharging patients as soon as they are deemed healthy and stable. Patients are matched to beds based on acuity, service, gender, and known MRSA/VRE colonization. The motif of this research was to extend the literature related to simulation and bed assignment in order to include infection control on the flow of hospital patients and proper allocation of resources.

Shenoy et al. (2018) developed a constrained-resource simulation model with the assumption of fixed capacity of beds available with competing access to the beds which resulted in a queue system. Data was inputted into the model and the following outcome was assessed in order to validate the model:

1. Time to bed arrival
2. Length of Stay
3. Patient-bed acuity mismatches
4. Occupancy rate
5. Idle beds
6. Acuity-related within-hospital transfers
7. Rooms with discordant allocation
8. Incident MRSA/VRE colonization due to transmission in discordant rooms

The outcomes were validated with historical data however the last two had no previous data to be compared to. The simulation was conducted in the Massachusetts General Hospital in Boston. The hospital model included 14 Observation, 613 General Care (52% medical, 48% surgical), 57 Step-Down (63% medical, 37% surgery), and 98 ICU (35% medical, 65% surgery) beds.

The schematic of the model is present in the graph below. Patient goes through 6 events as illustrated. Patients arrive on an hourly basis and are given 4 different attributes: **acuity** on arrival, medical or surgical **service required**, **gender**, and **MRSA** and **VRE flag status** - whether or not the patient is infected. Next, patients who are waiting to be admitted are assigned to a queue based on the attributes given. The model searched for available beds based on the approximated work-up time - "an approximation of the time required by clinicians to evaluate and begin initial management of the patient". The model takes into account that during this work-up time a patient might experience a change in one of his/her attributes - mainly their acuity level. For example, if a patient's condition improves therefore, their acuity will decrease and vise-versa. Based on that the attribute is updated until a bed match is found. Transportation of patients and the cleaning process of rooms is allocated as a delay time in this model. The patient who is assigned a bed is not immediately taken to their bed according to this delay inputted. At every hour interval, the model uses the inputted discharge distribution to determine if a patient is ready to be discharged. This model takes three types of discharges into account: home, facility or death. For bed allocation, the model matches patients to beds according to the acuity and service required. In this hospital acuity is based on the level of care required and increases from Observation Unit, General Care Unit, Step-Down Unit, to ICU. The model also works on the assumption that patients who are waiting to be admitted have a priority on patients who require internal bed transfers. Moreover, for double-occupancy rooms only, an incoming patient must either be matched to a room in which the current occupant is of the same gender and the same MRSA or VRE flag, or queue until a match becomes available. The model runs in 1-hour time steps. Updates happen at each time step with the hospital exception of 7:00PM to 8:00AM. The data inputted into the model were the following: patient characteristics, patient arrivals, work-up time, delays to bed arrival, acuity changes, patient discharges and hospital structure. The data of patient characteristics were derived from historical data and literature concerning the numbers of MRSA and VRE patients. The arrival rate also depends on the hour of the day and the day of the week. The averages were calculated and are inputted into a Poisson Distribution. Work-up Times were derived from historical data related to the emergency department patients. The mean work up time for observation, general care, step-down and intensive care beds were calculated and are given to patients when they enter the acuity/service queue. Patient acuity change, on the other hand, is determined by an acuity transition probability matrix based on the observed frequency of acuity changes in the observed data. Also, patient discharges are based on a probability depending on the hour of day, day of the week, current acuity and is calculated by dividing the observed hourly frequency of discharges by the total number of patients, adjusted for acuity. This is automatically done by the model itself. As previously mentioned, the model outcomes studied were 8 different values. Log-normal descriptors for the patient-level outcomes of time to bed arrival and length of stay were used, summarizing the distributions with the geometric means. Now in order to validate the model, three techniques were implemented. A **face validation** was established with the hospital management. Moreover, an **internal validation** showed that the model accurately assigned patients to beds based on the aforementioned attributes. The model also perfectly responded to any changes in the patient characteristics. An **external validation** in which a comparison of the outcomes of the model and historical data took place and a match was found. For example, the observed geometric mean time to bed arrival was 6.7 h and the model output ranged from 6.2 to 6.5 h. Moreover, the bed occupancy rate observed realistically was 91% and the model generated a mean occupancy ranging from 86% to 87%. Finally, Shenoy et al. studied different scenarios of the model in order to conduct a sensitivity analysis of the data. Some of the findings recorded were the following. The length of stay was most sensitive to alterations in the distribution of the delays to initial bed arrival. Occupancy was most influenced by alterations in volume of arrivals (79% to 96%), and extremes for both the work-up time (76% to 88%) and increasing discharge probability on weekends (78% to 87%).

Chapter 3: Linear Programming and Simulation Procedure

The following steps have been adopted to tackle the study that was conducted at Rizk and its application will be elaborated further in Chapter 4.

3.1 Linear Programming Methodology

The bed assignment problem requires an optimal allocation of resources that respects the constraints set by customer preferences, capacity and budget. Linear programming is an adequate method to solve this model since it is an optimization technique that attributes values to the decision variables in order to optimize the objective function. The linear program should be modeled in a way that reflects the hospital goal. Some attributes such as the criticality of the case of the patient are prioritized by all hospitals, but other conditions such as the patient's preferences regarding the room's privacy matter in some hospitals more than others. To correctly identify the importance of each constraint in order to be aligned with the hospital's vision, it is fundamental to observe the system and interview stakeholders. Also, in order to assess the solution of the model, key performance indicators should be decided on. Those could be the ratio of successful assignments, the cost of the assignments or the computation time of the model.

Objective function:

Based on the goal of the hospital, the objective function can be a minimization, maximization or mixed statement. The latter would compute the difference between the benefits of assigning patients to beds and the penalties occurred due to the deviations from hospital or patient requirements. The objective also varies depending on the hospital studied. Indeed, if it is a high capacity health institution an optimal bed assignment model is fundamental for patient flow. On the other hand, if it is a low capacity hospital, a good bed management system should target decreasing costs of staffing and underutilizing resources.

Constraints:

As for the constraints, they also highly depend on the system under study. If the hospital is divided into units corresponding to specific services lines and those units are also divided into subgroups of clinical specializations, appropriate constraints should reflect this division.

Constraints can be divided into soft and hard constraints. Soft constraints are the one that meet customer preferences like room-type requirements, gender requirements, bed characteristics and staff-to-patient ratio requirements. Hard constraints are the necessary conditions like only one patient is assigned to each bed, patients with critical cases are assigned first and patients with contagious viruses are isolated.

As a general rule, clinical attributes such as isolation orders, are dictated by the physician's best judgment for patient safety and best clinical outcome and care. Nonclinical attributes such as comfort are requested by the patient and aren't prioritized over clinical requirements but should be accounted for nonetheless in optimal solutions. Constraints should be ranked by order of importance to determine their respective weights. The rank should be determined by the stakeholders namely the physicians, the patients, the nurses and the bed assignment team.

Complexity of the model:

Ideally, the model should account for the dynamic nature of hospitals. This includes the length of stay estimates of the patients, the patient transfers from other hospitals, the patients admitted from the emergency room…An ideal solution would not sequentially attribute a bed to each patient thus only finding locally optimal solutions for each case, but would compute a system-wide solution that would satisfy the optimality of the whole bed management model. In addition, each time a patient is admitted, the model runs again providing a new optimal arrangement that may require to move already admitted patients to make room for incoming patients. Depending on the hospital policy and priorities, new assignments of occupied beds may be admissible or not: already admitted patients that have been assigned beds might not be moved under any circumstances (by making their beds unavailable in the model thus restricting its new assignment). Another requisite for a good model is a timely solution that balances well the trade-off between the time taken to generate an assignment and its optimality. This raises the option of opting for heuristics in case the optimal solution takes too long to be determined.

3.2 Simulation Modeling Methodology

Simulation Modeling is a tool used in various areas to imitate a real world process. Areas where simulation modeling is applied include manufacturing, business processing, construction engineering and several others. Simulation is mainly used to observe and analyze the operating characteristics of the system under study. Moreover, what is significant about simulation is that it can be used on existing systems as well as new systems. When it comes to existing systems it is used as an analysis tool in order to predict the effect of changes in the system. On the other hand, it is used as a design tool for new systems to predict the performance of the system in alternative scenarios and circumstances. Simulation purposes are numerous such as verifying analytic solutions and even studying the internal interactions of a complex system. To develop a simulation model there are 12 important steps used to guide the model builder as follows:

1. *Problem Formulation*: The model starts with defining a clear and coherent problem statement which both the analyst and policymakers should agree on.
2. *Setting objectives and overall project plan*: After agreeing that Simulation is the appropriate tool for the mentioned problem, objectives and an overall project plan need to be set. The project plan is to develop alternative scenarios for the problem along with a method to evaluate the effectiveness of the set alternatives. All details regarding the plan for the study in terms of the project duration and cost of the study need to be mentioned.
3. *Model Conceptualization:* What is important about this step is for the builder to keep in mind that the essence of the real system is needed. It is best to start with a simple model and build towards more complexity which should not exceed the level of complexity required to achieve the purpose of the objective at hand.
4. *Data Collection:* It is important to start collecting the data required at the early stages of developing a simulation model due to the fact that it takes a large amount of time. The type of data to be collected is determined from the set objective.

5. *Model Translation:* The model must be entered into a computer recognizable format. The model could either program the simulation model in a simulation language or use a special purpose simulation software.
6. *Verified?:* Verification is achieved when the input parameters and logical structure of the model are correctly represented in the computer program that has been prepared for the model.
7. *Validated?:* Validation involves an iterative process of comparing the simulation model with the real life system behavior and utilizing the observations made to improve the model and achieve model accuracy.
8. *Experimental Design:* At this stage, the alternative scenarios to be simulated are determined. There are cases where the alternatives to simulate are a function of runs that have been conducted. Decisions such as the length of the initialization period, length of simulation runs and the number of replications need to be made for each system design that is simulated.
9. *Productions runs and analysis:* The following step is conducted to estimate the measures of performance for the system design that is being simulated.
10. *More runs?:* The model builder decides if additional runs are needed based on the analysis of the runs already completed.
11. *Documentation and Reporting:* This step involves two stages; documenting and reporting. There are two types for documenting which are program and progress documentation. Understanding how the program operates for future work and developing a comprehensive chronology of work with respective decisions are the purposes of program and progress documentation respectively. When it comes to the second stage, reporting, it is necessary to report the analysis of the simulation model results in order to evaluate the final formulation, the alternative scenarios, the results and potential solutions that were recommended.
12. *Implementation:* The final step depends on the success of the previous eleven steps. If the model and its assumptions are clearly set and understood by the model builder, then the prospect of a robust implementation is enhanced.

Chapter 4: Linear Programming and Simulation at LAUMC - Rizk

4.1 Linear Programming Model

The following model was developed after the two hospital visits conducted with Rizk and understanding how the procedure works at the hospital itself.

Indices:

i: patient

j: room

h: gender

l: clean

f: infected

t: criticality

a: age

Sets:

H: gender: male and female

R: rooms: critical, clean, infected, first class, isolation, pediatric

O: clean case and unclean case

N: infected case and uninfected case

Q: critical case and non-critical case

U: children and adults

Decision variables:

x_{ij}=1 if patient i is assigned to room j

0 otherwise

Variables:

c_i: levels of criticality of the patient

G_{hj}= 1 if gender h is in room j

0 otherwise

K_j: capacity of room j

T_i= 1 if patient i is critical

0 otherwise

L_i= 1 if patient i is clean

0 otherwise

F_i=1 if patient i is infected

0 otherwise

S_i=1 if patient i is a first class patient

0 otherwise

A_i=1 if patient i is a child

0 otherwise

Z_i=1 if patient i needs isolation

0 otherwise

α_{lj}=1 if clean case is present in room j

0 otherwise

β_{fj}=1 if infected case is present in room j

0 otherwise

σ_{tj}=1 if critical case is present in room j

0 otherwise

γ_{aj}=1 if a child is present in room j

0 otherwise

Model:

Max $\sum_i \sum_j c_i x_{ij}$ — The objective function aims to maximize the admission of patients in the system based on their criticality.

Subject to:

$\sum_j x_{ij}=1 \ \forall \ i$ Each patient is only assigned one room.

$\sum_i x_{ij} \leq K_j \ \forall \ j$ Room capacity is not exceeded.

$\sum_h G_{hj} \leq 1 \ \forall \ j$ Male and female patients cannot be assigned the same room.

$c_i=T_i+1$ The patient is either non-critical or critical.

$x_{ij} \leq MT_i \ \forall \ i, j \in$ *critical rooms*

If the patient is critical it is preferred that he is assigned to a room dedicated for the critical cases.

