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Using Case-Based Reasoning for Simulation Modeling in Healthcare

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USING CASE-BASED REASONING FOR SIMULATION MODELING IN HEALTHCARE

by

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ABSTRACT

The healthcare system is always defined as a complex system. At its core, it is a system composed of people and processes and requires performance of different tasks and duties. This complexity means that the healthcare system has many stakeholders with different interests, resulting in the emergence of many problems such as increasing healthcare costs, limited resources and low utilization, limited facilities and workforce, and poor quality of services.

The use of simulation techniques to aid in solving healthcare problems is not new, but it has increased in recent years. This application faces many challenges, including a lack of real data, complicated healthcare decision making processes, low stakeholder involvement, and the working environment in the healthcare field.

The objective of this research is to study the utilization of case-based reasoning in simulation modeling in the healthcare sector. This utilization would increase the involvement of stakeholders in the analysis process of the simulation modeling. This involvement would help in reducing the time needed to build the simulation model and facilitate the implementation of results and recommendations. The use of case-based reasoning will minimize the required efforts by automating the process of finding solutions. This automation uses the knowledge in the previously solved problems to develop new solutions. Thus, people could utilize the simulation modeling with little knowledge about simulation and the working environment in the healthcare field.

In this study, a number of simulation cases from the healthcare field have been collected to develop the case-base. After that, an indexing system was created to store these cases in the case-base. This system defined a set of attributes for each simulation case. After that, two retrieval approaches were used as retrieval engines. These approaches are K nearest neighbors and induction tree. The validation procedure started by selecting a case study from the healthcare literature and implementing the proposed method in this study. Finally, healthcare experts were consulted to validate the results of this study.

To my great father, **Hashim**

To my lovely mother, **Maha**

To my beloved siblings **Fatmah**, **Amjaad**, **Ahamd**, and **Abdallah**

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LIST OF ACRONYMS / ABBREVIATIONS

ABS	Agent-Based Simulation
AI	Artificial Intelligence
A&E	Accident and Emergency Department
CBR	Case-Based Reasoning
CVD	Cardio Vascular Disease
DES	Discrete-Event Simulation
DSS	Decision Support System
ED	Emergency Department
GA	Genetic Algorithm
GDP	Gross Domestic Product
ICU	Intensive Care Unit
IT	Information Technology
KBS	Knowledge-Based System
KDD	Knowledge Discovering and Data Mining
MCS	Monte-Carlo Simulation
NHS	National Health Service
OR	Operations Research
SD	System Dynamics
SE	Systems Engineering
VA	Veterans Affairs
WHO	World Health Organization

CHAPTER 1 INTRODUCTION

1.1 Introduction

Simulation is an operations research approach that uses mathematical modeling. In simulation, computers are used to perform experiments on hypothetical models that have been created to represent the real contexts. It can be defined as "the recreation of an actual event that has previously occurred or could potentially occur". Nowadays, simulation is used in several areas to help in educating, training, evaluating, and creating new things (Hunt, Shilkofski, Stavroudis, & Nelson, 2007) (Mielczarek & Uziałko-Mydlikowska, 2010).

There are many benefits that can be gained from using a tool like simulation. One of these benefits is assessing the performance of humans, whether in teams or individually. Researchers can utilize this benefit by designing the simulation experiment so that it can evaluate the performance of individuals under different scenarios. Another benefit to using simulation is simulations can help to evaluate system performance during the design phase. In this phase, the system can be tested under different scenarios and all the needed changes could be added without losing resources. The system safety and functionality can be measured and enhanced using simulation, leading to finding all the gaps before proceeding to the implementation phase (Halamek, 2013).

The spending on healthcare services has increased tremendously in the last few decades. There are several reasons for this increase, including an increasing population and the cost of new advancements and technologies that have been developed in the medical field. This increase is clear from the numbers taken from World Health Organization (WHO), where the U.S. spending increased from 8.2% ($485 billion) of the GDP in 2000 to 10.4% ($947 billion) in 2010. In Europe, the average increase in spending on healthcare is higher than 4% of the GDP; for example, in France healthcare spending increased from 196.3 billion Euros in 2005 to 234.1 billion Euros in 2010. The increase in population has led to more healthcare being needed and larger healthcare facilities. This growth is not fixed and cannot be predicted precisely, which adds to the complexity of the process of decision-making in healthcare. The demonstrated success of computer modeling in other areas led decision-makers in healthcare to adopt it in trying to solve healthcare issues. The use of computer models is not limited to decision-making, but can be found in many other areas related to healthcare like teaching and training (Mustafee, Katsaliaki, & Taylor, 2010) (L Aboueljinane, Sahin, & Jemai, 2013).

Huge increases in competition between facilities in the same sector mean that it is important for a facility to achieve optimum efficiency, effectiveness, and quality to stay in business. This is also the case in healthcare, where all facilities should deliver the best service at an affordable cost to gain success. This reason, along with several others, convinced healthcare managers to make use of operation research (OR) tools, especially simulation. The literature reveals that four simulation techniques are most commonly used to solve problems in healthcare. These techniques are discrete-event simulation (DES), system dynamics (SD), agent-based simulation

(ABS), and Monte Carlo simulation (MCS) (Mustafee et al., 2010) (Swisher, Jacobson, Jun, & Balci, 2001).

New advancements and developments in technology in the industrial field have also pointed decision makers towards using artificial intelligence methods in solving problems. Nonetheless, some such processes, such as model-based reasoning and rule-based reasoning, do not work well in domains like engineering due to their complex nature. Case-based reasoning (CBR), however, could be used with such domains since it uses old cases to solve new problems and does not require a lot of background knowledge on the part of the users (Guo, Peng, & Hu, 2013).CBR can be defined as “adapting old solutions to meet new demands, using old cases to explain new situations, or reasoning from precedents to interpret a new situation.” CBR should be used within a learning system since it uses experience that has been gained. The process of CBR has five main steps:

1. Assigning indexes: to differentiate between cases and save them in the case-base.
2. Case retrieval: to retrieve similar cases from the case-base.
3. Case adaptation: to find a solution for the new problem from old similar cases.
4. Case testing: to test the new solution and see the result(s).
5. Case storage: to save the solution in the case-base to be used to solve future problems (Huang, Chen, & Lee, 2007).

1.2 Problem Statement

The healthcare system in most countries is facing many problems. The main cause of these problems is increases in healthcare costs (Li & Benton, 1996). These costs constitute a large percentage of countries' GDP and so is affecting economies worldwide. This increase stems from several sources (L Aboueljinane et al., 2013). The main source is the increase in population, which has led to an increase in the need for healthcare services. Another source is the aging of population, meaning more primary and secondary care is now needed (Thorwarth & Arisha, 2009). The development of new technologies and the huge advancements in the medical field also add to total healthcare costs (L Aboueljinane et al., 2013). Other problems that affect the healthcare system are related to limited resources, which prevent the proper delivery of healthcare services (Faezipour & Ferreira, 2013). Resources that are limited include 1) healthcare facilities like hospitals, clinics, and care houses and 2) healthcare providers like physicians, nurses, and others (Tien & Goldschmidt-Clermont, 2010). All of these problems affect the efficiency and effectiveness of healthcare processes and the quality of the services provided. To find solutions for these problems, researchers and healthcare managers have started to apply engineering tools. Simulation is one such tool that has been used to solve problems in many areas of the healthcare sector (Mielczarek & Uziałko-Mydlikowska, 2010). For example, it has been used to improve the performance of the healthcare system by studying different scenarios and alternatives to solve problems with patient flow, resources optimization, wait times, among others. However, simulation has not been as fully utilized in the healthcare sector as in others sectors such as manufacturing, military, and aerospace (Jahangirian et al., 2012). Issues with

simulation application arose such as little or no stakeholder involvement, simulation solutions and recommendations not being implemented and/or not being used in the process of decision making, no availability of real data or guidelines for models building, and the complex nature of the healthcare environment. These issues have reduced the effectiveness of simulation application in the healthcare field as compared to other fields (Roberts, 2011).

1.3 Research Objectives

The objective of this research is to study the utilization of case-based reasoning in simulation modeling in the healthcare sector. This utilization would increase the involvement of stakeholders in the analysis process of the simulation modeling. This involvement would help in reducing the time needed to build the simulation model and facilitate the implementation of results and recommendations. The use of case-based reasoning will minimize the required efforts by automating the process of finding solutions. This automation uses the knowledge in the previously solved problems to develop new solutions. Thus, people could utilize the simulation modeling with little knowledge about simulation and the working environment in the healthcare field. The objectives of this research are:

- To study the utilization of case-based reasoning in simulation modeling in the healthcare sector.
- To allow for more stakeholder involvements in the simulation process.

- To simplify the process of choosing the best simulation technique to solve the given problem.
- To minimize the time needed to build the simulation model.

1.4 Research Questions

The development of this study for simulation modeling in healthcare would allow this research to answer the following research questions:

- What is a suitable simulation technique to use in solving any given problem in the healthcare area?
- What is the effect of using case-based reasoning on simulation modeling in healthcare?

1.5 Research Contributions

The development of this study will help in improving the utilization of simulation in the healthcare sector by simplifying the modeling process. This utilization will assist people with very little knowledge about simulation to use this powerful tool in solving healthcare problems. This will reduce the need to have more simulation experts in the process of building the simulation model. The enhancement of stakeholders' involvement would increase the knowledge about the simulation advantages among healthcare executives and managers and this will help in improving the utilization of simulation in more applications. Moreover, it will facilitate the use

of the simulation in the decision making process in various healthcare areas. It will also show the efficiency and effectiveness of the simulation process to decision makers and this would help in implementing the simulation solutions and recommendations. The use of case-based reasoning will allow the utilization of previous simulation models and facilitate the reuse of these models with few modifications. Furthermore, the use of case-based reasoning in simulation modeling will minimize the time required to build the simulation model, which allows more time for analysis and experimentation, especially in projects with tight time frames, resulting in the finding of an optimum solution. Ultimately, this study will help improve the efficiency of the healthcare delivery process, leading to better quality services with better resource utilization at less total cost.

1.6 Dissertation Outline

The rest of this dissertation will be organized as follows: chapter 2 contains a literature review; chapter 3 contains a description of the research methodology; chapter 4 includes CBR methodology development, Chapter 5 includes implementation and results, and chapter 6 contains conclusions and future research directions.

CHAPTER 2 LITERATURE REVIEW

2.1 Introduction

In this chapter, simulation is defined as one of the systems engineering tools that have been used to solve problems and improve performances in industrial and service fields. Healthcare problems and issues found in the literature are presented in detail. The systems engineering tools and methods that have been used in healthcare problems are summarized to provide background on their use in the healthcare arena. Simulation modeling and techniques are defined and their applications in the healthcare sector are also presented to provide some background. Finally, a complete overview of case-based reasoning (CBR) models and applications in the literature is offered.

2.2 Systems Engineering

Systems engineering is usually used to design and control system operations in order to meet performance targets. One of the most important concepts in systems engineering is systems modeling. It can be defined as "the activity of identifying the most relevant system characteristics and representing them in a mathematical model". The resulting mathematical model is analyzed to understand the actual system in order to enhance its performance and behavior (Kopach-Konrad et al., 2007).

2.2.1 Systems Engineering Tools and Techniques

There are several methods, tools and techniques used in systems engineering. Some of them are:

- Engineering economy and financial engineering models: used for cost-effectiveness analysis and investment optimization.
- Project management models: used to control timing and tasks in projects.
- Stochastic process models: used to optimize system performance under uncertainty.
- Statistical modeling: used to find correlations, patterns, distributions in data.
- Operation research (OR) models: used for optimizing resource allocation and effective resource distributions.
- Human factor models: used for optimizing performance of people in complicated systems.
- Simulation models: used for studying real systems in order to improve system behavior and performance.
- Process flow models: used to organize, synchronize, and coordinate work tasks (Kopach-Konrad et al., 2007).

Operation research (OR) was developed in 1930s in the UK, where it was used as a decision making tool in several sectors, including industry and the military. In recent years, it has become a useful tool in the healthcare sector to do analysis and inform decisions. Some OR tools used to solve problems in the healthcare sector can be found in Table 1. These OR tools are used in many healthcare areas such as planning, modeling, scheduling, evaluation, design, and financial

analysis. This application has led to many improved results, enhancing quality of service while at the same time reducing costs (Mustafee, Katsaliaki, Gunasekaran, Williams, Fakhimi, et al., 2013).

Table 1: Some OR techniques that are used in Healthcare applications (Mustafee, Katsaliaki, Gunasekaran, Williams, Fakhimi, et al., 2013).

OR Techniques used in Healthcare
Mathematical Modeling
Modeling Systems
Discrete-Event Simulation
Monte-Carlo Simulation
System Dynamics
Markov Models
Forecasting
Cohort Simulation
Scheduling
Distributed Simulation
Simulation Exercise
Multiple OR Techniques

2.2.2 Systems Engineering in Healthcare

One of the main and most complicated problems that faces U.S. policy makers is to provide healthcare services with the best quality and at reasonable costs. According to the literature, the quality of healthcare services in the US has major problems that affect the healthcare system. Also, according to new statistics, healthcare costs are increasing every year. Moreover. The U.S. healthcare system is classified as a complicated and adaptive system, which makes solving these problems difficult. This kind of system is not like a regular industrial or service system in terms

of performance and outcomes, which are found from a group of factors and connections between them. This situation has directed organizations towards the application of systems engineering methods and techniques to improve this healthcare system. The target of this use is to provide solutions that will help enhance the services and outcomes of this system (Basole, Bodner, & Rouse, 2013).

Systems engineering could be used with complicated systems that consist of people, materials, resources, and information. It helps in the synchronization, integration, and coordination of such complex systems by using modeling and analysis methods. These methods, which have been used in many other sectors like logistics, manufacturing, transportation, and distribution, are used to solve issues and problems in many areas, including scheduling, planning, operation management, process flow analysis, facility design, economic analysis, and resource utilization, most of which can be found in the healthcare sector. Thus, the use of systems engineering in healthcare would enhance and improve and the healthcare delivery system (Kopach-Konrad et al., 2007).

To apply systems engineering in the healthcare sector to improve the delivery system, the following process needs to be conducted:

1. Define system scope and purpose: identify functions, resources, and performance measures.
2. Define and collect required data.
3. Design system models which are then validated and verified.

4. Use the designed models to study the real system.
5. Analyze these models to set performance target and levels.
6. Create implementation plans and then evaluate the performance of the system (Kopach-Konrad et al., 2007).

2.3 Healthcare

Several scholars in the literature consider the healthcare system to be a complex system of systems. Systems of systems are defined as "large-scale integrated systems, which are heterogeneous and independently operable on their own, but are networked together for a common goal". Complex systems "have many autonomous components, are self-organizing, display emergent macro-level behavior based on the actions and interactions of the individual agents, and adapt to their environment as they evolve" (Faezipour & Ferreira, 2013).

Another way of viewing the healthcare system is "an integration or combination of three essential components – people, processes and products". The people in the system can be categorized into two main classes: 1) those receiving services, such as patients, consumers, and organizations; and 2) those providing services, such as physicians, nurses, staff, providers, and organizations. Processes involved in this system can be either procedural, like evolving, standardized, network-oriented, and decision-focused processes or algorithmic, like decision-making, data mining, and systems engineering processes. Products can be divided into physical

products such as facilities, sensors, machines, tools or virtual products such as simulation, e-commerce, e-collaboration (Tien & Goldschmidt-Clermont, 2010).

This healthcare system has many stakeholders, which adds complexity to the system. The main stakeholders in this system are physicians, nurses, patients, healthcare facilities, and governmental agencies. Moreover, the healthcare system needs to be sustainable because resources are limited and the demand is increasing (Faezipour & Ferreira, 2013).

Primary and secondary care are considered the main services that any healthcare facility should provide. Costs of these services increase from time to time and this puts a pressure on all healthcare providers to improve their quality and efficiency while maintaining the same cost level or trying to reduce it. Hospitals are the most important among healthcare organizations. Emergency departments (ED), the most crowded department in most hospitals, experiences the heaviest load in the system. From all issues that can be found in any hospital, extended wait times is considered one of the problems that all departments suffer from. Thus, solving flow and wait problems will help in improving the quality of healthcare and at the same time reduce costs. (Al-Refaie, Fouad, Li, & Shurrab, 2014).

The emergency department is the only department in the hospital that is open 24/7 to give care to all kinds of patients. The US Emergency Medical Treatment and Active Labor Act (EMTALA) compels all EDs to perform services without any financial considerations. For this reason, the ED is considered one of the most important areas of healthcare (Paul, Reddy, & DeFlitch, 2010).

Emergency departments are considered to be the main source for patients to be admitted to hospitals. They face a very high demand and this demand has a huge uncertainty. Moreover, patients admitted through the ED have a variety of illnesses and require several resources to receive necessary care and treatment (Thorwarth & Arisha, 2009).

EDs are different from one place to another, but all have some common processes such as admission, triage, and discharge. These ED processes are complicated and have a lot of uncertainty, which might result in several problems such as low utilization of resources, long waiting times at different stations, and the lack of enough personnel in the ED (Gul & Guneri, 2015).

Overcrowding is one of the major problems that EDs face in the US. This problem is caused by an increase in the number of visits to the ED and a decrease in available resources. Specifically, statistics show that while visits increased by 23.6 million in the period from 1993 and 2003, at the same time, 198,000 hospitals and 425 EDs were closed. This has resulted in a huge increase in the demand for limited resources. Overcrowding is shown in the ED as overcapacity in number of patients, very long waiting times that lead some patients to leave without treatment, ambulance diversions, and treating patients in the hallways. These issues often result in high stress levels among physicians, nurses, and other staff, medical errors, low productivity, and patient dissatisfaction (Paul et al., 2010).

The management process in any healthcare facility is considered to be a difficult and complicated process for several reasons. However, the main reason is that a balance must be maintained between two opposing targets: effective medical treatment and total medical cost savings. Ultimately, the essential target of any healthcare facility is to give efficient, quality medical treatment without exceeding planned costs (Mielczarek & Uziałko-Mydlikowska, 2010).

One of the main problems in healthcare management is the effective allocation and utilization of scarce resources. Another important problem is the poor health conditions that serve as a huge barrier in the way of economic improvements in many countries. The healthcare systems are considered as complicated structures that rely on a group of different economical and organizational factors and their connections. Thus, healthcare managers are forced to use complicated decision support methods due to this complex nature of the healthcare systems. However, some of these factors are uncertain and this will affect the efficiency of the system and this will add negative impacts on the quality of the healthcare delivered (Aktaş, Ülengin, & Şahin, 2007) (Eldabi, Paul, & Taylor, 1999).

Healthcare costs almost doubled in the 1970s and doubled again in the 1980s. This increase led to the creation of new laws and systems to control healthcare costs. These new changes forced all healthcare executives towards focusing on ways to reduce healthcare costs while improving the quality healthcare delivery (Li & Benton, 1996).

The national health policy was developed in the beginning of the 1970s with the purpose of making healthcare available for all people in the USA. During the same period, several healthcare programs like Medicaid and Medicare were established with the sponsorship of the federal government to serve the same goal (Li & Benton, 1996).

According to the World Health Organization (WHO), there are several factors that have caused the increase in healthcare costs. The two main causes are an aging population and a growing population. These add about one percent to the portion of the healthcare costs in the GDP in developed countries every five years (Thorwarth & Arisha, 2009).

This increase in healthcare costs has led researchers and healthcare experts to apply new methods and techniques to control and minimize costs in the healthcare sector. Among these new methods, they have chosen the area of operations research to find new ideas and solutions that can be applied in healthcare facilities. Researchers tried several operation research tools and decided to focus on simulation, mainly because it has been successfully used in many other sectors such as Military, Manufacturing, and logistics to good effect. The application of simulation in healthcare facilities allows healthcare professionals to create models that show the state of the facility at any time in any situation. Moreover, these models can display the flow of entities inside the facility, allowing the opportunity to observe and study the main performance measures such as waiting times, queue size, and utilization. This allows managers to try different scenarios and compare results or answer what-if questions. The flexibility of these scenarios can take into account all the variability and uncertainty that healthcare managers must consider, and this can help them in making decisions and finding new solutions (Thorwarth & Arisha, 2009).

2.3.1 Healthcare and Operations Research

Researchers and healthcare managers started using operations research tools and methods to solve healthcare problems in the 1950s. They used these tools to examine different connections between parts of the system to enable them to make better managerial, financial, medical, and technical decisions. They created models to express the then-current systems and used operations research tools to develop a systematic problem-solving approach. This approach allowed them to analyze all the new solutions and strategies on the model without changing the existing system or losing any resources. After that, they can take decisions and make the required changes and implement the new solutions and procedures (Mielczarek & Uziałko-Mydlikowska, 2010).

Most of the recent studies in healthcare have a group of targets and objectives that are required to be met. Some of these objectives are improving the quality of services, reducing the total costs, enhancing the utilization of resources, minimizing the waiting times, and increasing processes efficiency. However, healthcare costs are increasing because of several factors and this adds more constraints in solving any healthcare problem. The use of operations research (OR) tools will help in reaching these healthcare targets in an effective way (Bhattacharjee & Ray, 2014).

In healthcare systems many decisions have to be made. These decisions could be operational, strategic, or tactical. Some of them are made daily, weekly, monthly, semi-annually, or annually. There are many tools that could be used to support the process of decision-making. One of these tools is modeling, which includes several techniques, such as simulation modeling, Markov modeling, decision trees, and others. Markov modeling and decision trees can be used with

aggregate solutions only while simulation modeling can be used with aggregate and individual entities (Chahal & Eldabi, 2011).

The area of healthcare is growing quickly due to the increasing demand for services. This growth requires larger and more complicated healthcare systems, which results in greater healthcare costs. These demands for services cannot be determined precisely and this adds uncertainty to the picture. All of this, directed healthcare managers towards using computer modeling to be able to solve this problem. This modeling technique will allow them to predict the effect of any suggested change and evaluate any new strategy or policy before implementation. This modeling is not only used managers of healthcare, but it can be used to solve many other problems such as food poisoning and air pollution. One of the best modeling techniques is computer simulation. In simulation, stakeholders can model any real system and apply any changes to it. This will help them in improving the current systems, increasing their efficiencies, and enhancing the quality of delivery (Katsaliaki & Mustafee, 2011).

The spending on healthcare is taking a large percentage of the GDP of most countries. This percentage is increasing almost every year and those countries are trying to control this by pushing healthcare organizations towards applying new strategies that will help them increasing the efficiency of processes while reducing costs. This spending has a median of 8.8% in the Organization for Economic Co-operation and development and it reaches up to 15% in the USA. This required change is not an easy job because of the complications and uncertainty that can be found in most processes. This will work as a barrier that prevents achieving better results. Thus,

these healthcare facilities need to find tools that will help them in getting these required results. Simulation can be one of these tools due to its great benefits. It gives several solutions that can improve those healthcare systems. It is considered the second most commonly used OR tool after statistical analysis (van Lent, VanBerkel, & van Harten, 2012).

The population of most countries is increasing and this causes more demand for healthcare services. This demand is faced with limitations in infrastructures and fixed budgets for healthcare costs. Thus, people in charge have to come up with new tools and methods to help them in creating new plans and strategies that will cover this increased demand with the required services. One of the tools that can be used is computer simulation instead of using classic statistical techniques. This tool could be used in all healthcare area like hospitals, and clinics for planning and analysis in almost all departments. Discrete-event simulation is considered one of the best simulation techniques for use in healthcare. DES can be defined as "computer techniques that represent sequential events describing the behavior of a system". It was originally developed to help in solving problems in industry and aerospace sectors. It is called discrete because variables in these models are discrete (Villamizar, Coelli, Pereira, & Almeida, 2011).

Articles about the application of simulation in healthcare started to appear in the literature from the 1970s. In the 1990s, the number of these articles increased to reach the thousands. Moreover, the rate of publication in the last ten years has reached its highest levels. These applications cover most of the problems in the healthcare area such as reducing costs, enhancing customer satisfaction, risk assessments, and analysis. However, the healthcare sector is not taking

advantage of applying simulations as well as the manufacturing sector has (Robinson, Radnor, Burgess, & Worthington, 2012) (Thorwarth & Arisha, 2009).

The studies using computer simulation in healthcare delivery can be categorized in five branches: hospital scheduling and organization, infection and communicable diseases, costs of illness and economic evaluation, screening, and miscellaneous (Mielczarek & Uziałko-Mydlikowska, 2010).

Most of the time the application of simulation in healthcare involves modeling complicated systems that have many stakeholders with conflicts of interest. Stakeholders can be defined as "groups or individuals who can affect or be affected by organizations with their managerial behaviors". This term was first used in strategic management. Most studies that include stakeholders focus on identifying them, classifying them, and explaining their influence in the organization. However, this involvement is necessary to get the required results from this simulation study. The stakeholders have knowledge about all parts of the system. If they are not involved in the simulation study, the results of the study might not be implemented because of their resistance to change (Tako & Kotiadis, 2015) (G. Lim, Ahn, & Lee, 2005).

There are several reasons for lower stakeholder engagement in healthcare compared to in the commercial and defense sectors. These include:

1. Organizational structure: many people in big healthcare facilities will resist any attempt to make organizational changes due to the lack of proper rules and setting that can be found in manufacturing organizations.
2. Competitive structure: the competition level in the commercial field is much higher than in the healthcare field. This forces the managers and decision makers in commercial organizations to look for improvement everywhere to be able to survive in this environment. However, this is not the case in the healthcare field, where competition only exists in certain areas.
3. Data capture: the use of data in healthcare environment is much more difficult than in manufacturing due to several restrictions, such as privacy regulations. These restrictions affect the usefulness of simulation and decrease stakeholder engagement (Jahangirian et al., 2012).

There are many examples of successful application of computer simulation in healthcare problems in the literature. For example, it has been used as an optimization tool for the usage of hospital rooms in the Netherlands. In another study, simulation was used to find the optimal staff size in a hospital in the USA. Much literature also exists about using simulation to solve problems in emergency departments (Coelli, Ferreira, Almeida, & Pereira, 2007).

In the American healthcare system, outpatient care is considered one of the important parts that grow in a fixed rate. The main reason behind the growth in outpatient care is the huge advancements that have taken place in diagnostics, procedures, and medications. This means a

good percentage of patients who previously may have had to spend time in health care facilities to now complete their treatment as outpatients. This can be shown in the Annual Survey of Hospitals that was done by the American Hospital Association, which reported that outpatient visits increased 71.3% in the period from 1985 to 1995. This increase shows that more research is needed in this area to make plans to deal with such growth. This is an area where simulation techniques have been commonly used: to model and analyze outpatient clinics. This simulation application allows researchers to evaluate and estimate the impact of change in these facilities (Cote, 1999).

Brailsford and Vissers (2011) showed the applications areas of OR tools and methods in the healthcare sector from the perspective of "a product life cycle". This explanation has the following steps to develop and manage healthcare services:

1. Consumer needs identification.
2. New service development to satisfy needs.
3. Forecasting of the demand of new service.
4. Finding resources to deliver the new service.
5. Allocating these resources.
6. Creating plans to use these resources.
7. Adapting new criteria for performance.
8. Managing the performance.
9. Evaluating the results.

Brailsford & Vissers (2011) also categorize the decision-making levels for operation and processes as:

- Provider level.
- Organization or department level.
- State or national level

Day, Ravi, Xian, and Brugh (2014) developed a simulation model that combines two simulation techniques, DES and ABS. Their model uses DES to model the operation in the clinic and ABS to the model the population that is receiving care in the clinic. They used this model to compare strategies and alternatives to find the one that would most improve the healthcare delivery system.

Oddoye, Jones, Tamiz, and Schmidt (2009) used simulation and multi-objective analysis for healthcare planning in a medical assessment unit. This simulation model provided effective solutions for determining the needed resource levels for patients to finish with the least possible delays.

Ahmed and Alkhamis (2009) combined simulation and optimization to design a decision support system for an emergency department in a hospital in Kuwait. This methodology was used to find the optimal staff size to increase patient throughput and minimize total time in the system without exceeding the budget.

2.4 Simulation Modeling

Simulation is an operations research approach that uses mathematical modeling. In simulation, computers are used to perform experiments on hypothetical models that have been created to represent the real contexts. There are several types of simulation that can be found in the literature, including discrete event simulation (DES), continuous or system dynamics simulation (SD), combined discrete-continuous simulation, Monte Carlo simulation (MCS), and agent-based simulation (ABS) (Mielczarek & Uziałko-Mydlikowska, 2010).

Another definition for simulation is as a “decision support technique that allows stakeholders to conduct experiments with models that represent real-world systems of interest”. These simulation models help in representing the most complicated systems and trying different solutions and procedures to find the ones that will most effectively reduce the effect of uncertainty in most healthcare areas (Mustafee et al., 2010).

Simulation can be explained as building a model to find the impact of changing the structure and inputs of a certain system. The model represents a complicated dynamic process that cannot be analyzed directly. Therefore, simulation models are always considered a cheaper and simpler way to study the behavior of any system under several scenarios (Coelli et al., 2007). The steps of the simulation process are shown in Figure 1.

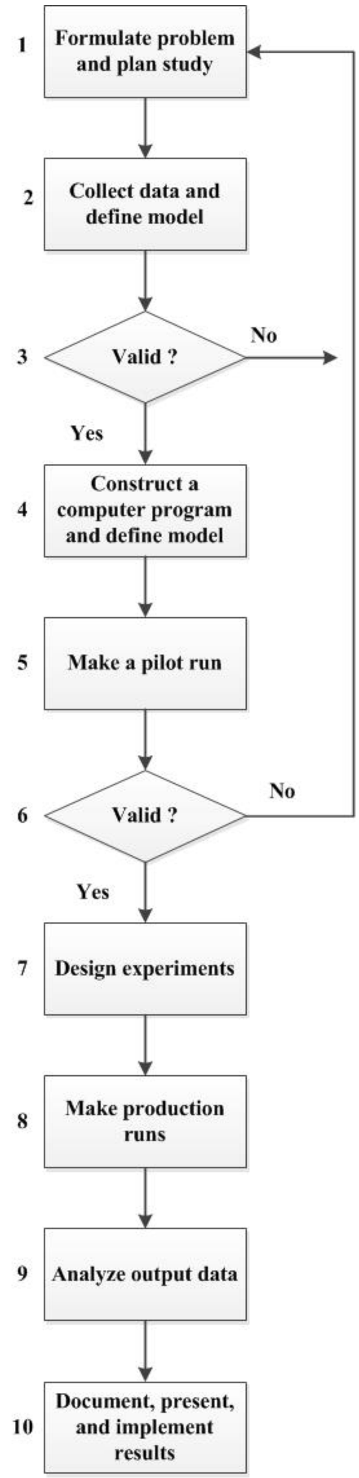

Figure 1: Steps in the simulation process (Baldwin, Eldabi, & Paul, 2004).

There are many benefits that can be gained from using a tool like simulation. One of these benefits is assessing the performance of humans, whether in teams or individually. Researchers can utilize this benefit by designing the simulation experiment so that it can evaluate the performance of individuals under different scenarios. There are several examples in the literature where examiners designed a simulation-based study to measure the performance of people involved in a certain process under different planned scenarios that, for various reasons, cannot be studied in real environments. These studies helped in answering many clinical questions and allowed the investigation of cases that happened before (Halamek, 2013).

Another benefit to using simulation is simulations can help to evaluate system performance. This evaluation step is usually done in the design phase of any system. In this phase, the system can be tested under different scenarios and all the needed changes could be added without losing resources. The system safety and functionality can be measured and enhanced using simulation, leading to finding all the gaps before proceeding to the implementation phase (Halamek, 2013).

Research articles that use simulation in the literature can be classified into three categories:

a. Real Problem-Solving articles: in these papers, simulation is used to solve a real problem with real data. These types of problems usually have a high level of user engagement and implementation.
b. Hypothetical Problem-Solving articles: in these papers, simulation is used to solve a real problem but with hypothetical data. In these problems, user engagement is not high.

c. Methodological articles: in these papers, simulation is used only as tool in order to find a solution. In these problems, user engagement is low and/or not necessarily needed (Jahangirian et al., 2012).

Simulation can offer solutions that allow decision makers to improve processes, enhance productivity, and reduce costs. However, there are several reasons that may prevent many people from utilizing this technique and getting the most out of it.

1. The simulation process is time consuming and requires a lot of information about the application area.
2. The simulation models that are developed to solve problems cannot be reused to solve similar problems since they are specific and customized.
3. The creation of models and gathering information and knowledge about the field is not consistent and depends on the modeler experience (Zhou, Chen, He, & Chen, 2010).

It is very clear from the literature that simulation is commonly applied in the manufacturing and defense fields and is considered a very important part of any project in both fields. However, this is not the case in healthcare since it has been extensively used and has become a significant factor only in the past 30 years. Simulation applications in different sectors are shown in Table 2. In some studies, it is considered a part of the process of making decisions while in other studies, it is only used as an analysis tool. Many scholars in the literature have directed healthcare researchers to look at the various sectors and learn from them to increase the returns from simulation application in healthcare (Jahangirian et al., 2012).

Table 2: Simulation applications in different sectors (Jahangirian et al., 2012).

Application Area Category	Healthcare	Commerce	Defense
Policy	Finance	Financial Management	Mission Policy Making
	Policy	Strategy	Acquisition Policy Making
	Governance	Organizational Structure	Military Decision Making
	Regulation		
High-Level Planning	Public Health	Capacity Planning	Command and Control Systems
	Community Service Planning	Supply Chain Management	Warfare
		Facility Location	Military Mission Management
Workforce	Workforce / staff Management	Workforce Planning	Training
		Management Training and Education	
Operational Planning	Planning	Assembly Line Balancing	Planning
		Just-in-Time	
		Transportation Management	Process Modeling
		Process Engineering - Manufacturing	
		Project Management	Interoperability and Information Sharing
		Cellular Manufacturing Design	
	System / Resource Utilization	Inventory Management	Integrating Heterogeneous Systems
		Production Planning and Inventory Control	
		Purchasing	Optimization
		Resource Allocation	
		Scheduling	Workflow Management
		Maintenance Management	Estimation of System Availability
Quality and Evaluation	Quality Management	Quality Management	Logistics Evaluation and testing
	Performance Monitoring and Review		
R & D	Research and Development	Knowledge Management	Satellite Engineering
Risk	Risk Management	Forecasting	System Capability Analysis
	Forecasting	Risk Assessment	

Application Area Category	Healthcare	Commerce	Defense
Behavior	Patient Behavior / Characteristics	Organizational Behavior	Human-in-the-Loop Experiments
			Modeling Tactical Human Behavior

Many scholars have focused their research on the use of simulation in solving healthcare problem in the last few years. This application of simulation in healthcare is not as great as in other sectors such as military or logistics, but it is increasing at a fixed rate. These researchers have studied several problems in hospital management, emergency systems, policies, and clinics. Another new area is the use of simulation in the process of dealing with epidemiological issues, and for example, preventing the spread of diseases such as Human Immunodeficiency Virus (HIV), Ebola, and new influenza viruses (Mielczarek & Uziałko-Mydlikowska, 2010).

The simulation as a tool has several features that make it suitable to be used to solve problems in healthcare. Some of these features are:

- It can be used to model complex systems.
- It can be used to model stochastic systems.
- It is easy to use.
- It can be used to model complicated systems with all assumptions.
- It can be used to do “what-if” analysis.
- It is widely accepted in many fields, including healthcare (Roberts, 2011).

The applications of simulation in healthcare have several classifications in the literature. One of the first classifications categorized the models into the following:

1. Hospital system models: include admissions, bed planning and allocation, staff planning, materials handling, and specialized hospitals like cancer care and rehabilitation care.
2. Hospital department models: include the emergency department, operating rooms, labs, pharmacy, and intensive care unit (ICU).
3. Ambulatory care models: include outpatient clinics, room design, flow control and appointment scheduling.
4. Other ambulatory care: include dental practice, public health control, mental health, drug recovery and rehabilitation, and home care.
5. People planning models: include provider planning and forecasting, skills and staffing.
6. Health care systems planning: includes Certificate of Need, managed care, community healthcare, and healthcare maintenance organizations.
7. Other healthcare models: include transplant management, patient education centers, and blood banking.
8. Medical decision-making: includes screening, organ transplantation, treatment, and cost-effectiveness (Roberts, 2011).

Another newer classification for simulation application in healthcare categorizes these models as:

1. Optimization and Analysis of Patient Flow.
    a. Outpatient scheduling.
    b. Inpatient admissions and scheduling.
    c. Emergency department models.
    d. Specialized clinics.
    e. Scheduling of physician, nurses, and staff.
2. Allocation of healthcare assets.
    a. Bed sizing and planning.
    b. Room sizing and planning.
    c. Staff sizing and planning (Roberts, 2011).

There are several other ways to classify models that use simulation in solving healthcare problems in the literature. One of the classifications divides these models into system-level models, human body models, and healthcare units' models. Another divides them into health and care systems operation, epidemiology, medical decision-making, extreme event planning, and health and care systems design (Mielczarek, 2014).

There are several challenges that face people who work in developing simulation models in the healthcare sector. Some of these challenges are:

- Barriers to implementation: there are several issues that may affect the implementation of simulation in healthcare.

- The decision making structure in healthcare: the existence of multiple stakeholders could affect the simulation process.
- Personal simulation models: there are no common rules to create the simulation models, and they depend on the modeler perspective and skills.
- Multiple goals and stakeholders' interests: conflicting goals and stakeholders' interests.
- Stakeholders' involvement: this might affect the simulation process and recommendations.
- Lack of validation: the validation process is not easy because of the absence of real data (Roberts, 2011).

Several scholars have claimed that involving clients of simulation in model building would lead to their gaining important experience about the system. This might be true hypothetically, but it is not an easy job to measure this learning. This involvement may save a big amount of time in modeling a discrete-event simulation model (Monks, Robinson, & Kotiadis, 2014).

(Monks et al., 2014) wanted to check the assumption that decision makers and simulation clients learn more about the system when they are involved in the process of building the model. They performed two experiments to check the difference in the learning experience of those people. In the first, they involved simulation clients in the model building. In the second, they reused an old model. Clients in both experiments learned about the system, but the problem is that in the first experiment they had less time for experimentation since both experiments had the same time constraint.

There are many simulation applications in healthcare. Examples of these applications are given below:

Eldabi et al. (1999) suggested the use of simulation models to support decision makers in the healthcare sector, giving them the opportunity to change these models, try several alternatives and check the resulting numbers to choose the best solution.