$x_{ij} \leq ML_i \ \forall \ i, j \in$ *clean rooms*

If the patient is clean it is preferred that he is assigned to a room dedicated for the clean cases.

$x_{ij} \leq MF_i \ \forall \ i, j \in$ *infected rooms*

If the patient is infected it is preferred that he is assigned to a room dedicated for the infected cases.

$L_i+F_i=1 \ \forall \ I$ A patient is either infected or clean.

$x_{ij} \leq MA_i \ \forall \ i, j \in$ *pediatric rooms*

If the patient’s age is between 1 and 14, it is preferred that he is assigned to a room dedicated for children.

$x_{ij} \leq MZ_i \ \forall \ i, j \in$ *isolation rooms*

If the patient requires isolation, it is preferred that he is assigned to an isolation room.

$\sum_i Z_i x_{ij}=1 \ \forall \ i,j \in$ *isolation rooms*

Only patients requiring isolation are placed in isolation rooms and only one patient is admitted to each isolation room.

$x_{ij} \leq MS_i \ \forall \ i, j \in$ *first class rooms*

If the patient has a first class insurance, it is preferred that he is assigned to a room dedicated for the first class.

$\sum_i S_i x_{ij} = 1 \ \forall\ j \in$ *first class rooms*

Only first class patients are placed in first class rooms and only one first class patient is admitted to each first class room.

$\sum_l \alpha_{lj} \leq 1 \ \forall\ j,\ l \in O$ A clean case cannot be in the same room as an unclean case.

$\sum_f \beta_{fj} \leq 1 \ \forall\ j,\ f \in N$ An infected case cannot be in the same room as an uninfected case.

$\sum_t \sigma_{tj} \leq 1 \ \forall\ j,\ t \in Q$ A critical case cannot be in the same room as a non-critical case.

$\sum_a \gamma_{aj} \leq 1 \ \forall\ j,\ a \in U$ A child cannot be in the same room as an adult.

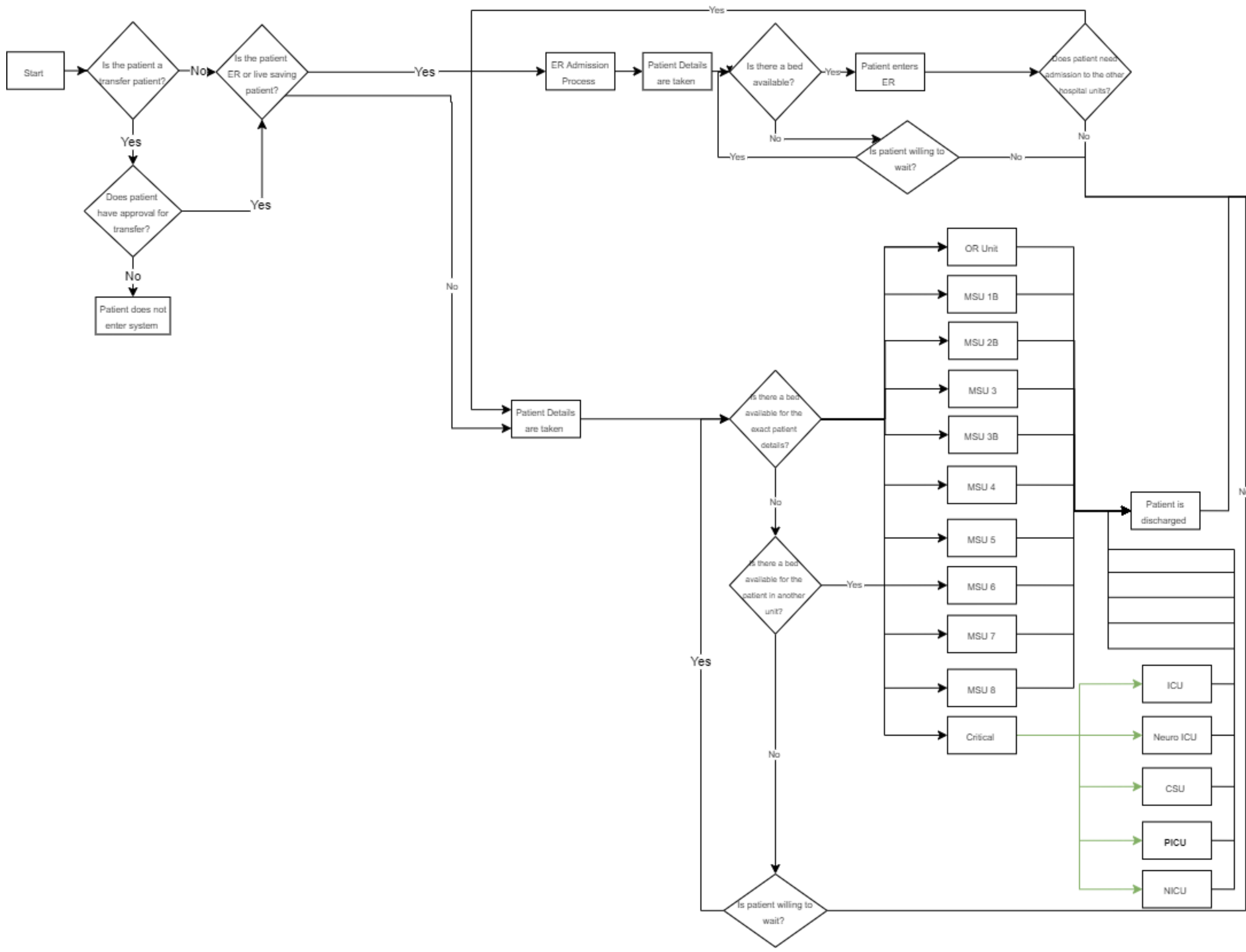
The current assignment of patients to beds in the hospital studied follows five main criteria: gender, age, status, medical condition and criticality. It is preferred that each patient goes to a room that fulfills all its medical requirements and preferences. But in case such a room is not available, he will be assigned a room that still meets its hard constraints (gender, medical condition, status and isolation).

4.2 Simulation Modeling

4.2.1 Goal of the study

The goals of this study were mainly to optimize the utilization of bed resources and decrease the number of lost patients at Rizk hospital. The latter is to improve the number of patients in each department at each phase and to reduce the average patient length of stay in the departments. Based on enabling these goals, this study will emphasize on finding the optimal allocation of bed resources at the hospital. In order to reach these goals, the team started by creating a conceptual model of the hospital's current process and later turned it into a computational model using "Arena".

4.2.2 Conceptual Model



The process of assigning a bed to a patient in Rizk hospital is modeled in the above graph. The patient enters the hospital or the system in the hospital and is assessed to whether or not he/she is a transfer patient from another hospital or not. If the patient is a transfer patient, approval from the ABC manager, case manager and medical director is needed. An all or non-approval is required for this transfer. Whether the patient is a transfer patient or not, the hospital staff assesses if the case entering is an ER or Lifesaving case. If so, then this patient is taken to the ER and goes through the ER admission process. Otherwise, patients are either considered as direct admission or surgery patients who have prior appointments. Direct admission is referred to medical treatments, doctor's appointments and all non-emergency and surgical cases. Accordingly, the patient goes through the admission process of their assigned case/unit.

1. In case the patient is an ER Patient, a triage process happens where all necessary patient details are extracted. After those details are collected, the staff assesses the availability of a bed in the ER. In the case where a bed is available, the patient is directly admitted and doctors perform the necessary treatments. The patient is then discharged with either of two cases: Patient goes home or patient needs hospital admission to become an in-patient. In the second case, the patient goes back to the step of "case being assessed" as shown in the figure. Now in the case where there is no bed available in the ER, patients can either wait in the waiting room or go to another hospital.
2. If the patient requires surgery (OR) or direct admissions to the hospital units, a similar process of collecting patient details is done. After that, the staff assesses the availability of beds in two cases:
    a. First the staff assesses if there is a bed available that meets all the patient attributes and requirements in the necessary unit where he/she should "idealistically" be put. In the case where there is a bed available, the patient is assigned the bed and all necessary medical procedures are done for patient satisfaction.
    b. In case there is no bed available, the staff assesses whether or not there is a place for the patient in a secondary unit that meets "most" of the patient's attributes. In this case, the hospital puts strict conditions on when this case can happen. For example, there is no possibility to put an infected patient with a clean patient even if there is a bed available. In case these secondary conditions are met, the patient is assigned the bed and all necessary medical procedures are done for patient satisfaction. On the other hand, if no bed is available and both the primary and secondary conditions are not met, the patient is given the option to wait until a bed is available or leave the hospital, as illustrated.

In all cases, when the patient is assessed, several attributes are extracted and bed availability is assessed accordingly.

- Case
- Gender
- Age
- Criticality
- Class (1st Class - 2nd Class - Government)
- Insurance
- Clean/Infected
- Isolation

The units illustrated in the graph all hold a different functionality as follows:

- MSU 6-7: Infected Medical cases/Infected Surgical Cases/Isolation
- Msu 8: Clean Medical and Surgical cases
- MSU 4-3: First Class/ Surgical Clean cases
- MSU 4: Orthopedic Cases. Cardiac Care/ First Class
- MSU 3: Gynecology/ Maternity/ Female treatments
- MSU 3B: Pediatric Unit (1 month - 17 years) - Medical Treatments
- MSU 2B: Oncology/ Chemotherapy (in patient 2-5 days) (no infectious diseases)
- MSU 5: Orthopedic Unit/Second Class/Clean cases
- Critical:
    a. ICU: 7 beds/Cubicle/Single Rooms/Infected Critical cases/ Isolation Critical patients
    b. Neuro ICU: Stroke Center: 1 room for isolation 3 beds for open space
    c. CSU: Open space with 6 beds - No segregation - Clean Cases (open heart and cardiac cases, post-op surgery)
- PICU: 2 beds
- NICU: 8 beds (newborns - preterm babies - respiratory distress)
- MSU 1: 1-day treatment

The beds are divided onto the units as follows:

Table 3: LAUMC Bed Distribution

Unit	Number of beds
CSU	6
ICU	7
MSU1	15
MSU2B	12
MSU 3	20
MSU 3B - PED	13
MSU 4	12
MSU 5	16
MSU 6	17
MSU 7	14
MSU 8	11
Neuro ICU	4
NICU	8
ER Beds	15
PICU	2

4.2.3 Computational Model

A simulation model developed on Arena further translated Rizk's bed assignment strategy. The team started by modeling the exact conceptual model above; however, after several trials and discussions, many assumptions were taken into consideration for the final model. These include the following:

- Transfer patients from different hospitals will be ignored in this study due to the lack of data.
- NICU unit will be ignored due to the lack of data related to the number of newborn babies at Rizk.

- Gender attribute will not be studied due to the lack of data related to the room divisions in every unit at Rizk.
- Class and insurance attributes will be taken as one attribute: Class.

Several other assumptions are explained below.

4.2.3.1 Data Collection

The data collection process started with two hospital visits from the team. During those visits, the team sat with the ABC manager and the case manager for two different interviews. The interviews transcribed in Appendix I revolved around asking questions related to the current "bed assignment strategy" adopted at Rizk. The hospital process was first explained in the PFM graphed above. The next step in the formation of the simulation model included several hospital visits where the team would have collected all the necessary numerical data that they needed, however, due to the rise of the COVID-19 pandemic and the enforced country lockdown, the team resorted to getting all the data from relevant research. The team adopted several assumptions based on the interviews conducted with the hospital and the research present. The data used is summarized in the following table:

Table 4: Simulation Model Data Table

Data	Expression	Reference
Patient Arrival Time	EXP(19)	Haddad, M. G., Zouein, P. P., Salem, J., & Otayek, R. (2016). Case study of lean in hospital admissions to inspire culture change.
ER Interarrival	EXP(40)	
OR Patients Arrival Time	EXP(40)	
Admission Process	UNIF(15,20)	Rizk Interview
ER Admission Time	0.5 + 5 * BETA(2.77, 3.11)	Keserwan Medical Center - KMC
Critical	-0.5+LOGN(3.71,3.8)	Baru, R. A. (2015). A decision support simulation model for bed management in healthcare
MSU Distribution	LOGN(37.3,30.3)+2	
MSU 1	UNIF(120,360)	Based on conversation with Rizk
OR Process	TRIA(1.2,190,876)	Costa A., Jr (2017). Assessment of operative times of multiple surgical specialties in a public university hospital.

ER Process	UNIF(120,300)	Landa, P., Sonnessa, M., Tanfani, E., & Testi, A. (2014). A discrete event simulation model to support bed management
Does patient need transfer to hospital (%)	0.026	Hanmer, J., Lu, X., Rosenthal, G. E., & Cram, P. (2014). Insurance status and the transfer of hospitalized patients: an observational study.
Patient Waits	0.5	Assumption

Moreover, data needed for the assignment of attributes to patients were based on the interviews conducted with the hospital. The MSUs are distributed based on different cases and attributes as shown in section 4.1.1. The team took this data, counted the number of beds that could occupy a specific attribute, and assigned the percentage based on that. For example: Infected patients are put in MSU 6 (17 beds), MSU 7 (14) and the ISU (7), therefore, a total of 38 beds are allocated for infected cases (38/160=0.23). The team rounded down and took 20% of the patients as infected patients. This interpretation was done for all other attributes except the age one which was taken based on the interviews at Rizk.

Table 5: Simulation Model Attributes

Attribute	Distribution	Description
Age	DISC(0.40,1,1,2)	1= Less than 18, 2= Older than 18
Infection	DISC(0.2,1,1,2)	1= Infected, 2= Not infected
Class	DISC(0.2,1,1,2)	1= 1st Class, 2= All other
Criticality	DISC(0.2,1,1,2)	1= Critical, 2= Non-Critical
Isolation	DISC(0.1,1,1,2)	1= Needs Isolation, 2= No isolation
Diagnosis	DISC(0.15,1, 0.26, 2, 0.42, 3, 0.80, 4, 0.94, 5, 1.0, 6)	1= Cardiac, 2= Chemo, 3= Gynecology, 4= Medical, 5= Orthopedic, 6= Neuro

For the decision nodes in the model the following was adopted:

- **OR Patient transfer:** OR patients are considered surgical patients that are transferred to the following units: CSU - MUS3 - MSU4 - MSU6 - MSU 7 - MSU 8 and if their surgery does not require staying in the hospital overnight they would go to MSU1. Hence, the team *assumed* that the decision node "N-way by chance" decides on which unit the patient is assigned equally to the first 6 units (14%) and the remaining 16% are assigned to MSU1. No other condition is tested in this decision since OR patients are pre-determined by a set schedule and their beds in the units are reserved. This model *assumes* that no unexpected surgeries (from the ER or other units) occur.

- **Hard Constraints:** the following decision node studies the patient's assigned attributes matches the attributes to the conditions of the units and assigns the patient to the route to that specific unit, otherwise the patient goes to the 2nd constraints decision node. The conditions are as follows:
  - ***MSU3:*** Infection == 2 && Class == 1 && Age == 2 && Criticality == 2 && Isolation == 2 && Diagnosis==3
  - ***MSU2B:*** Infection == 2 && Class == 2 && Age == 2 && Criticality == 2 && Isolation == 2 && Diagnosis==2
  - ***MSU3B:*** Infection == 2 && Class == 2 && Age == 1 && Criticality == 2 && Isolation==2 && Diagnosis==4
  - ***MSU4:*** Infection == 2 && Class == 1 && Age == 2 && Criticality == 2 && Isolation == 2 && (Diagnosis==1 || Diagnosis==5)
  - ***MSU5:*** Infection == 2 && Class == 2 && Age == 2 && Criticality == 2 && Isolation == 2 && Diagnosis==5
  - ***MSU6:*** Infection == 1 && (Class == 1 || Class == 2) && Age == 2 && Criticality == 2 && Isolation == 1 && Diagnosis==4
  - ***MSU7:*** Infection == 1 && Class == 2 && Age == 2 && Criticality == 2 && Isolation == 1 && Diagnosis==4
  - ***ICU:*** Infection == 1 && (Class == 1 || Class == 2) && Age == 2 && Criticality == 1 && Isolation == 1 && (Diagnosis==2 || Diagnosis==3 || Diagnosis==4 || Diagnosis==5)
  - ***NEUROICU:*** (Infection == 1 || Infection == 2) && Class == 2 && Age == 2 && Criticality == 1 && (Isolation == 1 || Isolation == 2) && Diagnosis==6
  - ***CSU:*** Infection == 2 && Class == 2 && Age == 2 && Criticality == 1 && Isolation == 2 && Diagnosis==1
  - ***PICU:*** Infection == 2 && (Class == 2 || Class==1) && Age == 1 && Criticality == 1 && Isolation == 2 && Diagnosis==4

- *MSU8:* Infection == 2 && Class == 2 && Age == 2 && Criticality == 2 && Isolation == 2 && Diagnosis==4

- **2nd Constraints:** the hospital's policy studies all the hard constraints before seeing if the constraints can be relaxed and patients can be put in different units. The hospital relaxes their conditions on some units by stating that either class or age can be put in all units and these following constraints result:
  - ***MSU2B:*** Infection==2 && (Class==1 || Class==2) && (Age==2 || Age==1) && Criticality==2 && Isolation==2 && Diagnosis==2
  - ***MSU3B***: Infection==2 && (Class==2 || Class==1) && Age==1 && Criticality==2 && Isolation==2 && Diagnosis==4
  - ***MSU4***: Infection==2 && (Class==1 || Class==2) && (Age==2 || Age==1) && Criticality==2 && Isolation==2 && (Diagnosis==5 || Diagnosis==1)
  - ***MSU3***: Infection==2 && (Class==2 || Class==1) && (Age==2 || Age==1) && Criticality==2 && Isolation==2 && Diagnosis==3
  - ***MSU5***: Infection==2 && (Class==2 || Class==1) && (Age==2 || Age==1) && Criticality==2&&Isolation==2 && Diagnosis==5
  - ***MSU6***: Infection==1 && (Class==1 || Class==2) && (Age==2 || Age==1) && Criticality==2 && Isolation==1 && Diagnosis==4
  - ***MSU7***: Infection==1&& (Class==2 || Class==1) && (Age==2 || Age==1) && Criticality==2&&Isolation==1 && Diagnosis==7
  - ***MSU8***: Infection==2 && (Class==2 || Class==1) && (Age==2 || Age==1) && Criticality==2 && Isolation==2&& Diagnosis==4
  - ***ICU***: Infection==1 && (Class==1 || Class==2) && (Age==2 || Age==1) && Criticality==1 && Isolation==1 && (Diagnosis==2 || Diagnosis==3 || Diagnosis==4 || Diagnosis==5)
  - ***NEUROICU***: (Infection==1 || Infection==2) && (Class==2 || Class==1) && (Age==2 || Age==1) && Criticality==1 && (Isolation==1 || Isolation==2) && Diagnosis==6
  - ***CSU***: Infection==2 && (Class==2 || Class==1) && (Age==2 || Age==1) && Criticality==1 && Isolation==2 && Diagnosis==1
  - ***PICU***: Infection == 2 && (Class == 2 || Class==1) && Age == 1 && Criticality == 1 && Isolation == 2 && Diagnosis==4

Finally, for the sake of animation, the team assumed a route of 10second between all departments and 5seconds from every department to the exit.

4.2.3.2 Model Logic

ER patients and regular patients are distinguished through the creation of two different create nodes with a distinct arrival rate each. The branch of the model that welcomes ER patients follows this course: upon an emergency patient's arrival, bed availability is checked at a decision node by examining if the current number of busy beds is less than 15, which is the total number of ER beds. This is done through the NR() function that detects the number of busy units of the resource in function, which in our case is the number of beds. Two possible outcomes result from this node: a bed is vacant and the patient proceeds to the admission office or all ER beds are occupied and the patient has to wait for a bed to be available. Some people decide not to wait for their turn, so another decision node decides which people are willing to wait and which are not based on probability. Naturally, those who refuse to wait exit the system and those who want to wait go to the waiting room. In the latter case, the patient has to hold in the ER queue that obeys the vacancy condition NR(ERBED)<15. Once a bed is free, a waiting patient will proceed to the admission office after passing again through the bed availability decision node. IN the ER admission, the patient seizes one of the admission staff, delays them for the duration of the admission process and releases them once done in order to proceed to the actual ER process which also follows the seize, delay and release course. The ER process resources are the 15 ER beds. After the diagnosis and necessary treatments are completed, the patient goes through a new decision node that dictates if his/her stay is done and he/she can exit the system or if he/she has to be transferred to another hospital unit. The latter happens according to a certain probability and transfers the patient directly to the hospital admission further discussed later. As for the branch that welcomes regular patients, it follows this course: when a patient arrives, he/she directly proceeds to the admission office. The admission staff attend to the regular hospital patients as well as the patients that have to be transferred from the emergency department to another hospital unit. Once admitted, the patient is assigned a list of attributes based on discrete functions with probabilities. Those attributes will later determine which MSU he/she has to go to. In other words, based on the patient's age, class, criticality, isolation requirement, diagnosis and infection status he/she will go to the hospital unit that conforms to his/her attributes. The next step is to check those characteristics to decide on the path of the patient. The first decision node consists of hard constraints, meaning the attributes have to be perfectly met in order for the patient to be assigned a bed. For instance, MSU4 is equipped to assist non-critical and non-infected adult patients of first class that do not need to be isolated and are diagnosed with an orthopedic or cardiac case. The hard constraints decision node only allows patients with those exact characteristics to be sent to MSU4. Naturally, a lot of the patients cannot perfectly fit the requirements of each unit, which is why another decision node with soft constraints is added. That node directs the patients that could not be assigned by the previous decision node to an appropriate unit that can still assist them adequately. The constraints being relaxed are mainly the class and age attributes since they are considered to be the most flexible. Consequently, patients with attributes compatible to the unit's characteristics are assigned a bed in those units and patients that do not fit the conditions leave the system. The hospital units that are within this flow are: MSU2B, MSU3, MSU3B, MSU4, MSU5, MSU6, MSU7, MSU8, ICU, NEUROICU, CSU and PICU. Once the patient is in one of those units, he/she seizes a bed until his/her treatment is over and he/she leaves the system. A third branch-that eventually connects to the second branch- is dedicated to OR patients. The latter have their own arrival rate that fluctuates between 30 and 35 arrivals per day. Note that there is a schedule prepared a day ahead by the hospital staff that lists all the operations that will take place the following day along with their detailed information. After entering the system, OR patients go to the OR rooms where they occupy a bed. When their operation is done, they either go to MSU1, a unit dedicated for patient use after surgeries or they go to any other hospital unit based on their treatment needs. The route they follow is determined by a decision node with probabilities. After being assigned a unit, the patient seizes a bed until his/her treatment is done and he/she leaves the system.