Djanatliev, German, Kolominsky-Rabas, and Hofmann (2012) proposed a hybrid simulation environment to evaluate new technologies in healthcare. This hybrid simulation combines ABS and SD. It uses ABS to model patients' behavior and SD to model the environments around patients.

Rohleder, Bischak, and Baskin (2007) investigated the role of DES and SD in redesigning patient service centers. The DES model was used for resource utilization and improving system performance. The SD model was used to predict demand patterns, create new policies to minimize variability in demand, and study the effect of changes.

Figueredo, Siebers, Aickelin, Whitbrook, and Garibaldi (2015) compared SD and ABS using a case study of immune-senescence. The reason for this comparison was to test if the two methods would give different insights. The two methods gave similar results, but SD was more suitable for modeling this process.

2.4.1 History of Simulation

In 1911, Orville Wright created the first flight simulator. This is considered to be among the earliest simulation applications. This development was described as a safe way to teach people by creating the same environment on the ground instead of in the air. From this point, simulation became the first step in training every pilot (Hunt et al., 2007).

Edwin Link was born in 1904. He started taking lessons in how to fly in 1920. After that, he purchased a Cessna AA airplane in 1928. In 1929, he created his first prototype for flight training (simulator) -- the “blue box”. A year after that, he opened a flying school. Then, his trainer was adopted by the Army to enhance the pilot training process before and during World War II. These flight simulators improved in several ways after the invention of computers in 1950s (Rosen, 2008).

The application of simulation in medicine goes back to the 1960s, starting with the use of mannequins for training purposes. After that, they came up with the Harvey cardiology simulator and developed the Resusci-Anne, the mannequin used in all CPR training. With advancements in computers and information technologies, medical simulators have gotten better, becoming a close representation of the human body. Use of these simulators allows those in training to improve their skills without endangering live patients, thereby avoiding medical mistakes as much as possible (Hunt et al., 2007).

2.5 Simulation Techniques

There are four simulation techniques that are used most commonly in the literature. These techniques are: discrete-event simulation (DES), system dynamics (SD), Monte Carlo simulation (MCS), and agent-based simulation (ABS). Other less commonly used simulation techniques that can be found in the literature are distributed simulation, intelligent simulation, simulation gaming, traffic simulation, virtual simulation, and Petri-Nets (Katsaliaki & Mustafee, 2011) (Mustafee et al., 2010).

The literature of simulation application in healthcare reveals that DES is the most suitable technique to solve problems related to operational and tactical decision making; SD can be used effectively to solve strategy and policy problems and for making qualitative and theoretical analysis; ABS is useful for behavioral problems and for some strategy and policy problems; and MCS is suitable for financial and risk analysis when uncertainty has a place in the problem (Ali et al., 2009). A mapping of appropriate method to healthcare applications is provided in Table 3.

Table 3: Mapping method for simulation applications in healthcare from the literature (Ali et al., 2009).

Area Code	**Healthcare Application Area**	**Appropriate Simulation Method(s)**
Policy	Finance, Policy, Governance, Regulation	SD and ABS
Strategy	Public Health, Community Service Planning	DES and SD
Training	Workforce / Staff Management	DES
Operations	Planning, System / Resource Utilization	DES
Evaluation	Quality Management, Performance Monitoring and Review	DES
Research	Research and Development	SD and DES
Risk	Risk Management, Forecasting	MCS
Behavior	Patient Behavior / Characteristics	ABS and MCS

2.5.1 Discrete-Event Simulation

K.D. Tocher developed DES in the United Kingdom in the 1950s. It appeared first in the manufacturing sector. Tocher created the first DES language for the United Steel Corporation. In this technique, the system state changes over time and moves from one state to another. This change can be approached as happening every fixed amount of time, called “the time slicing approach,” or at unequal and variable times, called “the next-event approach.” This technique is usually used to represent queuing systems (Mustafee et al., 2010) (Robinson et al., 2012). Specifically, DES can be defined as “a simulation method used to characterize and analyze queuing processes and networks of queues in which there is an emphasis on the use of resources”. The main components of any DES model are entities, resources, events, and attributes (Marshall et al., 2015).

Another definition for DES is as “a classical operational technique, designed for optimization of system performance at a very detailed level”. It is classified as a stochastic modeling approach that can be used to model queuing systems. In DES models, system states change at discrete times and entities move in the system, form queues, and perform activities. All of the times used in the model are drawn from predetermined probability distribution. These models can be used to model any system to any level of detail. The computer software used to execute DES models have screens that show the system while the simulation is running to give an impression of the operation used in simulation (Viana, Brailsford, Harindra, & Harper, 2014).

DES models can be defined as "computer programs that model the logical flow of complex processes occurring at discrete times and use random numbers to mimic the inherent variability in them (e.g., arrival and service times)". Simulation models must be validated after they are created. This validation process is done by using real data in the model and checking whether the results are close to what really happened or not. When real data are not available, then modelers can consult system experts to do the validation. After validation, simulation models are appropriate to use for analysis (Werker, Sauré, French, & Shechter, 2009).

DES is used in many sectors like banking, manufacturing, hospitality, and transportation. It is also used in many areas in the healthcare sector such as surgery rooms, inpatient clinics, and outpatient clinics. In DES models, entities move in the system, contributing to different process and using several resources. In healthcare models, these entities can be patients (most of the time), nurses, physicians, or staff. These entities follow certain paths and participate in different activities and utilize some resources. At the end of the simulation run several outputs are produced to evaluate the system under study (Mielczarek & Uziałko-Mydlikowska, 2010).

DES has several advantages over other modeling approaches. Some of these advantages are:

- The ability to model patients as single entities.
- The ability to include resources constraints in the model.
- The ability to represent clinical decision processes.
- The ability to show the simulation models through animation.

- The ability to create realistic models with all levels of detail needed (Davies & Davies, 1995).

The main motive for using DES is to model processes that are interconnected and subject to variability, variability that may be predictable or unpredictable. These features make processes complicated and therefore difficult to analyze. Thus, DES is useful to investigate performance under proposed changes and how to improve these processes (Robinson et al., 2012). Moreover, simulation helps in making strategic decisions, taking medical decisions, and in healthcare management (Werker et al., 2009).

DES models in the healthcare literature are used to solve problems in two main areas: patient flow and allocation of resources. Patient flow includes problems related to patient admissions and scheduling, flow schemes and patient routing, scheduling and availability of resources. Allocation of resources issues include room size and planning, bed size and planning, and staff size and planning (Mielczarek & Uziałko-Mydlikowska, 2010).

2.5.1.1 Discrete-Event Simulation Applications in Healthcare

There are many studies in the literature that use DES in solving the problems of healthcare clinics. These studies cover several topics such as admission policies, patient scheduling, patient arrival rates, physician utilization, patient flow, waiting time, and individual evaluations (Swisher et al., 2001).

DES is used in healthcare to investigate the effects of changes on outcomes. These outcomes are mean values that can be used to indicate the performance of the system, allowing decision makers to try test different scenarios to choose the one that best resolves the problem (Marshall et al., 2015).

DES is considered a tool that is widely accepted in making management decisions in the healthcare sector. This is because:

1. It gives applicable design methodology in the process of service development.
2. It transfers the improvement methods from the industry sector to the healthcare sector (Chemweno, Thijs, Pintelon, & Van Horenbeek, 2014).

DES in healthcare is not like DES in manufacturing with respect to stakeholders. The two main differences are the amount of stakeholder engagement and the necessity of managing the conflict of interests between multiple stakeholders in healthcare. The application of DES in healthcare allows managers to study all processes and test all alternatives to find the optimal solutions before doing any changes. It will also allow them to optimize resources and solve any problems in the planning phase. The first application of DES appeared in the literature in the 1960s. After that, DES was used to solve several problems in healthcare like studying emergency departments, finding bed sizing, the containment of infections in hospitals, planning for outbreaks due to diseases, and finding the best policy in supply chains (Robinson et al., 2012).

DES is usually used to solve the healthcare problems that have limited resources with uncertainty in demand. The clearest example can be found in accident and emergency (A&E) departments, where resources are limited and patients can arrive any time with any number. Another type of problem where DES is used deals with the flow of patients and related issues such as bed and staff sizing, patient admission and scheduling, and time spent in the system. This simulation technique helps in measuring the efficiency of any healthcare delivery system and this gives the managers the opportunity to improve current systems and plan for new future plans. These problems can be grouped as follows:

1. Economic health models that are used to assess the economic impacts of different healthcare interventions alternatives.
2. Models to evaluate different policies and strategies.
3. Models to develop methodologies for new techniques in health-related matters.
4. Models for management, planning, and reorganizing of healthcare services by evaluating effectiveness and utilization.
5. Models for A&E departments.
6. Models to investigate the public response under bio-terrorism and contagious diseases (Mustafee et al., 2010).

There are many DES applications in the healthcare field. Caro, Möller, and Getsios (2010) claim that DES is the best modeling method for health economic evaluations. This is because DES is considered the easiest simulation technique in application, and it gives adequately accurate results that will help in making healthcare decisions.

Al-Refaie et al. (2014) applied DES to enhance the performance of the ED in a Jordanian hospital. The results of this implementation decreased the waiting time in the ED, improved staff utilization, and increased the number of treated patients. These results were reached after testing different scenarios and choosing the optimal one that reduced to reduce the bottleneck and improve the quality of service.

Baril, Gascon, and Cartier (2014) studied the interactions and relationship between patient flow types, appointments scheduling rules, and resources capacity in terms of number of nurses and rooms using DES. They proposed new means to enhance the performance of outpatient orthopedic clinics. They suggest defining the appointment-scheduling rule based on patient flow type to get better results. They focused on the big variation in workload during different weeks to develop patient flow that can be changed according to expected workload.

Lina Aboueljinane, Sahin, Jemai, and Marty (2014) used DES to develop a model for the evaluation of the performance of SAMU "the acronym for Urgent Medical Aid Services in French" for 94 operations. They managed to create a model that could find the effect of any change in location and resources without deviating from the required target. However, the most important limitation of this study is that costs were not included in the process of comparing alternatives and all other financials were not taken into consideration.

Kadri, Chaabane, and Tahon (2014) used DES with the objective of managing and reducing strain situations in a pediatric emergency department at a hospital in France. They started by

characterizing strain situations, states, and corrective actions. After that, they implemented DES to model and analyze this department. They developed a decision support system (DSS) that is simulation-based in order to stop these situations by investigating the connections between strain signs and the related corrective actions.

Nikakhtar and Hsiang (2014) showed that unusual conditions like epidemics would have a big impact in any healthcare system, leading to disturbed system performance. This will force healthcare executives to work on find emergency plans in order to be able to handle such situations. The authors of this paper created a DES model that can be used to tackle such a case with different scenarios.

Chemweno et al. (2014) implemented DES to show the diagnostic path of stroke patients in a hospital. They evaluated different policies using waiting time as a performance measure.

Shi, Peng, and Erdem (2014) used DES in a Veterans Affairs (VA) primary clinic to model the visit of patients. This model included different categories of patients, where each category of patient follows different paths and requires different services. The resulting simulation model was used to control and improve the clinic operation and to enhance the efficiency of the patients' visit.

Pinto, Silva, and Young (2015) proposed a framework to develop general DES models for analyzing an ambulance service system. After that, they used this method to do a comparison between two provisions in UK and Brazil.

Werker et al. (2009) used DES to model a radiation therapy planning process to reduce waiting time. They tested different scenarios and reached a predicted improvement of about 25%.

Villamizar et al. (2011) developed a DES model for a physiotherapy clinic in Brazil. This model was used to analyze the number of patients visiting the clinic and all their measures such as arrival time, waiting time, and finishing time. They also used this model to find resource utilization and required resources to increase the number of patients that the clinic could serve.

Coelli et al. (2007) developed a DES model to show the working routine of a clinic. This model was used to optimize resources and solve problems.

Brailsford and Schmidt (2003) developed a DES model that uses the PECS architecture to model human behaviors. This model can help policy-makers and health planners to create more effective and efficient screening programs to enhance the overall population health.

Mielczarek (2014) used a DES model to find the number of emergency services delivered in a hospital in Poland and the costs associated with these services.

Jahn, Theurl, Siebert, and Pfeiffer (2010) used DES to model capacities of resources, waiting lines and queues, and to measure waiting time. This model was used to reduce the waiting time and to allow decision makers to make the necessary changes in order to improve this system.

Vataire et al. (2014) developed a DES model to estimate cost and health outcomes of different alternative treatments for patients with major depressive disorder. This model was used to conduct analysis to find the best strategy with the lowest cost.

Radhakrishnan, Duvvuru, and Kamarthi (2014) used DES modeling to evaluate if the use of wearable health monitoring devices is effective in minimizing the primary care patient load and in enhancing communications between different healthcare units.

M. E. Lim, Worster, Goeree, and Tarride (2013) developed a DES model with "a hierarchy of heterogeneous interacting pseudo-agents" for the ED in a hospital. This model was used to improve physician and delegate utilization and enhance the performance of the ED.

2.5.2 System Dynamics

Jay Forrester was the developer of SD in 1950s at the Massachusetts Institute of Technology. SD can be defined as "a simulation modeling method used for representing the structure of complex systems and understanding their behavior over time". It is considered to be a simulation and modeling approach for decision-making analysis of industrial management problems in the long-term. This approach can handle system structures assumptions as well as investigate the impacts of changes on systems. Thus, it could be used to simulate complicated systems like a waste management system and to express nonlinear relationships. The first usage of SD was to utilize science and engineering to find the main factors that lead to the success or

failure of corporations. The main components of any SD model are feedback loops, flows (rates), stocks (accumulations), and time delays. The output of SD models will be in the form of trends and patterns. These outputs allow decision makers analyzing alternative policies and strategies to choose the best one(s) (Marshall et al., 2015) (Chaerul, Tanaka, & Shekdar, 2008) (Mustafee et al., 2010).

SD is considered “a more strategic tool, typically used at a much higher level, for understanding overall system behavior”. The main principle in any system dynamics model is that “the structure of a system determines its behavior over time”. SD models include all nonlinear relationships. SD has a qualitative and a quantitative part. The qualitative part is constructed by creating casual loop diagrams. These diagrams show the relationships between different system elements nodes and arcs that form a network. These relationships can be found by discussions between the modeler and stakeholders. The arcs in the network have two signs, positive and negative, to indicate the impact. The goal of this is to investigate feedback loops, which can be either balancing loops, where a steady state is reached and maintained, or a vicious circle, where growth is not controlled. The quantitative part is constructed by using stock-flow diagrams. These SD models are considered deterministic, and they cannot include the variability of individuals (Viana et al., 2014).

In the SD models, feedback loops are used to create a different way to study the system. This design will move the concentration of the model from entities to accumulated flows. These loops will help in expressing nonlinear relationships and the addition of effects will assist in

recognizing different dynamic behaviors and discovering future trends for any required change (Mielczarek & Uziałko-Mydlikowska, 2010).

Several simulation programs can be used to study and analyze SD models, for example, Stella, Powersim, Vensim, and i-think. The literature shows that SD has been used to solve problems in many areas that have feedback systems, including agricultural systems, ecological systems, political systems, environmental systems, and social-economic systems (Chaerul et al., 2008).

2.5.2.1 System Dynamics Applications in Healthcare

SD is commonly used to model healthcare systems using a top-level approach. This makes this technique helpful in the process of designing new policies as it can test the impact of changes on the current system. This can be done by taking into account several elements and factors related to time and cost. Functions commonly performed using SD in the literature include:

1. Evaluating health policies
2. Using it as teaching tool to develop new policies by studying different strategies
3. Modeling large and complicated healthcare systems
4. Modeling infrastructures
5. Creating economic health models (Mustafee et al., 2010)

Examples of SD applications in the healthcare sector are given below:

Chaerul et al. (2008) developed an SD model for a hospital waste management system in Indonesia. This model was used to analyze this system to study and control the health risks resulting from the system.

Faezipour and Ferreira (2013) developed an SD model to study the complicated relationships in the healthcare system. This model was used to measure and enhance patient satisfaction with the healthcare system.

Lane, Monefeldt, and Rosenhead (2000) developed an SD model to study the dynamics of accidents and emergency departments. This model was used to improve resources utilization (bed capacity) and enhance system performance by reducing patient wait times.

Ng, Sy, and Li (2011) developed an SD model to study healthcare accessibility and affordability in Singapore. This model was used to assess the sustainability and effectiveness of different policy instruments. This helped decision makers in dealing with complications in the healthcare system.

Kasiri, Sharda, and Asamoah (2012) used an SD model to analyze the benefits of healthcare IT. This model was used as a non-traditional approach for this IT cost-benefit analysis.

2.5.3 Agent-Based Simulation

ABS can be defined as "a simulation method for modeling dynamic, adaptive, and autonomous systems". ABS is usually used to study systems by applying inductive and deductive reasoning. The main components of any ABS model are agents (with behavior and characteristics), agents' relationships (interactions and outcomes), and agents' environments (manager of agents). Three main concepts are the foundation of ABS: dynamics, structure, and agency (Marshall et al., 2015) (Kaushal et al., 2015).

Another definition for ABS is "a computational technique for modeling the actions and interactions of autonomous individuals (agents) in a network". ABS is considered the newest simulation technique since it was found in 1990s. Its initial purpose was to solve technology and financial problems. Unlike SD, this technique uses a bottom-up modeling approach: it concentrates on individual agents, which have behaviors, attributes, and the ability to make decisions, and their interactions and actions. Thus, it sees the behavior of the system emerging from those agents. ABS is mainly used to model populations or complicated and dynamic environments under different scenarios when there are assumptions on the individual level and relationships between agents. ABS has applications in several areas such as biological, social, and physical systems (Mustafee et al., 2010) (Katsaliaki & Mustafee, 2011) (Kim & Yoon, 2014).

ABS is used in healthcare for modeling natural disasters like infectious diseases, chemical spills, hurricanes, flooding, or forest fires. It is also used for public health planning and making decisions about new healthcare investments. The results of ABS models could be used to perform sensitivity analysis to help in planning, test new assumptions, and study the effect of different scenarios. The output of ABS models can be disease trends and patterns, health outcomes, or other measures like utilization, productivity, and costs (Marshall et al., 2015).

2.5.3.1 Agent-Based Simulation Applications in Healthcare

There are many ABS applications in the healthcare field that could be found in the literature. Some of these applications are presented next:

Cabrera, Taboada, Iglesias, Epelde, and Luque (2011) proposed an ABS model to model emergency departments. The target of this model is to assist ED managers in choosing guidelines and strategies that make the operation of the ED reaches the optimal.

Cuadros, Abu-Raddad, Awad, and García-Ramos (2014) used ABS approach to improve the methods that are used to control and prevent the spread of dangerous diseases or infections in effective ways. This approach will help in providing evidences that could be used in the research of this area.

Kaushal et al. (2015) created an ABS model for an ED in a hospital. This model was used to evaluate fast track treatment strategies in order to minimize the patient waiting time. It was also used a cost-effective tool to assess the performance of the operation in the ED.

Kim and Yoon (2014) used ABS modeling approach as a way to evaluate the concepts of new healthcare services. This model was used to forecast the service factor in the new service by analyzing customers' needs.

Taboada, Cabrera, Iglesias, Epelde, and Luque (2011) proposed an ABS model for ED in hospitals. This model was used to analyze the performance of EDs in several hospitals. It will provide managers and decision makers to enhance resources utilization and improve the efficiency of the system during all circumstances.

Taboada, Cabrera, Epelde, Iglesias, and Luque (2013) developed an ABS model for ED in a hospital. This model was used as a part of DSS to allow decision makers to enhance resources utilization and improve the efficiency of the system.

Soto-Ferrari, Holvenstot, Prieto, de Doncker, and Kapenga (2013) developed an ABS model to be used for pandemic and seasonal influenza outbreaks. This model was used to study different situations in order to create plans for operations. The results of this model could be used to improve the public health system.

Liu and Wu (2014) used ABS model to do the analysis and get recommendation to help decision-makers in making decisions on the designs of accountable care organizations payment model. This model will be used to find the optimal design that would attain the best financial and quality outcomes.

Schaaf, Funkat, Kasch, Josten, and Winter (2014) developed ABS model for the ED in a hospital. This model used to minimize the total waiting time of patients, enhance resources utilization and improve the performance of the ED.

2.5.4 Monte-Carlo Simulation

MCS is a simulation technique that uses statistics. It was developed during World War II. This technique is used when uncertainty is present and exact results cannot be found. Random sampling from a chosen probability distribution is used with computational algorithms to find the results and the probability of each result (Mustafee et al., 2010).

Monte-Carlo simulation can be defined as "a computational algorithm that uses repeated random sampling to compute a given outcome". This technique is designed in a way that variables get values from random distributions instead of fixed or a range of values. The distributions used in MCS models investigate the sensitivity of changing to a new utility and how it may be affected, including the probability of it being affected in various ways. A combination of Markov chain

models and MCS facilitates the stochastic merge of numerous distributions to get one outcome (Mustafee, Katsaliaki, Gunasekaran, Williams, Ben-Assuli, et al., 2013).

Due to the static character of the Monte Carlo modeling, it cannot be used to study evolving systems. Therefore, these models are used to estimate the effect of a new change or decision by evaluating the probability of the outcomes and their expected values, which information is provided in the form of a spreadsheet (Mielczarek & Uziałko-Mydlikowska, 2010).

2.5.4.1 Monte-Carlo Simulation Applications in Healthcare

MCS is used mainly in the literature to examine healthcare intervention evaluations and health economics. It has been used when Markov models and decision trees cannot serve the purpose due to the homogeneity assumptions. MCS is mainly used in the following contexts:

1. To evaluate the risk of exposure to some elements such as water pollution, air pollution, soil contamination, food poisoning, or drug dose-response portions.
2. To assess the cost-effectiveness of using new technologies or applying different healthcare strategies.
3. To investigate the use of medical interventions and their effect on health and the transmission of diseases.
4. To create new methodologies and to do feasibility studies (Mustafee et al., 2010).

Some of MCS applications in the literature are presented below:

Lesosky et al. (2011) developed a MCS to model “the rate and spread of MRSA transmission among patients in medical institutions”. This model was used study “disease-transmission dynamics inter-institutional transfer patterns” in order to create strategies to be implemented to control and deal with the disease transmission.

Mustafee, Katsaliaki, Gunasekaran, Williams, Ben-Assuli, et al. (2013) used MCS to analyze the implications of admission decisions. This model could be used to “study the cost-effectiveness of using therapy, treatment, or medication in the healthcare sector in CVD diagnoses and other diagnoses”.

Sparrow (2007) used MCS models to study “the likelihood of random clustering of cases arising in units within a healthcare setting resembling the National Health Service (NHS) and separately within the practices of individual surgeons”. This model was used to get more knowledge about the rate of the disease and to study different situations.

Burns, Hertel, and Ansari (2009) used MCS to calculate the radiology dose rate that healthcare providers are exposed to when dealing with externally or internally contaminated victims. This model was used to investigate if the dose rates exceed the recommended guidelines or not.

2.6 Simulation Modeling Development Methodologies

After the wide spread of using simulation to solve problems in many fields, efforts were directed towards creating methodologies, methods, and techniques that could be used to simplify, facilitate, and automate the development simulation models. There are several simulation development methodologies in the literature especially for DES. Some of these methodologies and techniques will be presented next.

2.6.1 Lackner's Formalism (Lackner's calculus)

Michael Lanckner is considered one of the first scholars to identify the necessity to develop a new theory for models and systems to differentiate this development process from the simulation programming language developments. He presented a discrete events systems theory that states "change, not time, is primitive; the theory, and the "Calculus of Change" require that time is defined in terms of change (Page Jr, 1994).

2.6.2 The Discrete Event System Specification formalism

The discrete event system specification formalism is a methodology developed by Zeigler in 1976. This formalism defines three main elements in any discrete event simulation, which are the system, the model, and the computer. These elements have two categories of relationships, which are modeling and simulation. Modeling will include relationships between models and systems

whereas simulation will have relationships between computers and models. The system is defined as “some part of the real world, which is of interest”. Models have five main classes, which are time base (continuous and discrete), the set of descriptive variables (continuous and discrete), relationships in the model (stochastic and deterministic), relation between the model and its environment (autonomous and non-autonomous), and the model’s rules of interaction (time invariant and time variant) (Page Jr, 1994).

2.6.3 System Entity Structure

System entity structure is defined as “a mechanism to describe hierarchically structured sets of objects and their interrelations”. It is considered as a labeled tree that has different type of variables attached. This tree works as a graphical representation that shows how the system of interest is decomposed into smaller related and connected parts. One of the methods that use system entity structure is the knowledge-based simulation design methodology. This methodology uses simulation and modeling techniques to create and evaluate models of designed systems. In this methodology, the design process consists of a sequence of activities that decomposes different design levels in a hierarchal structure. It also classifies components of the system into different categories. Finally, it uses simulation to experiment and develop required solutions (Page Jr, 1994).

2.6.4 Activity Cycle Diagrams

Tocher is considered one of the first scholars that introduced the description of the logical flow of simulation using diagrams. This use of diagrams is one of the early efforts that represented simulation models with graphical explanations. This use of diagrams was widely used in simulation activities in the UK starting from the 1960s. In this approach, each simulation model is represented as connected and related entities. In these models, entities are either active or idle whereas activities are active or passive. The life cycle of these models consists of activities and queues for entities associated with them (Page Jr, 1994).

2.6.5 Event-Oriented Graphical Techniques

Another simulation models development techniques that use graphical representations are event-oriented graphical techniques. The most commonly used technique among these techniques is the event graphs. This formalism was introduced by Schruben in 1983. In this technique, main elements of any discrete event simulation model are state variables that could be used to determine the system's state, events that change the values of these state variables, and relationships between different events. The event graph is defined as "a directed graph that depicts the interrelation of the events in an event scheduling discrete event simulation" (Page Jr, 1994).

2.6.6 Petri Net Approaches

Petri net is defined as "an abstract formal model of information flow". The main use of these Petri nets is to model systems when concurrency is exhibited. This use is driven by the desire to model using Petri nets and then derive the properties of the system after modeling. Thus, Petri nets are used as modeling tools in discrete event simulation to build models for general systems. In this modeling, the system will be represented by two different sets, which are events and conditions and the relationships between them. One of the popular implementations of these nets in discrete event simulation is simulation net. These simulation nets are considered as an extension to Petri nets with more details (Page Jr, 1994).

2.6.7 Logic-Based Approaches

These logic approaches used systems theoretical foundations by Zeigler as the main source for discrete event modeling and simulation. There several logic approaches that could be found in the literature. One of these approaches is called DMOD. In this approach, the simulation model will be represented by a "7-tuple" that is composed of events, times, and relationships. Another approach is called UNITY. In approach, a defined formalism will be used to develop simulation models (Page Jr, 1994).

2.6.8 Control Flow Graphs

Control flow graph is a mechanism introduced by Cota and Sargent in 1990. It is considered as a theoretical tool to develop parallel simulations algorithms. The control flow graph is defined as "a directed graph that represents the behavior of an individual process, or class of processes, in a discrete event model" (Page Jr, 1994).

2.6.9 Generalized Semi-Markov Processes

The implementation of Markov process to analyze discrete events systems is not new and started with the advancement of digital computers. These generalized semi-Markov processes are used to study discrete events systems in a formal basis. They offer the ability to study these systems analytically and using the discrete event simulation (Page Jr, 1994).

2.7 Case-Based Reasoning Methodology

Learning algorithms have two major categories: lazy and eager. The lazy learning (LL) algorithms include case-based reasoning (CBR), memory-based reasoning, and instance-based reasoning. The eager learning (EL) algorithms include neural networks and rules and tree generators. Each category has its strengths and weaknesses. Thus, to tackle real complicated

problems hybrid reasoning needs to be used to develop intelligent systems (Daengdej, Lukose, & Murison, 1999) (Khan, Awais, Shamail, & Awan, 2011).

Many artificial intelligence (AI) technologies have been created in the last few decades. Examples of these technologies are genetic algorithms, fuzzy logic, logic programing, neural networks, constraint-based programing, and rule-based reasoning. Programing languages like Prolog or algorithms like the Rete algorithm are used to characterize these technologies. CBR is considered a relatively new AI methodology. that has It was developed between the end of the 1970s and the beginning of the 1980s to solve problems in any field. It is a simple and clear process used to utilize the knowledge gained from the past to find solutions for current problems or to make decisions. It uses the same process that is used by humans in solving new problems. It can be explained as "CBR basically packages well-understood statistical and inductive techniques with lower-level knowledge acquisition and representational schemes to effect efficient processing and retrieval of past cases (or experience) for comparison against newly input cases (or problems)". It uses database management and machine learning techniques to perform the retrieval process (Mott, 1993) (Yeh & Shi, 2001) (Watson, 1999) (Bichindaritz & Marling, 2006).

Case-based reasoning (CBR) can be defined as "a computerized method that attempts to study solutions that were used to solve problems in the past to solve, by analogy or association, current problems". CBR has four main processes that use gained experience in solving new problems. These processes are retrieve, reuse, revise, and retain. They are also known in the literature as the 4R processes. The traditional CBR approach is shown in Figure 2. It is considered to be a part of

machine learning and a new approach that is created to fill in the gaps from available limitations in current rule-based systems and help in gaining more knowledge. CBR has some advantages over other rule-based systems. One of these of advantages is that it can be closer to the decision processes that are used by people since it uses similar solved problems. Another advantage is that it has an easier and automated process to extract new knowledge from old solved cases. It is different from other rule-based system, where in cases where no solution can be found, new rules must be developed and after that added to the main knowledge base. In CBR, every solved case is available in the knowledge base and it can be used to find solutions for other similar cases in the future. Thus, CBR helps in resolving the issues of rule-based systems when it comes to knowledge acquisition. The development of a case base in CBR can also be done faster than developing a knowledge base in rule-based systems. This is because most organizations record their previously solved cases and it could be just a matter of gathering these cases and adding them together. Another advantage is the execution of the CBR process has a faster running speed than any other rule-based system. This speed comes from the fact that there is no need to apply complicated rules; rather, similar solved cases are retrieved and studied to find ways to solve the new problem. Finally, unlike with rule-based systems, in CBR, there is no need to fully understand the reasons that made the old solution successful. It is just a matter of finding a way to solve the available problem. (Ketler, 1993) (Daengdej et al., 1999) (An, Kim, & Kang, 2007) (Yang & Wang, 2008).

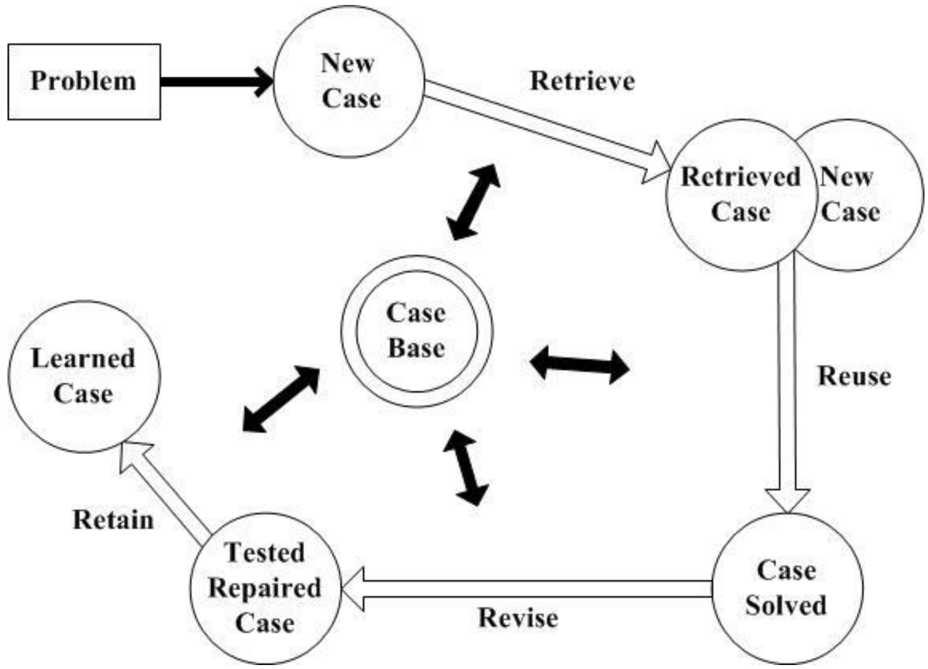

Figure 2: The traditional CBR process (Zhao, Cui, Zhao, Qiu, & Chen, 2009).

The CBR approach consists of two main phases: the construction of the case base and using this case base to find a solution for the problem. The process of creating a case base has three steps: 1) understanding the domain of the problem, 2) creating an operational indexing mechanism, and 3) storing all previously solved cases. After that, any new problem can be analyzed to find similar cases and complete the second phase, deriving a solution. This approach is shown in Figure 3.

Another use of CBR is to interpret situations. In this case, CBR is implemented to find similar problems in order to understand, evaluate and analyze the current situation (Ketler, 1993) (Ross, Fang, & Hipel, 2002).

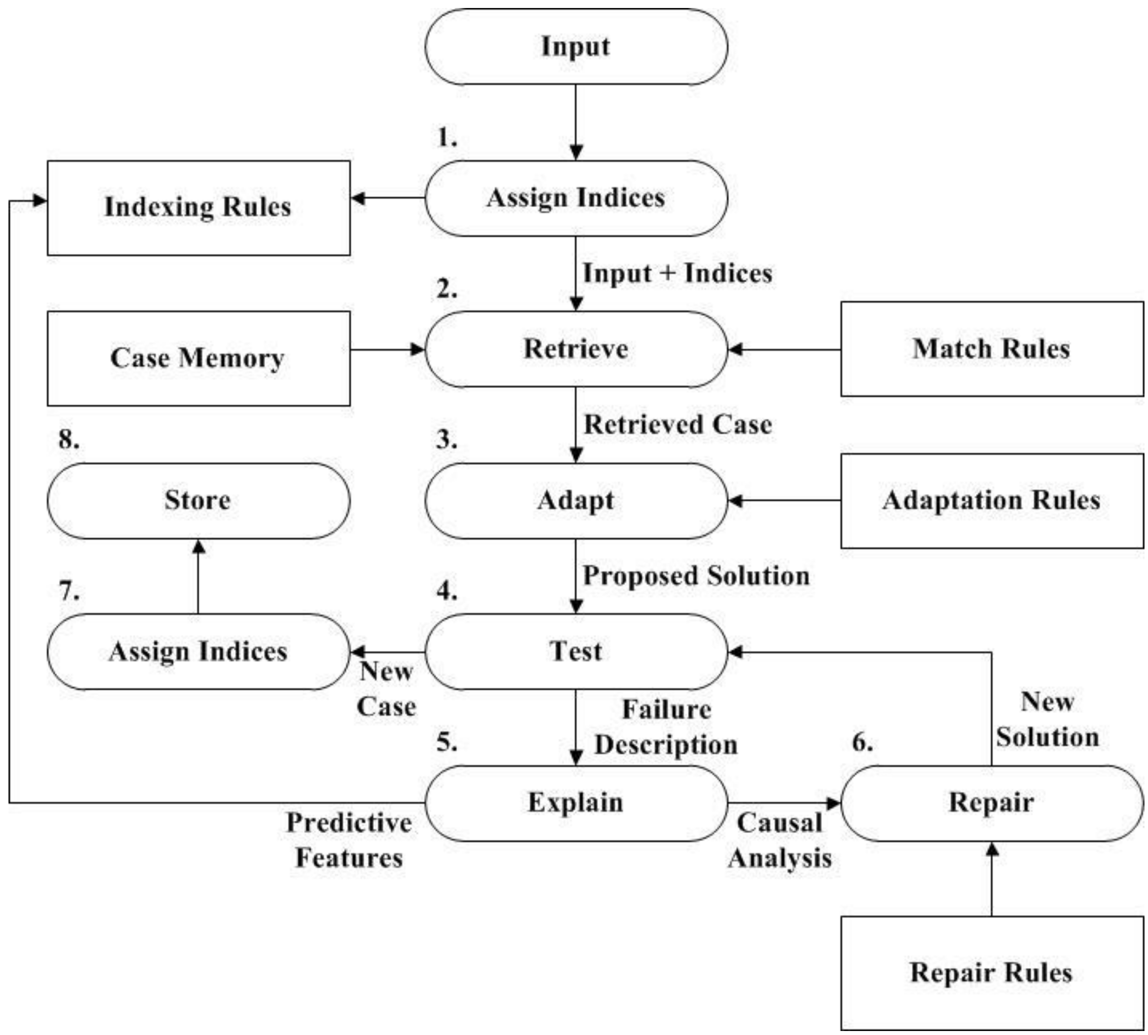

Figure 3: The detailed process of CBR approach (Ketler, 1993).

In the CBR methodology, the cases stored in the case-base contain knowledge that including three features. These features are:

1. Operational: implementation and modeling details
2. Specific: knowledge about a certain application or problem
3. Contextual: information about similar processes (Zhou et al., 2010)

The presence of a large database of solved problems minimizes the analysis needed for new problems given that old solutions to similar problems can be used. This is how CBR works with domains that are not fully understood. However, for a CBR system to work effectively, it needs to be built on domain analysis that involves knowledge engineering. The process of developing a knowledge-based system (KBS) involves: "identifying a real world problem solving task that is to be tackled, representing the key components of this task in the KBS, and implementing the inference process that produces solutions". From this, it is clear that the two main elements in the process of knowledge engineering are problem representation and the inference mechanism. The representation should detect all the main characteristics of the problem by analyzing it while the inference mechanism is used for retrieving similar problems from the case-base to find the solution for the new problem (Cunningham & Bonzano, 1999).

CBR has a middle position compared to other approaches on the spectrum of knowledge-based technologies. It can be located between rule-based systems and pattern recognition or neural networks (Mott, 1993). A comparison between CBR and other approaches is shown in Figure 4.

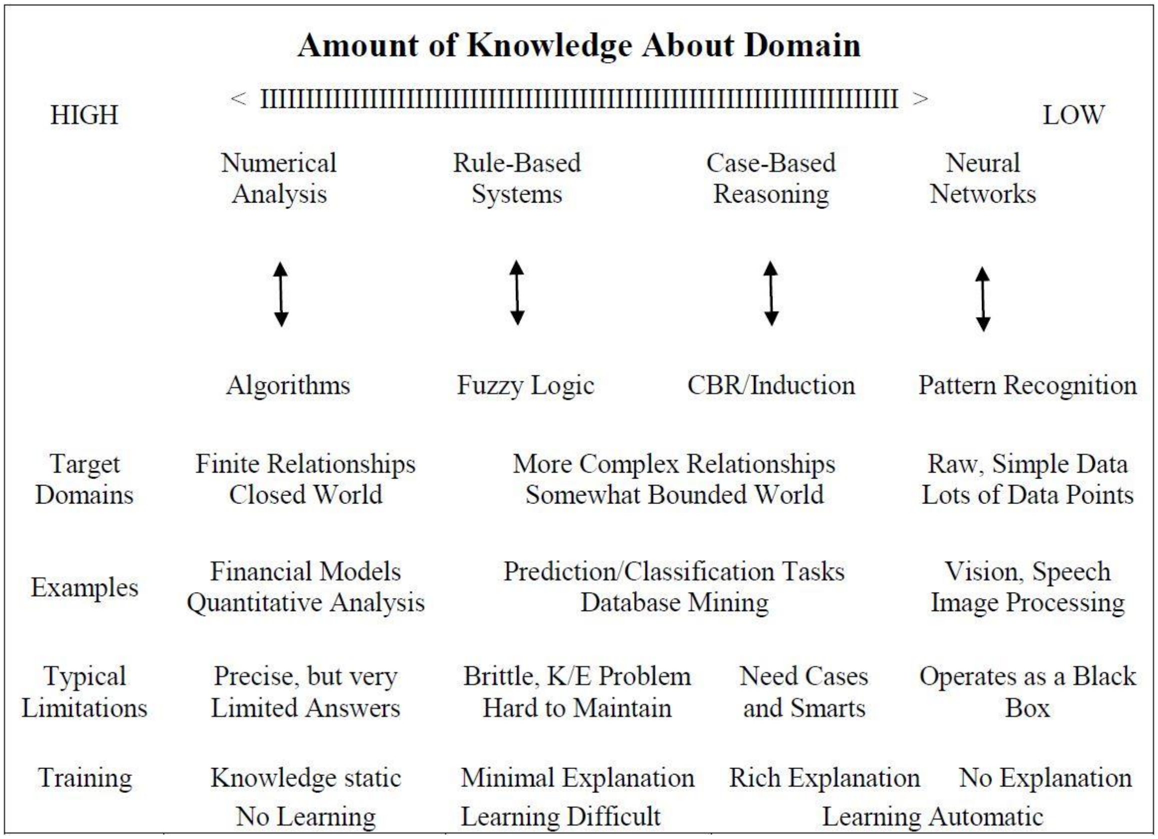

Figure 4: Comparison between CBR and other knowledge-based technologies (Mott, 1993).

Several scholars have developed models for CBR as a way to offer more explanation to understand the CBR process. All of these models use the assumption that the case-base should be prepared before the start of the process. Most of these CBR models are application-oriented. There are four CBR models that can be found in the literature. These models are:

1. Hunt model: this model includes analysis of the new case to find the features that could be used to retrieve similar cases. This model is shown in Figure 5 (Finnie & Sun, 2003).

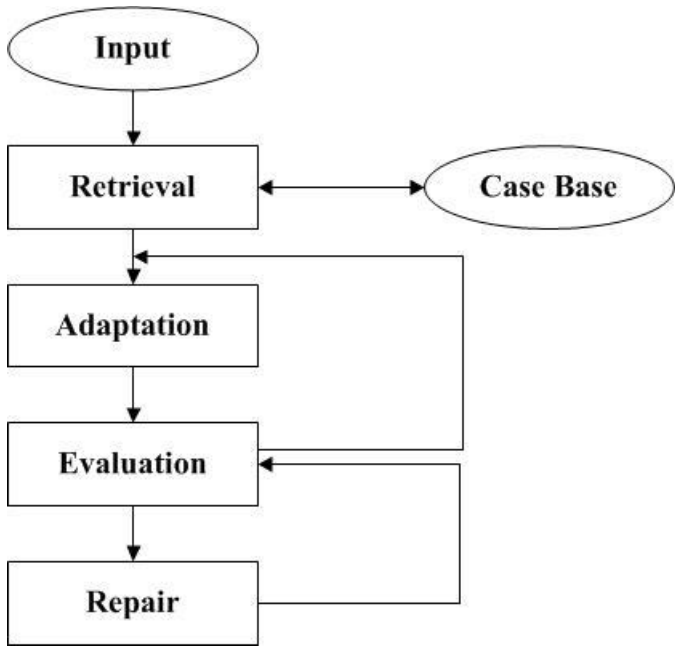

Figure 5: Hunt model of CBR (Finnie & Sun, 2003).

2. Allen model: the steps in this CBR model are
   - Presentation: to describe the current problem.
   - Retrieval: to retrieve matching cases.
   - Adaptation: to develop a solution for the new problem.
   - Validation: to validate the new solution using feedbacks.
   - Update: to add the solution to the case-base for future use (Finnie & Sun, 2003).

3. Kolodner and Leake model: the retrieved cases in this model are analyzed to find the most important cases. The least important cases are ignored. This model is shown in Figure 6 (Finnie & Sun, 2003).

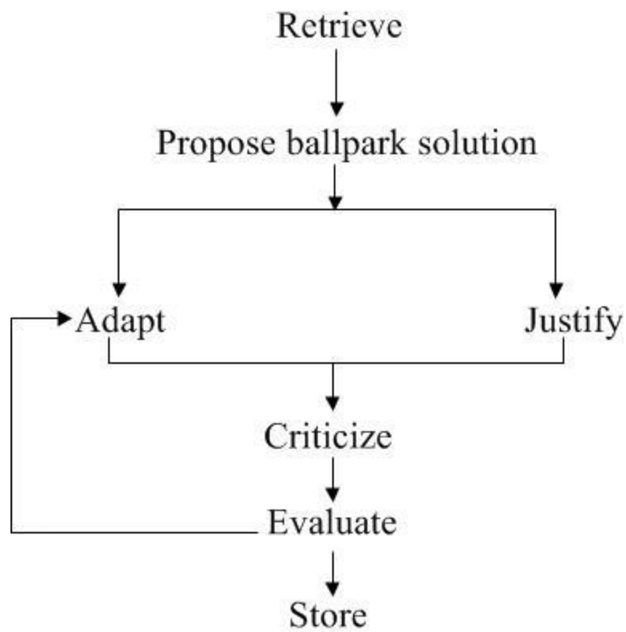

Figure 6: Kolodner and Leake model of CBR (Finnie & Sun, 2003).

4. Aamodt and Plaza model (R4 model): this model is the first CBR model, and it contains the traditional 4 steps. This model is shown in Figure 7 (Finnie & Sun, 2003).

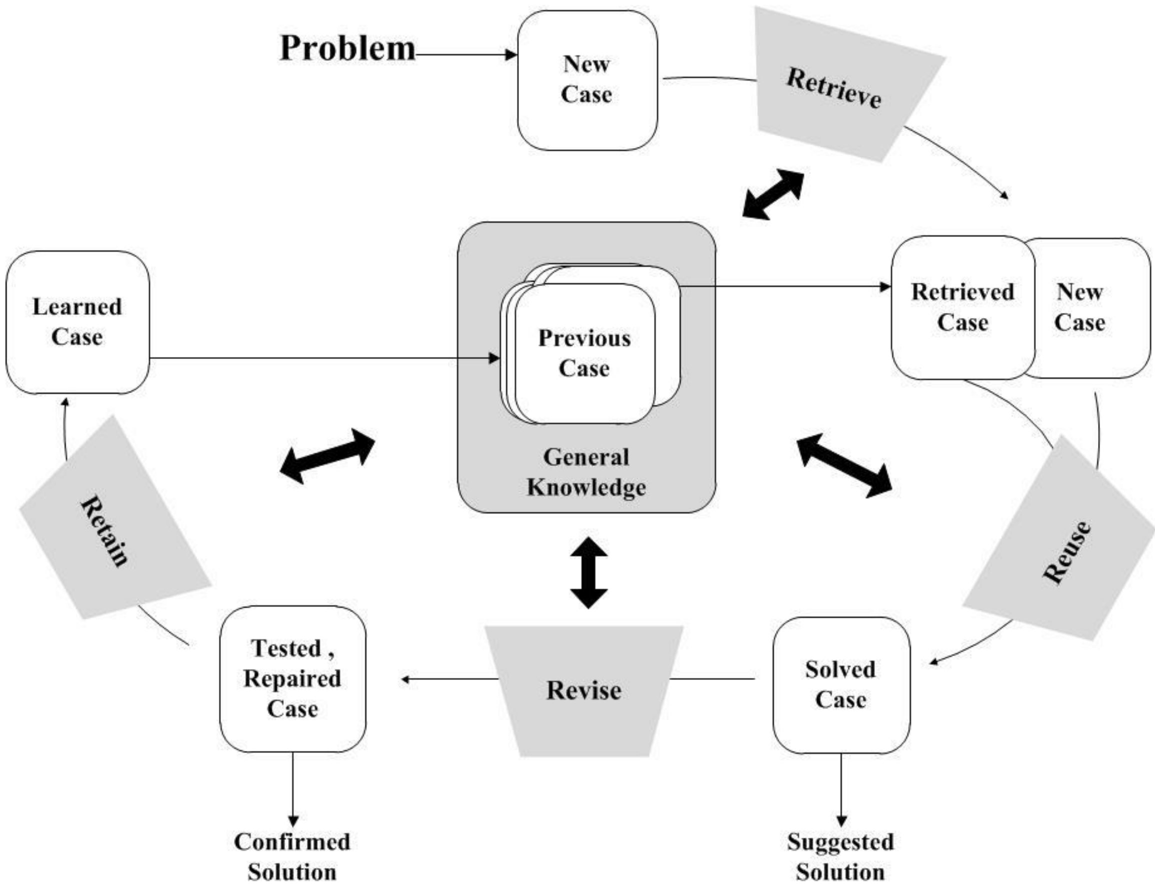

Figure 7: Aamodt and Plaza model of CBR (Finnie & Sun, 2003).

CBR is considered a simple process to implement compared to other algorithms. There are several programs that can be used to implement CBR, for example, CRB-Works, CASPIAN, Spotlight, ESTEEM, ReCall, ReMind, and KATE. In CBR processes, all cases must be reviewed to find ones similar to that for which a solution is being sought. The comprehensiveness of this review affects the efficiency of the CBR, especially when the case-base is large. Several studies have been done of the review process to improve the efficiency of the CBR. The most common study involves K/CBR, which combines CBR with a K-means approach. In this approach, all

cases are classified in clusters and then the evaluation is done with cases that are in the cluster that is similar to the current problem (Yang & Wang, 2008) (Watson, 1999).

The process of CBR application includes two major tasks: classification and synthesis. In the classification task, the case which is found to be the best match is used to get the class or type of solution needed. Then, in the synthesis task, several old solutions or parts of them are used to develop a new solution that will be used to solve the current problem. For CBR systems that include synthesis tasks, they combine CBR with other technologies, creating a hybrid system to be used in the adaptation process (G. Lim et al., 2005).

Fuzzy logic can be defined as “a way of formalizing the symbolic processing of fuzzy linguistic terms, such as excellent, good, fair and poor, which are associated with differences in an attribute describing a feature”. Fuzzy logic can be used to find similarities, for example, “excellent” is more similar to “good” than “poor”. In CBR, assigning numbers to fuzzy terms could be used as a function with attributes as a way to quantify the process of finding similar cases (Watson, 1999).

Database technology can also be used with CBR. Database technology offers efficient ways to deal with huge amounts of data. Clear problem descriptions are required to use this technology in order to form effective queries to retrieve similar cases (Watson, 1999).

CBR was originally used to solve problems in areas like strategic planning, legal precedence, problem diagnosis, political analysis, fraud detection, situation assessment, design and

configuration, message classification, tactical planning, construction industry, supply chain management, and product design and development (Ketler, 1993) (Yang & Wang, 2008). Moreover, it has been used to solve problem in several area such as E-commerce, intelligent frequently asked questions (FAQ) systems, and software engineering (Khan et al., 2011). There are several applications of CBR in the medical field as well. Most of these applications are in the area of medical diagnosis. CBR has also been applied to decision support systems in the healthcare sector (Huang et al., 2007).

Yang and Wang (2008) proposed a new CBR approach called GCBR to enhance the efficiency of CBR and to produce better knowledge. This approach involves two phases and combine CBR with genetic algorithm (GA) and knowledge discovering and data mining (KDD) processes. In the first phase, GA is used to retrieve cases. In the second phase, KDD processes are used on those retrieved cases.

Zhou et al. (2010) studied two main difficulties in the application of CBR in simulation, which are case representation and case matching. They proposed a model that detects the characteristics of simulation models and orders them in robust way. They also developed algorithms to search for similar cases by counting similarities that is different from a domain to another. The application of CBR processes for simulation modeling is not an easy job and might face several difficulties. These difficulties appear in “representing simulation cases; indexing and matching cases; adapting cases; and retaining cases”.

2.8 Literature Gap Analysis

It is clear from the review of the literature that the application of simualtion in healthcare field is not like applications in other sectors like manufacturing, military, and aerospace. This highlights a gap that needs to be filled by improving these simulation applications to have the effects and impacts like other simulation applications.

The four simulation techniques outlined above, DES, SD, ABS, and MCS, are those most commonly used to solve problems in the healthcare field. The literature reveals many applications of simulation techniques. DES is used more than other techniques in healthcare. Examples of DES in healthcare are given in Table 4.

Table 4: Examples of DES applications.

Reference	**DES**	**SD**	**ABS**	**MCS**	**Simulation with another tool**	**CBR**	**Objective(s)**
Caro, Mšller, and Getsios (2010)	x						To model health economic evaluations
Al-Refaie et al. (2014)	x						To enhance ED operations by decreasing waiting time and improving resource utilization.
Baril, Gascon, and Cartier (2014)	x						To improve resources utilization by studying patients' flows and scheduling rules.
Nikakhtar and Hsiang (2014)	x						To study the effect of unusual conditions like epidemics on any healthcare system
Pinto et al. (2015)	x						To analyze ambulance service system
Werker et al. (2009)	x						To model radiation therapy planning process
Brailsford and Schmidt (2003)	x						To model healthcare planning

SD has been used to invistegate and study the dynamic relationships in healthcare areas and to solve other problems. Examples of SD applications are presented in Table 5.

Table 5: Examples of SD applications.

Reference	**DES**	**SD**	**ABS**	**MCS**	**Simulation with another tool**	**CBR**	**Objective(s)**
Chaerul et al. (2008)		x					To model hospital waste management system
Faezipour and Ferreira (2013)		x					To study the complicated relationships in the healthcare system
Lane, Monefeldt, and Rosenhead (2000)		x					To study the dynamics of accidents and emergency departments
Ng, Sy, and Li (2011)		x					To study healthcare accessibility and affordability
Kasiri, Sharda, and Asamoah (2012)		x					To analyze the benefits of healthcare IT

ABS has been used to study individuals' characteristics, relationships, and behaviors as well as solving other problems. Examples of ABS appliations are presented in Table 6.

Table 6: Examples of ABS applications.

Reference	**DES**	**SD**	**ABS**	**MCS**	**Simulation with another tool**	**CBR**	**Objective(s)**
Cabrera, Taboada, Iglesias, Epelde, and Luque (2011)			x				To model ED
Cuadros, Abu-Raddad, Awad, and Garc'a-Ramos (2014)			x				To control and prevent the spread of dangerous diseases or infections in effective ways
Kim and Yoon (2014)			x				To evaluate the concepts of new healthcare services
Soto-Ferrari, Holvenstot, Prieto, de Doncker, and Kapenga (2013)			x				To be used for pandemic and seasonal influenza outbreaks
Liu and Wu (2014)			x				To help decision-makers in making decisions on the designs of accountable care organizations payment model

MCS has been used to model evaluations, interventions, and economic problems in the healthcare field and to solve other stochastic problems. Examples of MCS applications are in Table 7.

Table 7: Examples of MCS applications.

Reference	**DES**	**SD**	**ABS**	**MCS**	**Simulation with another tool**	**CBR**	**Objective(s)**
Lesosky et al. (2011)				x			To model “the rate and spread of MRSA transmission among patients in medical institutions”
Mustafee, Katsaliaki, Gunasekaran, Williams, Ben-Assuli, et al. (2013)				x			To analyze the implications of admission decision
Sparrow (2007)				x			To study “the likelihood of random clustering of cases arising in units within a healthcare setting resembling NHS and separately within the practices of individual surgeons”

Several studies have combined more than one simualtion technique in order to study complex systems, to investigate the effect of different alternatives, or solve complicated problems in healthcare. Examples of these studies are given in Table 8.

Table 8: Examples of combined simulation techniques applications.

Reference	**DES**	**SD**	**ABS**	**MCS**	**Simulation with another tool**	**CBR**	**Objective(s)**
Day, Ravi, Xian, and Brugh (2014)	x		x				To model clinics operations and choose the best strategy among several alternatives
Djanatliev, German, Kolominsky-Rabas, and Hofmann (2012)		x	x				To evaluate new technologies in healthcare. ABS used to model patients' behavior and SD to model the environments around patients.
Rohleder, Bischak, and Baskin (2007)	x	x					To redesign patient service centers. DES model was used for resource utilization and improving system performance. SD model was used to predict demand patterns, create new policies to minimize variability in demand, and study the effect of changes.

In several studies, a simulation tool is combined with a different type of tool in order to solve complicated problems in complex systems. Examples of such studies are given in Table 9.

Table 9: Examples of simulation combined with other tools applications.

Reference	**DES**	**SD**	**ABS**	**MCS**	**Simulation with another tool**	**CBR**	**Objective(s)**
Oddoye, Jones, Tamiz, and Schmidt (2009)					x		To determine the optimal resources level that will reduce time delays in medical assessment unit
Ahmed and Alkhamis (2009)					x		To find the optimal staff size to increase patient throughput and minimize total time in the ED

CBR has been used to solve problems in different areas and has been combined with other techniques. However, it has not been used with simulation for several reasons. There is only one study in the literature that studied the first two steps in the CBR process when it is applied to simulation cases. This study is shown in Table 10.

Table 10: Example of simulation combined with CBR application.

Reference	DES	SD	ABS	MCS	Simulation with another tool	CBR	Objective(s)
Zhou et al. (2010)					x	x	To study two main difficulties in the application of CBR in simulation, which are case representation and case matching

The proposed CBR methodology in this dissertation is unique in that it uses CBR to improve simualtion applications in healthcare areas. This methodology will have a case-base that contains solved cases from all healthcare areas and uses all four common simulation techiques. This will help in improving these appications and reducing the required analysis for developing a new solution for the current problem by following the CBR approach. A comparison between this methodology and available applications in the literature is given in Table 11.

Table 11: CBR methodology compared with other applications.

Reference	DES	SD	ABS	MCS	Simulation with another tool	CBR	Objective(s)
CBR methodology for Simulation Modeling	x	x	x	x	x	x	To improve simulation modeling in healthcare
Caro, Mšller, and Getsios (2010)	x						To model health economic evaluations
Al-Refaie et al. (2014)	x						To enhance ED operations by decreasing waiting time and improving resource utilization.
Faezipour and Ferreira (2013)		x					To study the complicated relationships in the healthcare system
Lane, Monefeldt, and Rosenhead (2000)		x					To study the dynamics of accidents and emergency departments
Cabrera, Taboada, Iglesias, Epelde, and Luque (2011)			x				To model ED
Cuadros, Abu-Raddad, Awad, and Garc'a-Ramos (2014)			x				To control and prevent the spread of dangerous diseases or infections in effective ways
Lesosky et al. (2011)				x			To model "the rate and spread of MRSA transmission among patients in medical institutions"
Mustafee, Katsaliaki, Gunasekaran, Williams, Ben-Assuli, et al. (2013)				x			To analyze the implications of admission decision
Day, Ravi, Xian, and Brugh (2014)	x		x				To model clinics operations and choose the best strategy among several alternatives

Reference	DES	SD	ABS	MCS	Simulation with another tool	CBR	Objective(s)
Djanatliev, German, Kolominsky-Rabas, and Hofmann (2012)		x	x				To evaluate new technologies in healthcare. ABS used to model patients' behavior and SD to model the environments around patients.
Rohleder, Bischak, and Baskin (2007)	x	x					To redesign patient service centers. DES model was used for resource utilization and improving system performance. SD model was used to predict demand patterns, create new policies to minimize variability in demand, and study the effect of changes.
Oddoye, Jones, Tamiz, and Schmidt (2009)					x		To determine the optimal resources level that will reduce time delays in medical assessment unit
Ahmed and Alkhamis (2009)					x		To find the optimal staff size to increase patient throughput and minimize total time in the ED
Zhou et al. (2010)					x	x	To study two main difficulties in the application of CBR in simulation, which are case representation and case matching

The CBR methodology for simulation modeling developed in this research will be compared to other methodologies, techniques, and methods for simulation models development, especially DES, from the literature. This comparison will be done based on several points that determine the level of knowledge required to implement these methodologies and their characteristics and properties. These points are:

- The level of simulation knowledge required for implementations.
- The level of mathematical modeling and formulation.
- The applicability of the framework / methodology in any field.

- The implementation difficulty level.
- Required implementation time.
- The clearness and simplicity of the steps in the framework/methodology.
- The ability for automation in the framework/methodology.
- The support of any verification or validation techniques.

This comparison is shown in table 12.

Table 12: Comparing CBR methodology and other methodologies and techniques

	CBR Methodology	General Systems Theory	Activity Cycle Diagrams	Event-Oriented Graphs	Petri Nets	Logic-Based	Control Flow Graphs	Generalized Semi-Markov Process
Simulation Knowledge	Low	High	High	High	High	High	High	High
Mathematical Modeling and Formulation	Low	High	Moderate	Moderate	High	High	Moderate	High
Applicability to any field	High	High	High	High	High	High	High	High
Implementation Difficulty	Low	High	Moderate	Moderate	High	High	Moderate	High
Implementation Time	Short	Long	Medium	Medium	Long	Long	Medium	Long
Clearness and Simplicity of Process	High	Low	Moderate	Moderate	Low	Low	Moderate	Low
Automation	High	Low	Low	Low	Low	Low	Low	Low
Support of Validation and Verification	High	High	High	High	High	High	High	High

CHAPTER 3 RESEARCH METHODOLOGY

3.1 Introduction

The objective of this dissertation is to study the utilization of CBR methodology in simulation modeling in the healthcare field. The proposed research methodology plan is given in Figure 8. The first step was reviewing the literature about the main topics in this research. After that, a literature gap analysis was performed. Then, a case-base for simulation applications in healthcare was created. After forming the case-base, the complete methodology was developed. Finally, a case study was used to validate the study and explain the implementation process.

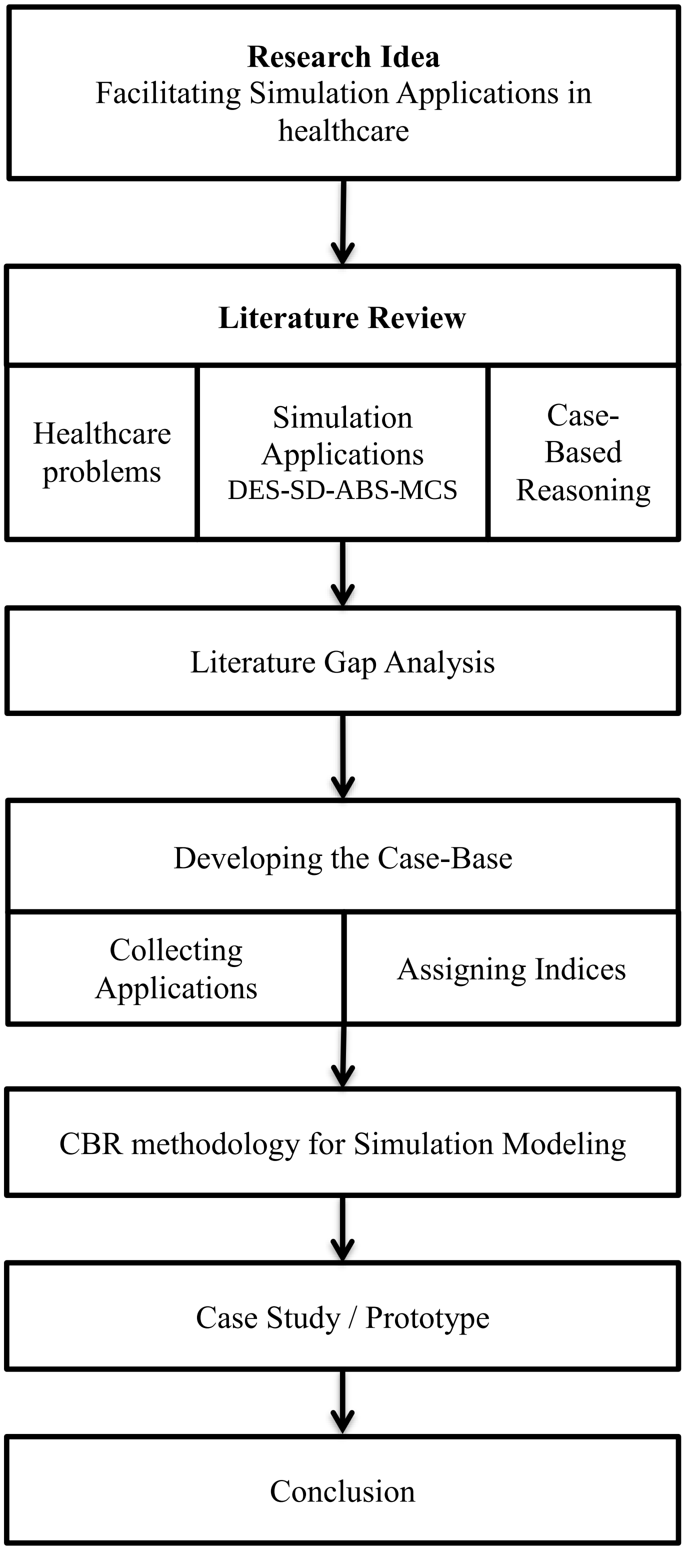

Figure 8: The proposed research methodology plan.

3.2 Literature Review Summary

From the literature review presented in chapter 2, several points can be made about the main topics of this research: healthcare problems, simulation applications in healthcare, and case-based reasoning. First, the literature presents healthcare problems, such as increasing healthcare costs, limited resources and low utilization, limited facilities and workforce, and bad quality of delivered services. With respect to simulation techniques (DES, SD, ABS, and MCS), the literature demonstrates that using simulation techniques to solve healthcare problems is not a new idea, but their application in healthcare has increased a lot in recent years. It also shows that simulation application faces many challenges due to the realities of this context, includinglack of real data, complicated healthcare decision making processes, low stakeholder involvements, and the complicated nature of healthcare problems. The literature also describes case-based reasoning (CBR), an AI methodology that utilizes the gained knowledge and experience in solving new problems. It shows how this methodology has been used to solve problems in many fields. However, it has not been used with simulation because of difficulties in implementing the CBR process with simulation cases.

3.3 Literature Gap Analysis Summary

The simulation modeling in healthcare are not utilizing all benefits of the simulation tool. Based on the results of its use in other sectors such as manufacturing, these benefits could lead to benefits in several areas in healthcare as well. In examples from other sectors, simulation is an essential part of the decision making process as well as other processes like design,

implementation, and improving. This shows that there is a gap in the simulation applications in the healthcare area.

There are many applications in the literature that show the use of several AI methods and techniques to solve problems in many areas. CBR is one of the methods that can be used to solve new problems from the knowledge gained from previous solved cases. It has not been used, however, with simulation applications, and there is only one study that tried to create a model to detect the characteristics of simulation models and order them to start the path in implementing CBR with simulation.

The CBR methodology proposed in this research would apply the CBR to simulation modeling in healthcare. This application will enhance the use of simulation in healthcare applications by utilizing previous simulation models used to solve old problems in finding solutions for current issues and problems. This will reduce the amount of analysis required and minimize the time needed to build the simulation model. Thus, more time will be available for experimentation and trying different alternatives. Moreover, the use of CBR will help in increasing the stakeholders' involvement, which will add to knowledge about the system and facilitate the implementation of simulation results and recommendations. This methodology will have a case-base that contains solved cases from all healthcare areas using all four common simulation techniques.

3.4 The Development of the Case-Base

The development of the case-base is the initial step in using the CBR methodology since it depends on it. This case-base would contain all previously solved cases organized in a well-defined structure to simplify the searching process to find similar cases to the new problem. Thus, it is an important phase that requires optimum design. This phase has two main steps: 1) collecting solved cases in the specific chosen area and 2) defining indices and assigning them to cases before storing them in the case-base. In this research, all relevant simulation applications in healthcare are going to be collected. These applications are going to be analyzed to pick cases that represent all areas in healthcare and all related objectives. After that, the classifications of simulation applications in healthcare are going to be studied carefully to come up with A comprehensive indices that will cover all healthcare areas and possible objectives. Then, all selected cases will be given indices before they are stored in the case-base. This case-base will be organized using the proposed indices where each category has its set of possible related objectives and in front of each objective the used simulation techniques. For the healthcare areas that have no simulation applications, mapping methods that suggest an appropriate simulation technique based on similar simulation applications in other sectors will be used.

3.5 The CBR Methodology

After the case-base is developed and becomes ready to be used, then the CBR process is prepared for implementation. The CBR methodology for simulation modeling in healthcare will follow the traditional CBR process, shown in Figure 9. This process has the following steps:

- Case retrieval: in this step, the new problem is analyzed to find the indices of the application area and objective(s). These indices are used to retrieve similar solved cases from the case-base. In the case where no applications are found, the suggested simulation technique is used.
- Case reuse: in this step, similar solved case(s) are studied to develop a solution for the new problem. This step should be done with more stakeholder involvement since they have more knowledge about the process and objectives.
- Case revision: in this step, the proposed solution for the new problem is reviewed to check if it is valid or not. Any necessary modifications for the new solution to be able to apply it to the current problem are done in this step.
- Case retention: in this step, if the proposed solution is used to solve the problem, then it will be assigned an index and added to the case-base for future use on similar problems.

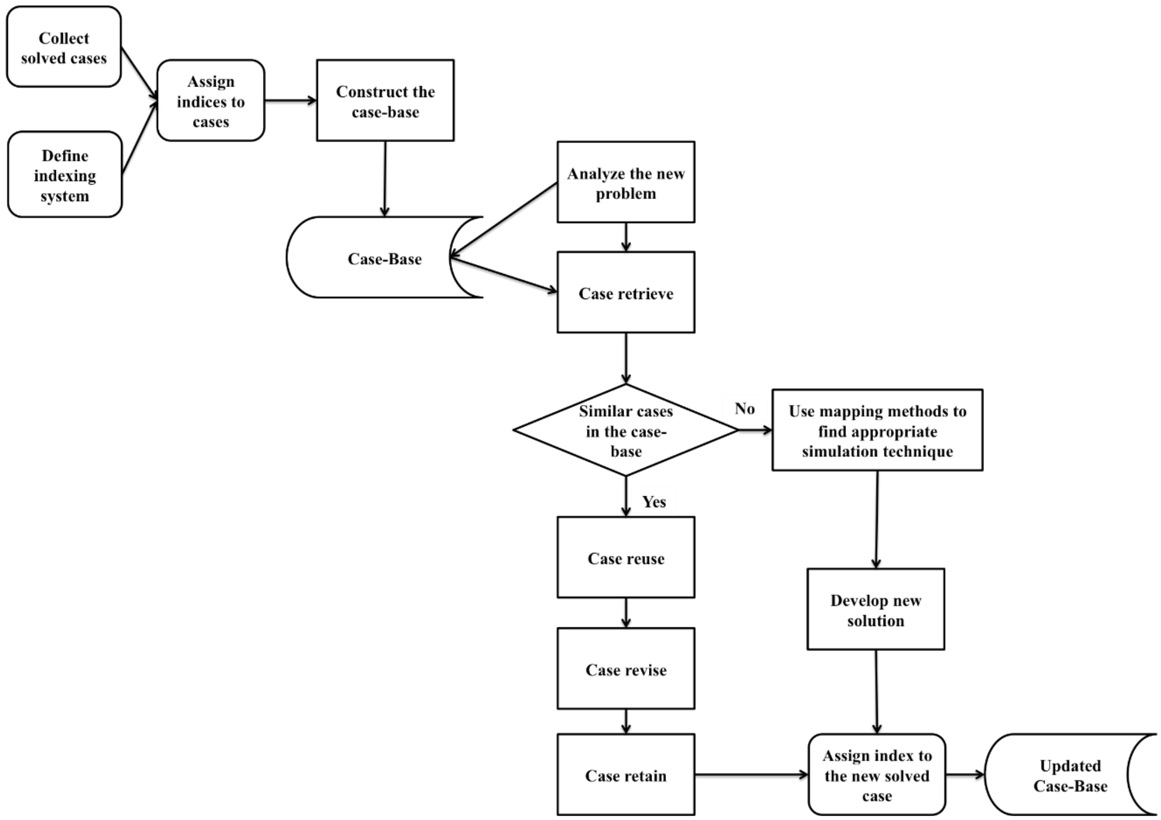

Figure 9: The CBR methodology structure for simulation modeling in healthcare

3.6 Case Study

After the CBR methodology is completed, a case study from the healthcare sector that has an ED problem will be chosen. This case study will also demonstrate the process of implementing this study and how each step is executed. By using this methodology, a proposed DES simulation model will be used to find the solution to the existing problem. Then, the results of this study is verified and validated. The verification process will insure that the simulation model is built right while the validation process will check if this model is the right model. The verification process

will use the animation feature in the SIMIO software to do a structured walk-through or step-by-step analysis. The validation process will also use the animation features to check the model operational behavior. Moreover, sensitivity analysis will be performed to make sure that the outputs are close to the real system. Another method to validate this model would be consulting an expert in simulation and get his/her opinion about the model.

3.7 Conclusion

After implementing the case study, this research will have a conclusion that summarizes the contribution and important points. This conclusion will also express the limitations of this study and suggests future research direction to improve and enhance this research effort. These limitations will highlight the points that need to be enhanced or was not covered in this study such as other simulation techniques and more healthcare areas. This will help in creating more directions for future research since the application of simulation in healthcare is not popular as manufacturing and aerospace fields. Another direction of improvement for this research will be adding cases from different healthcare sectors and studies that used other simulation techniques to enrich the developed case-base and to start creating more complicated case-bases. These complicated case-bases will help in enhancing the use of simulation in healthcare by facilitating more solved cases from all healthcare area and these cases used all simulation techniques with other OR tools to reach to the best possible solutions. Creating more case-bases and making them as the database for all healthcare fields could achieve this goal.

CHAPTER 4 CBR METHODOLOGY DEVELOPMENT

4.1 Introduction

The healthcare system is always defined as a complex system. This is because it is composed of people and processes that are interrelated and performing different tasks and duties. This system has many areas and departments that are independent but interrelated with each other at the same time. Each department has its own staff and operations and serves a specific category of people and processes. Each also has its own defined goals and targets that are related to the organization's goals. This means the healthcare system has many stakeholders with different interests. Another point of complication is that each healthcare organization or facility is specifically designed to serve a specific purpose, such as specialized hospitals or clinics. Thus, there are no common design rules that can be found between healthcare facilities that share the same target. Moreover, no two facilities operate the same even if they are in the same city, state, or country. This problem is also clear in the simulation applications in healthcare: there are many applications that can be found in the literature, but there are no similar applications, even when solving similar issues or problems. This holds true when comparing applications in different departments or areas in healthcare. Each department has different problems and targets and uses different simulation techniques in order to study and solve these problems. The best example to show this complication is the ED, which is found in almost every hospital and is considered one of the most important departments in any healthcare facility. This ED has many problems and the literature discusses a lot of applications that have been used to try to solve them. DES has been

used to solve resources allocation and optimization problems and patients flow problems. SD has been used to study the dynamics of the ED to solve related issues. ABS has been used to study the characteristics and behaviors of the people providing and receiving services in order to improve the ED operations. Finally, MCS has been used to control and prevent the spread of dangerous diseases. All of this shows that the applications of simulation in healthcare are complicated and require good knowledge about the department or the area, as well as all aspects of the simulation techniques, in order to choose the right tool for the right problem.

The proposed CBR methodology aims to improve the application of simulation in healthcare field. This will be done by collecting solved problems in healthcare using simulation and organizing them in a case-base. Then, to solve any new problem that arises in this field the similar solved cases from the case-base will be retrieved and analyzed to find the appropriate simulation technique, which could be used to solve this problem. Moreover, the application of CBR will help in making faster applications with less analysis required by increasing the stakeholders' involvement in the process of analyzing similar cases and building the new simulation model. This. Thus, the application of simulation could be done with people that have little knowledge about simulation and also could be done with people that are not from the area or the department. This ability to use simulation without the need to compare different techniques to choose the best one for the problem and without the need to know more information about the application area would increase the number of people that can utilize these applications. Thus, the simulation modeling in healthcare will be simplified, improved and enhanced when using this methodology.

4.2 CBR Methodology Development

In this section, the development of the CBR methodology will be explained. While this methodology will help in facilitating and improving the simulation applications in healthcare, healthcare is a huge field that has many areas and applications. Moreover, there are several simulation techniques that have been used to solve problems in the healthcare area. This will make it not possible in the time of this dissertation to construct a case-base that covers all the healthcare areas with all simulations techniques. Thus, this study will focus on Emergency Departments (ED) and the Discrete Event Simulation (DES) technique. This choice was made because of the importance of the ED in the healthcare and the wide applications that could be covered by using the DES technique.

4.2.1 Constructing the Case-Base

This step is the first step in creating the CBR methodology. As mentioned above, it consists of two phases: 1) collecting solved cases and 2) defining indices and assigning them to the cases. The first phase starts with a search for solved cases in the healthcare area that used DES to solve problems in the ED. The second phase will begin after gathering these solved cases, when an indexing system is defined and the cases are organized according to their classification in the case-base.

To overcome the diversity issue with the solved cases that could be found in the healthcare literature, one of the committee members of this dissertation suggested collecting just new and recent simulation cases that used DES to solve ED problems. This idea directed the search towards simulation courses and simulation organizations. However, there were no healthcare simulation cases databases to be found. Thus, the decision was made to create such a database (case-base) by adopting new and recent ED case studies.