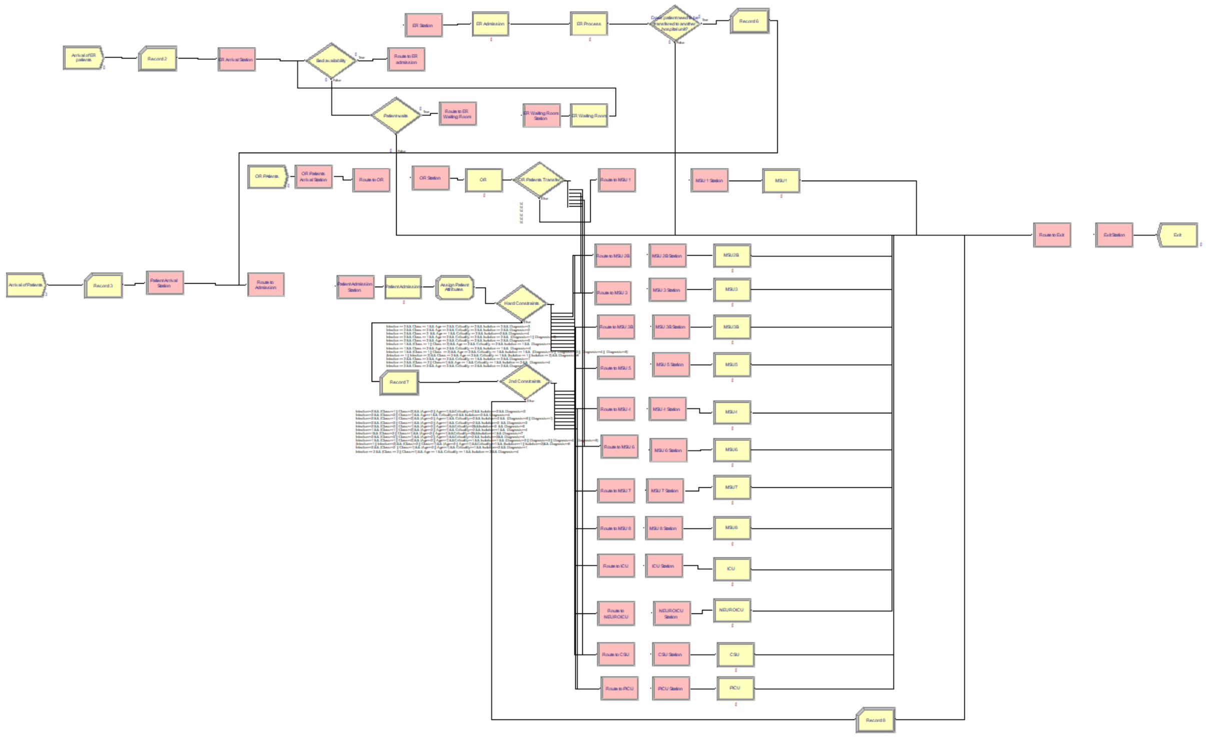


Figure 4: ARENA Logic Model

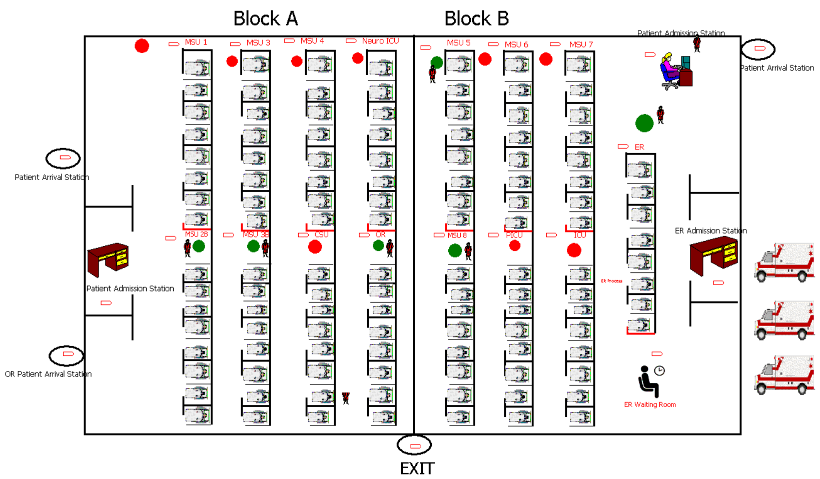


Figure 5: ARENA Animation

4.3.2.3 Model Results

The model was run for a 100 replications with each replication having a duration of 10,080 minutes which is equivalent to 7 days. Naturally, a day consisted of 24 hours since hospitals provide their services around the clock. As for the warm-up period, after evaluating many alternatives, eight days was concluded to be the best option to adopt since after that duration the system is stable (specifically the number of patients leaving the system reaches a constant value). Concerning the results, an average of 815 patients entered the system of which 710 left by the end of the simulation. The difference in numbers represents those who are still being treated in the hospital units. The average time an entity spends in the system is 836 minutes (13.9 hours). Regarding the queues, as expected the OR department does not have any queue since all the operations happen according to a schedule set a day ahead of time. All the critical units- namely CSU, ICU, NEUROICU and PICU- have null or extremely low number of patients waiting in their queues which is a beneficial outcome since critical cases need to be attended fast. In addition, the non-critical units also show a very low number of people in queues. Only two units display somehow negative results: MSU8 that has an average of 10.5 patients in its queue and MSU4 that has an average of 8. Nonetheless, most units have nearly nonexistent queues. Since this project aims to optimally allocate patients to beds, the most important results are the bed utilization values. If we combine the number scheduled and total number seized tables, we can calculate on average how many times each bed was used. The results are very valuable since they reflect which beds are being used a lot and which ones are not being used often enough. Better bed allocation can thus be deduced with the aim of a more efficient bed utilization.

Table 6: Bed Utilization Analysis

Resources	Number Scheduled	Total Number Seized	Average usage/ bed
CSUBED	6	15.8	2.63
ERBED	15	253.44	16.90
ICUBED	7	1.69	0.24
MSU1BED	14	4.89	0.35
MSU2BBED	12	34.33	2.86
MSU3BBED	13	46.16	3.55
MSU3BED	20	53.63	2.68

MSU4BED	12	56.41	4.70
MSU5BED	16	21.17	1.32
MSU6BED	17	7.7	0.45
MSU7BED	14	4.58	0.33
MSU8BED	11	53.12	4.83
NEUROICUBED	4	6.21	1.55
ORBED	35	31.65	0.90
PICUBED	2	12.08	6.04

The "number busy" section of the results displays results that agree with the average usage/bed calculated above. Units can be divided into high, moderate and low bed utilization. In fact, some of the most used beds are MSU4BED with 10.94 beds busy out of 12 beds and MSU8BED with 10.21 beds busy out of 11 beds. Other units have a moderate bed usage such as MSU3 where 10.42 beds are used on average out of 20 beds and the MSU2B unit where 6.63 beds are used out of 12 beds. And at the lower end, ICUBED shows a very low utilization since only 0.03 beds are busy out of 7 total beds. The instantaneous utilization further assures those results since the percentage utilization ranking is as follows.

Table 7: Bed Utilization Ranking - 1

MSU8BED	MSU4BED	MSU3BBED	MSU2BBED	MSU3BED	ERBED	MSU5BED	PICUBED
93%	91%	67%	55%	52%	35%	26%	12%

MSU6BED	MSU7BED	CSUBED	NEUROICUBED	ORBED	ICUBED	MSU1BED
10%	7%	5%	3%	3%	1%	1%

Table 8: Bed Utilization Ranking - 2

In addition, the scheduled utilization conforms with the results deduced above. For instance, MSU8BED scores a high value of 92.8% whereas ICUBED only amounts to 0.43%. Two counters are also of interest in this study. The first one compute the number of lost patients that left either because they could not find a bed or their attributes did not fit any unit's requirements. Their number amounts to 210.31 which is 25.81% of all the entities that enter the system. The second counter adds up the number of patients that passes through the soft constraints. That value is of importance since it shows how many people did not meet the units' conditions perfectly and had to have some of its attributes relaxed. Exactly 364 patients pass through the soft constraints which is 44.66% of all the cases. This number is very high and hints at the advantages that could result from revising the conditions the hospital abides by.

4.2.4 Model Validation and Verification

4.2.4.1 Model Validation

The first step taken is to determine the warm-up period in order to reach a steady-state behavior of the system. Our analysis shows that a warm-up period of 8 days is sufficient for the simulation. The tables below summarize our results for a replication length of 7 days:

Table 9: Warm-Up Period Analysis with 30 Replications

Number of replications	30											
Warm-up period	1	2	3	4	5	6	7	8	9	10	20	50
Patients out	632	528	421	316	210	105	0	709	709	709	709	709

Table 10: Warm-Up Period Analysis with 50 Replications

Number of replications	50											
Warm-up period	1	2	3	4	5	6	7	8	9	10	20	50
Patients out	631	528	422	317	211	106	0	708	708	708	708	708

Table 11: Warm-Up Period Analysis with 100 Replications

Number of replications	100											
Warm-up period	1	2	3	4	5	6	7	8	9	10	20	50
Patients out	632	529	423	318	212	106	0	710	710	710	710	710

Additionally, the logic of the model was verified with the ABC Manager and Case Manager during the second interview when the team shared with them the conceptual model, and using the check model function on ARENA. Finally, the arrival time of patients in the ER, OR and hospital are exported from Arena to Excel to examine if they are set appropriately in the simulation. The interarrival times are analyzed through Arena's Input Analyzer and the plots are drawn using Seaborn data visualization library.

Table 12: Input Analyzer Results

Arrival to	**Distribution**	**Mean**	**Chi-Square Test, P-value**	**KS Test, P-value**
Hospital	Exponential	19.1	0.318	>0.15
ER	Exponential	39.6	0.531	>0.15
OR	Exponential	44.1	0.307	>0.15

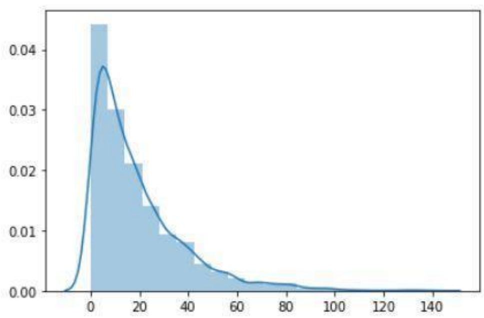


Figure 6: Exponential distribution with mean (19.1)

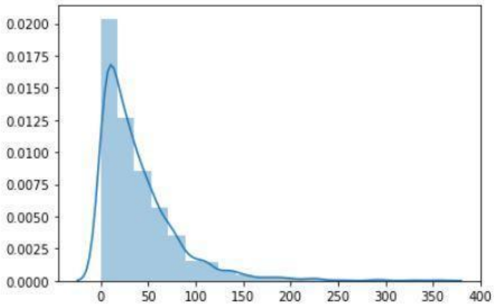


Figure 7: Exponential distribution with mean 39.6

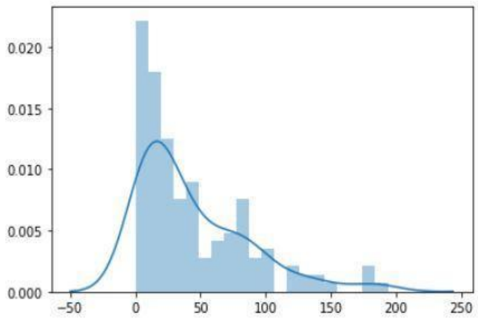


Figure 8:Exponential distribution with mean 44.1

The P-value for each distribution shows that the arrival times in the simulation are properly set.

4.2.4.2 Model Verification

Due to the lack of data, we will explain our methodological approach to the statistical analysis that would have been adopted with real data.

To determine if the actual values and simulated values obtained are similar from each other, a parametric two-sample t-test or a non-parametric test is used. If the data collected from the hospital is normally distributed, the t-test method is appropriate to determine our hypothesis testing. Otherwise, we run the non-parametric alternative Kruskal-Wallis test. The simulation output is gathered through 100 IID replications for a time period of one week. We chose to test the following three null hypotheses with a 95% confidence level:

a) H_0: There is no statistical difference between the simulated number of patients exiting the hospital per week and actual number of patients exiting the hospital per week.

H_1: There is a statistical difference between the simulated number of patients exiting the hospital per week and actual number of patients exiting the hospital per week.

b) H_0: There is no statistical difference between the simulated LOS of the patient in the hospital and actual LOS of the patient in the hospital.

H_1: There is a statistical difference between the simulated LOS of the patient in the hospital and actual LOS of the patient in the hospital.

c) H_0: There is no statistical difference between the simulated number of patients cured per week and actual number of patients cured per week.

H_1: There is a statistical difference between the simulated number of patients cured per week and actual number of patients cured per week.

The critical value of the t-test is $t_{99,0.975=}$ 1.984. Assuming normality, in order to prove that the simulation model represents the real model, t values of each hypothesis should be less or equal than 1.984 and greater or equal than -1.984. In Kruskal-Wallis's test, the test statistic should be less or equal to $X^2_{0.05,1} = 3.841$. The P-value method also works for both tests.

4.2.5 Alternative Simulation Scenarios

After validating the proposed simulation model, several what if scenarios were developed and analyzed in order to determine performance measures and quantify how these impact the bed utilization and allocation at Rizk. The scenarios tested are as follows:

4.2.5.1 **Scenario 1:** Removal of 3 beds from units with low utilization

From the obtained results in the developed model it is evident that the utilization of beds among the units vary significantly. The following units recorded the lowest percentage of bed utilization and were chosen for this scenario: MSU 1, MSU 6-7, ICU, CSU, Neuro ICU and PICU. PICU and Neuro ICU were disregarded since they only have 2 and 4 beds respectively. A low utilization is due to the fact that the beds allocated to that unit are more than how much is needed. By removing beds, this could significantly increase the bed utilization in the respective unit, reduce the average length of stay, waiting time of patients and increase the number of patients admitted to the hospital and thus improve bed allocation at the hospital. By trial and error, the number 3 for the beds was chosen since it showed better utilization. The following table shows the comparative analysis of the respective units before and after adding 3 beds.

Table 13: Scenario 1 Bed Utilization Results

	Number of Beds		Bed Utilization	
Unit Name	**Before**	**After**	**Before**	**After**
MSU 1	14	11	1%	2%
MSU 6	17	14	10%	12%
MSU 7	14	11	7%	10%
CSU	6	3	5%	10%
ICU	7	4	1%	2%

Table 14: Scenario 1 Results

	Before	After
Length of Stay	836	836
Number In	815	815
Number Out	710	710
Number of Lost Patients	210	210

4.2.5.2 <u>Scenario 2:</u> Partition of beds between high and low utilization units

As previously mentioned, the percentage of bed utilization significantly differs between departments with the highest recorded as 93% in MSU 8 and 1% recorded in both ICU and PCU. This scenario aims at establishing a certain balance on bed utilization between the units of high utilization and low utilization. With that being said, three factors will be looked at in order to choose how to partition the beds: (1) The number of beds in the unit, (2) The location of the unit and (3) The percentage of bed utilization in the unit. Based on data provided by colleagues who had conducted a project at Rizk before the layout of the departments are between two blocks, A and B, as follows:

Block A: MSU 1, MSU 2B, MSU 3, MSU 3B, MSU 4, NeuroICU, CSU, OR and Admissions
Block B: MSU 5, MSU 6, MSU 7, MSU 8, PICU, ICU and ER

Based on the latter the following will be applied:

1. ***Add 3 beds to MSU 8 from MSU 6***, since they both belong to the same block (B) and record in the both the highest and lowest utilization categories respectively.
2. ***Add 3 beds to MSU 4 from MSU 1***, since they both belong to the same block (A) and record in both the highest and lowest utilization categories respectively.
3. ***Add 3 beds to MSU 3B from CSU***, since they both belong to the same block (A) and record in the highest and lowest utilization categories respectively.