To prepare these simulations required, several real cases published in recognized journals and repositories were collected and analyzed. These cases were given to ten different teams of with expertise in DES and SIMIO background. The following table provides brief summaries of these ten cases:

Table 13: ED cases

Case Number	Reference	Summary
Case 1	Chetouane et al. 2012	This case is about a problem related to optimizing the operation and processes of a regular ED
Case 2	Patvivatsiri 2006	Operation and processes of the ED is optimized for a mid-size hospital during extreme events
Case 3	Gul & Guneri 2012	The purpose of this study is to optimize the operation and processes of the ED of a regional hospital
Case 4	Yeh & Lin 2007	Optimizing the operation and processes of the ED of a small hospital in a city is the target of this case
Case 5	Zeinali et al. 2015	The aim of this research is to optimize the operation and processes of the ED in a specialized hospital.
Case 6	Ahmed & Alkhamis 2009	This is about optimized processes and operations in an ED of a mid-size governmental hospital
Case 7	Lim et al. 2013	The case solved in this problem is to optimize the operation and processes of the ED of a local hospital
Case 8	Meng 2013 HBR	The effort done in this study was directed to optimize operation and processes of the ED of a large hospital
Case 9	Wylie 2004 HBR	The operation and related processes of a Primary Care Clinic in a university are optimized to improve the student health services
Case 10	Terry & Chao 2012 HBR	The crowding problem in an ED of a medical center that is located in a metropolitan area is solved in this study

Details of these cases are shown in the Appendix.

After finishing the process of collecting these solved cases then the first phase of constructing the case-base is over. Thus, phase two should start by defining the indexing system that could be used to organize these cases. Scholars and scientists in the literature did not use a certain classification to categorize ED problems; they classified them based on the objective of the study/author. This classification is wide and might cause confusion to readers who are not familiar with simulation applications. Thus, these problems will be classified into few main categories that cover all problems. The ED problems that were simulated and solved using DES can be classified into three main categories:

1. Optimization problems: this category includes all problems dealing with long wait times, cost and financial issues, utilization of resources, patient flow, and other related attributes of the ED system.
2. Crowding problems: this category includes all problems dealing with crowding or overcrowding in the ED.
3. New design/methodology problems: this category includes all problems dealing with new alternative designs for the ED, the application of new methodologies in the ED, or the introduction of new processes into the ED system.

4.2.2 The Indexing System

In this section, an indexing system will be created to define each case in the case-base. This system will specify the most important features of the solved cases and differentiate between them when storing them in the case-base. After that, the retrieval engine will use these features from the new problem to retrieve the similar cases from the case-base. Thus, this system is important and should include all the necessary details.

The indexing systems in the CBR literature define attributes to describe each case in the case-base. These attributes could be numerical or non-numerical attributes. The numerical attributes contain information that could be expressed in numbers. However, the non-numerical attributes contain information that cannot be written in numbers only such as locations, programs used, names, etc. In most of the cases, these non-numerical attributes will be defined as an enumerated list to simplify the retrieval process.

For this case-base, the collected and developed cases are classified into three categories, which are optimization, crowding, and new designs/methodologies problems. This classification will be considered as the first and most important attribute since these cases come from different categories and each category has its own objective and these objectives may have different solutions methods or techniques. Thus, the case-base will be divided into three main sections and each section will contain cases from the same category.

The second attribute that will be defined for these ED cases solved using DES is the path that patients use or take inside the ED. This path will differentiate between EDs that have different layouts or use different processes. This path will describe how patients move inside the ED from entrance to exit. However, before outlining different paths of the EDs, main stations that are used to describe these paths will be defined. These stations are found in almost all EDs and are used to describe the detailed process inside every ED. The most important stations that could be found in every ED are:

- Entrance Station: in this station, patients arrive to the ED through various means. The majority of patients arrive as walk-in patients using their own cars or with the company of someone. Other patients arrive in ambulances and some patients might arrive in medical helicopters.
- Triage station: in this section, a triage nurse will perform the triage process to classify patients into the different triage levels.
- Registration: in this section, the information of the patients are collected and registered. This information includes personal information, insurance, and any other needed information about the patients.
- Treatment: in this station, physicians, specialty doctors, or nurse practitioners treat patients.
- Lab: in this station, all necessary processes to support the treatment of patients are done. These processes include x-ray, CAT scan, MRI, blood samples, etc.
- Exit: in this station, patients leave the ED either to be admitted to the hospital or discharged to go home.

There are four different paths that could found in the literature of ED problems. These paths include all-important stations, defined above, in different orders. These paths will be expressed as follows:

- Path 1: this path is considered the most commonly used path in EDs. In this path, patients arrive to the ED through the entrance station. Then, they move to the triage station. In the triage station, the triage nurse will perform the triage process. After that, patients with levels 1 and 2 (in the 5-level triage scale) skip the registration to the treatment station or to the hospital depending on their conditions. Other patients will go to registration station to give their information. Then, they proceed to the treatment station to receive the needed treatment. After that, they go to the lab station to have x-rays, CAT scans, or any other tests. Finally, they leave the ED through exit station.
- Path 2: in this path, patients once they arrive to the ED go to the registration station. Patients arrived by ambulances will have a quick bedside registration if their conditions allow it. Then, all patients proceed to the triage station. After that, to the treatment station and then lab station to do needed tests. Finally, they leave the ED.
- Path 3: in this path, patients will go through entrance then registration and triage stations. After that, they meet with medical assistants to get their vital symptoms and decide the needed tests before patients go to the treatment station. Then, patients precede to the lab station and after that the treatment station. Finally, they leave after getting the recommended treatments.

- Path 4: In this path, patients will go to triage station upon arrival. After that the registration station and then lab station. Finally, they go to the treatment station before leaving the ED. All these paths are shown in figure 10.

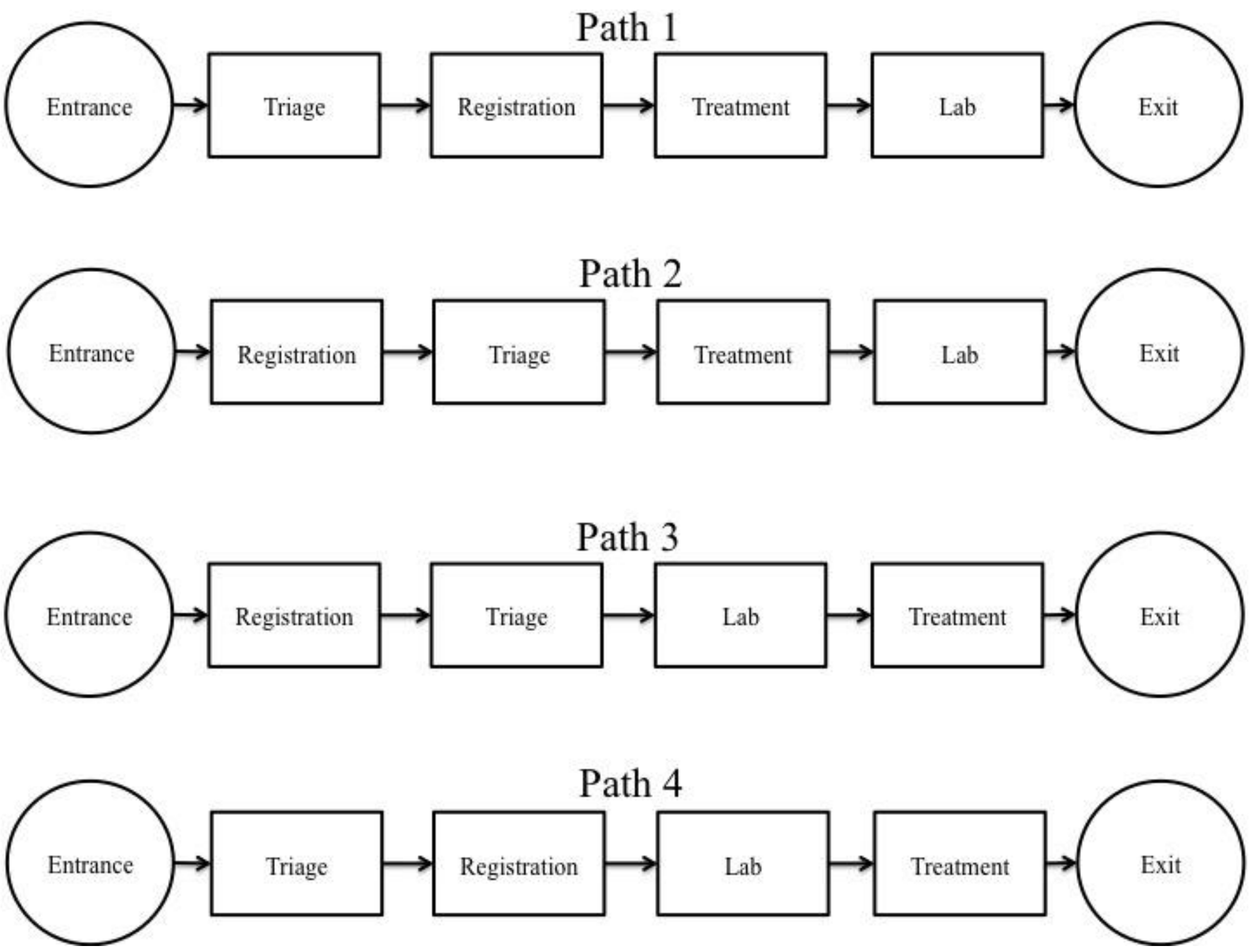

Figure 10: Different paths in the EDs

The third attribute is the number of doctors in the ED. This attribute will count all people performing the treatment process in the treatment station. This will include physicians, specialty doctors, and nurse practitioners that treat low acuity patients in some EDs. The fourth attribute is the number of nurses in the EDs. This attribute will include all types of nurses such as triage nurses, emergency nurses, and regular nurses. These two attributes will start from one since all EDs will have at least one doctor and one nurse. The fifth attribute is the number of lab technicians in the EDs. This will include all people working in the lab station. Finally, the last attribute is the number of staff in the EDs. This will include all people working in non-medical and administrative jobs in the registration station and any other stations. These two attributes will start from zero since not all EDs have them and some EDs let nurses do these jobs. After finishing the indexing system, the case-base of the developed case will be show in table 14.

Table 14: The developed case-base for ED problems using DES

Categories										
Optimization Problems					**Crowding Problems**					**New design/methodology Problems**
Case 1					**Case 10**					
Doctors	Nurses	Lab techs	Staff	Path	Doctors	Nurses	Lab techs	Staff	Path	
3	5	1	0	Path 1	32	75	0	0	Path 2	
Case 2										
Doctors	Nurses	Lab techs	Staff	Path						
3	13	1	0	Path 1						
Case 3										
Doctors	Nurses	Lab techs	Staff	Path						
10	12	0	5	Path 2						
Case 4										
Doctors	Nurses	Lab techs	Staff	Path						
3	6	2	0	Path 1						
Case 5										
Doctors	Nurses	Lab techs	Staff	Path						
1	4	0	2	Path 1						
Case 6										
Doctors	Nurses	Lab techs	Staff	Path						
2	10	3	2	Path 2						
Case 7										
Doctors	Nurses	Lab techs	Staff	Path						
2	4	1	1	Path 4						
Case 8										
Doctors	Nurses	Lab techs	Staff	Path						
2	5	2	0	Path 2						
Case 9										
Doctors	Nurses	Lab techs	Staff	Path						
3	6	1	1	Path 3						

4.2.3 The Retrieval Engine

There are several techniques and algorithms in the literature that have been used to create retrieval engines for the CBR methodology. Examples of these techniques include nearest neighbor, induction, fuzzy logics, database technology, and several others. The most commonly used techniques are nearest neighbor and induction with decision trees (Watson, 1999).

In the nearest neighbor algorithms, the similarities between the new case and all cases stored in the case-base are calculated using similarity functions and measures. These functions are used to find the similarities between all attributes in the new case and each one of the cases and then find the total similarity for each stored case. These total similarities are then normalized to fall between 0 and 1 or to find the similarity percentages. These functions use various similarity metrics such as Euclidean distance, city block distance, probabilistic similarity measures, and geometric similarity metrics. In this approach, weights may be used to differentiate between of attributes and to show, which are the most important, and those that have the least effects. These weight ranges from 0 to 1 and assigned using the appropriate techniques based on the field of the cases. In the inductive retrieval, the stored cases are pre-indexed by creating a decision tree that is used to represent all the cases in the case-base. The most important attribute will be used to the root of the decision tree. After that, other attributes are added to complete the decision tree. When having a new problem, this approach will start from the root node to find similar cases using an attribute at each step until reaching to the last one. Since these stored cases are pre-indexed then the retrieval times could be fast. However, the main disadvantage of this approach comes when some information is missing or one of the attributes has no similar cases in the case-

base. In this case, no similar cases will be retrieved from the case base (Khan et al., 2011) (Ross et al., 2002).

4.2.3.1 The Nearest Neighbor Approach

The first approach that will be used as a retrieval engine in this study is the nearest neighbor. This approach has several versions that could be found in the literature such as *K* nearest neighbor algorithm and *R* nearest neighbor algorithm. In the *K* nearest neighbors, the *K* cases from the case-base with the highest similarity percentages will be retrieved where *K* is predefined parameter. However, in the *R* nearest neighbors, all cases from the case-base that have similarities percentages more than or equal to *R* are retrieved where *R* is a predefined values. These similarity percentages are found from the following equation:

$$Similarity\ Percentage\ (NC, SC) = \frac{\sum_{i=1}^{n} f(NC_i, SC_i) * w_i}{\sum_{i=1}^{n} w_i} * 100\%$$

Where,

NC is the new case.

*SC*s are stored cases in the case-base.

n is the number of attributes in each case.

f is the similarity function.

In this study, *K* nearest neighbor algorithm will be used and the Euclidean distance will be chosen as the similarity function for all numerical attributes. The Euclidean distance is calculated using the following equation:

$$D_i = \sqrt{\sum_{x=1}^{m} (an_x - a_{ix})^2}$$

Where,

D_i is the Euclidean distance between stored case i and the new case.

an_x are the attributes of the new case.

a_{ix} are the attributes of the case i.

m is the number of numerical attributes.

The numerical attributes in the developed ED cases are attributes 3 (# doctors), 4 (# nurses), 5 (# lab technicians, and 6 (# staff). These attributes will have equal weights in the similarity function as most of the studies in the literature use for the first CBR models in any field. The non-numerical attributes which are the category of the problem and the path of patients in the ED will not have a certain similarity function. This is because the retrieval engine will only retrieve cases, which have the same category of the new case. However, for the paths of patients a similarity measure matrix will be developed by using the order of stations in each path. These paths were created by find the most commonly used path in the EDs and give it the first position (path 1). After that, one change in the order of stations is made when moving from path 1 to path 2. Similarly, one change in the order of stations will be made as moving from path 2 to path 3,

path 3 to path 4, and path 4 to path 1. In the similarity matrix, each change will add 10 units of distance to similarity function and this distance will be added to the calculated Euclidean distance. This similarity (distance) matrix is shown in table 15.

Table 15: The similarity (distance) matrix between different paths

Similarity (distance) matrix				
	Path 1	**Path 2**	**Path 3**	**Path 4**
Path 1	0	10	20	10
Path 2		0	10	20
Path 3			0	10
Path 4				0

In this approach, there will be no need to calculate the similarity percentages since there are no weights associated with attributes. Moreover, distance measures are inversely proportional to the similarity percentages (as the distance gets shorter the similarity percentage gets higher). So, the similarity function will be found using the following equation:

$$f(NC_i, SC_i) = \begin{cases} \infty & if\ NC_1 \neq SC_1\ (not\ the\ same\ category) \\ Similarity\ (distance)\ matrix & for\ i = 2\ (path\ attribute) \\ D_i & for\ 3 \leq i \leq n \end{cases}$$

After finding these similarity (distance) measures between the new case and all the cases stored, with the same category, in the case-base. These measures will be used to retrieve the K stored cases with the shortest total distances. Then, the CBR methodology will proceed to the next step. The detailed flow chart of this approach is shown in figure 11.

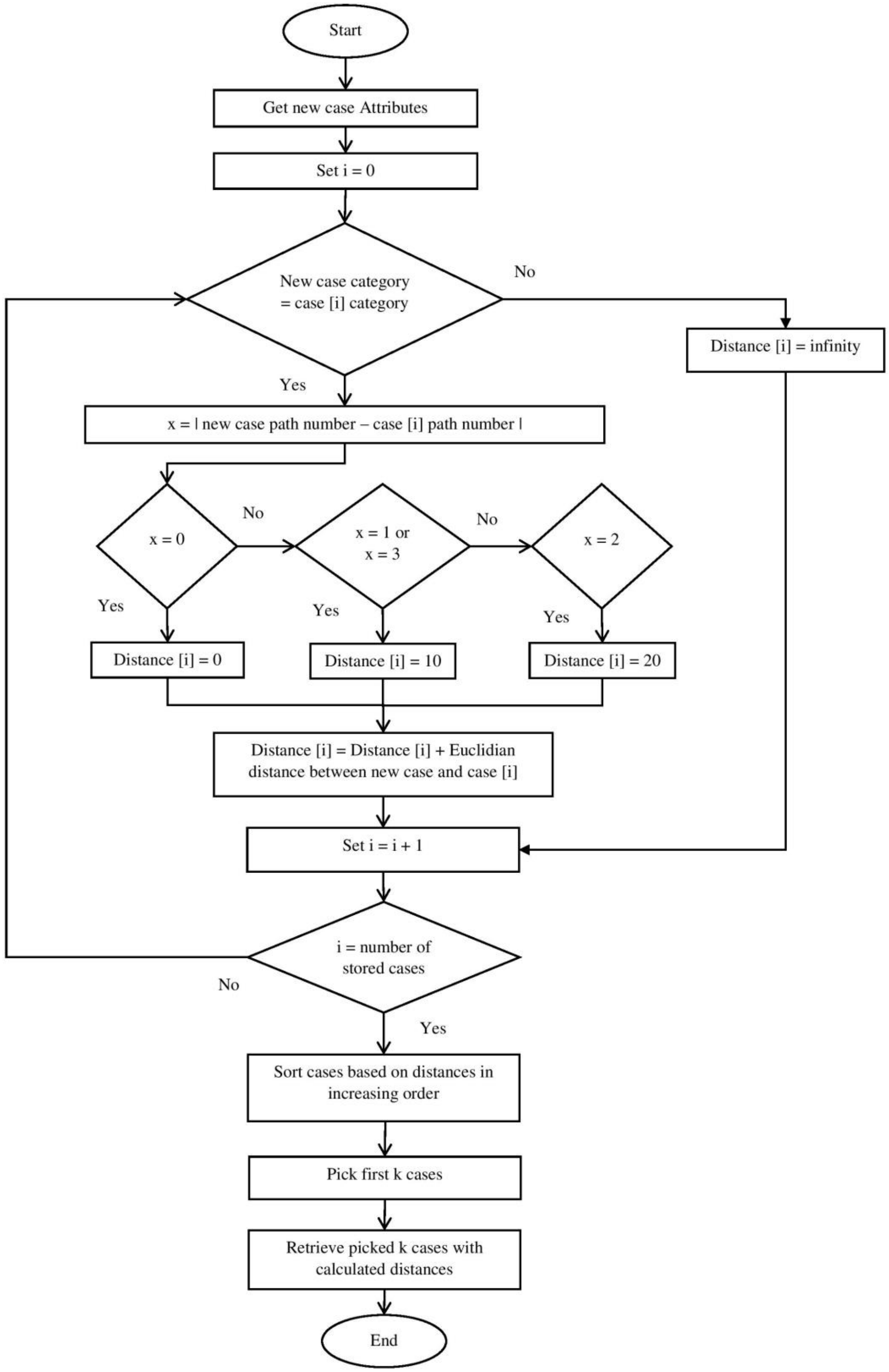

Figure 11: Flow chart of K nearest neighbor approach

4.2.3.2 The Induction Tree Approach

In order to give more retrieval options to this study, another approach will be used as a retrieval engine. This approach will use the defined indexing system to develop a decision tree that will represent the case-base. The use of this decision tree will make the retrieval times faster and will give different results that the *K* nearest neighbor approach. This approach starts by creating the decision tree for the developed case-base. This tree will represent the hierarchical structure of these simulation cases stored in the case-base. The assignments of attributes among different tree levels will show the relative importance of these attributes in the process of developing a solution to the new problem. This *T* tree will represent the stored simulation cases in the case-base. The definition of this tree will be:

$$T = \{N, E\}$$

Where,

N is the set of nodes (attributes).

n is the number of node in the tree.

E is the set of edges connecting nodes and correlating attributes.

l is the level of the node, where

$l = 0$	Root node
$l = 1$	Category of the case
$l = 2$	Path number
$l = 3$	# Doctors
$l = 4$	# Nurses

$l = 5$ # Lab technicians

$l = 6$ # Staff

$l = 7$ Case Number

For each node in N, degree = number of directly connected nodes in levels $l - 1$ and $l + 1$

In this decision tree, there are three types of nodes, which are:

a) Root node: is a pointer that references all sub-nodes in the first level (starting node of the tree).

b) Intermediate nodes: are all nodes in the tree with level $1 < l < 7$. They contain the set of all child nodes C_l in the direct lower level that are connected by edges.

c) Leaf nodes: are all nodes in the tree with degree = 1 and $l = 7$. Each leaf node expresses a specific set of attributes relating to its parents.

The tree of the developed case-base is shown in figure 12.

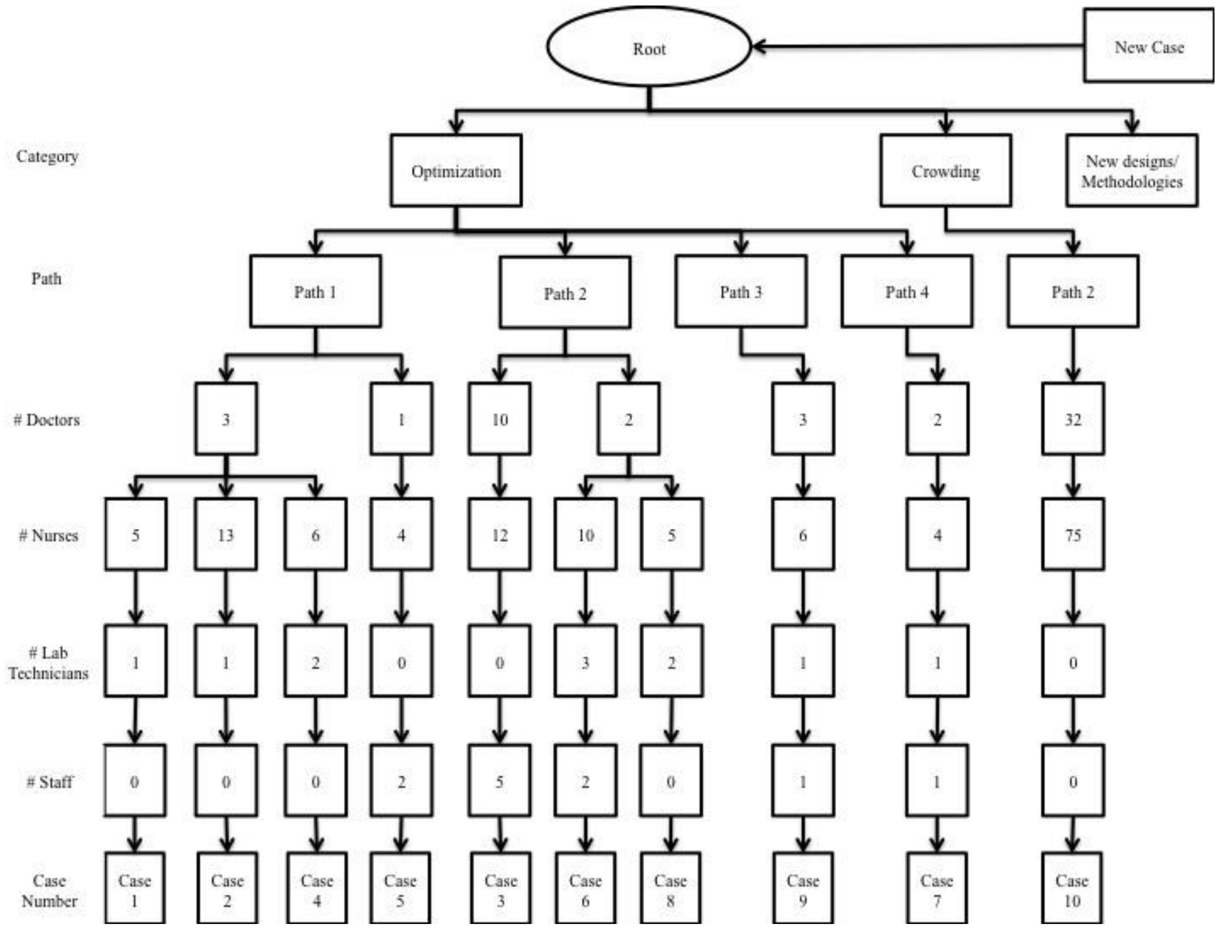

Figure 12: Decision tree of the developed case-base

For all simulation cases stored in the case-base, let each case A_x be described as a set of different attributes composing a distinctive case $\{a_1, a_2, \dots a_{l-1}\}$. Also, for each attribute a_i there is a set V_i that contains all possible values of this attribute $\{v_{i1}, v_{i2}, \dots v_{ir}\}$. For example, the first attribute a_1 that is the category of the simulation problem has V_1 = {Optimization, Crowding, New design/methodology}.

After developing the decision tree, this approach is ready to be used. When a new case arrives, the attributes of this case will compose a new set $G = \{g_1, g_2, \ldots g_{l-1}\}$ that contains all the attributes values. This set will be used as a target set to retrieve similar cases from the case-base. This retrieval process will match the elements of this target set against all elements in the same level in the case-base. This comparison will be used as a guide for the search to traverse through the decision tree.

The approach starts at the root node ($l = 0$). At this root node, the first step in the retrieval process is to match g_1 to an element in V_1 (all children of the root node). This means that:

$$if\ g_1 \in V_1 \rightarrow AttributeMatch = \ Match$$

$$if\ g_1 \notin V_1 \rightarrow AttributeMatch = No\ Match$$

If there is no match in the attribute match, then there is no possible case with the same category as the target case. Thus, the retrieval process will terminate since there are no similar cases in the case-base. However, if there is a match in the attribute match then the approach will choose the edge that is connected to the node (at $l = 1$) with the same category as the target case.

The approach after that matches all remaining attributes of set $\langle G \rangle = \{g_2, \ldots g_{l-1}\}$. For the second attribute, g_2, it will be compared to a subset of $\langle V_2 \rangle$; where V_2 is the set that contains all the possible paths of patients in the ED, and $\langle V_2 \rangle$ contains all paths under matched category g_1. Due to the nature of this attribute, there are four different paths in the case-base. The attribute match function yields three possible results as follows:

$$g_2 = v_{2i} \rightarrow AttributeMatch = \ Perfect\ Match$$

$$g_2 \neq v_{2i} \rightarrow \begin{cases} Path_i \vartriangle Path_{i\pm1}\ or\ Path_i \vartriangle Path_{i\pm3} \rightarrow AttributeMatch = \ Partial\ Match \\ Path_i \vartriangle Path_{i\pm2} \rightarrow AttributeMatch = \ Somewhat\ Match \end{cases}$$

Based on the value of the attribute match, the approach will choose the edge that is connected to the node (at l = 2). This choice will yield the same path number when perfect match is found. However, when there is no perfect match then a partial match will be chosen if it is available, or it will go to somewhat match otherwise.

The approach after that matches all remaining attributes of set $\langle G \rangle = \{g_3, \ldots\ g_{l-1}\}$. For the third attribute, g_3, it will be compared to a subset of $\langle V_3 \rangle$; where V_3 is the set that contains all the possible number of doctors in the ED, and $\langle V_3 \rangle$ contains all number of doctors under matched path g_2. Starting from this attribute g_3 all the remaining attributes are numerical attributes and will have similar matching functions. For g_3, the attribute matching function will use the absolute difference between g_3 and each element in $\langle V_3 \rangle$ as follows:

$$\forall v_{3i} \in \langle V_3 \rangle, z_i = |v_{3i} - g_3|$$

$$when\ z_i = 0 \rightarrow AttributeMatch = \ Perfect\ Match$$

$$when\ 1 \leq z_i \leq 5 \rightarrow AttributeMatch = \ Partial\ Match$$

$$when\ 6 \leq z_i \leq 15 \rightarrow AttributeMatch = \ Somewhat\ Match$$

$$when\ z_i \geq 16 \rightarrow AttributeMatch = \ Different$$

Based on the difference value z_i, the approach will choose the node (at l = 3) corresponding to the minimum difference value. The attribute match value indicates the degree of similarity between the target case attribute value g_3 and each one of the elements in the subset $\langle V_3 \rangle$. Similarly, the same matching process will be used in matching of the remaining attributes of the target case, which are g_4 (number of nurses), g_5 (number of lab technicians), and g_6 (number of staff). These attribute matching functions are shown as follows:

For g_4 (number of nurses):

$$\forall v_{4i} \in \langle V_4 \rangle, z_i = |v_{4i} - g_4|$$

$$when\ z_i = 0 \rightarrow AttributeMatch = \ Perfect\ Match$$

$$when\ 1 \leq z_i \leq 5 \rightarrow AttributeMatch = \ Partial\ Match$$

$$when\ 6 \leq z_i \leq 15 \rightarrow AttributeMatch = \ Somewhat\ Match$$

$$when\ z_i \geq 16 \rightarrow AttributeMatch = \ Different$$

Based on the difference value z_i, the approach will choose the node (at l = 4) corresponding to the minimum difference value. The attribute match value indicates the degree of similarity between the target case attribute value g_4 and each one of the elements in the subset $\langle V_4 \rangle$.

For g_5 (number of lab technicians):

$$\forall v_{5i} \in \langle V_5 \rangle, z_i = |v_{5i} - g_5|$$

$$when\ z_i = 0 \rightarrow AttributeMatch = \ Perfect\ Match$$

$$when\ 1 \leq z_i \leq 5 \rightarrow AttributeMatch = \ Partial\ Match$$

$$when\ 6 \leq z_i \leq 15 \rightarrow AttributeMatch = \ Somewhat\ Match$$

$$when\ z_i \geq 16 \rightarrow AttributeMatch = \ Different$$

Based on the difference value z_i, the approach will choose the node (at l = 5) corresponding to the minimum difference value. The attribute match value indicates the degree of similarity between the target case attribute value g_5 and each one of the elements in the subset $\langle V_5 \rangle$.

For g_6 (number of staff):

$$\forall v_{6i} \in \langle V_6 \rangle, z_i = |v_{6i} - g_6|$$

$$when\ z_i = 0 \rightarrow AttributeMatch = Perfect\ Match$$

$$when\ 1 \leq z_i \leq 5 \rightarrow AttributeMatch = Partial\ Match$$

$$when\ 6 \leq z_i \leq 15 \rightarrow AttributeMatch = Somewhat\ Match$$

$$when\ z_i \geq 16 \rightarrow AttributeMatch = Different$$

Based on the difference value z_i, the approach will choose the node (at l = 6) corresponding to the minimum difference value. The attribute match value indicates the degree of similarity between the target case attribute value g_6 and each one of the elements in the subset $\langle V_6 \rangle$.

Finally, the subset $\langle V_7 \rangle$ that contains the children of the node matched with g_6 will be returned as the result of this retrieval engine. This result will define the case(s) A_x from the case-base that are similar to the target case G. These cases will be taken to the next step of the CBR methodology. The flow chart of this approach is shown in figures 13 and 14.

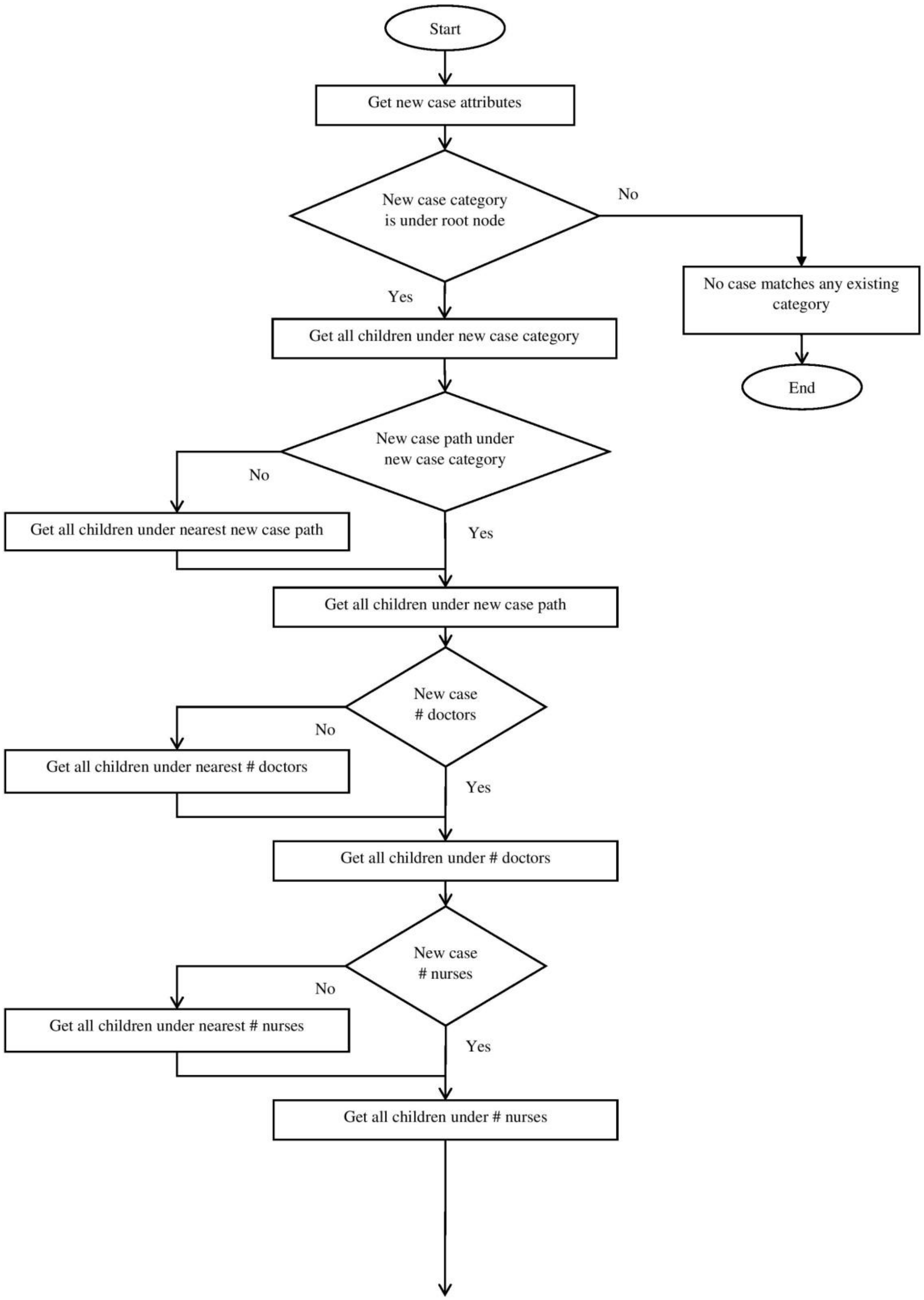

Figure 13 Flow chart of induction tree approach (part 1)

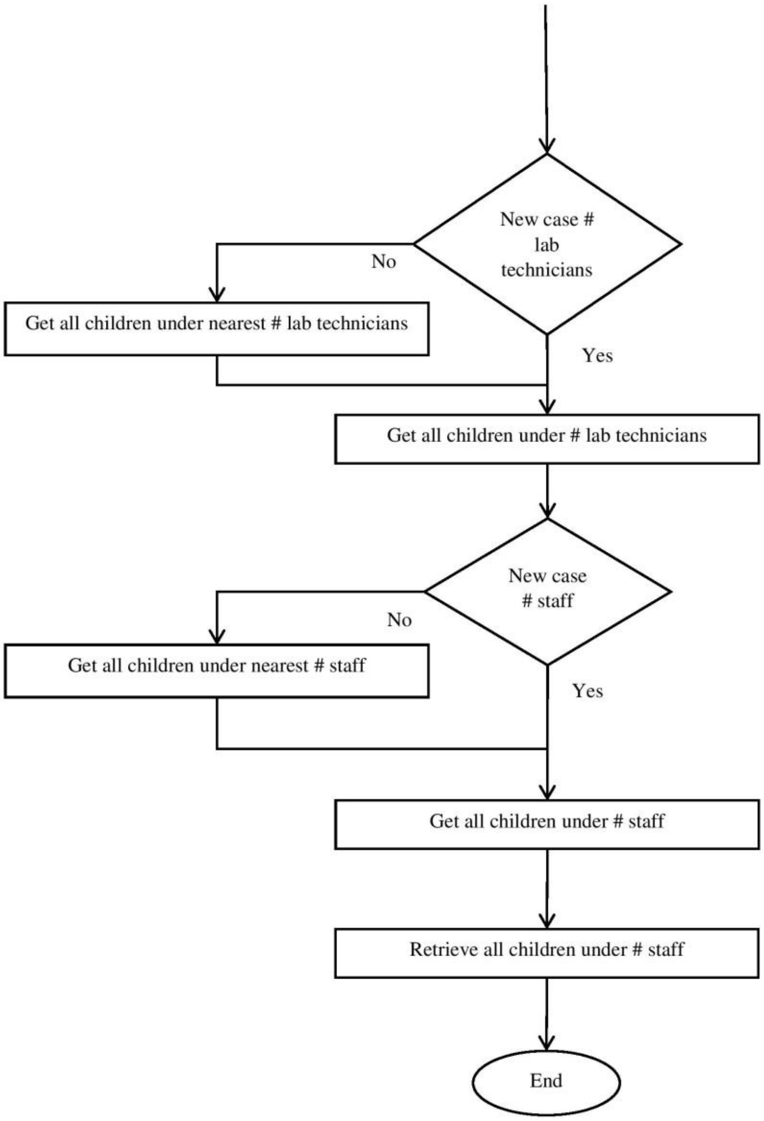

Figure 14: Flow chart of induction tree approach (part 2)

4.2.4 The CBR Methodology Retrieval Code

After completing the development of this CBR methodology, it is clear that it has several steps and will take a lot of time to be implemented by hand especially when the case-base gets bigger. This is because it has many complicated calculations that could waste a great amount of time in the retrieval step in particular. Moreover, the probability of making mistakes will be higher when doing everything without the help of any software. Thus, a java code was created to perform the retrieval step of this study. In this code, the developed case-base will be entered and saved in a clear table. Then, when a new problem arises the code will take all the data of this new case and apply both retrieval approaches to retrieve all similar cases. Then, the rest of the methodology could be applied easily after finding all the similar cases in the case-base in order to find the new solution. Finally, after solving the new case then it could be added to the stored case-base in the code to update the case-base for any future use. The interface of this code will be shown in figure 15.