Table 15: Scenario 2 Bed Utilization Results

	Number of Beds		Bed Utilization		Waiting Times	
Unit Name	**Before**	**After**	**Before**	**After**	**Before**	**After**
MSU 8	11	14	93%	88%	1298.22	602.12
MSU 6	17	14	10%	12%	0	0
MSU 4	12	15	91%	84%	976.85	368.56
MSU 1	14	11	1%	2%	0	0
MSU 3B	13	16	67%	55%	95.0572	12.9725
CSU	6	3	5%	10%	0	0.7433

Table 16: Scenario 2 Results

	Before	After
Length of stay	835.78	804.54
Number in	815	814
Number out	710	725
Number of lost patients	210	211

4.2.5.3 <u>Scenario 3:</u> Constraints Relaxation

As mentioned in the model results section, two counters are of interest: the lost patients counter and the soft constraints counter (which adds up the number of entities that pass from the hard constraints to the soft constraints). In order to decrease both those counter values, a promising approach was to further relax the constraints. By examining the attributes taken into account while assigning patients to beds, the most flexible characteristic was deemed to be the diagnosis of the patients since equipment can be transported when needed and doctors can attend their patients regardless of their location most of the time. Indeed, the infection status, isolation need and criticality cannot be changed and the age and class have already been relaxed in the soft constraints when possible. Consequently, the diagnosis attribute was eliminated and the units were merged whenever their new constraints were similar. As a result, the capacities of MSU2B and MSU5 were added to MSU8 and the capacity of MSU3 was added to MSU4 since they now accepted the same set of patient attributes. After those changes were applied, the flow of patients increased enormously in the hospital units to the point where we had to decrease the MSUs' process times to be able to run the model on the student version of Arena without exceeding its capacity and getting an error.The results were naturally positive: the number of lost patients decreased from 210.31 to 111.18 which is an improvement of *47.14%* and the number of patients proceeding to the soft constraints decreased from 364 to 163.83 which is an improvement of *54.99%*. This alternative way of assigning patients to beds assures that more entities are being appointed to rooms that satisfy perfectly their necessary needs as well as their age and class attributes, since the entities assigned by the hard constraints increased considerably. Additionally, the hospital is losing much less patients and thus increasing its revenues.

4.2.6 Scenario Discussion

Both scenarios 1 and 2 yielded significant results in terms of improving bed utilization. When it comes to scenario 1, an increase in bed utilization was observed in each unit as shown in table 17. The overall improvement for the system in this scenario is **72.56%**.

Table 17: Scenario 1 Unit Percentage Improvements

Unit Name	Percentage improvement
MSU 1	100%
MSU 6	20%
MSU 7	42.8%
CSU	100%
ICU	100%

Other parameters that were analyzed in this scenario are length of stay, number of patients in/out, the number of lost patients and waiting time in the queue for every unit. However, the percentage of change in each was considered insignificant due to the fact that they scored below 0.5%.

On the other hand, scenario 2 recorded significant positive change in several parameters as demonstrated in table 18. The results in table 18 show that the objective behind scenario 2 was achieved, a decrease in bed utilization of the units that were categorized as high utilization and increase in utilization in the units that were categorized as low utilization. The bed utilization of MSU 8, MSU 4 and MSU 3B decreased by 5.37% , 7.69% and 17.9% respectively while also recording a decrease in waiting time by 53.61%, 62.2% and 86.35%. While in units where beds were removed, MSU 6, MSU 1 and CSU the bed utilization increased by 20%, 100% and 50% the waiting time of these units was not recorded since they were below 0.5% and thus considered insignificant.

Table 18: Scenario 2 Unit Percentage Improvements

	Percentage Improvement

Unit Name	Bed Utilization	Waiting Time
MSU 8	5.37%	53.61%
MSU 6	20%	-
MSU 4	7.69%	62.2%
MSU 1	100%	-
MSU 3B	17.9%	86.35%
CSU	50%	-

Furthermore, when it comes to the average length of stay, it decreased by almost 4%, from 835.78min to 804.54min and the number out shows us that the number of patients that were fully treated and left the system also increased from 710 to 725 and this shows a financial advantage to the hospital.

Looking into the results obtained from both scenarios 1 and 2, both can have a positive impact on the hospital's bed allocation process. However, it is evident that scenario 2 has greater impacts than scenario 1 since it does not only positively impact bed utilization but also the waiting time (queue) in the hospital's units and the number of patients waiting in the system. Scenario 2 can be complemented with scenario 3. By relaxing the strategy of admission of patients to the hospital through eliminating the diagnosis attribute and merging units with similar constraints and combining that with scenario 2 an optimal solution can be proposed for the hospital.

4.2.7 COVID-19 Case Study

Due to the current situation and pandemic the world is witnessing, and seeing the importance of this research in relation to the crisis, the team decided to develop a model and strategy for Rizk Hospital on how to deal with the situation. All the data for this case was extracted from the official Lebanese Ministry of Public Health (MoPH) website and several assumptions were handled. A new create module was added to the existing model defining COVID-19 patients that enter the system. The numbers in table in Appendix J, as previously mentioned, were taken from MoPH's website up until the cases confirmed on May 20. These numbers were put on Arena's Input Analyzer and the results in figure 10 showed the interarrival function of COVID-19 cases in Lebanon.

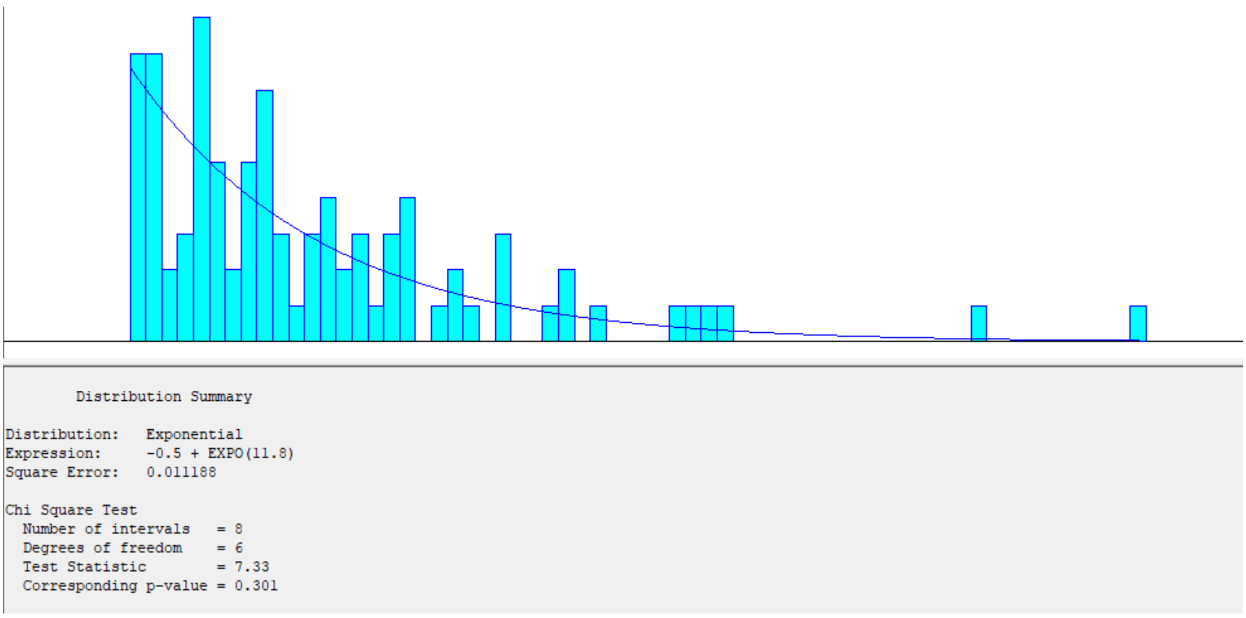


Figure 9: Input Analyzer COVID-19 Case

The corresponding Chi Square Test p-value (0.301) is greater than 0.1, therefore we accepted this interarrival distribution. According to MoPH and an article published on the website on May 21 titled "Suppressing COVID-19 Transmission", approximately 20% of patients will require hospitalization. The team assumed that from these 204 patients 20% will opt to be hospitalized in a private hospital. This study also assumes that the only private hospital to accept COVID-19 patients will be Rizk. Hence, Rizk will admit 41 cases. From which, 5% will need to be admitted to an intensive care unit (MoPH).

For Rizk to be able to accommodate to these patients who need treatment, they will need rooms allocated for infected patients, requiring isolation and class should not be a matter. This is why MSU6 would be the perfect fit to accommodate these patients. Based on the model results, MSU6 utilization was approximately 10% and MSU7 a solid 7%. Both these units accept the patients with the same attributes however, MSU6 is more flexible in accepting classes. This is why patients who were routed to MSU6 will now be routed to MSU7 and two rooms in MSU7 can be allocated for first class patients. Even the patients who went from the OR to MSU6, are now assigned to MSU7 instead. Therefore, MSU6 will solely be used for COVID-19 patients. Moreover, 2 beds from the ICU will be reserved and used for the intensive patients. A new create module was added in the updated model to accommodate for the maximum number of patients that Rizk will admit. Moreover, the decide module translates the 5% intensive cases and the isolation cases. By applying these changes to the simulation model and running it for a total of 7 days, with a warm up period of 8 days and 100 replications, the following resulted:

Table 19: COVID-19 Scenario Results

		Bed Utilization	
Unit Name	**Number of Beds**	**Before**	**After**
MSU 6	17	9.8%	16.71%
MSU 7	14	7.1%	17.62%
ICU	7	0.43%	0.57%

The results in the table above show that the hospital's bed utilization increased and based on the model that was adopted, Rizk is able to accommodate for COVID-19 patients with a few changes. However, for this conclusion to be conclusive, more data related to staff allocation, financial gain and loss, is needed.

Chapter 5: Conclusion

5.1 General Improvements

Bed availability is affected by many factors such as the patient admissions process, flow and discharge process. In order to efficiently manage beds, hospital staff should have access to an accurate up-to-date vision of the current state of the system. Many digital software solutions can provide doctors and nurses remote access to this critical data whenever it is needed. Indeed, when employees can retrieve real-time monitoring data by simply checking a mobile app, they will be able to efficiently allocate resources and resolve shortage issues.

One of the initiatives that can facilitate bed management is a digital ward whiteboard that provides an operational summary with key data such as capacity, planned admissions, occupancy and expected discharges. This visual management tool can also act as a Jidoka framework, since by displaying the expected number of patient admissions and the current occupancy, excess patient flow can be predicted and dealt with on the spot.

Another digital solution is a real-time mobile application that displays all the data required for efficient bed assignment. The data in question consists of the units' capacity, occupancy, expected arrivals, estimated departures and expected availability. The interface of the software should naturally be user friendly and even include a colored visual representation of the hospital divided by units, so the person in charge can know the system status at a glance. That data can also be shared with the appropriate staff for easier communication and decision-making.

The bed assignment procedures in LAU Medical center are currently handled by a single person during each of the two hospital shifts. That employee is in charge of the OR schedule that is set daily and also allocates patients to beds by communicating through phone calls with the hospital units and checking their occupancy each time she receives a bed request. The current bed management method is time-consuming, prone to human error, and inefficient since it is done manually. By adopting the digital solution proposed above, the bed manager can efficiently assign resources without contacting any other party since all the data required for the decision-making will be available through the mobile app.

"Flow"- the software that provides all the services and tools mentioned above- costs 350$/month which is negligible compared to its advantages when it comes to patient care and experience, employee efficiency and morale and hospital performance. It is a paperless application that ultimately helps reduce patient length of stay. Based on a case study conducted by Servelec, Flow has the potential to save a hospital with 700 beds over £2 million in only 3 years.

5.2 Limitations and Future Work

This study is limited to primary interviews conducted with Rizk Hospital and data extracted from research articles that have previously applied discrete event simulation in healthcare systems. The latter is due to the on-going events that have been going on in the country in the past year. This has greatly impacted the project's data collection process and thus the output of the project.

The most important limitation in discrete event simulations is the model itself being unique to the real system; meaning that the simulation model represents only the underlying system at hand. The latter is a limitation in the work achieved by this study due to the fact that the distribution functions used for the computational model are not from the hospital under study. The data collected is from different hospitals conducted in several research articles and this affected the expected output parameters.