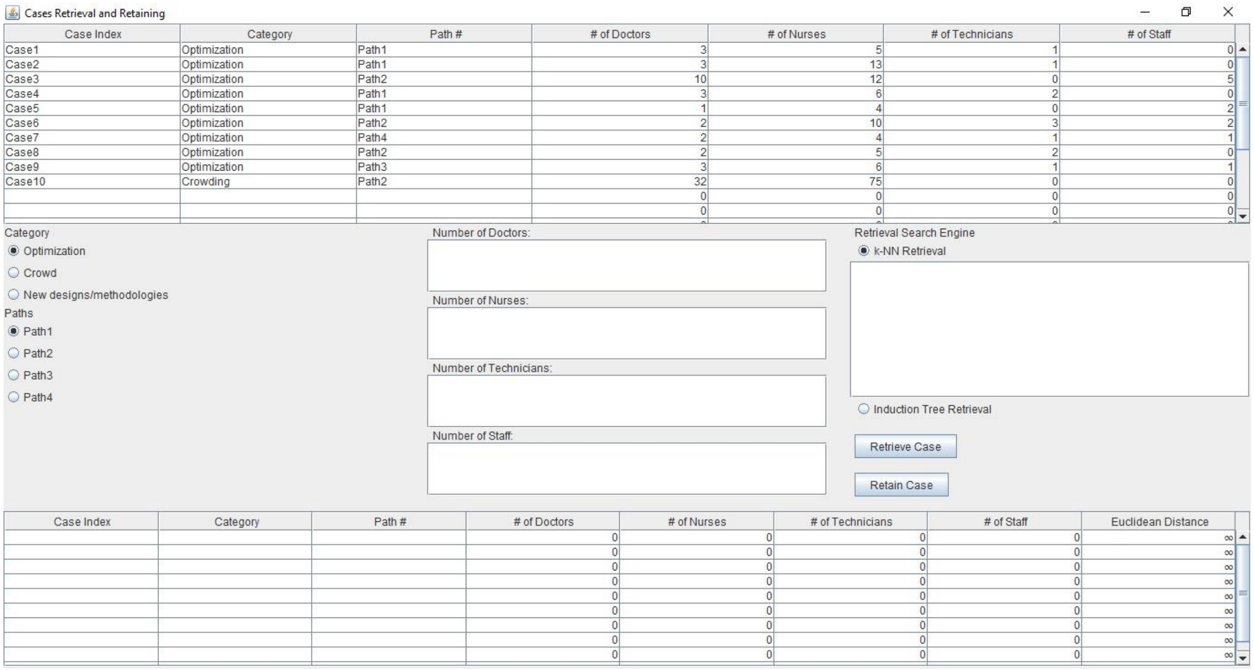

Figure 15 The interface of the CBR methodology retrieval code

4.3 Conclusion

After completing the development phase, the CBR methodology is ready for implementation. In this phase, a new ED simulation problem will be chosen from the literature and this methodology will be used to develop a DES solution for this problem. The solution process will use CBR and the developed case-base to find the best solution using the information from the retrieved cases from the case-base. The implementation will be shown in the next chapter.

CHAPTER 5 IMPLEMENTATION AND RESULTS

5.1 CBR Methodology Implementation

A case study was selected from the literature to demonstrate how this development works. The case study chosen was from a regional hospital that provides specialized and primary healthcare services. This hospital has more than 2000 employees including the medical personnel. The ED of this hospital receives over 50,000 patients each year. The management of the hospital would like to improve the performance of its ED while keeping the same level of the quality of healthcare services provided (Duguay & Chetouane, 2007).

5.1.1 Define and Analyze the New Problem (Case Study)

This ED problem was simulated using DES in 2007 to improve the performance of the system by enhancing the utilization of resources and trying to minimize the total time each patient spends in the ED. The process of this ED is as follows: When patients enter the ED, they pick a number and wait in the waiting area for the triage nurse to be available. At the triage station, the triage nurse uses an emergency severity index list to assess the patient’s status and give it a code number (from 1 to 5), where code 1 means the most critical. Patients with codes 1 and 2 (critical conditions) go directly to the intensive care unit (ICU) and leave the ED for the hospital, there to receive the required care. Patients coded 3-5 proceed to registration and wait for an available registration nurse to get their information. Then they wait for a physician to be free to do the first

assessment. After that, several patients will need to have lab tests and then wait for another (second) assessment by the physician before leaving the ED (either being discharged or admitted to the hospital). Each physician will have a nurse to help him/her during the assessment process. These employees of this ED work in three shifts: nightshift from 12 am to 8 am, day shift from 8 am to 4 pm, and evening shift from 4 pm to 12 am. Moreover, some extra shifts are used when needed during the crowded times in the day (from 10 am to 9 pm). This ED process is illustrated in figure 16. The collected data of this case study is shown in tables 16 and 17 (Duguay & Chetouane, 2007).

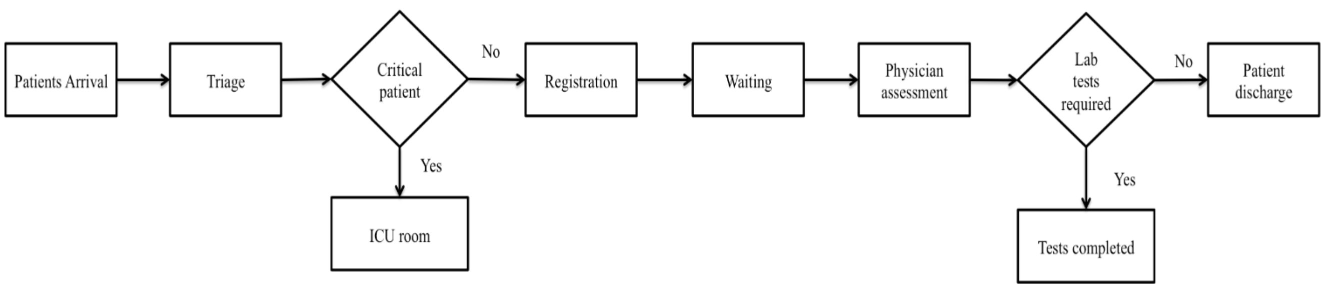

Figure 16: The process chart of the ED (Duguay & Chetouane, 2007)

Table 16: Data of the ED case study – part 1 (Duguay & Chetouane, 2007)

Resources	**Number**		**Probabilities**	**%**	
Examination rooms	5		Code 1 & 2 patients	7	
Triage nurses	3		Code 3 patients	18	
Registration nurses	3		Code 4 patients	55	
Physicians	5		Code 5 patients	20	
Nurses	5		Patients that need lab tests	23	
Lab technicians	1				
Working schedules	**Night Shift (12:00 am - 8:00 am)**	**Day Shift (8:00 am - 4:00 pm)**	**Evening Shift (4:00 pm - 12:00 am)**	**Extra Shift 1 (10:00 am - 5:00 pm)**	**Extra Shift 2 (5:00 pm - 11:00 pm)**
Physicians	1	1	1	1	1
Nurses	1	1	1	1	1
Registration Nurses	1	1	1	0	0
Triage Nurses	1	1	1	0	0

Table 17: Data of the ED case study – part 2 (Duguay & Chetouane, 2007)

Patients interarrival times in minutes (Maximum of Each day)				
Monday	**Tuesday**	**Wednesday**	**Thursday**	**Friday**
Exponential (7)	Exponential (9.5)	Exponential (10)	Exponential (10)	Exponential (10)

Patients arrival rates (patients/hour)	
Time	Rate
12 am- 1 am	5
1 am – 2 am	4
2 am – 3 am	3
3 am – 4 am	3
4 am – 5 am	2
5 am – 6 am	2
6 am – 7 am	3
7 am – 8 am	5
8 am – 9 am	6
9 am – 10 am	7
10 am – 11 am	7
11 am – 12 pm	8
12 pm- 1 pm	9
1 pm – 2 pm	8
2 pm – 3 pm	8
3 pm – 4 pm	7
4 pm – 5 pm	8
5 pm – 6 pm	9
6 pm – 7 pm	9
7 pm – 8 pm	10
8 pm – 9 pm	9
9 pm – 10 am	8
10 pm – 11 pm	7
11 pm – 12 am	6

Service times in minutes		
Triage	**Registration**	**Lab tests**
Poisson (6)	Triangular (3,5,7)	Triangular (30,45,60)

1st Assessment		
Code 3 patients	**Code 4 patients**	**Code 5 patients**
Triangular (25,30,40)	Triangular (25,30,40)	Triangular (25,30,40)
2nd Assessment		
Code 3 patients	**Code 4 patients**	**Code 5 patients**
Triangular (10,12,15)	Triangular (8,10,12)	Triangular (6,7.5,9)

In this case study, the simulation time was one whole day (24 hours), and patient arrival rates to Canadian EDs in the literature during different hours of the day were used. The system was also studied under the maximum arrival rates of each working day as a worst-case scenario and for comparison purposes.

5.1.2 Case Retrieve

The first step in the CBR methodology is case retrieve. In this step, all cases similar to the case study are recalled from the case-base. To retrieve these cases, it is necessary to define the target set of the new case. This set contains all the attributes values and it will be used to do the retrieval process. The target set of this new problem is G = {Optimization, Path 1, 5, 11, 1, 0}. This set shows that in this problem, the objective of the study is optimization and the path of patients inside the ED is Path 1. It also shows that in this ED, there are 5 doctors (physicians), 11 nurses, 1 lab technician, and no other staff for administrative purposes.

After defining the target set, the retrieval code will be used to find the similar cases in the case-base using both approaches. When using the nearest neighbor, the first step is to define K and it will be 3 in this case since the developed case-base is small. The results of the retrieval process are cases 2, 4, and 1 in this order according to the similarity function (Euclidean Distance). The results of the retrieval code are shown in figure 17.

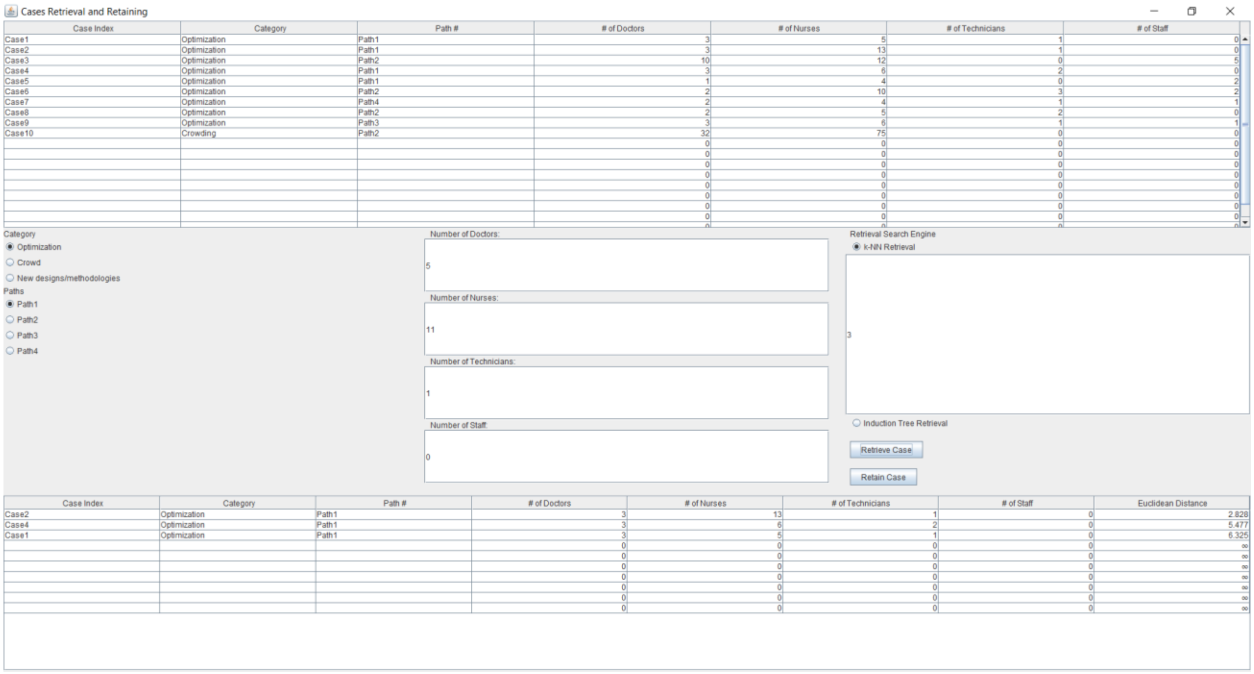

Figure 17: The results of the retrieval code using the nearest neighbor approach.

After that, the induction tree approach will be used to retrieve similar cases from the case-base. The result of the induction tree approach is case 2 and it can be shown from the retrieval code in figure 18.

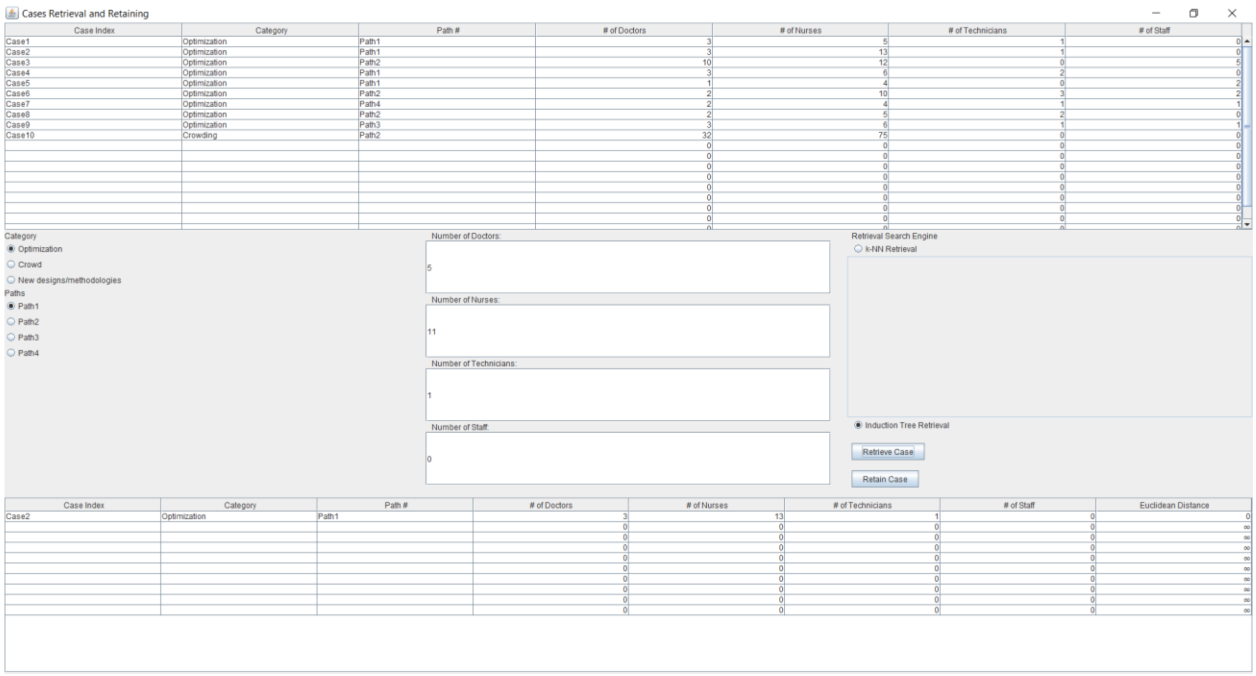

Figure 18: The results of the retrieval code using the induction tree approach.

From the retrieval results, it is clear that case 2 is the most similar case to the new problem since it was retrieved using both approaches and it will be studied and analyzed with other retrieved cases to find the solution to the new problem.

5.1.3 Case Reuse

In this step, all retrieved cases are studied to find the best way to solve the problem in the current case study. After reading and analyzing all the cases, it was clear that the first step in solving the problem would be to create a simulation model for the ED and then study the results of this model to find the required modifications to the current system. This simulation model was done as a DES and it reflected the ED situation to enable understanding of the current problem and to

find possible solutions. This model was created using SIMIO since all models in the case-base used SIMIO as their simulation environment. The use of SIMIO made the development of a model much easier since the developer did not have to start from scratch but could use the modeling information from the retrieved cases to develop a model that represents the ED of the case study.

The process of building this model started by entering the data collected from the ED and then creating a layout that represented the ED system. The first type of data that entered was the information about different types of patients since they are considered one of the most important components of the system. The modeling team was advised to use a rate table to enter the arrival rates of patients during all hours of the day. A data table is considered the best way to represent the percentages, priorities, and specific processing times of patients with different codes in the system. The rate table and data table used in the model are shown in figures 19 and 20, respectively.

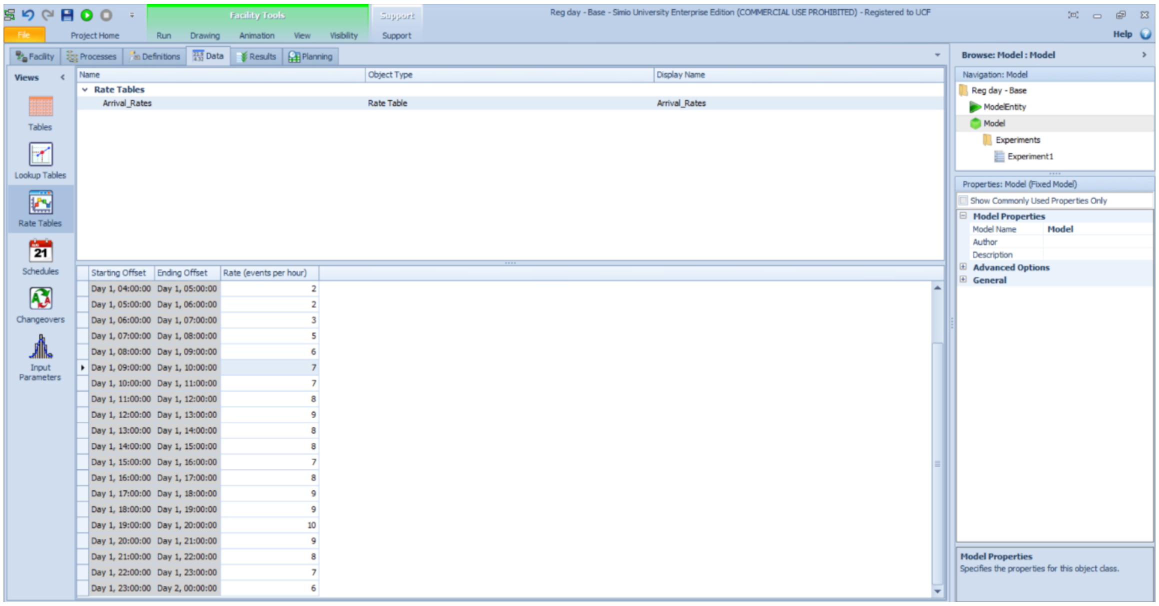

Figure 19: Rate table used in the SIMIO model

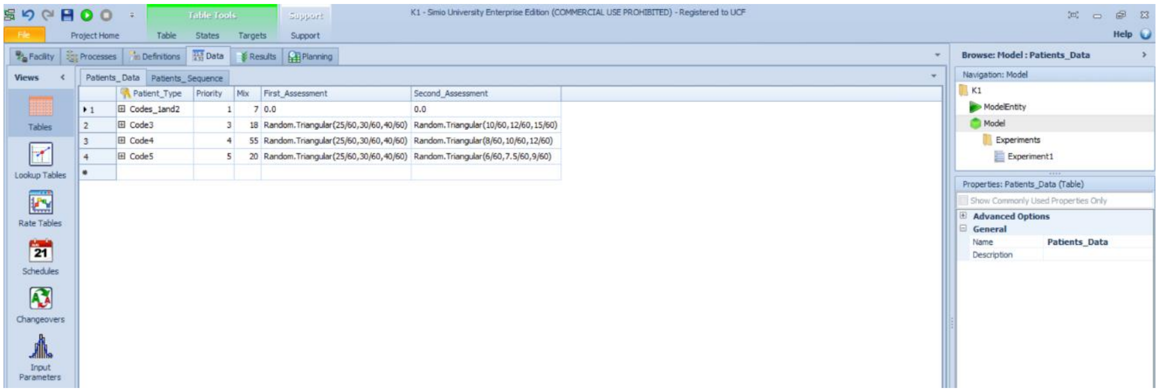

Figure 20: Data table used in the SIMIO model

After defining the data table, a sequence table that is connected to the data table was developed to outline the sequences of different types of patients in the ED. The developed sequence table is shown in figure 21.

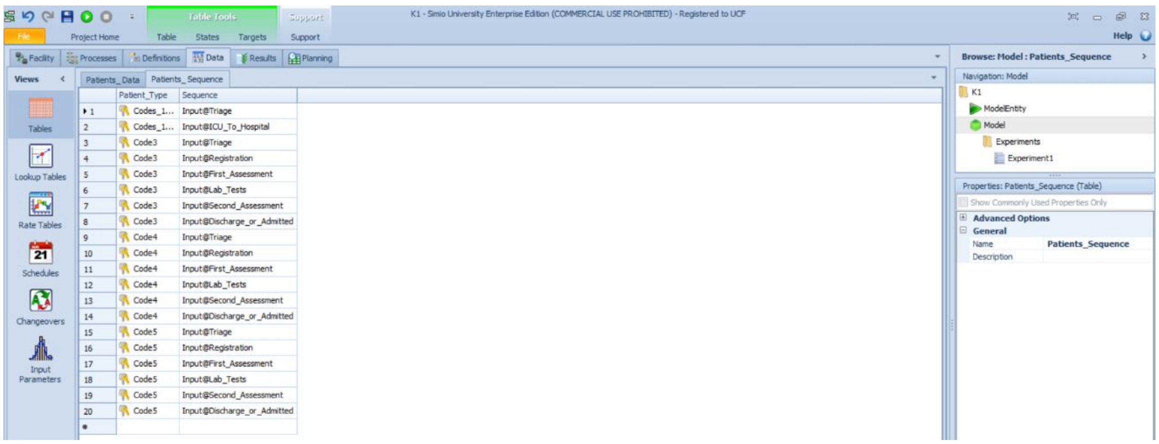

Figure 21: Sequence table used in the SIMIO model

After entering the collected data of patients, the data of the medical staff had to be stated in the model. This staff has specific working schedules and works in different shifts. The best way to enter this data in SIMIO was to define a work schedule with a detailed day pattern for each type of personnel in the ED. Such schedules are shown in figures 22 and 23.

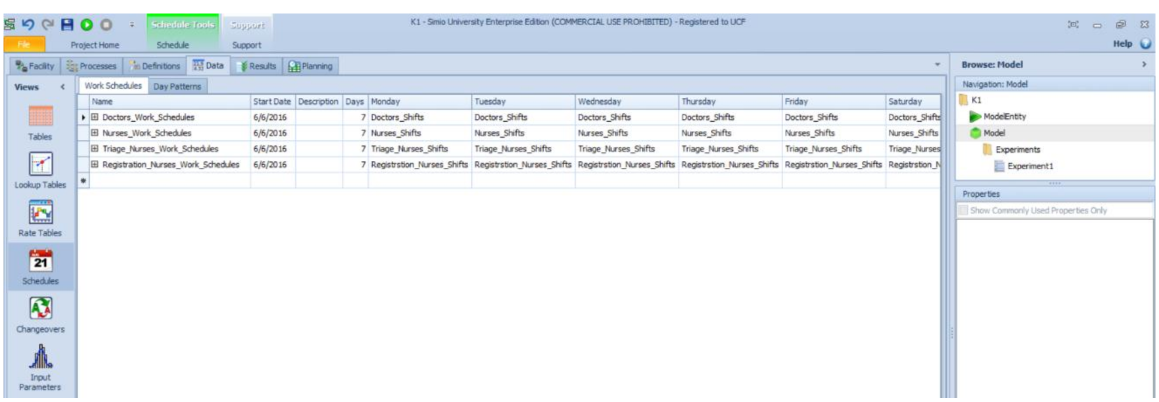

Figure 22: Work schedules used in the SIMIO model

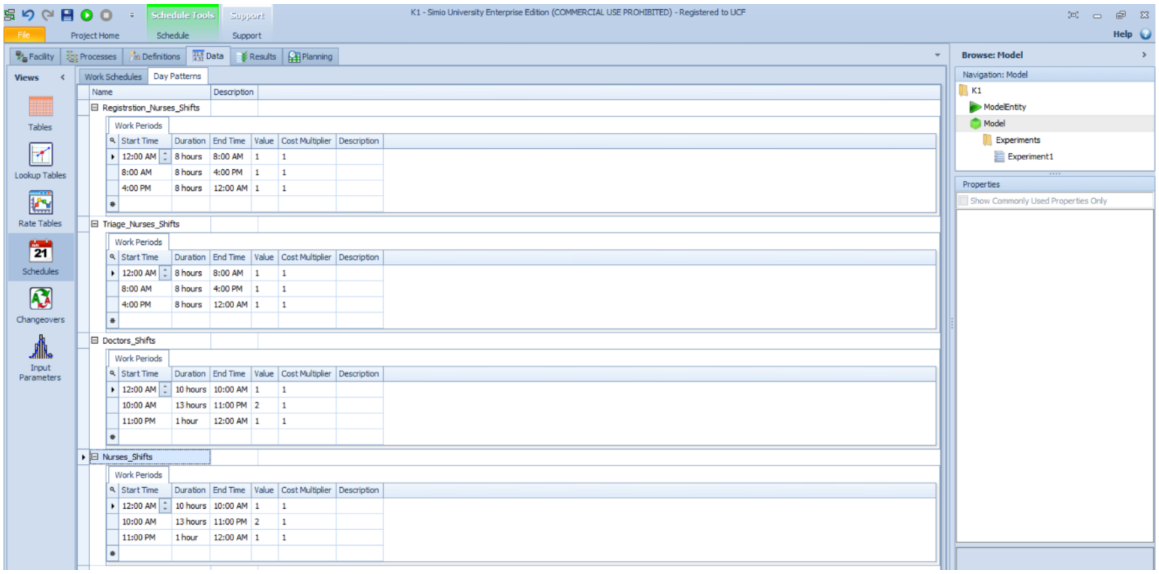

Figure 23: Day patterns used in the SIMIO model

The medical staff was represented in two different ways according to their job type and duties. For example, doctors and nurses were modeled as resources with different capacities, as explained in the work schedules. This is because they were working in more than one station during the simulation. However, registration and triage nurses were modeled within their stations since they were doing their jobs at one station only and did not move during the simulation. To complete the modeling of movable resources, processes had to be defined for the purpose of calling different resources when needed at different stations. These processes are shown in figure 24.

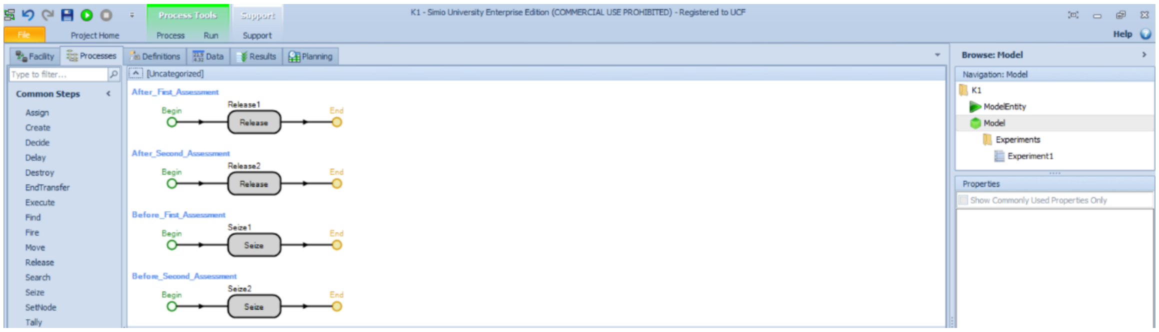

Figure 24: Defined processes used in the SIMIO model

After completing the steps of defining the data collected, the modeling team moved to creating the main model. Different of types of patients were modeled using different model entities to enable them to be followed during the simulation. All stations were modeled as servers, where each server in the model has a defined capacity and service times. The developed model is show in figure 25.

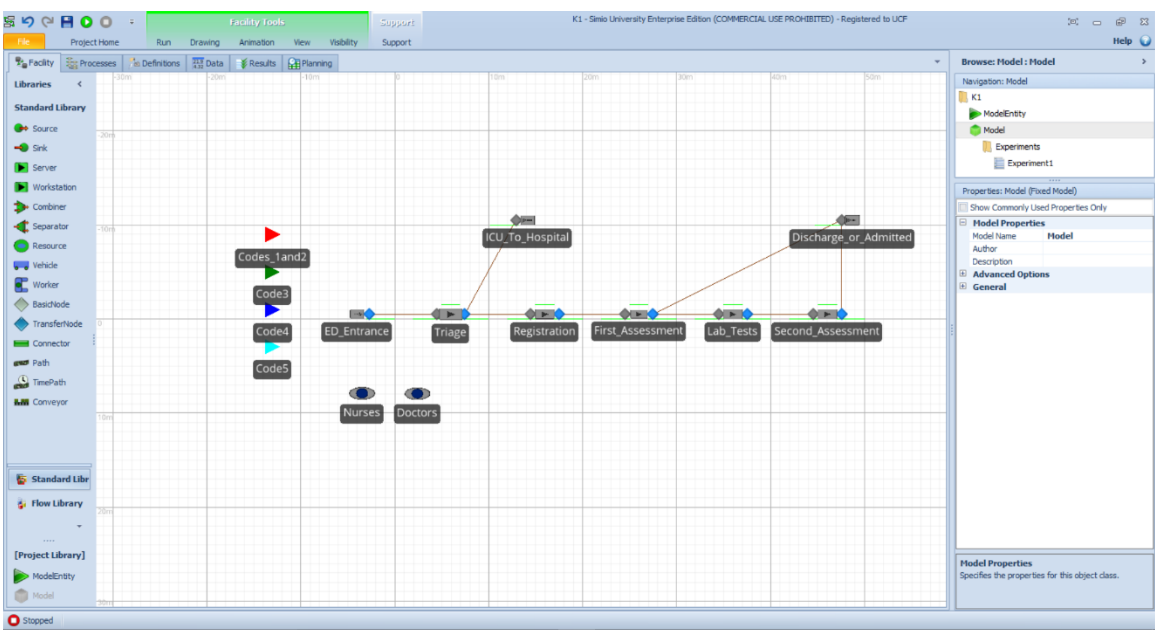

Figure 25: Developed model in SIMIO

After finishing the modeling process, the model was ready for simulation. The simulation was done using an experiment in SIMIO, since this feature run the same model for a defined number of replications and calculate means and confidence intervals for outputs and this helps in reducing the variability in the results of the simulation. This model was simulated using different arrival rates of patients during the day and then using the maximum arrival rate of each working day. The use of fixed arrival rates was the planning for the worst-case scenario that the ED could face in any given day. The results of these simulation runs are shown in tables 18-21.

Table 18: Results of the simulation run using Monday's maximum arrival rate

Mondays maximum arrival rate - the time unit is hours					
Code 3 patients					
Average time in the system	95% CI		Avg. number in the system	Numbers entered	Numbers served
	Min	Max			
1.89	1.45	2.51	2.83	37	24
Code 4 patients					
Average time in the system	95% CI		Avg. number in the system	Numbers entered	Numbers served
	Min	Max			
11.86	8.58	15.54	46.33	113	28
Code 5 patients					
Average time in the system	95% CI		Avg. number in the system	Numbers entered	Numbers served
	Min	Max			
5.86	0.81	11.53	21.1	42	0
Doctors Utilization	Nurses Utilization	Triage station		Registration station	
		Utilization	Avg. time in station	Utilization	Avg. time in station
99.20%	99.20%	84.63%	0.31	65.72%	0.02
First assessment station		Lab tests station		Second Assessment station	
Utilization	Avg. time in station	Utilization	Avg. time in station	Utilization	Avg. time in station
99.20%	5.3	44.94%	0.3	57.67%	1.05

Table 19: Results of the simulation run using Tuesday's maximum arrival rate

Tuesday maximum arrival rate - the time unit is hours					
Code 3 patients					
Average time in the system	**95% CI**		**Avg. number in the system**	**Numbers entered**	**Numbers served**
	Min	**Max**			
1.76	1.51	2.1	1.86	26	24
Code 4 patients					
Average time in the system	**95% CI**		**Avg. number in the system**	**Numbers entered**	**Numbers served**
	Min	**Max**			
9.12	6.22	11.59	26.36	82	38
Code 5 patients					
Average time in the system	**95% CI**		**Avg. number in the system**	**Numbers entered**	**Numbers served**
	Min	**Max**			
4.4	0.81	10.55	15.23	31	0
Doctors Utilization	**Nurses Utilization**	**Triage station**		**Registration station**	
		Utilization	**Avg. time in station**	**Utilization**	**Avg. time in station**
99.18%	99.18%	61.84%	0.09	47.56%	0.01
First assessment station		**Lab tests station**		**Second Assessment station**	
Utilization	**Avg. time in station**	**Utilization**	**Avg. time in station**	**Utilization**	**Avg. time in station**
99.14%	5.14	46.35%	0.23	5372.00%	0.89

Table 20: Results of the simulation run using Wed, Thu, and Fri maximum arrival rate

Wednesday, Thursday, and Friday maximum arrival rate - the time unit is hours					
Code 3 patients					
Average time in the system	**95% CI**		**Avg. number in the system**	**Numbers entered**	**Numbers served**
	Min	**Max**			
1.8	1.46	2.92	1.97	26	25
Code 4 patients					
Average time in the system	**95% CI**		**Avg. number in the system**	**Numbers entered**	**Numbers served**
	Min	**Max**			
8.81	5.48	13.78	23.98	77	38
Code 5 patients					
Average time in the system	**95% CI**		**Avg. number in the system**	**Numbers entered**	**Numbers served**
	Min	**Max**			
5.69	0.81	11.02	14.32	29	0
Doctors Utilization	**Nurses Utilization**	**Triage station**		**Registration station**	
		Utilization	**Avg. time in station**	**Utilization**	**Avg. time in station**
99.15%	99.15%	58.36%	0.09	45.12%	0.008
First assessment station		**Lab tests station**		**Second Assessment station**	
Utilization	**Avg. time in station**	**Utilization**	**Avg. time in station**	**Utilization**	**Avg. time in station**
99.11%	4.78	46.73%	0.25	61.56%	0.97

Table 21: Results of the simulation run using regular day arrival rates

Regular arrival rates - the time unit is hours					
Code 3 patients					
Average time in the system	**95% CI**		**Avg. number in the system**	**Numbers entered**	**Numbers served**
	Min	**Max**			
1.62	1.4	1.89	1.89	28	26
Code 4 patients					
Average time in the system	**95% CI**		**Avg. number in the system**	**Numbers entered**	**Numbers served**
	Min	**Max**			
5.64	3.86	8.41	19.66	83	35
Code 5 patients					
Average time in the system	**95% CI**		**Avg. number in the system**	**Numbers entered**	**Numbers served**
	Min	**Max**			
4.42	0.65	10.49	12.55	32	1
Doctors Utilization	**Nurses Utilization**	**Triage station**		**Registration station**	
		Utilization	**Avg. time in station**	**Utilization**	**Avg. time in station**
98.02%	98.02%	62.78%	0.18	49.13%	0.02
First assessment station		**Lab tests station**		**Second Assessment station**	
Utilization	**Avg. time in station**	**Utilization**	**Avg. time in station**	**Utilization**	**Avg. time in station**
97.94%	2.86	45.31%	0.27	51.35%	0.77

After completing the simulation runs, the results of these runs were analyzed to find and locate any bottlenecks in the system in order to propose possible solutions. Our case study results revealed that code 3 patients had acceptable average waiting time in the system, which was less two hours using all arrival rates. However, code 4 patients have large average wait times in the system, up to 11 hours. This length of wait time is not acceptable. Moreover, code 5 patients had an even worse situation since they did not have a chance to receive the required care; moreover, this constitutes a violation of hospital policy. Upon looking at the number of served patients from each code category, the results confirm that only code 3 patients received the required care and very few patients from code 4. These results highlight the main problem in the system, which is that not all patients are receiving the necessary care, especially patients with lower priorities. These results are shown in figure 26.

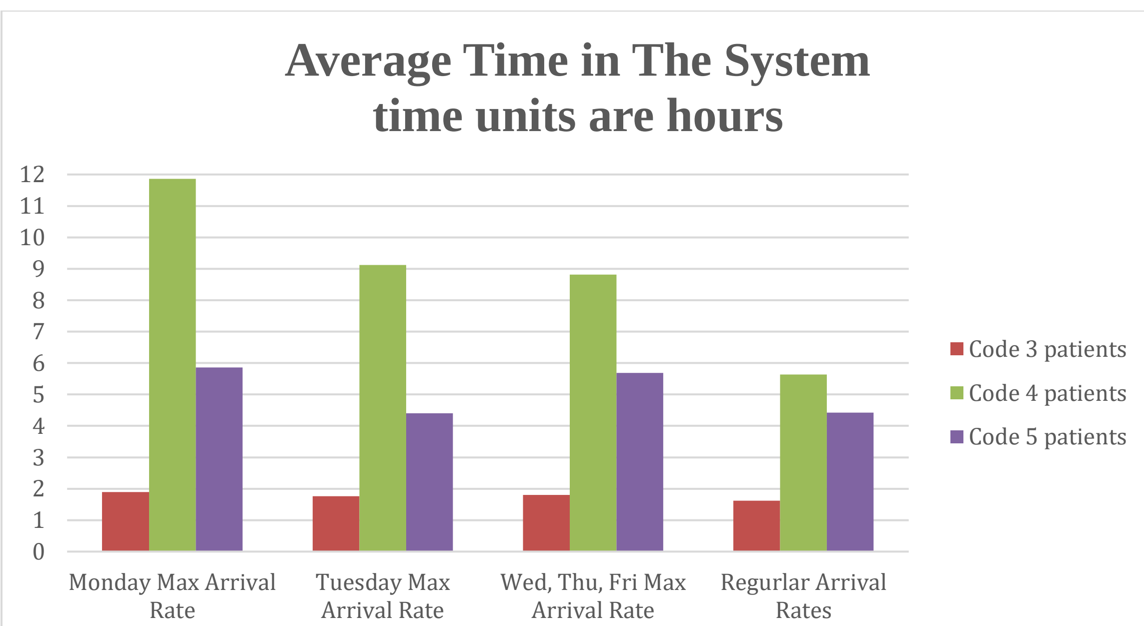

Figure 26: Average time in the system for patients with different codes.

The next step is to locate the cause of the problem. When looking at the results, it is clear that triage and registration stations are not causing any problems since the average stay in these stations was less than 20 minutes in all of the runs. The first assessment station, on the other hand, showed a patient waiting time of up to more than 5 hours, which seems to indicate it might be causing the problem. The utilization of resources connected to this station was more than 99% in most runs. These numbers indicate that the problem is rooted in a lack of a sufficient number of doctors and nurses to satisfy the current demand. Thus, the ED needs to assign more doctors and nurses to serve the large number of patients visiting the ED every day.

After finding the main problem and the cause of this problem, the modeling team should go back to the retrieved cases to look for solutions to similar problems. The common solution used in similar cases was to hire more resources to be able to meet the increasing demand and to keep the quality of the provided services. The best approach in applying this solution is by suggesting different alternatives and tests them to see what the best one is and to be able to compare between the benefits and the costs of these alternatives.

From the similar problems in the retrieved cases, the following alternatives are suggested as potential solutions:

Alternative 1: hire one more doctor and one more nurse and revise the work schedule to have an equal number of resources at each main shift. This alternative is laid out below.

Table 22: Alternative 1 details

Alternative 1: Hire one more doctor and one more nurse			
Working schedules	**Night Shift (12:00 am - 8:00 am)**	**Day Shift (8:00 am - 4:00 pm)**	**Evening Shift (4:00 pm - 12:00 am)**
Physicians	2	2	2
Nurses	2	2	2
Registration Nurses	1	1	1
Triage Nurses	1	1	1

Alternative 2: hire two more doctors and two more nurses and schedule the most resources in the evening shift since more patients visit the ED during this time. This alternative is explained below.

Table 23: Alternative 2 details

Alternative 2: Hire two more doctors and two more nurses			
Working schedules	**Night Shift (12:00 am - 8:00 am)**	**Day Shift (8:00 am - 4:00 pm)**	**Evening Shift (4:00 pm - 12:00 am)**
Physicians	2	2	3
Nurses	2	2	3
Registration Nurses	1	1	1
Triage Nurses	1	1	1

Alternative 3: hire three more doctors and three more nurses and schedule more resources in the day and evening shifts.

Table 24: Alternative 3 details

Alternative 3: Hire three more doctors and three more nurses			
Working schedules	**Night Shift (12:00 am - 8:00 am)**	**Day Shift (8:00 am - 4:00 pm)**	**Evening Shift (4:00 pm - 12:00 am)**
Physicians	2	3	3
Nurses	2	3	3
Registration Nurses	1	1	1
Triage Nurses	1	1	1

Alternative 4: have the maximum number of doctors and nurses that could be working at the same time in the ED. This means having 5 doctors and 5 nurses at each shift. This alternative might not be feasible or implementable. However, it can give an idea about how the system will behave when having the maximum possible number of resources. Moreover, the results for this alternative will help decision makers when comparing the other alternatives. It is also possible to utilize the results of this suggestion in planning for extreme events.

Table 25: Alternative 4 details

Alternative 4 (Extreme scenario): This alternative is for comparisons of results			
Working schedules	**Night Shift (12:00 am - 8:00 am)**	**Day Shift (8:00 am - 4:00 pm)**	**Evening Shift (4:00 pm - 12:00 am)**
Physicians	5	5	5
Nurses	5	5	5
Registration Nurses	1	1	1
Triage Nurses	1	1	1

This step of the CBR methodology involves stakeholders more than any other step. This is because they have more knowledge about the system and they have the ability to direct the modeling team towards what is the best for the system. Their involvement helps in the decision making process since most of the work done in building the solution is under the supervision of the stakeholders.

5.1.4 Case Revise

This step was performed after finding the main problem in the current case study and locating the cause of the problem and coming up with suggested solutions. The proposed alternatives were tested to check whether they solved the problem or not. This testing of the alternatives involved the stakeholders to get their immediate feedback and to receive and test any new suggestions. Thus, the proposed alternatives were used in the simulation model and the results were analyzed. The results of the simulation runs of these alternatives are shown in the following tables.

Table 26: Results of alternative-1 simulation run using Monday's maximum arrival rate

Mondays maximum arrival rate - Alternative 1 - the time unit is hours					
Code 3 patients					
Average time in the system	**95% CI**		**Avg. number in the system**	**Numbers entered**	**Numbers served**
	Min	**Max**			
1.6	1.34	1.91	2.47	38	35
Code 4 patients					
Average time in the system	**95% CI**		**Avg. number in the system**	**Numbers entered**	**Numbers served**
	Min	**Max**			
7.5	5.21	9.97	35.4	114	45
Code 5 patients					
Average time in the system	**95% CI**		**Avg. number in the system**	**Numbers entered**	**Numbers served**
	Min	**Max**			
1.07	0.74	1.99	20.73	41	0
Doctors Utilization	**Nurses Utilization**	**Triage station**		**Registration station**	
		Utilization	**Avg. time in station**	**Utilization**	**Avg. time in station**
99.19%	99.19%	85.22%	0.3	65.70%	0.018
First assessment station		**Lab tests station**		**Second Assessment station**	
Utilization	**Avg. time in station**	**Utilization**	**Avg. time in station**	**Utilization**	**Avg. time in station**
99.20%	3.73	56.53%	0.31	62.02%	0.81

Table 27: Results of alternative-2 simulation run using Monday's maximum arrival rate

Mondays maximum arrival rate - Alternative 2 - the time unit is hours					
Code 3 patients					
Average time in the system	**95% CI**		**Avg. number in the system**	**Numbers entered**	**Numbers served**
	Min	**Max**			
1.55	1.34	1.79	2.44	38	37
Code 4 patients					
Average time in the system	**95% CI**		**Avg. number in the system**	**Numbers entered**	**Numbers served**
	Min	**Max**			
7.92	5.56	10.5	33.78	116	58
Code 5 patients					
Average time in the system	**95% CI**		**Avg. number in the system**	**Numbers entered**	**Numbers served**
	Min	**Max**			
6.58	0.74	17.95	20.56	41	0
Doctors Utilization	**Nurses Utilization**	**Triage station**		**Registration station**	
		Utilization	**Avg. time in station**	**Utilization**	**Avg. time in station**
99.19%	99.19%	86.03%	0.31	66.00%	0.018
First assessment station		**Lab tests station**		**Second Assessment station**	
Utilization	**Avg. time in station**	**Utilization**	**Avg. time in station**	**Utilization**	**Avg. time in station**
99.19%	4.3	62.00%	0.45	60.14%	0.62

Table 28: Results of alternative-3 simulation run using Monday's maximum arrival rate

Mondays maximum arrival rate - Alternative 3 - the time unit is hours					
Code 3 patients					
Average time in the system	**95% CI**		**Avg. number in the system**	**Numbers entered**	**Numbers served**
	Min	**Max**			
1.46	1.14	1.68	2.28	38	36
Code 4 patients					
Average time in the system	**95% CI**		**Avg. number in the system**	**Numbers entered**	**Numbers served**
	Min	**Max**			
6.31	3.08	8.81	27.56	115	71
Code 5 patients					
Average time in the system	**95% CI**		**Avg. number in the system**	**Numbers entered**	**Numbers served**
	Min	**Max**			
3.53	0.74	8.86	20.97	41	0
Doctors Utilization	**Nurses Utilization**	**Triage station**		**Registration station**	
		Utilization	**Avg. time in station**	**Utilization**	**Avg. time in station**
99.19%	99.19%	84.93%	0.31	65.74%	0.019
First assessment station		**Lab tests station**		**Second Assessment station**	
Utilization	**Avg. time in station**	**Utilization**	**Avg. time in station**	**Utilization**	**Avg. time in station**
99.19%	3.46	73.77%	0.76	60.76%	0.46

Table 29: Results of alternative-4 simulation run using Monday's maximum arrival rate

Mondays maximum arrival rate - Alternative 4 - the time unit is hours					
Code 3 patients					
Average time in the system	**95% CI**		**Avg. number in the system**	**Numbers entered**	**Numbers served**
	Min	**Max**			
1.16	0.96	1.43	1.69	35	34
Code 4 patients					
Average time in the system	**95% CI**		**Avg. number in the system**	**Numbers entered**	**Numbers served**
	Min	**Max**			
1.65	1.3	2.65	8.39	113	103
Code 5 patients					
Average time in the system	**95% CI**		**Avg. number in the system**	**Numbers entered**	**Numbers served**
	Min	**Max**			
2.35	1.02	4.13	6.58	42	31
Doctors Utilization	**Nurses Utilization**	**Triage station**		**Registration station**	
		Utilization	**Avg. time in station**	**Utilization**	**Avg. time in station**
98.77%	98.77%	84.85%	0.35	64.86%	0.018
First assessment station		**Lab tests station**		**Second Assessment station**	
Utilization	**Avg. time in station**	**Utilization**	**Avg. time in station**	**Utilization**	**Avg. time in station**
98.66%	0.1	91.02%	2.07	26.00%	0.046

Table 30: Results of alternative-1 simulation run using Tuesday's maximum arrival rate

Tuesdays maximum arrival rate - Alternative 1 - the time unit is hours					
Code 3 patients					
Average time in the system	**95% CI**		**Avg. number in the system**	**Numbers entered**	**Numbers served**
	Min	**Max**			
1.46	1.21	1.68	1.67	28	26
Code 4 patients					
Average time in the system	**95% CI**		**Avg. number in the system**	**Numbers entered**	**Numbers served**
	Min	**Max**			
4.69	2.65	6.73	16.32	83	53
Code 5 patients					
Average time in the system	**95% CI**		**Avg. number in the system**	**Numbers entered**	**Numbers served**
	Min	**Max**			
2.1	0.72	6.95	15.06	31	1
Doctors Utilization	**Nurses Utilization**	**Triage station**		**Registration station**	
		Utilization	**Avg. time in station**	**Utilization**	**Avg. time in station**
99.03%	99.03%	63.13%	0.09	48.65%	0.01
First assessment station		**Lab tests station**		**Second Assessment station**	
Utilization	**Avg. time in station**	**Utilization**	**Avg. time in station**	**Utilization**	**Avg. time in station**
99.03%	2.52	57.52%	0.32	60.78%	0.63

Table 31: Results of alternative-2 simulation run using Tuesday's maximum arrival rate

Tuesdays maximum arrival rate - Alternative 2 - the time unit is hours					
Code 3 patients					
Average time in the system	**95% CI**		**Avg. number in the system**	**Numbers entered**	**Numbers served**
	Min	**Max**			
1.44	1.16	1.82	1.64	28	26
Code 4 patients					
Average time in the system	**95% CI**		**Avg. number in the system**	**Numbers entered**	**Numbers served**
	Min	**Max**			
4.41	2.48	6.54	14.84	84	64
Code 5 patients					
Average time in the system	**95% CI**		**Avg. number in the system**	**Numbers entered**	**Numbers served**
	Min	**Max**			
9.35	0.72	19.18	14.74	32	3
Doctors Utilization	**Nurses Utilization**	**Triage station**		**Registration station**	
		Utilization	**Avg. time in station**	**Utilization**	**Avg. time in station**
99.03%	99.03%	64.29%	0.1	49.30%	0.01
First assessment station		**Lab tests station**		**Second Assessment station**	
Utilization	**Avg. time in station**	**Utilization**	**Avg. time in station**	**Utilization**	**Avg. time in station**
99.03%	2.62	65.71%	0.54	57.35%	0.54

Table 32: Results of alternative-3 simulation run using Tuesday's maximum arrival rate

Tuesdays maximum arrival rate - Alternative 3 - the time unit is hours					
Code 3 patients					
Average time in the system	**95% CI**		**Avg. number in the system**	**Numbers entered**	**Numbers served**
	Min	**Max**			
1.31	1.1	1.61	1.35	25	24
Code 4 patients					
Average time in the system	**95% CI**		**Avg. number in the system**	**Numbers entered**	**Numbers served**
	Min	**Max**			
2.5	1.51	4.82	8.27	81	72
Code 5 patients					
Average time in the system	**95% CI**		**Avg. number in the system**	**Numbers entered**	**Numbers served**
	Min	**Max**			
9.88	2.48	18.1	11.71	31	12
Doctors Utilization	**Nurses Utilization**	**Triage station**		**Registration station**	
		Utilization	**Avg. time in station**	**Utilization**	**Avg. time in station**
98.97%	98.97%	61.09%	0.09	46.93%	0.01
First assessment station		**Lab tests station**		**Second Assessment station**	
Utilization	**Avg. time in station**	**Utilization**	**Avg. time in station**	**Utilization**	**Avg. time in station**
98.96%	1.81	69.03%	0.65	53.95%	0.55

Table 33: Results of alternative-4 simulation run using Tuesday's maximum arrival rate

Tuesdays maximum arrival rate - Alternative 4 - the time unit is hours					
Code 3 patients					
Average time in the system	**95% CI**		**Avg. number in the system**	**Numbers entered**	**Numbers served**
	Min	**Max**			
1.07	0.75	1.33	1.23	28	27
Code 4 patients					
Average time in the system	**95% CI**		**Avg. number in the system**	**Numbers entered**	**Numbers served**
	Min	**Max**			
1.37	0.98	2.08	4.71	83	78
Code 5 patients					
Average time in the system	**95% CI**		**Avg. number in the system**	**Numbers entered**	**Numbers served**
	Min	**Max**			
1.61	0.85	3.25	2.85	30	26
Doctors Utilization	**Nurses Utilization**	**Triage station**		**Registration station**	
		Utilization	**Avg. time in station**	**Utilization**	**Avg. time in station**
96.22%	96.22%	63.00%	0.09	48.40%	0.01
First assessment station		**Lab tests station**		**Second Assessment station**	
Utilization	**Avg. time in station**	**Utilization**	**Avg. time in station**	**Utilization**	**Avg. time in station**
95.78%	0.02	85.70%	1.56	20.73%	0.014

Table 34: Results of alternative-1 simulation run using Wed, Thu, and Fri maximum arrival rate

Wednesday, Thursday, and Friday maximum arrival rate - Alternative 1 - the time unit is hours					
Code 3 patients					
Average time in the system	**95% CI**		**Avg. number in the system**	**Numbers entered**	**Numbers served**
	Min	**Max**			
1.49	1.06	1.71	1.56	25	24
Code 4 patients					
Average time in the system	**95% CI**		**Avg. number in the system**	**Numbers entered**	**Numbers served**
	Min	**Max**			
4.04	1.91	7.19	13.37	79	55
Code 5 patients					
Average time in the system	**95% CI**		**Avg. number in the system**	**Numbers entered**	**Numbers served**
	Min	**Max**			
3.39	0.72	9.75	13.06	29	2
Doctors Utilization	**Nurses Utilization**	**Triage station**		**Registration station**	
		Utilization	**Avg. time in station**	**Utilization**	**Avg. time in station**
98.97%	98.97%	58.04%	0.09	45.82%	0.009
First assessment station		**Lab tests station**		**Second Assessment station**	
Utilization	**Avg. time in station**	**Utilization**	**Avg. time in station**	**Utilization**	**Avg. time in station**
98.96%	2.2	57.76%	0.29	63.67%	0.61

Table 35: Results of alternative-2 simulation run using Wed, Thu, and Fri maximum arrival rate

Wednesday, Thursday, and Friday maximum arrival rate - Alternative 2 - the time unit is hours					
Code 3 patients					
Average time in the system	**95% CI**		**Avg. number in the system**	**Numbers entered**	**Numbers served**
	Min	**Max**			
1.46	1.06	1.83	1.48	25	23
Code 4 patients					
Average time in the system	**95% CI**		**Avg. number in the system**	**Numbers entered**	**Numbers served**
	Min	**Max**			
3.61	2.1	6.96	11.93	81	67
Code 5 patients					
Average time in the system	**95% CI**		**Avg. number in the system**	**Numbers entered**	**Numbers served**
	Min	**Max**			
9.12	0.72	20.66	12.59	28	3
Doctors Utilization	**Nurses Utilization**	**Triage station**		**Registration station**	
		Utilization	**Avg. time in station**	**Utilization**	**Avg. time in station**
98.97%	98.97%	59.75%	0.08	46.22%	0.009
First assessment station		**Lab tests station**		**Second Assessment station**	
Utilization	**Avg. time in station**	**Utilization**	**Avg. time in station**	**Utilization**	**Avg. time in station**
98.96%	2.14	65.72%	0.47	62.39%	0.7

Table 36: Results of alternative-3 simulation run using Wed, Thu, and Fri maximum arrival rate

Wednesday, Thursday, and Friday maximum arrival rate - Alternative 3 - the time unit is hours					
Code 3 patients					
Average time in the system	**95% CI**		**Avg. number in the system**	**Numbers entered**	**Numbers served**
	Min	**Max**			
1.42	1.18	1.71	1.49	26	25
Code 4 patients					
Average time in the system	**95% CI**		**Avg. number in the system**	**Numbers entered**	**Numbers served**
	Min	**Max**			
2.54	1.56	4.09	8.31	80	71
Code 5 patients					
Average time in the system	**95% CI**		**Avg. number in the system**	**Numbers entered**	**Numbers served**
	Min	**Max**			
8.33	3.44	13.95	10.19	28	11
Doctors Utilization	**Nurses Utilization**	**Triage station**		**Registration station**	
		Utilization	**Avg. time in station**	**Utilization**	**Avg. time in station**
98.96%	98.96%	59.15%	0.08	45.94%	0.01
First assessment station		**Lab tests station**		**Second Assessment station**	
Utilization	**Avg. time in station**	**Utilization**	**Avg. time in station**	**Utilization**	**Avg. time in station**
98.95%	1.62	74.64%	0.91	59.29%	0.6

Table 37: Results of alternative-4 simulation run using Wed, Thu, and Fri maximum arrival rate

Wednesday, Thursday, and Friday maximum arrival rate - Alternative 4 - the time unit is hours					
Code 3 patients					
Average time in the system	**95% CI**		**Avg. number in the system**	**Numbers entered**	**Numbers served**
	Min	**Max**			
1.06	0.82	1.28	1.47	26	25
Code 4 patients					
Average time in the system	**95% CI**		**Avg. number in the system**	**Numbers entered**	**Numbers served**
	Min	**Max**			
1.35	0.99	2.15	4.44	78	73
Code 5 patients					
Average time in the system	**95% CI**		**Avg. number in the system**	**Numbers entered**	**Numbers served**
	Min	**Max**			
1.34	0.9	2.11	2.37	29	26
Doctors Utilization	**Nurses Utilization**	**Triage station**		**Registration station**	
		Utilization	**Avg. time in station**	**Utilization**	**Avg. time in station**
95.92%	95.92%	60.08%	0.09	45.87%	0.01
First assessment station		**Lab tests station**		**Second Assessment station**	
Utilization	**Avg. time in station**	**Utilization**	**Avg. time in station**	**Utilization**	**Avg. time in station**
94.96%	0.03	82.06%	1.26	19.32%	0.011

Table 38: Results of alternative-1 simulation run using regular day arrival rates

Regular arrival rates - Alternative 1 - the time unit is hours					
Code 3 patients					
Average time in the system	**95% CI**		**Avg. number in the system**	**Numbers entered**	**Numbers served**
	Min	**Max**			
1.53	1.23	2.1	1.73	27	25
Code 4 patients					
Average time in the system	**95% CI**		**Avg. number in the system**	**Numbers entered**	**Numbers served**
	Min	**Max**			
3.59	1.84	4.9	14.76	84	44
Code 5 patients					
Average time in the system	**95% CI**		**Avg. number in the system**	**Numbers entered**	**Numbers served**
	Min	**Max**			
1.78	0.69	4.25	8.87	31	5
Doctors Utilization	**Nurses Utilization**	**Triage station**		**Registration station**	
		Utilization	**Avg. time in station**	**Utilization**	**Avg. time in station**
93.78%	93.78%	62.33%	0.19	48.81%	0.01
First assessment station		**Lab tests station**		**Second Assessment station**	
Utilization	**Avg. time in station**	**Utilization**	**Avg. time in station**	**Utilization**	**Avg. time in station**
93.36%	1.76	51.64%	0.23	48.21%	0.55

Table 39: Results of alternative-2 simulation run using regular day arrival rates

Regular arrival rates - Alternative 2 - the time unit is hours					
Code 3 patients					
Average time in the system	**95% CI**		**Avg. number in the system**	**Numbers entered**	**Numbers served**
	Min	**Max**			
1.47	1.16	2	1.63	27	25
Code 4 patients					
Average time in the system	**95% CI**		**Avg. number in the system**	**Numbers entered**	**Numbers served**
	Min	**Max**			
3.81	1.65	5.89	13.56	85	56
Code 5 patients					
Average time in the system	**95% CI**		**Avg. number in the system**	**Numbers entered**	**Numbers served**
	Min	**Max**			
2.73	0.69	7.63	8.48	30	5
Doctors Utilization	**Nurses Utilization**	**Triage station**		**Registration station**	
		Utilization	**Avg. time in station**	**Utilization**	**Avg. time in station**
93.78%	93.78%	62.78%	0.21	48.60%	0.02
First assessment station		**Lab tests station**		**Second Assessment station**	
Utilization	**Avg. time in station**	**Utilization**	**Avg. time in station**	**Utilization**	**Avg. time in station**
93.36%	1.98	60.07%	0.48	46.88%	0.41

Table 40: Results of alternative-3 simulation run using regular day arrival rates

Regular arrival rates - Alternative 3 - the time unit is hours					
Code 3 patients					
Average time in the system	**95% CI**		**Avg. number in the system**	**Numbers entered**	**Numbers served**
	Min	**Max**			
1.32	1	1.59	1.42	26	24
Code 4 patients					
Average time in the system	**95% CI**		**Avg. number in the system**	**Numbers entered**	**Numbers served**
	Min	**Max**			
2.04	1.29	2.89	7.02	80	65
Code 5 patients					
Average time in the system	**95% CI**		**Avg. number in the system**	**Numbers entered**	**Numbers served**
	Min	**Max**			
2.71	1.44	6.66	7.01	30	9
Doctors Utilization	**Nurses Utilization**	**Triage station**		**Registration station**	
		Utilization	**Avg. time in station**	**Utilization**	**Avg. time in station**
93.59%	93.59%	60.89%	0.16	47.10%	0.01
First assessment station		**Lab tests station**		**Second Assessment station**	
Utilization	**Avg. time in station**	**Utilization**	**Avg. time in station**	**Utilization**	**Avg. time in station**
93.13%	0.78	66.25%	0.72	50.10%	0.4

Table 41: Results of alternative-4 simulation run using regular day arrival rates

Regular arrival rates - Alternative 4 - the time unit is hours					
Code 3 patients					
Average time in the system	**95% CI**		**Avg. number in the system**	**Numbers entered**	**Numbers served**
	Min	**Max**			
1.12	0.91	1.38	1.22	27	26
Code 4 patients					
Average time in the system	**95% CI**		**Avg. number in the system**	**Numbers entered**	**Numbers served**
	Min	**Max**			
1.37	0.94	2.05	5.18	84	77
Code 5 patients					
Average time in the system	**95% CI**		**Avg. number in the system**	**Numbers entered**	**Numbers served**
	Min	**Max**			
1.45	0.86	2.86	2.75	30	24
Doctors Utilization	**Nurses Utilization**	**Triage station**		**Registration station**	
		Utilization	**Avg. time in station**	**Utilization**	**Avg. time in station**
92.37%	92.37%	62.59%	0.19	48.33%	0.01
First assessment station		**Lab tests station**		**Second Assessment station**	
Utilization	**Avg. time in station**	**Utilization**	**Avg. time in station**	**Utilization**	**Avg. time in station**
91.42%	0.07	74.21%	1.15	19.04%	0.02

From the results of the simulation runs of the alternatives, it is clear that alternative 4 gives the best results under all arrival rates. However, this was expected since the ED in alternative 4 is working with full capacity in terms with resources (doctors and nurses in particular). The results of alternative 1 show acceptable improvements in the average time in the system for code 3 and

code 4 patients, but code 5 patients' results improved only slightly. The average time in the first assessment station also decreased by an acceptable amount.

The results of alternative 2 show greater improvements than those in alternative 1 for the average time in the system of code 3, 4 and 5 patients. They also show more reduction in the waiting time of all patients at the first assessment station. However, the cost of implementing alternative 2 is more than alternative 1. Alternative 3 results show greater improvements than those in alternatives 1 and 2. Similarly, alternative 3 will cost more than alternatives 1 and 2 when chosen. Thus, these results show that the more the hospital invests, the better the results will be. It is left to stakeholders and decision makers to choose the best solution for the system in terms of compromising between the cost of implementing different alternatives and the benefits that will be added to the system. These results are summarized in the following figures.

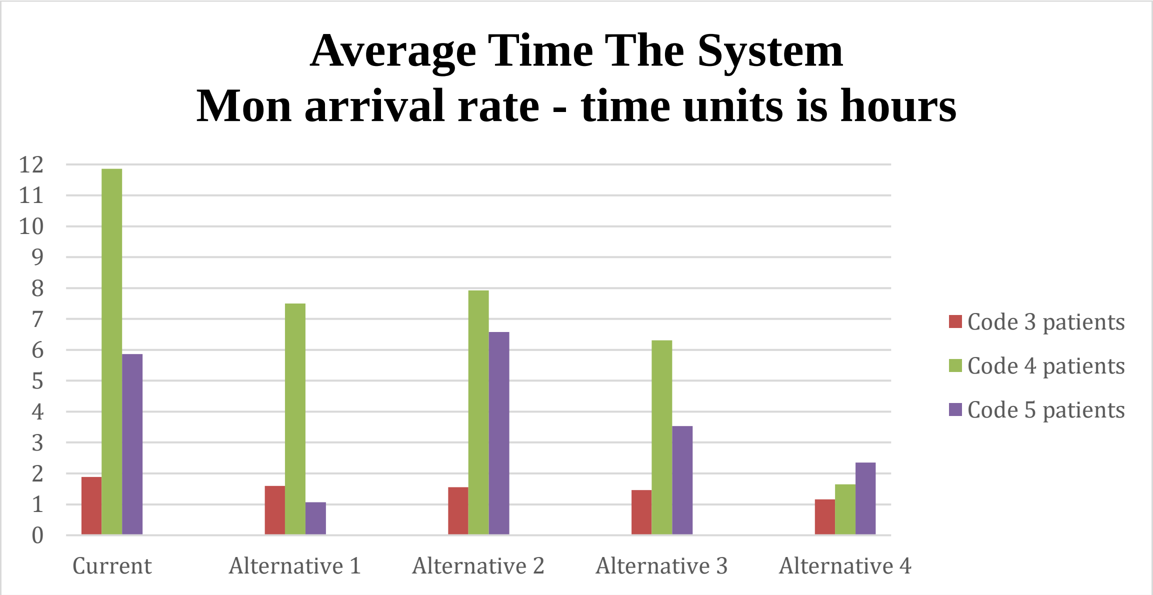

Figure 27: Average time in the system using Monday's maximum arrival rate.

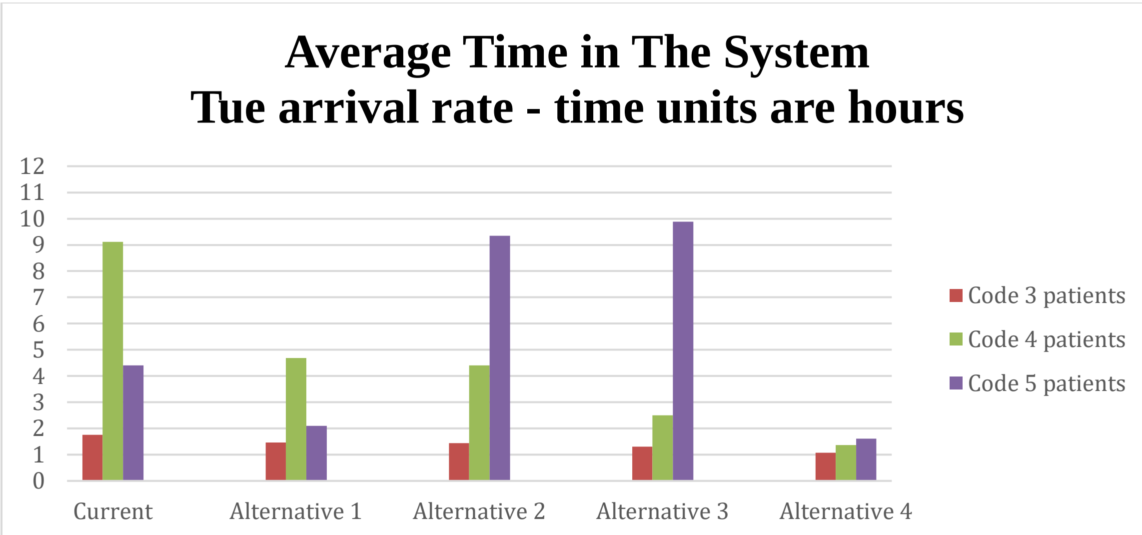

Figure 28: Average time in the system using Tuesday's maximum arrival rate.

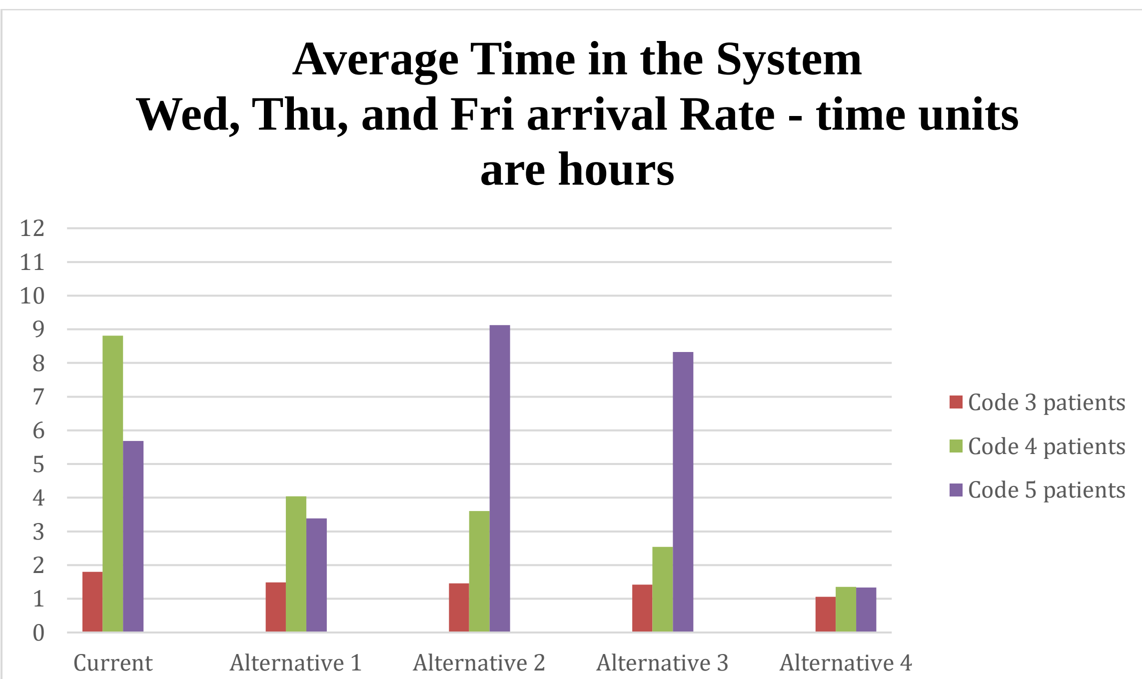

Figure 29: Average time in the system using Wednesday – Friday's maximum arrival rate.

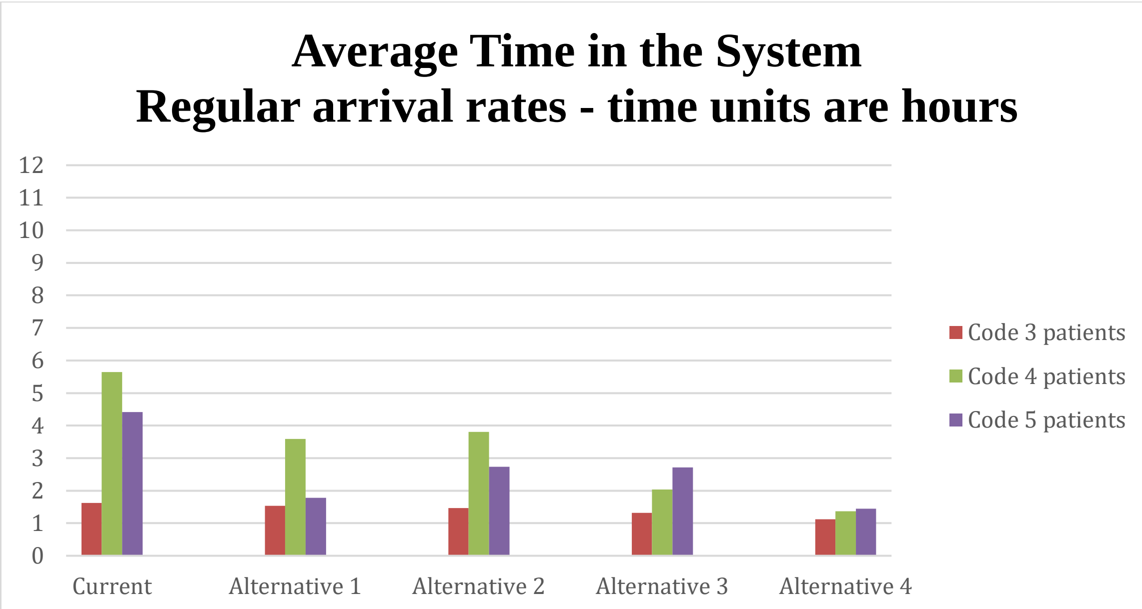

Figure 30: Average time in the system using regular arrival rates.

5.1.5 Case Retain

The new problem in this case study was solved using proposed solutions from previously solved cases. Thus, this solved case could be added to the case-base under the same category of the retrieved cases, which is as an optimization problem. The newly solved case took the optimization index and was given a number before joining the case-base. The developed case-base, after adding the new case, is the following:

Table 42: The developed case-base for ED problems using DES after adding the newly solved

Categories		
Optimization Problems	Crowding Problems	New designs/methodologies Problems
Case 1	Case 10	
Case 2		
Case 3		
Case 4		
Case 5		
Case 6		
Case 7		
Case 8		
Case 9		
Case 11 (New added case)		

5.2 CBR Methodology Verification and Validation

Verification is building the model right as planed whereas validation is building the right model that is a close representation to the actual system and could be used to find solutions. The verification of this model will be done using structured walk-through. There are several validation techniques in the literature that could be used to validate simulation models. Some of these techniques that were used in this study are:

- Animation: the animation of the model during the simulation run is used to check whether the model is a close representation to the real system or not.
- Event validity: events of the simulation model are compared to those in the real system.

- Traces: different entities in the model are traced to check their behavior to decide if the logic of the model is true or not.
- Historical (collected) data validation: results of the simulation model are compared to collected data from the real system.
- Face validity: subject matter experts are consulted to validate the model (Sargent, 2010).

The verification process starts by inviting another person that did not work with the modeling team. Then, perform a step-by-step walkthrough explanation of the system using the model. After that, the invited person will work with the modeler in identifying the points in the simulation model that do not reflect the actual system. This process was done to verify that the developed model reflects the real system.

To validate this CBR methodology, a new case study was chosen as a starting point for the validation procedure. After implementing the methodology to get the solution of the new case study, it is clear that it is capable of providing solutions for new problems in the same field as the saved cases in the case-base. In the historical data validation technique, the collected data from the real system will be used to build the simulation model and then check if the output of the model is close to the system. For this case study, the collected data from the ED was used to build the simulation model on SIMIO. After that, the developed model was simulated and the output of the model was compared to the real system collected data. This comparison will compare total time in the system for patients with triage levels and the waiting times before each station in the system. Table 43 shows these comparisons.

Table 43: Comparison of simulation model output and the collected data.

Waiting durations	Description
T1	Time between arrival and triage
T2	Time between triage and registration
T3	Time from registration to available exam room
T4	Time from first assessment to discharge

Simulation output vs. Real data collected (in minutes)

Days	T1			T2			T3			T4		
	Real data	Simulation		Real data	Simulation		Real data	Simulation		Real data	Simulation	
		Mean	95% CI		Mean	95% CI		Mean	95% CI		Mean	95% CI
Mon	12.7	17.0	(4.8-46.8)	1.7	1.0	(0.42-2.4)	235.0	136.0	(64.2-175.2)	36.0	57.0	(19.8-113.4)
Tue	6.6	5.4	(2.4-10.8)	0.6	0.5	(0.06-1.2)	144.0	97.3	(39.6-150.6)	36.0	46.1	(12-94.2)
Wed	10.0	4.9	(1.8-9.6)	1.8	0.6	(0.12-1.8)	121.0	92.4	(38.4-166.8)	40.0	51.2	(19.2-117.6)
Thu	10.0	4.9	(1.8-9.6)	1.8	0.6	(0.12-1.8)	121.0	92.4	(38.4-166.8)	40.0	51.2	(19.2-117.6)
Fri	17.9	4.9	(1.8-9.6)	2.2	0.6	(0.12-1.8)	101.0	92.4	(38.4-166.8)	42.0	51.2	(19.2-117.6)

Days	Code 3			Code 4			Code 5		
	Real data	Simulation		Real data	Simulation		Real data	Simulation	
		Mean	95% CI		Mean	95% CI		Mean	95% CI
Mon	89.6	91.2	(72.6-113.4)	257.9	277.9	(194.4-360.6)	327.2	381	(295.8-466.2)
Tue	68.1	89.6	(67.2-115.8)	172.9	189.9	(90-321.6)	204.2	187.8	(44.4-381)
Wed	72.1	84.3	(64.8-105)	201.9	180.5	(86.4-301.2)	228.2	247.8	(48.6-426)
Thu	54.7	84.3	(64.8-105)	144.9	180.5	(86.4-301.2)	161.2	247.8	(48.6-426)
Fri	87.2	84.3	(64.8-105)	163.9	180.5	(86.4-301.2)	180.2	247.8	(48.6-426)

From the table, it is clear that the waiting time before the first assessment station (T3) is the longest in the system. Moreover, the waiting time T3 has the highest difference between simulation results and collected data especially on Mondays where arrival rates are higher than all other days. This difference has several reasons as discussed by experts of this ED after building the simulation model. The main reason is that the medical personnel of the ED sometimes violates priorities of different triage levels patients to serve code 5 patients especially when they wait for long times to reduce the percentage of patients that leaves without being treated or seen by doctors. This treatment of code 5 patients is not organized and will increase the waiting time of other codes patients. Another reason is that when there are too many patients in the system then the medical personnel will be working all the time and sometimes they take

short and unplanned breaks to reduce fatigue. One more reason comes from cleaning times that were not collected. These times include the time to clean examination rooms after each patient to prepare them for next patients. They were not collected since it is difficult to collect them and no predicted times are available. The remaining of the comparison table has some differences that are considered acceptable by the system experts.