Due to the lack of data, the current model does not account for the gender constraint, which is a factor that determines patient allocation, and is relaxed in the model. Also, transfer patients which come from different hospitals to Rizk are not accounted for since they follow a distinct process and its respective data was not sufficient for analysis. The length of stay of patients is extracted from previous research, therefore this limited the stud’s capacity to validate and verify the data analysis. Furthermore, the model disregarded events from the actual system. For instance, at Rizk hospital, patient rooms are cleaned after each patient is discharged which requires approximately 30 minutes. This time increases for isolation patients to 4 hours. By disregarding this, there is no queue in the system, for the next patient in the queue is assigned to a clean bed as soon as a patient is discharged. Data of bed cleaning can in fact enable the determination of the appropriate statistical distribution for waiting time of patients.

In the model developed, nurses, doctors and their respective schedules were not taken into consideration. However, the simulation model would be more accurate and robust with the availability of such data. Also, important Key Process Indicators (KPIs) such as bed turnover time and operating costs were not mentioned due to insufficient data. The primary interviews are reflected in the work achieved on the conceptual model. Some KPIs like surgery costs were introduced briefly in the beginning of the interviews, however the team did not have the chance to enquire more information about them.

Future work to this model would be collecting and implementing actual data from the real system. The study made sure to detail the methods and tools to analyse the actual data of the system when possible. A lot of gaps need to be filled to enhance the model. First of them is introducing other key process inputs to the model to improve the model and accommodate multi-attributes and multi-resource constraints in maximizing bed admissions. The latter could demonstrate improved resource utilization and estimate costs associated with medical units. Designing such complex systems is challenging and requires full support of the hospital for extensive data collection and analysis to reflect and achieve the hospital's strategic goals.

5.3 Conclusion

This study aimed at tackling bed assignment and how beds are currently assigned to patients at LAUMC Rizk Hospital. It started with a literature survey on bed assignment problems as well as the methodologies utilized to analyze the problem specific to this study; Linear Programming and Simulation Modeling. A linear programming model was proposed in the beginning followed with a discrete event simulation model to look into and analyze the performance of existing operations.

A simulation model of the system at LAUMC Rizk Hospital was constructed using ARENA in order to develop a better understanding of the bed assignment problem for admitting patients in the hospital. The latter aimed to improve bed utilization by taking into consideration the medical, physical and societal conditions of patients. To achieve that the study looked into the results generated regarding patient statistics, average waiting times in departments, the instantaneous utilization of bed resources, and average length of stay. After obtaining and analyzing results from ARENA about the statistics of the current system, different alternative bed allocation scenarios were developed to investigate an appropriate solution for the system. Three scenarios were established and discussed, by looking into the scenario with the most statistical improvements, scenario 2 was chosen as a suitable improvement. Scenario 2 involves partitioning bed resources between departments of high utilization and low utilization. The latter lead to a decrease in the average length of stay, increase in the number of patients exiting the system, decrease in wait time in departments with high utilization and increase in utilization in units with low utilization. This proposed solution does not incur any additional cost to the hospital. In addition, to that scenario 3 looks into relaxing the strategy of admission of patients to the hospital by eliminating the diagnosis attribute and merging units with similar constraints. This scenario indicated a significant improvement by decreasing the number of lost patients due to the relaxed soft constraint. The optimal solution to this study would be a combination of both scenarios 2 and 3 which can be looked into more in the future with more precise and robust data. The paper also proposes general improvements that can be applied in the hospital to improve bed availability at the hospital along with their associated costs. Furthermore, the use of waiting rooms for patients being discharged later throughout the day will allow to free up more beds inside the units for patients admitted and waiting to be processed.

Finally, in light of the current COVID 19 pandemic which caused several limitations to the work of this project the study looked into an optimal strategy for Rizk to adopt. With few data on the current crisis, the strategy developed showed an increase in the bed utilization while incurring a few changes to the process in order to safely admit a patient in the hospital.

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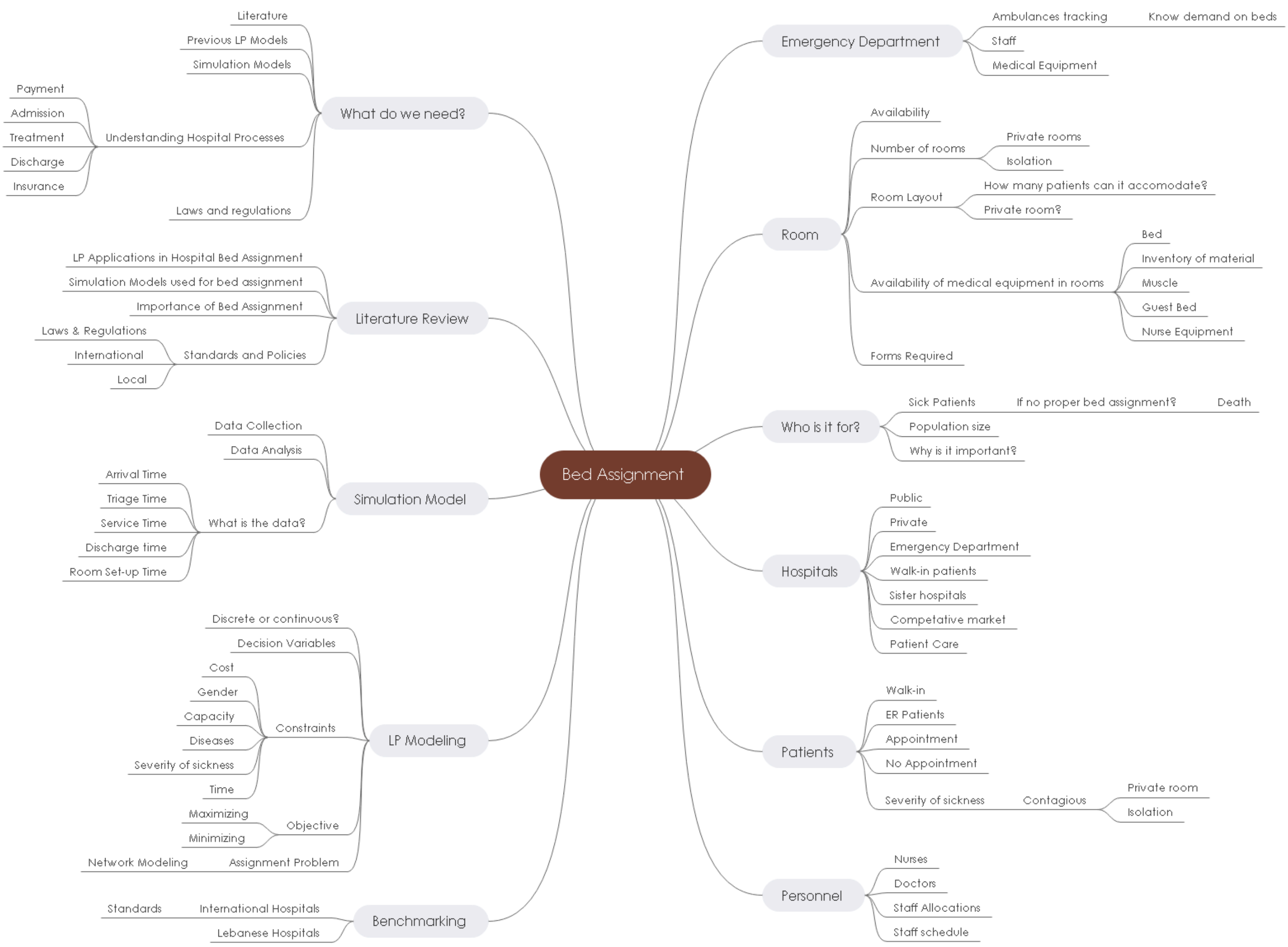
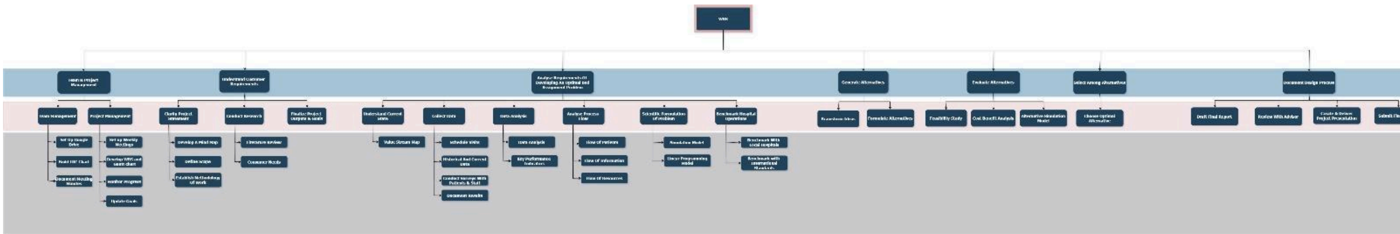
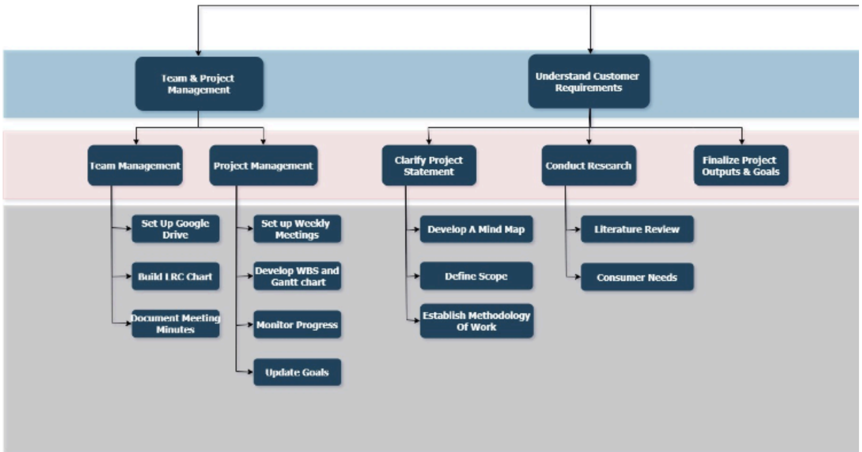
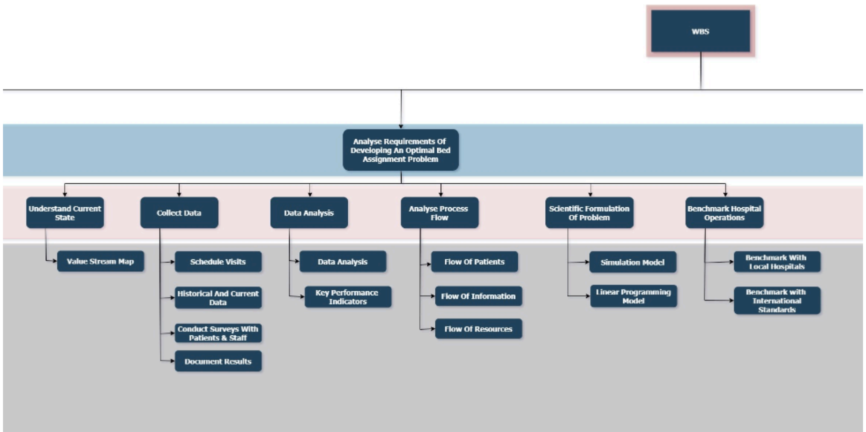
Appendix A: Mind Map