The face validity technique will be used as another way to validate this model. To perform the face validity, several healthcare experts were contacted in central Florida. These experts were selected based on their experience in the healthcare field and their knowledge about several healthcare systems including the ED. After that, three healthcare experts were chosen based on their various experience levels in the healthcare filed and their different positions within healthcare organizations. This variety will help in receiving feedbacks from different perspectives and will check and test the model from various angels.

The first expert was chosen from technical services department in a primary healthcare organization. He deals with the improvements of healthcare systems by using applying different tools and technologies. This choice will help in checking the model from technical point of view since he works with several simulation modeling techniques in addition to his experience in healthcare systems. The second expert was chosen from the corporate level of a healthcare facility. He works with the coordination between different healthcare systems and within each system. He also works with planning teams in order to improve the performances of different healthcare systems on the long-term range. This choice will provide a feedback from a person

within the decision making team and will give a strong validation to this model from a person with experience in many healthcare systems. The third expert was chosen form the operational level of a regional medical center. She deals on a daily and weekly basis with different performance measures of healthcare systems. Moreover, she works on the improvements of healthcare system function on the short-term range. This selection will provide a feedback from an experienced person in all the practical issues that face different healthcare systems.

Before meeting with the subject matter experts, several important point were developed to be discussed with these experts to validate the methodology, the simulation model, and the results of the developed alternative solutions. These points are:

- The methodology used to develop the simulation from previously solved cases in the healthcare field.
- The logic that was followed in the model for all different types of entities.
- How close the different states of the real system are represented in the simulation model.
- The progress of the simulation model over the simulation run time.
- The results of the simulation model for the current situation and the developed solutions and how they are related to the set of the input parameters used for each time.
- The behavior of the simulation model under extreme conditions and whether it is performing as it should be or not.

From the discussion of these point with subject matter experts, the simulation model that was develop using the CBR methodology will be verified and validated (Nayani & Mollaghasemi, 1998).

Separate meetings were scheduled with those subject matter experts to perform the face validity. In the meeting with the first expert, the discussion started by explaining the main points of this research. After that, the case study was shown with all the data. Then, the developed simulation model was described in SIMIO. He focused during the meeting on the details of creating the simulation model from the retrieved cases and the analysis process. He also recommended the use of the experiment and expressed how the use of averages and confidence intervals reflects more information about the system. Finally, he checked the results of the simulation model for the current situation and compared the results with the developed alternatives.

The discussion with the second expert started by describing the conceptual steps of this study. He discussed the CBR methodology and how it would work in the healthcare field. After that, the discussion moved to the case study. Then, the explanation went to SIMIO and the simulation model was shown with all details. The expert focused on the paths of different patients with different triage levels. He focused on patients coded with the first and second triage levels since they have the most critical conditions. Finally, the expert discussed the results of the simulation model at the current situation and with the developed alternatives. His response started by saying that the logic used to develop the simulation model from the previously solved cases is true in healthcare. He also commented about how the simulation model would deal with all special cases that might arrive to the ED. Moreover, he observed that the service times of the ED used in this case study are more efficient that the current service times in the central Florida EDs. The discussion with the third expert started by giving a quick overview about this study. After that, the discussion moved directly to the case study. The expert asked several questions about how

the ED in the case study works and how it would handle some of the special cases that every ED might receive. Then, the conversation shifted to SIMIO where the simulation model was explained in details. The expert focused on how each station in the model works and how they can handle different types of patients. After that, the expert asked about the results of simulating the current situation and how the analysis will be done. Finally, she asked about how the alternatives were developed and how they should be implemented. Her feedback started by conforming that the main problem in the case study is very common to be found in most EDs even in central Florida. She gave some few modifications that could be used to use this simulation model to simulate any ED in central Florida.

After meeting with the subject matter experts, they all validated the simulation model and gave some notes and recommendations so that this simulation model could be valid to represent the EDs a respective hospital in central Florida. Moreover, they all agreed on the point that the developed alternatives give better results but they might not be implemented completely due to increased costs. However, they emphasized about the importance of studying any ED under the worst-case scenario and how this ED would work in the case of extreme conditions.

CHAPTER 6 CONCLUSIONS AND FUTURE RESEARCH DIRECTIONS

6.1 Conclusions

The use of industrial engineering tools in solving problems and enhancing performance in the industrial and service sectors is not new. However, it has greatly increased in the last decade as managers and executives in these sectors, including healthcare, are trying to maintain and improve the level and quality of services while minimizing the increase in costs. They are hoping to imitate the successful use of engineering tools from other sectors like manufacturing and aerospace. The simulation technique is one tool that has had a huge effect in these sectors, and it is now considered one of the essential parts in any project or plan.

This research tries to improve and facilitate the use of simulation in the healthcare sector. It includes the use of case based reasoning, utilizing old solutions and case studies in finding new efficient and effective solutions for any new problems that arise. CBR focuses on increasing stakeholders' involvement during the process of analyzing the current problem and creating the proposed solution. This involvement will simplify many difficulties that may face the modeling team during analysis and save a considerable amount of time when developing the new solutions. Furthermore, the use of CBR in finding the solution will aid the modeling team by giving them a group of similar problems that were solved using simulation.

The implementation of the CBR methodology in this research focused on emergency departments. These departments are considered one of the most important parts of the healthcare system. They have also faced difficulties in the last few years, such as limited resources and increased number of visits each year. This study, when dealing with ED problems, concentrated on the discrete event simulation as the simulation technique to find solutions and improve performance. This choice comes from the wide range of healthcare problems that utilized DES in finding solutions, comparing alternatives, and others.

The first step in the CBR methodology is constructing the case-base. In this step, the search process started to look for solved simulation cases from simulation institutions or organizations. However, the healthcare simulation cases are not common like manufacturing cases. Furthermore, there are no published databases for such cases as exist for other sectors. Therefore, a new case-base was developed in this study. In the development phase of this case-base, several simulations from different EDs were collected. Moreover, these cases have different objectives, layouts, patients' paths, types of resources, and number of resources. These simulation cases were developed and built by different simulation programming teams.

After developing the case-base, an indexing system was created to store these cases in the case-base. This system defined a set of attributes for each simulation case. This set included numerical and non-numerical attributes to describe all the important features in the stored cases. After that, two retrieval approaches were defined as retrieval engines. These approaches are K nearest neighbors and induction tree. In the K nearest neighbor approach, similarity function (Euclidian

Distance) will be used to find the similarity percentages between the new case and stored cases and then retrieve K cases with the highest percentages. In the induction tree approach, a decision tree will be developed to represent all the stored cases in the case-base along with their attributes. Then, the approach will traverse through the tree by inducting the attributes one by one starting with the most important. After that, retrieving all the cases that are connected to the leaf node in the tree. A java code was developed to perform this retrieval step using these two approaches to minimize the retrieval time and to avoid making mistakes especially when dealing with big case-bases.

In the final part of the study, a case study from the literature was chosen to validate the use CBR in this research. The CBR methodology proposed a set of alternatives with different associated costs of implementations that could be used to improve the performance of the system. This implementation of the CBR shows that it could be applied easily in any organization by building the case-base from the historical data and stored cases of the organization and then utilizing this case-base to solve a new problem. This implementation insures an efficient, effective, and reliable way of utilizing previous cases to solve new ones. After finding the solution to the case study, the verification and validation processes started. The verification process was done using a structured walk through to insure that the simulation model represents the real system in the case study. Several validation techniques were used to validate the simulation model and the results. These techniques are animation, event validity, traces, and face validity. To perform the face validity, a group of healthcare experts were contacted. After that, meetings were scheduled with those experts and the case study with the simulation model was explained to the experts. Then,

the process of developing the alternative solutions was discussed with the results. Finally, all the experts validated the simulation model and the developed alternative solutions.

6.2 Contribution of this Research

The main contribution of this research is the use of CBR in simulation modeling in the healthcare area. This use of CBR along with the simulation tool in the healthcare field was not done before and it will help in improving the utilization of simulation in the healthcare sector by simplifying the modeling process. This utilization will give more people, which have little knowledge about simulation, the ability to use this great tool in finding solutions to healthcare problems. Furthermore, It will demonstrate the efficiency and effectiveness of the simulation modeling to decision makers and this would increase the acceptance of simulation solutions and recommendations among managers and executives.

6.3 Future Research Directions

This study could be considered as a decent move towards facilitating the simulation modeling in healthcare. It is also considered as a preliminary effort in finding a way to reduce the gap between simulation modeling in healthcare and its application in other sectors. More effort should be directed towards improving the simulation application in this context and enhancing the position of simulation in the healthcare decision making process. There are several areas that need more research to expand this research and make it more applicable to many fields within

the healthcare sector. However, there are some limitations that could be found when implementing this study on a large-scale or within huge organizations.

One of the future research directions that could be followed is regarding the indexing system used to described stored cases in the case-base. It includes two non-numerical attributes and four numerical attributes. These attributes are good enough to express all the important features of the cases in the case-base. However, there are other attributes that were not needed in this case-base but they will be needed, as this case-base gets larger. Most of these attributes are non-numerical such as the starting date of the case along with the duration, the simulation program used to solve the problem, the location of the problem in the organization (a hospital for example), and the name of the team leader that developed the solution. On the other hand, there are other numerical attributes that could be added to the indexing system to describe the costs related to these solutions such as the total cost of implementing the developed solution.

One of the most important research directions to improve this study would be in the area of case retrieval approaches. The used approaches in this study served the purpose, but as the case-base gets larger there will be a need to have other more efficient ways to retrieve the similar cases. Thus, new retrieval approaches might be developed using other techniques like fuzzy logic or any other data mining techniques such as neural networks. Moreover, in some situations there could be a need to use multilevel retrieval steps or combine more than one retrieval approach to get the best retrieval results. Another way to solve this complication is by using the Web Ontology Language (OWL) or, simply, ontology. This language will facilitate the storing of

cases in the case-base and will simplify the retrieval process. This process of using ontology starts by converting all solutions of cases into a general language from any program. After that, cases would be given indices and stored in the case-base. This would simplify the retrieval process and the addition of new cases, especially when dealing with huge case-bases. However, more research should be done in this area since the available literature has little information about how to use ontology with healthcare simulation applications.

The use of the CBR in simulation is different than any other similar technique. This is because in CBR a case-base that contains previously solved cases are developed and then used to find solution for new problems in the same area. This process of find these solutions starts by retrieving similar cases from the case-base and analyzing them to find the suitable solutions and after that these developed solutions are added to the case-base. This makes the CBR works as a learning machine that will have more knowledge and experience as the number of stored cases increases. Moreover, this knowledge in the case-base could be extended to cover more than area and using several tools. However, some other used techniques with simulation might give similar ideas to develop solutions for the new problems but they do not have the same capabilities and features like the CBR. For example, the simulation templates might give a predesigned template that could be used by people with little knowledge about simulation. However, this technique does not offer completely solved cases like the CBR. Moreover, these templates are not going to be updated after solving new case like the case-base in the CBR. Thus, this technique will be acquiring more knowledge each time a new case is solved. Another example is the use of simulation parsers. In this technique, a set of predefined information is given to the software and

it gives an output that could be used to develop solutions. The first point when comparing this with CBR is that it is not easy to work or develop. Moreover, it will not be developed after any new case is solved. Finally, it cannot cover more than one area with using more than one tool at the same time like the CBR. This shows that CBR would give more information and analysis in the form solved cases than any similar technique such as templates and parsers. Thus, CBR is an excellent methodology that could work in the best possible way when used in simulation modeling.

One of these limitation is that this study was implemented on a small set of ED cases due to the difficulty of finding solved cases and the time frame of the research. Moreover, all of the cases in the case-base developed for this study focused on cases that used DES only to solve the problem. This choice served the purpose of the implementation. However, this might not be the case when solving more complicated problems since many cases in the literature use more than one OR tool with simulation and sometimes more than one simulation technique. Thus, when the case-base includes complicated and sophisticated cases, cases that use several OR tools are to be expected. Thus, this study could be improved by creating case-bases that focus on solving problems in any given area using all tools. For example, adding all cases that deal with ED problems using all simulation techniques could expand the current developed case-base in this research. Moreover, cases that use simulation and other tools to provide solutions to ED problems could be also added. This would create a comprehensive case-base that could be used to solve any ED problem and with more than one tool or technique if possible. Another direction would be to create case-bases that could be used to solve problems in several areas. The most common example is a hospital. A typical hospital might include at least five departments like ED, ICU, Surgery rooms,

inpatients' clinics, and outpatients' clinics. Thus, to have a complete case-base to solve problems in this hospital, cases from all these departments would need to be added to the case-base. This would create a case-base that is huge and contains many cases that uses many tools and techniques.

Another limitation in this study is that one simulation program was used to simulate all cases. This situation might be preferable when dealing with a small number of cases and a small variety of problems. However, as the case-base gets larger and more varied, use of one simulation problem may not be feasible or applicable. This gives a clear direction for enhancing this study by adding solved cases by any simulation program. This will enrich the develop case-base and it will give more opportunities to modelers to find more than one program in the retrieved cases and this will give better chances in working with their preferred programs.

APPENDIX ED DEVELOPED CASES AND GROUPS' SOLUTIONS

<u>Case 1</u>

This emergency department (ED) works 24/7 to provide services for people. The arrival rates of patients to this ED are different during weekdays. When patients enter the ED, they pick a number and wait for the triage nurse to be available. At the triage, the nurse uses emergency severity index list to assess the patient status and give it a code number (from 1 to 5). Patients with code 1 (critical condition) go directly to the intensive care unit (ICU) and leave the ED. Other codes patients proceed to registration and wait for an available nurse to get their information. Then, they wait for a free physician to do the assessment. After that, several patients will need to have lab tests and then wait for another assessment by the physician before leaving the ED (either discharged or admitted to the hospital).

<u>Questions</u>

1- Develop a simulation model in SIMIO for this ED.
2- Improve the productivity of this system taking into consideration costs associated with adding new resources.

Data

Resources	Number		Probabilities	%
Examination rooms	5		Code 1 patients	2
Triage nurses	1		Code 2 patients	6
Registration nurses	1		Code 3 patients	18
Physicians	3		Code 4 patients	54
			Code 5 patients	20
			Patients that need lab tests	23
Service times in minutes				
Triage	Registration	1st Assessment	Lab tests	2nd Assessment
Poisson (6)	Triangular (3,5,7)	Triangular (25,30,40)	Triangular (30,45,60)	Triangular (8,10,12)
Patients Interarrival times in minutes				
Monday	Tuesday	Wednesday	Thursday	Friday
Exponential (7)	Exponential (9.5)	Exponential (10)	Exponential (10)	Exponential (10)

Group's Solution

Team A+ (Team 14)

Project Final Report

ED Case #1

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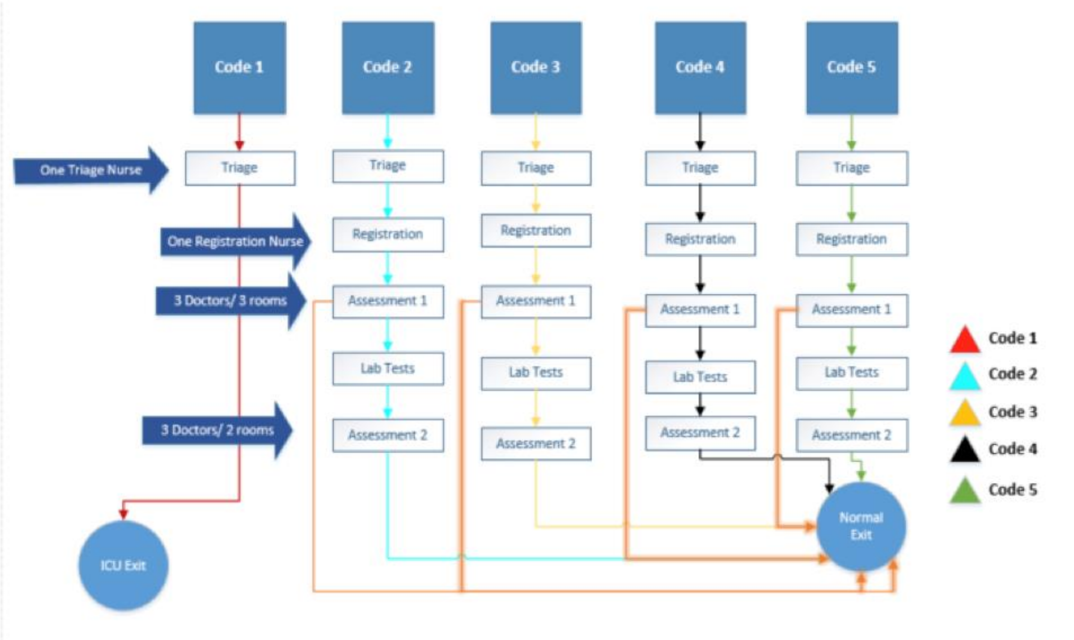


Figure 6-1: Overall Model Logic Flow Diagram

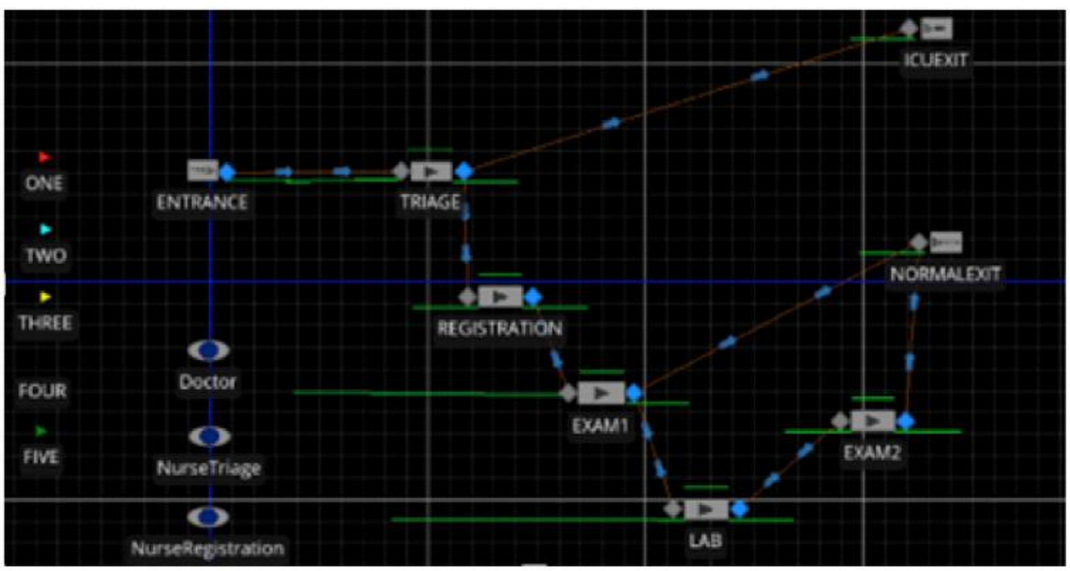


Figure 6-4: Simulation model at SIMIO software

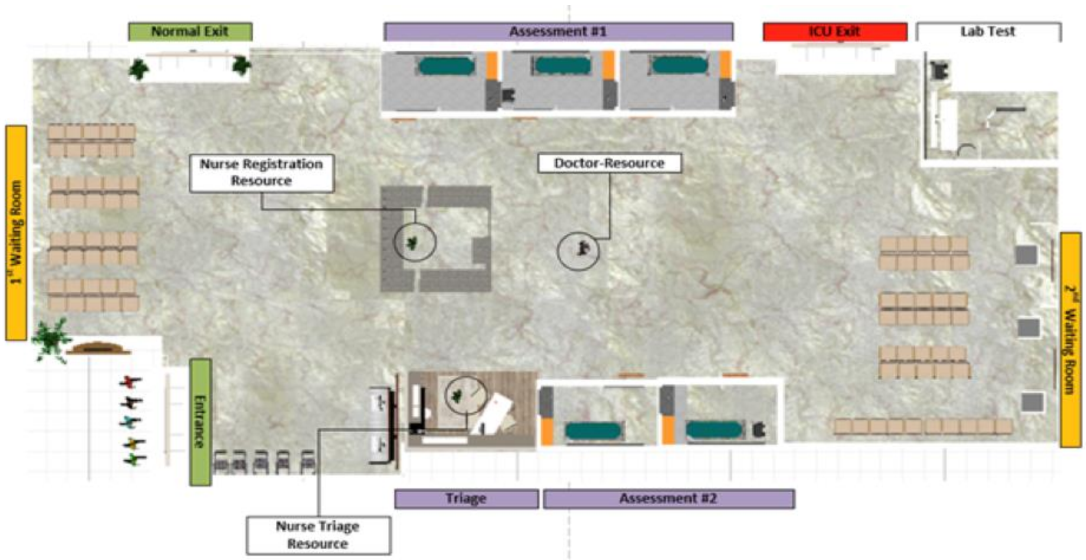


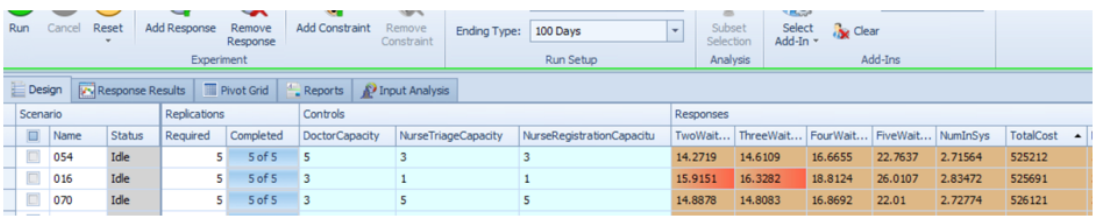
Figure 6-11: 2D Layout of the Emergency Department

Figure 6-12: 3D Layout of the Emergency Department

7. Results & Recommendations

7.1 Original Model

In Case#1, the hospital was originally running with 3 Doctors, 1 Triage Nurse, and 1 Registered Nurse. One of the clients' requirements was to reduce the total cost of the hospital. We knew that we can achieve this goal by optimizing the staff in order to reduce cost. The original data that was given showed no specifications how much the staff were being paid. In order to create a realistic scenario of the payments, we used SIMIO as a reference. By using this reference, we decided that realistic payments were as follows; $15,000 per month for Doctors, $4000 per month for Triage Nurses, and $6000 per month for Registered Nurses. There was also a penalty cost of $250 for every additional minute that a patient waited before seeing a Doctor. In order to create an accurate baseline model we ran the hospital for 100 days with a 50 day warm up period. Doing this, would allow our simulation model to achieve steady state. Once the simulation was completed, the total cost was $525,691 as shown in Figure 7-1 and the wait times experienced by both Code two and Code three were unacceptable for an emergency department (highlighted below in red).



Scenario			Replications		Controls			Responses					
	Name	Status	Required	Completed	DoctorCapacity	NurseTriageCapacity	NurseRegistrationCapacitu	TwoWait...	ThreeWait...	FourWait...	FiveWait...	NumInSys	TotalCost
	054	Idle	5	5 of 5	5	3	3	14.2719	14.6109	16.6655	22.7637	2.71564	525212
	016	Idle	5	5 of 5	3	1	1	15.9151	16.3282	18.8124	26.0107	2.83472	525691
	070	Idle	5	5 of 5	3	5	5	14.8878	14.8083	16.8692	22.01	2.72774	526121

Figure 7-1: Representation of Total Cost and Waiting Times

7.2 Optimizing the Model

In order to minimize the total cost and the wait times for codes two and three, we decided to create an Optimization with OptiQuest. Our main objective when creating the optimization is to minimize cost. Our second objective was to utilize the minimum amount of staff that was needed. Our constraints were based on the amount of time it took for a patient to enter till the patient was attended by a Doctor. Every code had a strict time constraint that had to be reached in order to be considered as a possible solution. Since, we are dealing with an emergency room where time is of the essence and every minute that passes increases the likelihood of complications for the patients. Thus, time constraints are of the utmost importance and therefore minimized as much as possible. The time constraints can be seen by the table below.

<u>Time Constraints for Codes 2-5</u>

- Code 2 < 15min
- Code 3 < 15min
- Code 4 < 25min
- Code 5 < 30min

**Please note that code 1's does not have to wait and are immediately sent to Intensive Care Unit*

7.3 Results of Optimized Model

After running hundreds of different simulations scenarios, we were able to come up with an optimal number of Doctors and Nurses. The ideal number of staff for our emergency department was as follows; 4 Doctors, 3 Triage Nurses, and 2 Registered Nurses. As one can see from the Figure 7-2, that if we ran the hospital for 100 days with a 50 day warm up period. The optimal total cost will be $489,469.

Design | Response Results | Pivot Grid | Reports | Input Analysis

Scenario			Replications		Controls			Responses					
	Name	Status	Required	Completed	DoctorCapacity	NurseTriageCapacity	NurseRegistrationCapacitu	TwoWait...	ThreeWait...	FourWait...	FiveWait...	NumInSys	TotalCost
☑	058	Compl...	5	5 of 5	4	3	2	14.3602	14.4296	16.1507	21.3906	2.70963	489469
☐	023	Compl...	5	5 of 5	4	2	4	14.1711	14.3274	16.1814	20.2778	2.68639	495505
☐	044	Compl...	5	5 of 5	4	4	2	14.3073	14.4442	16.5164	21.74	2.68915	496708

Figure 7-2: Representation of Optimal Total Cost

Comparing the original model to the optimized model would create $36,222 in saving in just 100 days. This would lead to 6.89% decrease in total cost of the hospital every 100 days. Most importantly we were able to decrease wait times significantly ranging from our low end of 9.8% to an astonishing 17.8% which can be seen from our table below. By saving this time will lead to countless lives being saved which cannot be calculated.

Cost/Time (min)	Before Optimization	After Optimization	Change	Percent
Cost	$525,691	$489,469	$36,222	6.89%
Average Time Code 2	15.9151	14.3602	1.5549	9.769967 %
Average Time Code 3	16.3282	14.4296	1.8986	11.62774 %
Average Time Code 4	18.8124	16.1507	2.6617	14.14865 %
Average Time Code 5	26.0107	21.3906	4.6201	17.76231 %

Figure 7-3: Representation of Optimization

7.4 Future Recommendations

Another recommendation that can be sought after for the client is the use of different kinds of staff members. For example, using a certified practitioner will be much cheaper to use than a Doctor. With the majority of the patients being code 4 and code 5 meaning that these patients are not that severe and may not need a Doctor for the 1st assessment. This will free up Doctors to focus on Code 2 and Code 3 which are in vital need of care. Doing this will decrease the total cost significantly and would also increase throughput of patients. Therefore, being cost effective and also reducing the total time in the system for the patients.

To eliminate bottlenecks in the system the client should invest in different types of lab equipment that can reduce test times shown in the figure below. As we can see that lab test takes on average 51.1 minutes and thus slows down our whole system significantly.

Case 2

This emergency department is a part of a mid-sized hospital. It is divided into three main sections. These sections are:

- Section A: this section is for severe patients and has six nurses and 21 beds.
- Section B: this section is for seriously injured patients and has four nurses and 11 beds.
- Section C: this section is for wounded patients and has two nurses and eight beds.

Patients enter this ED using one of three possible ways: walk-in, ambulance, or helicopter. These patients have different arrival rates. Ambulance and helicopter patients will be directed to section A without passing through the triage process. Walk-in patients will go to the triage area where a nurse will assess their sickness level and then send them to either section A, B, or C.

The treatment process is the same in all three sections, and three medical doctors are shared between them. It starts with a bedside registration and an initial assessment done by a nurse. Then, a medical doctor will perform the medical evaluation. Some patients will need more tests (such as blood tests, X-rays, MRI scans, CAT scans, and others) and will be sent to the labs area. Patients that do not need extra tests will have a final assessment done by a nurse and then leave the ED (either discharged or admitted to the hospital). After the extra tests, patients will see a medical doctor for a follow-up treatment and then a nurse will do the final assessment before leaving the ED.

Questions

1- Develop a simulation model in SIMIO for this ED.
2- Improve the productivity of this system taking into consideration costs associated with adding new resources.

Data

Patients arrival rates	Patients per week	Distribution in minutes
Walk-in	723	Poisson (13.49)
Ambulance	5	Poisson (288)
Helicopter	1	Poisson (10080)

Resources		
Station	**Beds**	**Nurses**
Section A	21	6
Section B	11	4
Section C	8	2

Probabilities	%
Section A patients	20
Section B patients	30
Section C patients	50
Patients that need more tests	12

Service Times in minutes

Triage	Lab tests	Registration		
		Section A	Section B	Section C
Triangular (20,23,25)	Triangular (94,156,194)	Triangular (15,20,25)	Triangular (15,20,25)	Triangular (15,20,25)

Initial nurse assessment			Medical evaluation		
Section A	Section B	Section C	Section A	Section B	Section C
Triangular (7,12,15)	Triangular (7,12,15)	Triangular (7,12,15)	Triangular (15,25,40)	Triangular (8,15,30)	Triangular (5,15,25)

Follow-up treatment			Final nurse assessment		
Section A	Section B	Section C	Section A	Section B	Section C
Triangular (25,60,150)	Triangular (25,45,60)	Triangular (15,20,45)	Triangular (30,50,120)	Triangular (30,50,90)	Triangular (15,30,60)

Group's Solution

WE ♥

SIMULATION

TEAM 9

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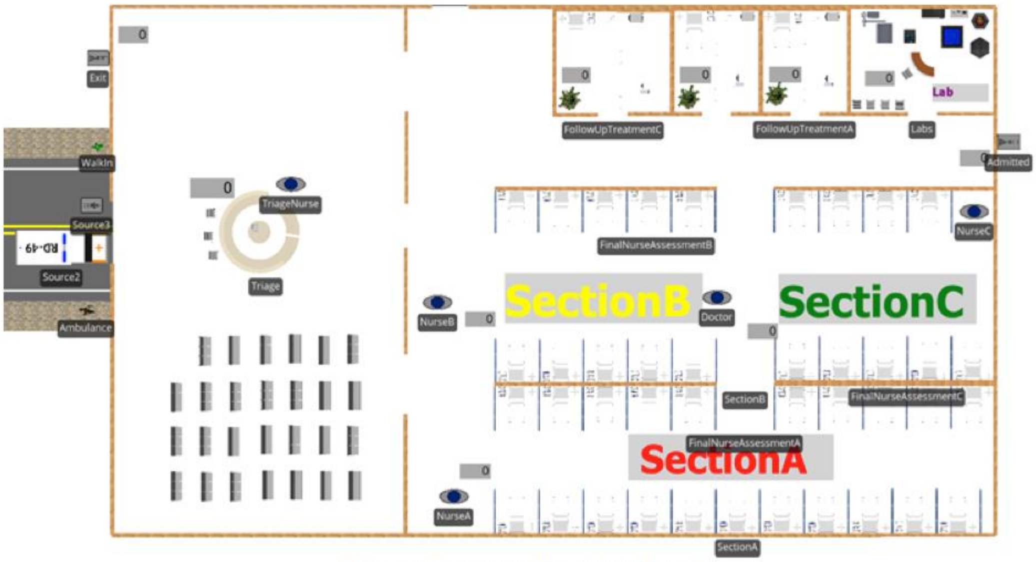

Figure 1: Emergency Department Layout

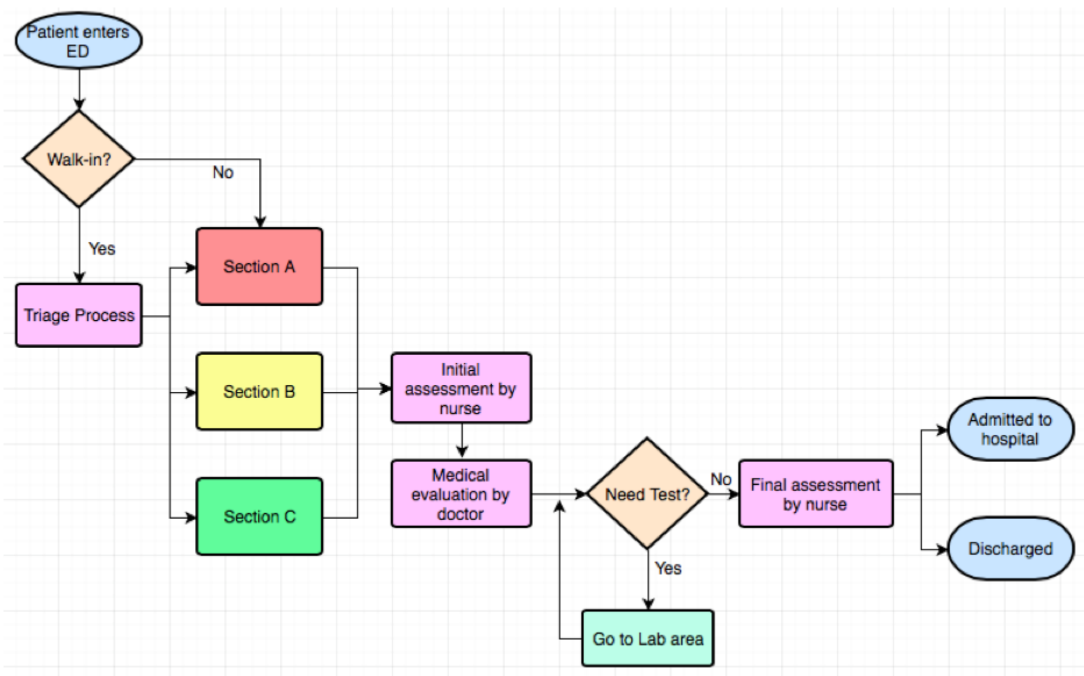

Figure 2: Emergency Department Flow Chart

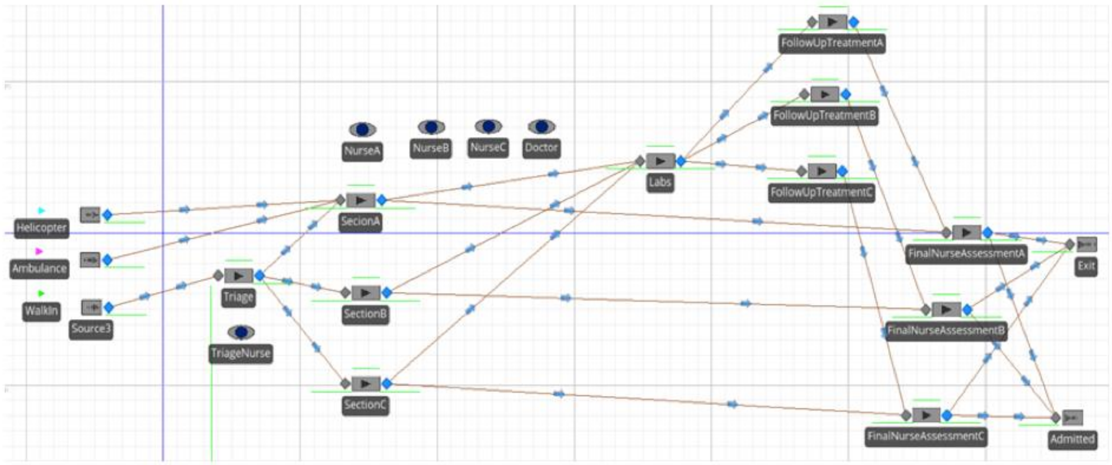

Figure 5: ED Complete Model

4.2 Results:

When we completed our model, we wanted to validate our results based on the data given by our client. To do so, we created a new experiment with a run length of one week, 25 repetitions, and 5 hours of warm-up.

Improved Scenario			
Total Arrivals			
	Average Total per week	Average Total per day processed	Given Arrival Data Per Week
Ambulance	32	4.57	5
Helicopter	1	<1	1
Walk Ins	2266	323.7	334

Table 1: Total Number of Arrivals

We obtained results for processing time per area, time in-queue waiting, nurse utilization, and weekly arrival rates from the helicopter, ambulance and walk-ins. After running the simulation for a week, the walk in number exceeded the helicopter and ambulance arrival rate. Out of three sources, walk-in arrivals were the highest with 2277 arrivals weekly. Below Table 2 represents arrivals per week. The medium size emergency department can only service 430 of those patients, averaging a 19% of patients serviced. The high amount of patients arriving per week and the inability to service them demonstrated a bottleneck in the registration/triage department. As seen in Table 3, the waiting time in the triage was rather long,

approximately a 10 hour waiting time and a processing time of 23 minutes. Patients on average were waiting 10 hours in the waiting area before being seen by a nurse or a doctor, while the actual triage process (e.g. paperwork, previous health records, billing etc.) was about 23 minutes on average. Since the waiting time was high it meant there were other instabilities in the process. We took a look at the nurse utilization and on average it was not at its optimal. As you can see in table 3, our nurses were not being utilized to their full potential in two of the emergency department sections.

Walk -Ins	2277	Total arrived
	430	Total Seviced
	18.9	Percent Serviced

Table 2. Num. of Walk-in Serviced

Triage	
Total being processed	Wait Time in Triage per day
22.6	9.96
Minutes	Hours

Table 3. Processing and Waiting time Triage

	Section		
Nurse Utilization per week	A	B	C
	18%	28%	70%

Table 4. Average Nurse Utilization. Per Week

Nurses designated for sections A and B, were only being utilized 18% to 20% of the time, respectively. While nurses in Section C were being utilized at 70% efficiency. Each nurse section had a set amount of beds. These beds were used for initial nurse assessment, medical evaluation, follow up treatment, and final nurse assessment. In Table 5, the number of beds for the original model in section A, B and C were 21, 18, and 11 respectively. This clarified that Section C nurses were being over worked and had the least amount of beds to attend patients in. The table also shows one triage nurse attending the incoming patients.