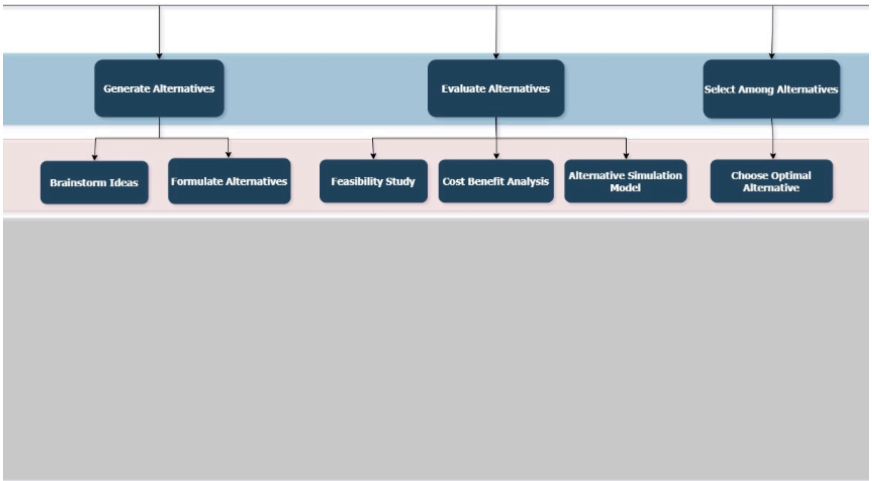


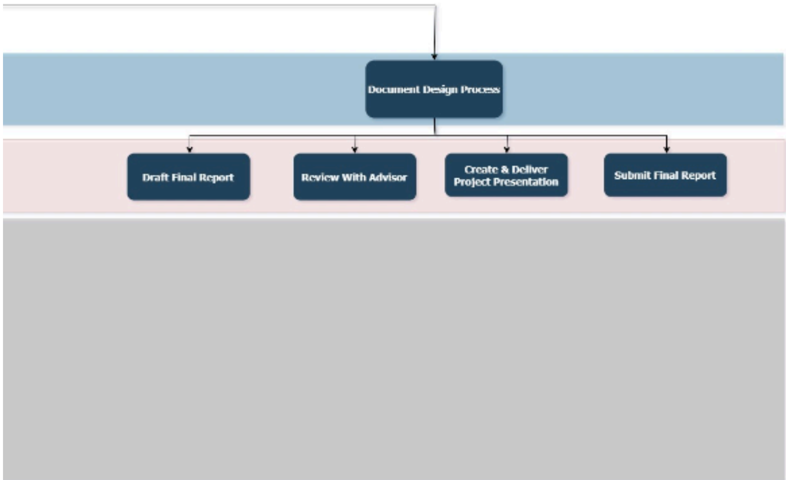
Appendix B: Work Breakdown Structure



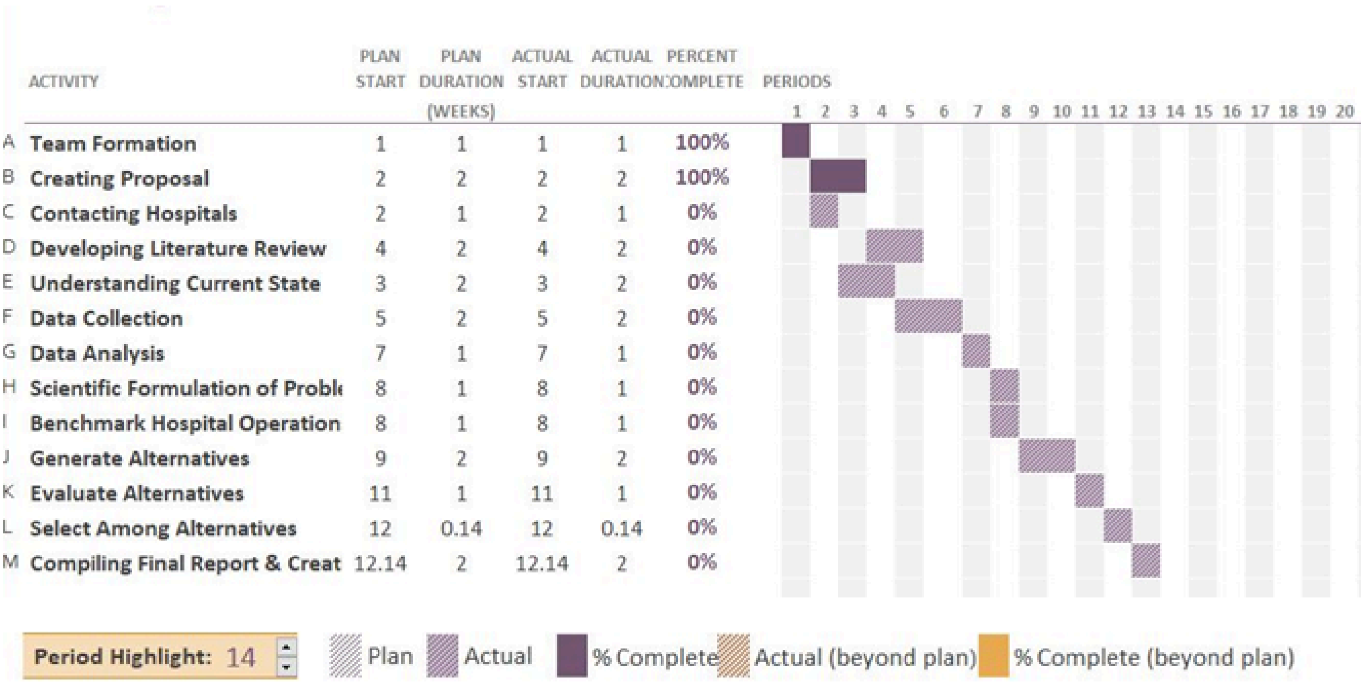





Generate Alternatives
Evaluate Alternatives
Select Among Alternatives
Brainstorm Ideas
Formulate Alternatives
Feasibility Study
Cost Benefit Analysis
Alternative Simulation Model
Choose Optimal Alternative


Document Design Process
Draft Final Report
Review With Advisor
Create & Deliver Project Presentation
Submit Final Report

Appendix C: Gantt chart

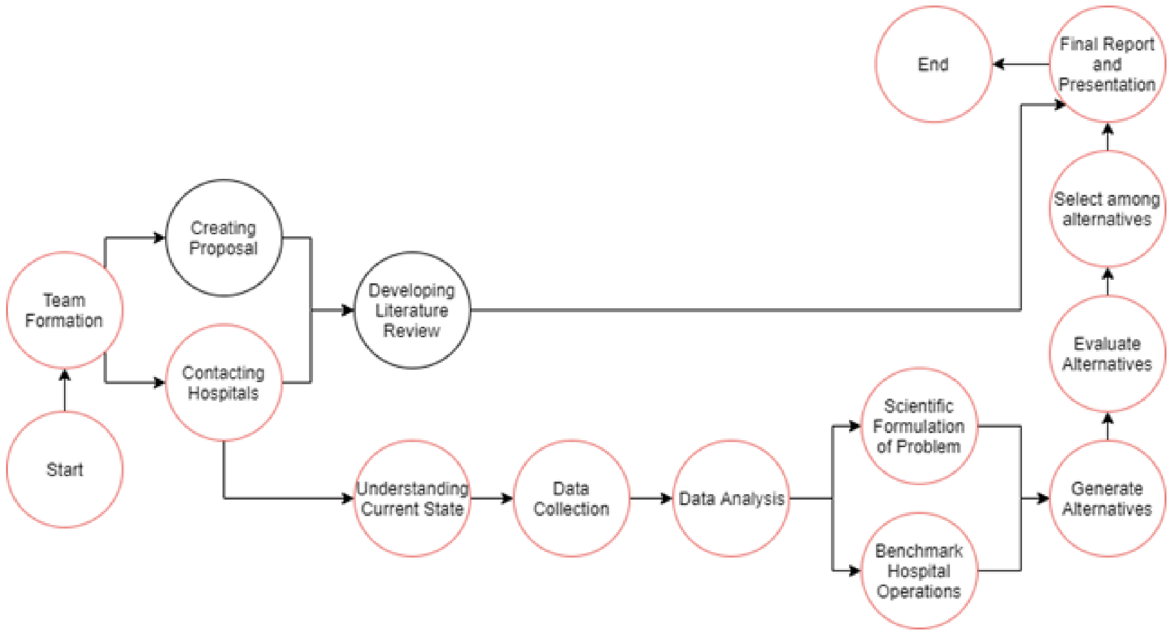


	ACTIVITY	PLAN START	PLAN DURATION (WEEKS)	ACTUAL START	ACTUAL DURATION	PERCENT COMPLETE
A	Team Formation	1	1	1	1	100%
B	Creating Proposal	2	2	2	2	100%
C	Contacting Hospitals	2	1	2	1	0%
D	Developing Literature Review	4	2	4	2	0%
E	Understanding Current State	3	2	3	2	0%
F	Data Collection	5	2	5	2	0%
G	Data Analysis	7	1	7	1	0%
H	Scientific Formulation of Proble	8	1	8	1	0%
I	Benchmark Hospital Operation	8	1	8	1	0%
J	Generate Alternatives	9	2	9	2	0%
K	Evaluate Alternatives	11	1	11	1	0%
L	Select Among Alternatives	12	0.14	12	0.14	0%
M	Compiling Final Report & Creat	12.14	2	12.14	2	0%

Appendix D: Linear Responsibility Chart

Linear Responsibility Chart		Team Members			
Task Number	Task	Joumana	Nathalie	Nagham	Wissam
1	Team & Project Management				
1.1	Team Management				
1.1.1	Setup Google Drive	1	2	2	2
1.1.2	Build LRC Chart	1	1	1	1
1.1.3	Document Meeting Minutes	3	1	1	3
1.2	Project Management				
1.2.1	Setup Weekly Meetings	1	2	2	2
1.2.2	Develop WBS & Gantt Chart	1	1	1	1
1.2.3	Monitor Progress	1	3	1	3
1.2.4	Update Goals	1	3	1	3
2	Understand Customer Requirements				
2.1	Clarify Project Statement				
2.2.1	Develop a Mind Map	1	1	1	1
2.2.2	Define Scope	2	2	1	1
2.2.3	Establish Methodology of Work	1	2	2	3
2.2	Conduct Research				
2.2.1	Literature Review	1	1	1	1
2.2.2	Consumer Needs	1	1	1	1
2.3	Finalize Project Outputs and Goals				
3	Analyze Requirements of Developing an Optimal Bed Assignment Problem				
3.1	Understand Current State				
3.1.1	Value Stream Map	2	1	2	1
3.2	Collect Data				
3.2.1	Schedule Visits	1	3	3	3
3.2.2	Historical and Current Data	1	2	2	1
3.2.3	Conduct Surveys with Patients and Staff	2	1	2	1
3.2.4	Document Results	3	1	1	3
3.3	Data Analysis				
3.3.1	Statistical Analysis	2	2	1	1
3.3.2	Key Performance Indicators	1	1	2	2
3.4	Analyse Process Flow				
3.4.1	Flow of Patients	1	2	2	1
3.4.2	Flow of Information	2	1	2	2
3.4.3	Flow of Resources	2	1	1	2
3.5	Scientific Formulation of Problem				
3.5.1	Simulation Model	3	3	1	1
3.5.2	Linear Programming Model	1	1	2	2
3.6	Benchmark Hospital Operations				
3.6.1	Benchmark with Local Hospitals	1	5	5	1
3.6.2	Benchmark with International Standards	5	1	1	5
4	Generate Alternatives				
4.1	Brainstorm Ideas	1	1	1	1
4.2	Formulate Alternatives	1	1	1	1
5	Evaluate Alternatives				
5.1	Feasibility Study	2	1	2	1
5.2	Cost Benefit Analysis	1	2	1	2
5.3	Alternative Simulation Models	3	3	1	1
6	Select Among Alternatives				
6.1	Choose Optimal Alternative	1	1	1	1
7	Document Design Process				
7.1	Draft Final Report	1	1	1	1
7.2	Review with Advisor	1	1	1	1
7.3	Create & Deliver Project Presentation	1	1	1	1
7.4	Submit Final Report	1	1	1	1

Appendix E: Critical Path Network



Appendix F: Literature Survey Table

Reference	Type/Where	Title	Relevant Findings
[1] Goldsman,D.,Nance, R., & Wilson. J. (2010)	**Conference Proceedings**	**A Brief History of Simulation**	Tocher developed the General Simulation Program and Dahl & Nygaard discovered the simulation languages SIMULA 1 & SIMULA 67 .
[2] Cignarale, C. (2013)	**Journal Article**	**Analysis and Optimization patient bed assignments within a hospital unit while considering isolation requirements**	-Healthcare Associated Infections have posed a constraint on patient bed assignment. -The need and impact of bed assignment optimization models.
[3] Roberts, S., & Pedgen. D. (2017)	**Conference Proceedings**	**The History of Simulation Modeling**	There are many products and languages of simulation with unique features. Simulation includes a problem-solving process which focuses on developing an optimal model. Its four worldviews most dominant in use are events, activities, processes and objects. -GPSS is a form of Process Modeling.

[4] Johnson, L. (1986, May 14).	**Personal Interview**	**Oral History of Harry M. Markowitz**	SimScript, created by Markowitz, is a language that allows a user to create, destroy, file, remove, cause events, etc. This facilitated the integration of a manufacturing facilities logistical planning actions in a computer.
[5] Schmidt, R., Geisler, S., & Spreckelsen, C. (2013)	**Research Article**	**Decision Support for Hospital Bed Management Using Adaptable Individual Length of Stay Estimations and Shared resources**	-A developed approach and heuristic techniques were used to solve the problem. -There is a trade-off between the computational time and the cost factors of the model. -Elective patients add to the model's uncertainty. -The objective function was developed based on the interview with the stakeholders (doctors, nurses…). -Patients' length of stay was proven to be a log-normally distributed random variable. -Discrete event simulation is a powerful tool to assess the outcomes. -Heuristics can be better than the approach depending on the desired outcome.
[6] Thomas, B. G., Bollapragada, S., Akbay, K., Toledano, D., Katlic, P., Dulgeroglu, O., & Yang, D. (2013)	**Research Article**	**Automated Bed Assignments in a Complex and Dynamic Hospital Environment**	-The patients' wait times impact revenue and staff and patient satisfaction. -The dynamic nature of the hospital and the interdependencies of assignments and their impact on the system as a whole should be taken into account. -Weights can be used to prioritize factors and constraints. -Bed assignments are fundamental in high and low occupancy hospitals. -Real-time visibility of the hospital's resources and collaboration and sharing of information amongst staff are fundamental for successful bed management. -Even though sequential assignments may be locally optimal for each patient, they may lead to suboptimal decisions from a system's perspective. -Bed assignment cannot be fully automated since manual entry of decisions is still needed for optimal results in cases where the algorithm lacks information that the bed management team has.

[7] Schäfer, F., Walther, M., Hübner, A., & Kuhn, H. (2019)	**Journal Article**	**Operational Patient-Bed Assignment Problem in Large Hospital Settings Including Overflow and Uncertainty Management**	-Large Hospitals with 500+ beds exhibit high ratios of emergency patient. -Shift in Demographics. -Adapting bed allocation strategy to instant changes. -Usage of the greedy look ahead (GLA) heuristic. - The study based its new decision support model on the main problems and findings stated. - Relevant stakeholders to the problem include patients, nursing staff and doctors and these stakeholders are affected by the solution. -GLA outperforms previous heuristics, and overflow was reduced by 96%.
[8] Dantzig (1963)	**Book**	**Linear programming and extensions**	-Many economical and mathematical theories and practices influenced the creation of LP and its development. -Computational complexity might rise the need to apply heuristics.
[9] Hillier and Lieberman (2010)	**Book**	**Introduction to Operations research**	-Military operations' increasing complexity lead to the creation of scientific methods such as LP. -LP is applied in all industries nowadays from the health sector to the logistics.
[10] Todd (2002)	**Research paper**	**The many facets of linear programming**	-Development of LP from 1950 to 1980 -Development of the simplex method and its importance -LP's special structure and its extension to quadratic programming and linear complementarity -Important mathematical and theoretical developments that can affect the model's solution
[11] Jacobson, S. H., Hall, S. N., & Swisher, J. R. (2006)	**Journal Article**	**Discrete-event simulation of health care systems.**	-DES evaluates the efficiency of an existing healthcare system, to ask "what if?" questions and to design new healthcare efficient operations. -Large number of DES health care studies reported as successful. -DES has become a popular and effective tool for healthcare.
[12] Fetter, R. B., & Thompson, J. D. (1965).	**Journal Article**	**The simulation of hospital systems.**	-One of the earliest DES applications -With increase in capacity led to increased waiting time for patients. -DES allows to analyze relationships between variables in the system.

[13] He, L., Chalil Madathil, S., Oberoi, A., Servis, G., & Khasawneh, M. T. (2019).	**Journal Article**	**A systematic review of research design and modeling techniques in inpatient bed management.**	- Bed management strategies of inpatient units. - Categorize recent studies based on their problem scoping, measurement metrics, constraints considered, and technical approaches. - Potential research gaps and future research -Simulation, LP modeling, queuing theory, mathematical modeling are the most used modeling techniques used in the literature of bed optimization directions.
[14] Kembe, M.M. , Agada, P.O., & Owuna, D. (2014).	**Research Article**	**A Queuing Model for Hospital Bed Occupancy Management: A Case Study**	-The model determined the optimal number of beds required in the wards. - Model guaranteed no patient turned away from the wards and little revenue is lost. -The holding cost of empty beds is an important consideration for the model since it has a significant financial impact.
[15] Guido, Groccia,& Conforti (2018)	**Research article**	**An efficient metaheuristic for offline patient-to-b e d assignment problems**	-Application of metaheuristic frameworks that use the re-optimization approach that consists of solving a sequence of hierarchical optimization subproblems. It also explains the procedure to follow to set appropriate penalty values in the constraints. -Evaluation of the model based on literature based benchmark situations. -List of heuristics and hybrid approaches used in the literature.
[16] Range & al (2014)	**Journal article**	**A column generation approach for solving the patient admission scheduling problem**	-This approach accomplishes lower bounds than those previously seen in the literature. -Evaluation of this approach shows promising results when tested but the study did not include emergency patients.
[17] Clerkin & al (1995)	**Journal article**	**A decision support system for hospital bed alignment**	-The assignment process developed in this journal matches the patient's requests with the bed's characteristics. -The data used by the system is fetched from the admission's processes and updated during the patient's stay.

[18] Demesteer et al. (2010)	**Journal article**	**A hybrid tabu search algorithm for automatically assigning patients to beds**	-This algorithm is known to be the first model to address the BAP. -A method was developed to reduce the calculation time imposed by the IP approach.
[19] Bilgin et al (2012)	**Research paper**	**One hyper-heuristic approach to timetabling problems in healthcare**	-This research focuses on computational efficiency. -Its main outcome was to find a balance between the quality of the solution and its computational time.
[20] Ceschia and Schaerf, (2016)	**Research article**	**Local search and lower bounds for the patient admission scheduling problem**	-The effectiveness of the neighborhoods experimented on depends on the weights attributed to the costs in the objective function. -Lower bounds are computed by relaxing some constraints. -Lower bounds are used to evaluate the solution.
[21] Lei, Na, Xin, and Fan (2014)	**Journal article**	**A mixed integer programming model for Bed planning considering stochastic length of stay**	-Two models were developed: a deterministic model and a stochastic model. -Results are compared for each model to determine which one solves the BAP better. -The stochastic LOS model proved to be a better bed planning tool that gives better results and less schedule conflict cost.
[22] Cardona, T. A., Guardiola, I. G., & Cudney, E. (2017)	**Journal Article**	**Simulation of VA hospital length of stay for analyzing additional inpatient bed capacity.**	-The existence of a relationship between the hospital's subsystems aids the user to build a more complete DES. -The representations of relationships (relationships between the subsystems of the hospital) with DES allow a more complete and accurate analysis than the one that could result from only using queuing theory.
[23] Clissold, A., Filar, J., Mackay, M., Qin, S., & Ward, D. (2015)	**Journal Article**	**Simulation hospital patient flow for insight and improvement**	-By increasing the demand (one to four patients by hour), the LOS increases in a nonlinear basis. -DES can be an effective tool for pediatric inpatient centers to determine appropriate allocation of resources.

[24] Harper, P. R., & Shahani, A. K. (2002)	**Journal Article**	**Modelling for the Planning and Management of Bed Capacities in Hospitals**	- Bed allocation and bed capacity planning affect both bed occupancy and refusal rates. -Statistical distributions of LoS are important in the development and use of planning tools.
[25] Mallor, F., Azcárate, C., & Barado, J. (2015)	**Research Article**	**Optimal control of ICU patient discharge: from theory to implementation**	-Service levels fluctuate based on the number of beds occupied in the ICU.
[26] G.B. Dantzig (1951)	**Journal Articl e**	**Application of the simplex method to a transportation problem**	-First assignment problem published.
[27] Olsen, L., McGinnis, J. M. (2010)	**Book**	**Redesigning the clinical effectiveness research paradigm: Innovation and practice-based approaches: Workshop summary.**	-Development of the first simulation model in a clinical trial during WWII.
[28]Zhang, C., Zhang, C., Grandits, T., Härenstam, K. P., Hauge, J. B., & Meijer, S. (2018).	**Journal Article**	**A systematic literature review of simulation models for non-technical skills training in healthcare logistics**	-Simulation models are used extensively in healthcare settings where different types of models can be used for addressing numerous problems that can arise in the medical field.

Appendix G: Interview with Rizk Hospital

Sectors of admission:

1. OR Schedule: is put one day before, throughout the day is changed based on the demand and the need
2. ER: Small ER because of renovation
3. Direct Admission: Treatment. Prior appointment on empty beds

Hospital Units:

- MSU 2B/3/4/5/6/7/8
- 3 Critical Areas: ICU/SCU/Neuro ICU
- Pediatric: PICU/NICU
- 1-day oncology (MSU 1B)
- 1-day surgery/pre op

Division of Units:

1. MSU 6-7: Infected Medical cases/Infected Surgical Cases/Isolation
2. MSU 8: Clean Medical and Surgical cases
3. MSU 4-3: First Class/ Surgical Clean cases
4. MSU 4: Orthopedic Cases. Cardiac Care/ First Class
5. MSU 3: Gynecology/ Maternity/ Female treatments
6. MSU 3B: Pediatric Unit (1 month - 17 years) - Medical Treatments
7. MSU 2B: Oncology/ Chemotherapy (in patient 2-5 days) (no infectious diseases) ‘
8. MSU 5: Orthopedic Unit/Second Class/Clean cases
9. **Critical:**
    a. ICU: 7 beds/Cubicle/Single Rooms/Infected Critical cases/ Isolation Critical patients
    b. Neuro ICU: Stroke Center: 1 room for isolation
       3 beds for open space
    c. CSU: Open space with 6 beds - No segregation - Clean Cases (open heart and cardiac cases, post-op surgery)

2. PICU: 1 room - 2 beds
3. NICU: 8 beds (newborns - preterm babies - respiratory distress)
   PICU-NICU are next to MSU 8
4. 1-day surgery: 14 beds
5. MSU1B: 1-day treatment

Isolation Types:

1. Protective (single rooms)
2. Strict (MDRO) Bacteria resisting antibodies
3. Contact
4. Droplets (secretion)
5. Airborne isolation

- Positive pressure rooms & negative pressure rooms

- 2 machines in the hospital to create positive pressure (can make a room suitable for protective isolation)
- Within Hospital pressure is based on need

Bed Assignment Process:

1. 7:00AM checks the list of units and already admitted patients, their doctors and empty beds
2. Accordingly starts assigning current patients based on gender, cases, class, disease, infections
3. Full coordination between nurses, case manager and patient's assignment
4. Check discharges and coordinate with the billing department to make the discharge faster
5. Coordinate with the infection control and housekeeping for faster bed availability
6. The class and disease are fundamental criterion for acceptance of patients

ABC Manager:

Admission, Billing and Collection Manager

- Cold Cases/ Emergency Cases/ Transfer
- Transfer patients:
  - o Communication through WhatsApp between: Medical Director/ABC Manager/ Case Manager to see if there is any availability, if the case can be treated in the hospital, and the financial impact of the transfer
- Regular Cost: 140,000 LBP - 150,000 LBP (minimum room charge: electricity, food, services, etc.)
- Insurance/night: $137 (3rd class)
- Government/Security Forces/NSSF/Army/Night Stay: 90,000L.L
- Surgery brings more profit to the hospital
- Surgery cost is based on codes: "K = $5" "ARE = $5" "NOP = $7"
  K refers to the type of patient and doctor, ARE refers to the anesthesia used and NOP refers to the block.
  - o ACL CODE: 29888 K95 ARE35
  - o Cost = 5*95 + 5*35 + 7*95
- Maximum allowed surgeries per day (30-35 which include 15-1day surgeries)
- Profit from patients who have insurance
- Objective of the hospital is to minimize cost and to maximize admission
- Short stay patients are preferred from a monetary perspective

Appendix H: COVID-19 Cases Table

Date	Cases
February 21	1
February 22	0
February 23	0
February 24	0
February 25	1
February 26	0
February 27	1
February 28	1
February 29	1
March 1	3
March 2	3
March 3	1
March 4	2
March 5	1
March 6	5
March 7	6
March 8	4
March 9	12
March 10	16
March 11	1
March 12	8
March 13	17
March 14	8
March 15	13
March 16	12
March 17	16
March 18	17
March 19	19
March 20	53
March 21	23
March 22	20
March 23	37
March 24	29
March 25	35

March 26	23
March 27	21
March 28	26
March 29	8
March 30	17
March 31	16
April 1	15
April 2	14
April 3	12
April 4	7
April 5	14
April 6	7
April 7	27
April 8	7
April 9	27
April 10	10
April 11	11
April 12	2
April 13	9
April 14	17
April 15	5
April 16	5
April 17	4
April 18	0
April 19	4
April 20	0
April 21	5
April 22	6
April 23	8
April 24	8
April 25	3
April 26	0
April 27	7
April 28	4
April 29	4
April 30	4
May 1	4

May 2	4
May 3	4
May 4	0
May 5	9
May 6	34
May 7	12
May 8	13
May 9	36
May 10	14
May 11	11
May 12	8
May 13	8
May 14	5
May 15	11
May 16	9
May 17	20
May 18	23
May 19	7
May 20	63
Total	**1018**
Needs Hospitalization	**204**
Private Hospitalization	**41**
Critical Patients	**2**