	Triage Capacity	1
	Triage Nurse Capacity	1
Section A	Registration	11 beds
	Initial Nurse Assessment	
	Medical Evaluation	
	Follow Up Treatment	1
	Final Nurse Assessment	10 beds
Section B	Registration	6 beds
	Initial Nurse Assessment	
	Medical Evaluation	
	Follow Up Treatment	1
	Final Nurse Assessment	5 beds
Section C	Registration	4 beds
	Initial Nurse Assessment	
	Medical Evaluation	
	Follow Up Treatment	1
	Final Nurse Assessment	4 beds

Table 5. Number of beds Model 1

4.1 Improved Model:

By having finished our model design using Simio and compute the relevant experiments for further analysis, we came to the conclusion that changes could be made to the original ED to make it more efficient. We found out that the beds and nurses from Section A were not fully utilized, and that Section C is in constant problems by trying to fit all those patients in such a small area. We believed that if we rearrange the numbers of beds and nurses from section A and C, we might improve the patient waiting time and throughput. We run a new experiment by moving three beds from section A to section C and also nurses between sections A, B, and C. Our results were slightly better than our first experiment, but this time we found out each section was being starved from the beginning of our simulation. This means that not enough people were going to the rooms. Our last chance to our models was to increase the number of triage nurses from one to three and the capacity of the triage from one to three as well. This allowed to process more walk-ins and obviously increasing the number of patients being treated. The average waiting time didn't increase significantly. We came to the conclusion that this setup could be a great solution for our ED and a deeper explanation will be covered in our conclusions section.

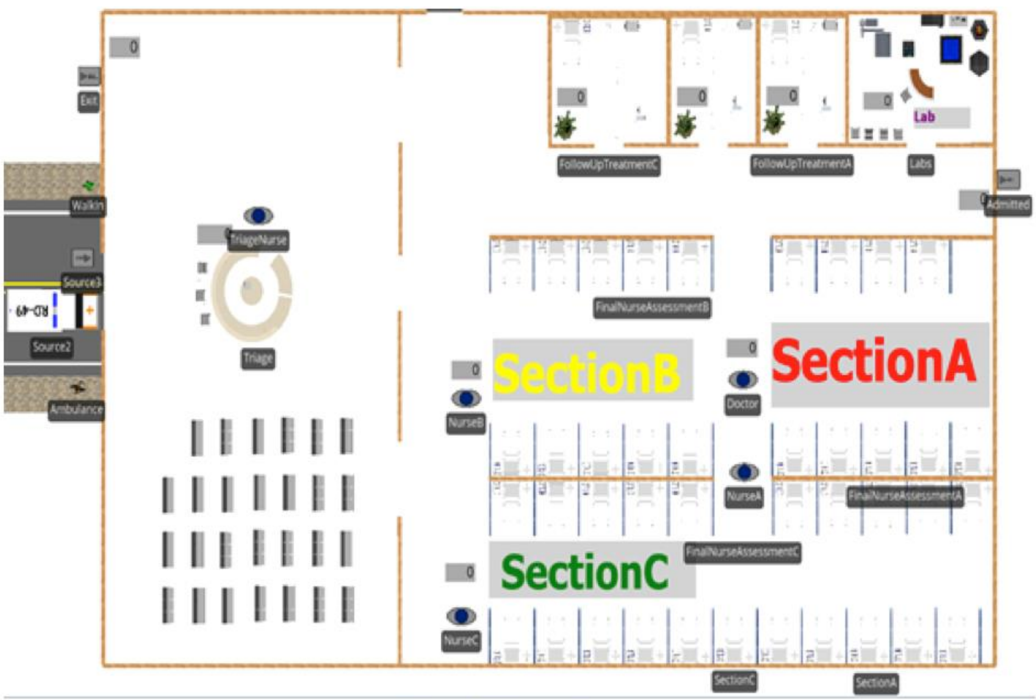

Figure 7: ED New Layout.

Conclusion:

After making the changes to the original model, we ran the improved model and compared the results from the original data to the new data. The triage was a main area of concern, which posed as a bottleneck to our system. Increasing the nurses in the triage to three nurses assisting the walk in patients helped decrease the amount of time the patients actually waited to be seen. Originally the patients waited almost 10 hours in the triage hour with a processing time of around 23 minutes. Once the improved model was run, we were able to essentially cut the waiting time in half for the walk in patients to just over five hours.

Triage		
Simulation Model	Total being processed	Wait Time in Triage per day
Original	22.6 Minutes	9.96 Hours
Improved	22.6 Minutes	5.2 Hours

Table 6: Improved Triage Data

Besides adding two triage nurses for the initial nurse assessment process in the triage, we reallocated the original 12 nurse from their original locations to be better used in other sections. Section A was used for severe/urgent patients which came in by helicopter or ambulance, they had 21 beds and 6 nurses allocated. Since they were urgent patients, logically they needed to have as many beds as possible to assist the patients who were critically injured, these patients cannot be waiting hours like those who were wounded. However in our model we only received 6 patients a week which were from ambulance and helicopter. The majority of our patients were coming from walk-ins, out of the 334 daily walk in patients 50% go to Section C and only 20% of those are for Section A. This kept both the beds and nurses severely underutilized in Section A. In order to utilize the beds and nurses to their fullest potential, we moved one of the beds from the initial medical evaluation, 2 beds from final nurse assessment and two nurses in Section A over to Section C. That increased Section C to a total amount of 11 beds and 4 nurses just by simply rearranging Section A and C. When taking into account the arrangement of Section B, the original model showed the beds were being used efficiently however the nurses were underutilized. So we moved one of the nurses from Section B over to Section C in order to help distribute the workload amount among the nurses. We decided not to move any beds from Section B because this area receives 30% of the total walk-ins and these patients are seriously injured which means they cannot be waiting for an extended period of time. This change left Section B with their original 11 beds but decreased the nurses from a total of 4 to 3 nurses. Section C now has a total of 11 beds and 5 nurses to assist with the 50% amount of walk-ins it receives. The following bed allocation is represented below showing the initial medical assessment and final nurse assessment bed allocations.

	Triage Capacity	3
	Triage Nurse Capacity	3
Section A	Registration	10 beds
	Initial Nurse Assessment	
	Medical Evaluation	
	Follow Up Treatment	1
	Final Nurse Assessment	8 beds
Section B	Registration	6 beds
	Initial Nurse Assessment	
	Medical Evaluation	
	Follow Up Treatment	1
	Final Nurse Assessment	5 beds
Section C	Registration	6 beds
	Initial Nurse Assessment	
	Medical Evaluation	
	Follow Up Treatment	1
	Final Nurse Assessment	5 beds

Table 7: New Model Beds and Triage Capacity

This reallocation of resources and beds was able to significantly increase the utilization of the nurses in each section. The six nurses from Section A originally were only being used 18% of the time which meant they were not working more than 80% of the time. With the decrease in nurses from six to four they were being utilized 85% of the time, which means a 67% increase in utilization. Section B similarly had a 54% increase in utilization and Section C had an 11% increase with simple changes to nurse and bed allocations. Below you can see the changes in utilization of the nurses from each Section by allocation different nurses to other areas.

	Section		
	A	B	C
Nurse Utilization per week: Original	18%	28%	70%
Number of Nurses Per Section	6	4	2
Nurse Utilization per week: Imrpoved	85%	82%	81%
Number of Nurses Per Section	4	3	5

Table 8: New model Nurse Utilization

Making simple changes to include additional triage nurses, reallocation of nurses and beds we were able to improve on the total amount of patients served. In terms of Ambulances and helicopter arrival we were able to assist all of those patients, again they only account for 6 of the weekly arrivals. The remaining 2000 or more patients weekly were walk in patients. We were able to increase the total serviced per week from 430 patients to 1203 patients per week. That was an improvement from 19% of the total walk in patients assisted to 53% assisted as shown in the table below.

Walk -Ins	Total arrived	Total Seviced	Percent Serviced
Original	2277	430	18.9
Improved	2266	1203	53.1

These changes show that with simple reallocation of nurse resources, reallocation of beds and only two additional triage nurses were able to assist more than 750 more patients a week in our emergency room department. We did further experiments in order to increase throughput even more by decreasing the processing time from about 23 minutes to only 10 minutes. We were able to process all the patients through the triage, however they were now waiting in queue after the initial nurse assessment to get a bed. In an actual hospital the patients would be essentially still be waiting in the triage. In fact decreasing the processing time of the triage but not increasing any of the bed capacities had the patients waiting for the same estimated amount of total time, which was approximately 5 hours. We believe, based on our simulation model experiment analysis, in order to be able to process all 2000 or more patients which arrive weekly to the emergency department as walk-ins, the emergency room would need to expand in bed, nurse and doctor capacity. However for the least amount of changes and least amount of cost simple reallocation and an additional 2 nurses in triage can significantly increase the total amount of throughput and productivity the ER department can withstand. This improved model shows how the productivity level of the Emergency Department can increase with as minimal costs as possible.

Case 3

This emergency department (ED) is a part of a regional hospital, and it has 23 patient-care beds. It is open 24 hours a day and works by three shifts. This ED is divided into five sections. Section 1 with a capacity of 12 beds, Section 2 with two beds, Section 3 with two beds, Section 4 with three beds, and Section 5 with four beds.

Patients arrive at this ED in two ways walk-in and ambulance. Walk-in patients go to the registration area, while ambulance patients go to the examination area and skip registration. In the examination area, all patients are assessed by a doctor and a nurse and then directed based on the acuity level to the proper section. Critical patients are sent to Section 1. Patients who had major injuries or accidents are placed in Section 2. Patients with infectious diseases are sent to Section 3. Finally, noncritical patients who have a stomachache, headache, or any other minor injuries are sent to Sections 4 and 5.

At each section, a doctor will treat every patient, and a nurse will be there for assistance. Some patients would need some extra tests such as blood tests and X-rays and then follow-up with a doctor and a nurse. After that, patients will be ready to leave the ED (either discharged or admitted to the hospital).

Questions

1- Develop a simulation model in SIMIO for this ED.

2- Improve the productivity of this system taking into consideration costs associated with adding new resources.

Data

Probabilities	%
Walk-in arrival	93
Ambulance arrival	7
Section 1 Patients	0.533
Section 2 Patients	0.005
Section 3 Patients	0.038
Section 4 Patients	0.25
Section 5 Patients	0.174

Resources	Beds	Nurses	Doctors	Receptionists
Section 1	12			
Section 2	2			
Section 3	2			
Section 4	3			
Section 5	4			
Morning shift		4	3	2
Evening shift		5	5	2
Afternoon shift		3	2	1

Service times in minutes						
Registration	**Examination**	**Section 1**	**Section 2**	**Section 3**	**Section 4**	**Section 5**
Triangular (3,5,7)	Triangular (5,10,15)	Weibull (1.285,51.345)	Exponential (0.02924)	Exponential (0.03733)	Exponential (0.0202)	Exponential (0.02001)

Patients arrival rates (patients/hour)				
Time	**Rate**		**Time**	**Rate**
12 am- 1 am	5.39		12 pm- 1 pm	9.08
1 am – 2 am	3.03		1 pm – 2 pm	8.55
2 am – 3 am	2.87		2 pm – 3 pm	7.82
3 am – 4 am	2.64		3 pm – 4 pm	7.37
4 am – 5 am	2.22		4 pm – 5 pm	8.23
5 am – 6 am	2.65		5 pm – 6 pm	7.92
6 am – 7 am	3.11		6 pm – 7 pm	8.16
7 am – 8 am	3.49		7 pm – 8 pm	9.63
8 am – 9 am	4.62		8 pm – 9 pm	10.49
9 am – 10 am	5.56		9 pm – 10 am	8.03
10 am – 11 am	6.22		10 pm – 11 pm	6.94
11 am – 12 pm	7.89		11 pm – 12 am	5.46

Group's Solution

Emergency Department Case 3

Simulate to Create

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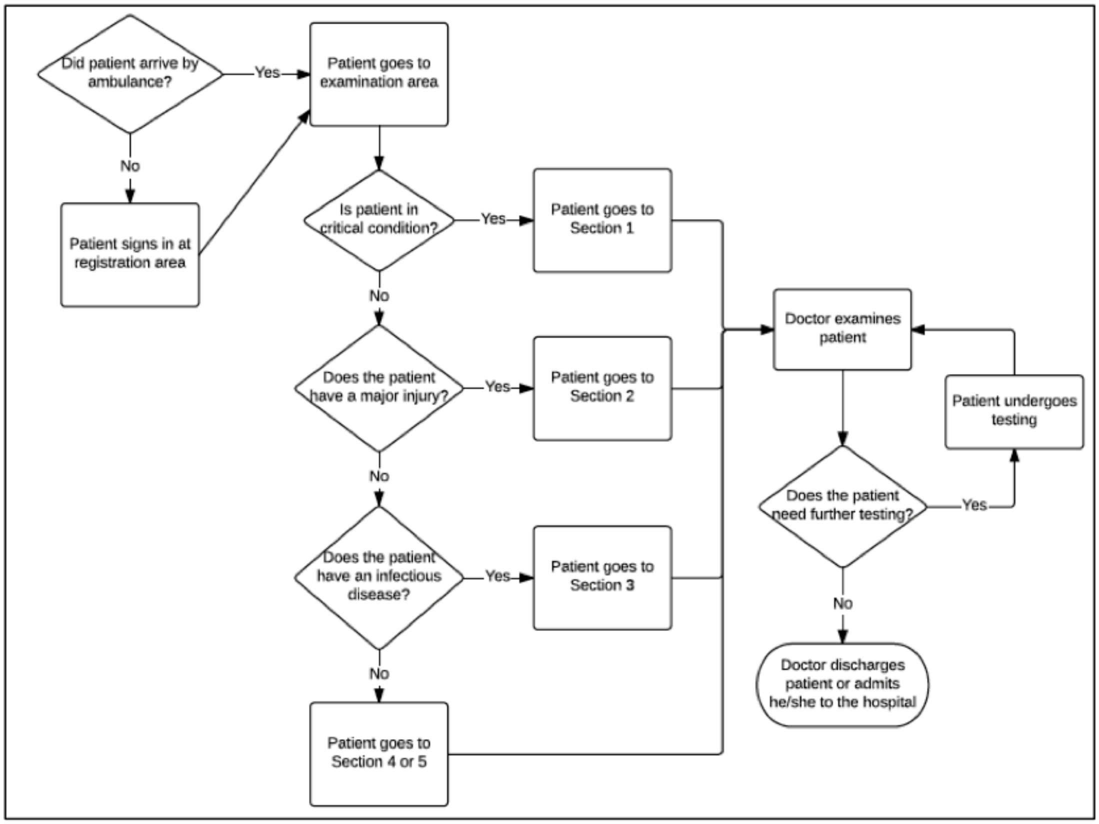

Figure 1: Patient Process Map

Figure 2: Emergency Department Facility Layout

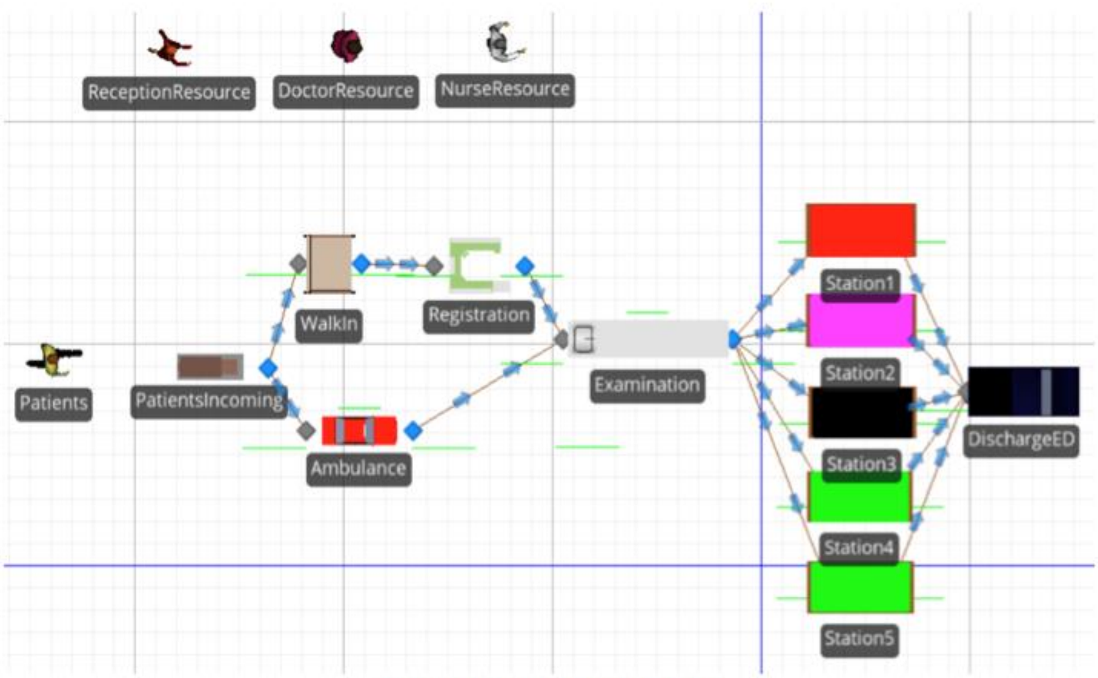

Figure 4: Initial Simio Model

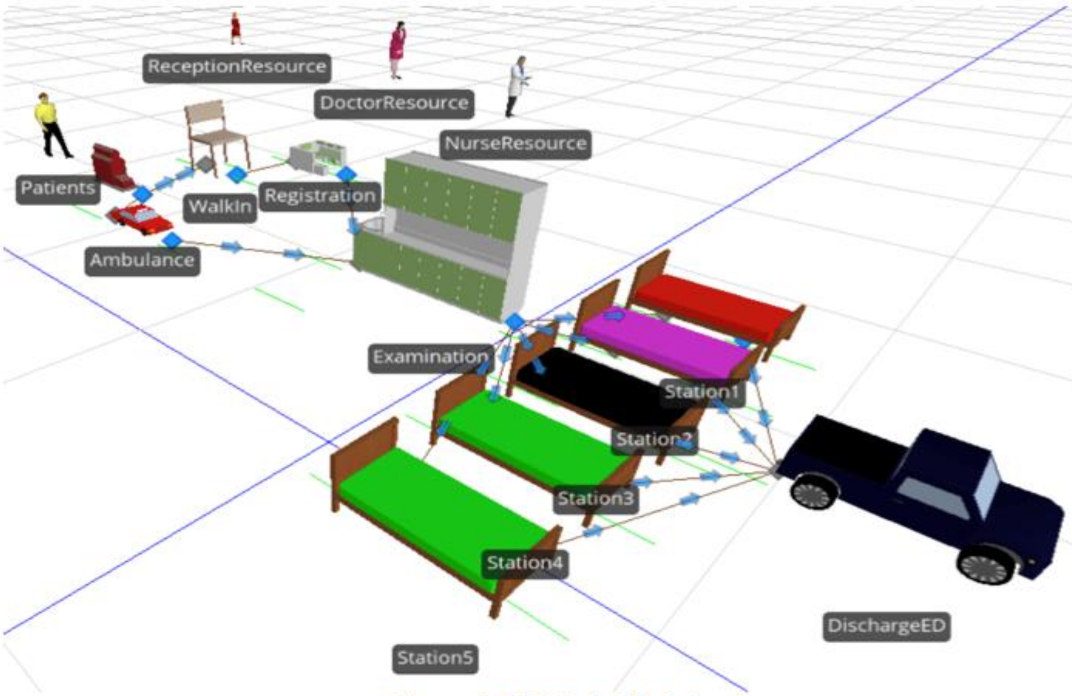

Figure 5: 3D Simio Model

Results and Recommendations

After creating and running our simulation, we are able to extract the data and analyze it to provide results and recommendations to the Emergency Department. After we ran the simulation for the first time, we were given results that would help us understand how the current process worked and ran. What we found out was that the average number of entities in the system was 6.6560 entities while the maximum was 32 entities, shown in Figure 14. The amount of time spent in the system was on average 1.0831 hours while the maximum was 64.4106 hours and the minimum was 0.0988 hours. The total number of entities created was 14,623.96 entities while the total number of entities destroyed was 14,627.04 entities.

NumberInSystem	Average	6.6560	6.4836	6.8574	0.0395
	Maximum	26.8000	24.0000	32.0000	0.8426
TimeInSystem	Average (Ho...	1.0831	1.0648	1.1113	0.0043
	Maximum (Ho...	23.0827	8.7786	64.4106	5.1953
	Minimum (Ho...	0.1212	0.0988	0.1449	0.0049
NumberCreated	Total	14,623.9600	299.0000	868.0000	57.6018
NumberDestroyed	Total	14,627.0400	300.0000	876.0000	57.3925

Responses					
utl1	utl2	utl3	utl4	utl5	UtlEx
21.0818	0.85466	7.59628	38.8228	22.303	29.628

Figure 14: Initial Model Results in Simio

After finding out the data with the given information, we ran it with the intent to have the highest utilization. This returned an average of 7.9702 entities in the system at one time with a maximum of 42 entities in the system at once, shown in Figure 15. The average time spent in the system was 1.2978 hours with a maximum of 34.7366 hours and a minimum of 0.0936 hours. The total number of entities created was 14,613.92 entities while the total number of entities destroyed was 14,618.4 entities.

NumberInSystem	Average	7.9702	7.6124	8.2770	0.0627
	Maximum	36.0400	29.0000	42.0000	1.3972
TimeInSystem	Average (Ho...	1.2978	1.2484	1.3331	0.0086
	Maximum (Ho...	18.5279	8.4776	34.7366	3.0650
	Minimum (Ho...	0.1258	0.0936	0.1582	0.0056
NumberCreated	Total	14,613.9200	400.0000	826.0000	48.6294
NumberDestroyed	Total	14,618.4000	405.0000	846.0000	49.0778

Responses					
utl1	utl2	utl3	utl4	utl5	UtlEx
42.1871	1.76199	14.5366	58.7533	45.2257	29.6...

Figure 15: Highest Utilization Model Results in Simio

We then ended the simulation with running it based off of rearranging the capacity in order to try and make the system more efficient and productive. The average number of entities in the system at once was 6.5398 entities while the maximum was 31 entities, shown in Figure 16. The average amount of time spent in the system was 1.0618 hours with a maximum of 75.1401 hours and minimum of 0.0958 hours. The total number of entities created was 14,655.92 entities while the number of entities destroyed was 14,657.76 entities. All of the information above can be seen in the table below. Table 1 shows the results of all of our experiments in order to make it easier to compare.

NumberInSystem	Average	6.5398	6.3066	6.7192	0.0391
	Maximum	25.9600	23.0000	31.0000	0.8382
TimeInSystem	Average (Ho...	1.0618	1.0403	1.0732	0.0034
	Maximum (Ho...	21.7201	7.4376	75.1401	6.0194
	Minimum (Ho...	0.1170	0.0958	0.1373	0.0054
NumberCreated	Total	14,655.9200	399.0000	976.0000	54.2090
NumberDestroyed	Total	14,657.7600	404.0000	976.0000	54.1388

Responses					
utl1	utl2	utl3	utl4	utl5	UtlEx
23.1209	1.84779	7.4641	23.4639	22.4916	29.6...

Figure 16: Rearranged Capacity Model Results in Simio

	No. Entities in System		Time Spent in System (hr.)			No. Entities		
Type of Simulation	**Avg.**	**Max.**	**Min.**	**Avg.**	**Max.**	**Created**	**Destroyed**	**Difference**
Normal	6.656	32	0.0988	1.0831	64.4106	14623.96	14627.04	-3.08
Highest Utilization	7.9702	42	0.0936	1.2978	34.7366	14613.92	14618.4	-4.48
Rearrange Capacity	6.5398	31	0.0958	1.0618	75.1401	14655.92	14657.76	-1.84

Table 1: Results Table

After running the simulation, we believed it was important to determine how long each station was being utilized, shown in Table 2. Station 1 had a throughput of 7,804.08 entities and was utilized for 6,020.8477 hours, which was 53.19% of the total time. Station 2 had a throughput of 73.76 entities and was utilized for 40.7622 hours, which was 0.36% of the total time. Station 3 had a throughput of 560.48 entities and was utilized for 361.6777 hours, which was 3.20% of the total time. Station 4 had a throughput of 3,646.24 entities and was utilized for 2,772.2363 hours, which was 24.49% of the total time. Station 5 had a throughput of 2,542.48 entities and was utilized for 2,123.2250 hours, which was 18.76% of the total time. All of the information above can be seen in the table below.

Station No.	Time Spent in Station (hr.) Min.	Avg.	Max.	Throughput	Total Time (based off avg. (hr.))	Percentage
1	0.0167	0.7715	8.6526	7804.08	6020.8477	53.19%
2	0.0011	0.5527	3.5795	73.76	40.7672	0.36%
3	0.0008	0.6453	64.104	560.48	361.6777	3.20%
4	0	0.7603	8.3746	3646.24	2772.2363	24.49%
5	0	0.8351	9.9147	2542.48	2123.2250	18.76%

Table 2: Results Table for Each Station

After collecting the data, putting it into tables, and analyzing it, we are able to give recommendations on how to make the hospital's emergency department more productive and efficient. Based off of the data, we recommend that they rearrange the capacity. This is because it has the greatest throughput of 14,655.92 entities. This is important because each simulation was ran for the same time, so if the throughput of one is higher than another, that means that option is more efficient and productive because they are able to put more entities through the system. This approach also resulted in the shortest average amount of time each entity spent in the system which was 1.0618 hours per entity.

If we were to recommend which station to try and improve, we would recommend to investigate Station 1. Station 1 takes up more than half of the total time of the system. This could be because of multiple reasons but it would be important to further investigate why. The throughput for Station 1 is also a lot higher than the throughput of any other station so that may be one of the reasons it has the highest total time.

All in all, it is important to provide this data and analysis for the customer, in this case the hospital because it gives them insight on how productive they should be and how they currently running. It also shows them alternatives on how they could improve throughput, productivity, efficiency and time spent in each station. But, in the end, the decision is made by the customer and is usually made based off of the findings the engineer provides but also is highly dependent on the cost of each option. We would recommend to rearrange the capacity but this may increase the amount of money spent on wages, upkeep, etc. and may not be worth it.

Case 4

This emergency department (ED) is a part of a small hospital in a city. It works 24/7 and has different patients' arrival rates during weekdays and weekends. When a patient enters the ED, he/she will go directly to the triage station. At the triage, a nurse will examine the patient and determine the level of condition from 1 to 4, where 1 is most critical. After the triage, patients go to the diagnostic station where doctors examine them and decide whether they should undergo extra lab tests or leave the ED. In this station, three doctors from different departments (external, internal, and pediatrics) examine patients with the assistance of a nurse. Extra tests include X-rays, blood samples, and other tests. In X-rays department, two technicians are there to do these tests. For blood samples, a nurse should be there to draw them. A nurse would do all other tests.

After these tests, all patients will proceed to the observation area. This area is divided into three sections: internal medicine, pediatric, and external medicine. At each section, a nurse and a specialized doctor will do the clinical examination. After that, patients leave the ED (either discharged or admitted to the hospital).

Questions

1- Develop a simulation model in SIMIO for this ED.
2- Improve the productivity of this system taking into consideration costs associated with adding new resources.

Data

Resources	Number	
Nurses	6	
Internal medicine doctors	1	
External medicine doctors	1	
Pediatric doctors	1	
X-rays technicians	2	

Probabilities	Weekdays (%)	Weekends (%)
Level 1 patients	28.8	22.9
Level 2 patients	54.8	50.4
Level 3 patients	16.3	26.4
Level 4 patients	0.1	0.3
Internal medicine patients	44.8	55.8
Pediatric patients	7.9	8.7
External medicine patients	47.3	35.6
Patients that need extra tests	95	90
Patients that need x-rays	30	30
Patients that need samples	30	30
Patients that need other tests	40	40

Service times in minutes and seconds

Triage	**External medicine diagnostic**	**Pediatric diagnostic**
Triangular (1:10, 2:30, 4:00)	Triangular (5:15, 7:35, 9:45)	Triangular (5:05, 7:45, 9:50)
Internal medicine diagnostic	**X-rays**	**Blood samples**
Triangular (4:30, 6:30, 8:45)	Triangular (1:15, 2:30, 4:25)	Triangular (00:45, 1:00, 1:30)
Other tests	**External medicine examination**	**Pediatric examination**
Triangular (2:00, 4:00, 6:00)	Triangular (4:30, 5:30, 7:00)	Triangular (3:40, 4:45, 6:15)

Internal medicine examination	
Triangular (3:30, 4:30, 6:00)	

Patients arrival rates (patients per hour)		
Time	**Weekdays**	**Weekends**
12 am- 1 am	5.39	5.06
1 am – 2 am	3.63	4.07
2 am – 3 am	3.08	3.19
3 am – 4 am	2.64	1.98
4 am – 5 am	2.42	1.54
5 am – 6 am	2.2	2.2
6 am – 7 am	2.53	2.97
7 am – 8 am	2.31	2.42
8 am – 9 am	4.62	3.52
9 am – 10 am	5.06	5.28
10 am – 11 am	4.62	3.74
11 am – 12 pm	5.39	5.06
12 pm- 1 pm	4.18	3.96
1 pm – 2 pm	3.85	3.74
2 pm – 3 pm	4.95	5.06
3 pm – 4 pm	2.97	5.72
4 pm – 5 pm	3.63	6.38
5 pm – 6 pm	3.96	4.62
6 pm – 7 pm	3.52	6.38
7 pm – 8 pm	3.74	6.6
8 pm – 9 pm	3.96	7.37
9 pm – 10 am	4.29	8.03
10 pm – 11 pm	5.94	7.04
11 pm – 12 am	7.04	6.93

Group's Solution

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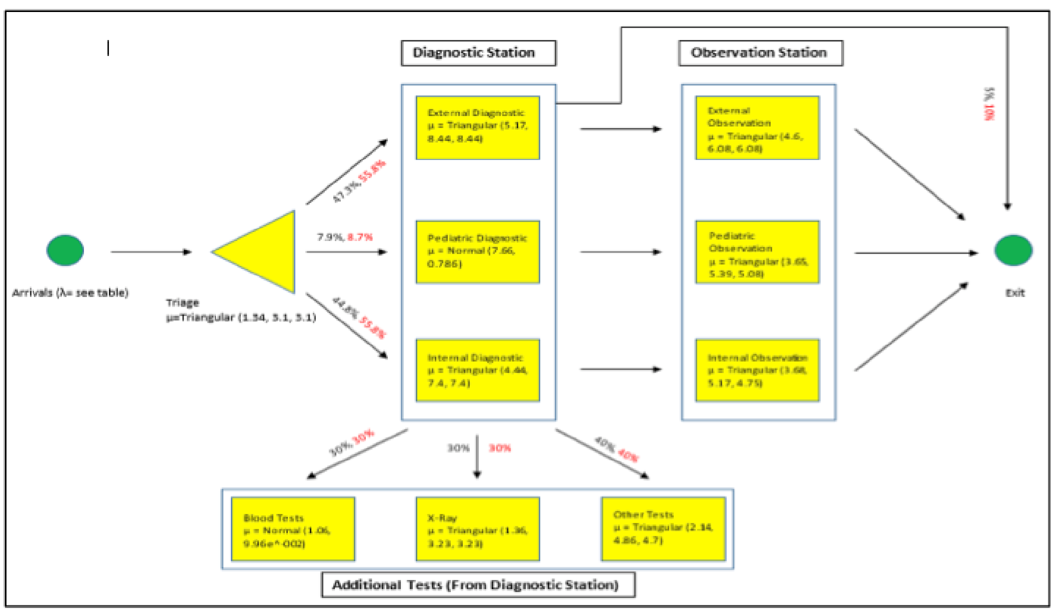

Figure #2: *Patient flow diagram of the case study*

5.0 Analysis

The study of the system must be achieved by analyzing both the weekday and weekend values of all objects. This discussion will be achieved by walking through the emergency department and examining each component of the model. The triage station, diagnostic station, observation station, and resources will be evaluated based off of the data that the Simio model generated. Before the group examines the more technical aspects of the model, a higher-level view of the system will be analyzed to provide additional scope.

Entities arrive according to the schedule provided in Figure #8. On weekdays patients arrive at an average of 3.99 per hour while the weekend arrival rate is about 4.7 arrivals per hour. The highlighted time frames represent consecutive periods that the system is faced with larger than average values of 7.06 patients per hour. This is roughly 50% higher than the average. The fact that they occur consecutively over a six-hour period only propagates queuing issues within the emergency department until the system recovers. From 6pm to 12am on the weekends, the emergency department should be prepared to deal with an influx of arrivals.

The difference in arrival rates of the weekdays and weekends can be seen throughout the model from this point on. To reflect the group's higher-level view, the number of patients, as well as their average and maximum time in the system, was calculated to give management an understanding of system performance. The number created/destroyed strongly reflects the average arrival rate for the day of the week as stated above. Dividing these numbers by the model run length of 1000 hours yields numbers almost identical to the average arrival rate. Lastly, the discrepancy between average and maximum time in system is somewhat concerning. Obviously, the average values are quite reasonable but the causes for such a large maximum time should be investigated with caution. Yes, the maximum value is large but this is also the longest throughput time of a single entity in 1000 hours of operation. The average value is a much better indicator of the system's health.

	Weekday	**Weekend**
Number Created/Destroyed	3954	4657
Avg. Time in System (min.)	27.11	34.17
Max. Time in System (min.)	123.56	182.99

Figure #10: *Patient Times in System*

The final component of this overview is the average and maximum times that patients spend in the system based off of their severity levels determined by the triage nurse. The main component to study here is the values for level 1 severity. Because these patients are the most critical, one might assume that their time in the system would be larger than all others. This is not the case because of the group's model logic. When patients queue in front of a server, the server evaluates them based off of their severity, not the time already spent waiting. In short, each server takes the most critical patient first and expedites them through the system. During weekdays, each patient level's time in system is less than 30 minutes and during weekends it is below 40 minutes.

	Weekday		**Weekend**	
	Avg.	Max.	Avg.	Max.
Level 1	27.45	119.03	34.53	163.68
Level 2	26.90	123.56	33.95	182.99
Level 3	27.20	122.31	34.20	164.26
Level 4	20.68	20.68	39.89	87.48

Figure #11: *Time in System According to Level*

5.1 Triage Station

The first server in the system is the triage nurse. Initially, the group hypothesized that this would be an obvious bottleneck. Upon further investigation this is not the case. Using weekday values as an example, from the patient arrival table, entities arrive about 4 times an hour, which correlates, to one patient every 15 minutes. Since the triage nurse's processing time is about 3.1 minutes, she is busy about 3 minutes for every 15 minutes of simulation time. Dividing 3.1 by 15 produces a value of 20%, which is a very rough estimate of the scheduled utilization. Entities spend less than 17 seconds waiting for the triage nurse on average. Clearly this station can handle a larger arrival rate.

	Weekday	**Weekend**
Scheduled Utilization (%)	16.61	19.57
Processing Time (min.)	3.07	3.30

Figure #12: *Triage Station Values*

5.2 Diagnostic Station

As alluded to above, the diagnostics station is the most intricate section of the group's model. It is divided into internal, external, and pediatric sections, each with a capacity of 1. In the diagnostics section patients also may receive medical tests consisting of blood work, x-rays, and other tests. Variables that management should consider are the scheduled utilization rate, time processing, and time waiting. The external section has the highest utilization rate while pediatrics has the lowest. These values are strongly dependent on the proportions of patients that fall into these categories and the availability of a doctor and nurse. This same argument can be made for the time processing and time waiting variables. The processing times of each category are noticeably larger than the distributions for the section's service time. This reflects the logic that a doctor and nurse must be available before processing can start. Clearly some time is spent waiting on a doctor while in the room, much like the real world. The time waiting variable reflects the time patients spend waiting outside of the room. The group believes that the utilization will increase and waiting time will decrease with an increase in capacity. This assumption is made because the doctor will spend less time traveling as well as a decrease in the queue outside the door because of the increased capacity in the respective section.

		Scheduled Utilization (%)		**Time Processing (min.)**		**Time Waiting (min.)**	
		Weekday	Weekend	Weekday	Weekend	Weekday	Weekend
Internal Diagnostics		28.76	36.81	13.90	18.40	3.12	7.71
External Diagnostics		35.26	42.78	18.91	24.37	7.16	14.45
Pediatric Diagnostics		5.35	5.93	10.92	10.89	0.39	0.47

Figure #13: *Diagnostic Station Values*

5.3 Observation Station

Many of the arguments stated in the diagnostics station also apply to the observation station. While external and pediatric sections still have the most and least utilization, respectively, the values of their utilization have decreased noticeably from the diagnostics station. This was unexpected to the group. We initially assumed that the utilization rates would be more or less equal because patients are on a direct path between their respective diagnostic and observation station. The discrepancy is due to the lack of testing done in the observation area. In the diagnostics section, patients spend their time speaking to doctors and nurses as well as receiving additional tests. In the observation station there is no testing, so that time segment is eliminated, causing the decrease in utilization. Again, waiting times are very reasonable but could possibly be decreased by increasing the server's capacity from 1.

		Scheduled Utilization (%)		**Time Processing (min.)**		**Time Waiting (min.)**	
		Weekday	Weekend	Weekday	Weekend	Weekday	Weekend
Internal Observation		21.60	30.57	10.87	16.09	4.31	4.53
External Observation		30.51	38.76	17.15	23.92	6.55	8.23
Pediatric Observation		2.80	3.31	5.72	6.08	0.96	4.73

Figure #14: *Observation Station Values*

5.4 Resources

According to the group's model, doctors, nurses, and technicians are defined as resources that travel with entities through the system and perform tasks at the server stations (diagnostic and observation). Each doctor has a capacity of one while the nurses have 6 and technicians have 2. Besides accompanying doctors in the observation and diagnostic stations, nurses are responsible for performing all tests besides the x-ray, which is the technician's responsibility. The most important variable to consider for these resources is the scheduled utilization. The individual doctor's utilization percentages are very dependent on the utilization of the two serving stations (diagnostic and observation) they are constrained to. This is evident because of the common utilization trend of external having the greatest and pediatric the least. The group does not recommend adding additional doctors for two reasons; none of the utilization rates are critical and they are the most expensive resource. The improvement that additional doctors would make to wait times would be very small compared to the required investment. The nurse's utilization rate of 23.5 is much lower than the group expected because we determined since they have several different responsibilities they would be much busier. Since there are 6 nurses initially the group believes that decreasing this number would increase the utilization rate without having a substantial impact in other areas of the model. It is worth noting that the same argument can be made for the x-ray technicians. Only 30% of patients require an x-ray and the processing time distribution has a mode of 3.23 minutes. Since technician utilization is so low the group is confident that we can reduce the number of technicians to 1 and not see substantial disruption to the system.

	Scheduled Utilization (%)	
	Weekday	Weekend
Internal Doctor	39.38	47.29
External Doctor	47.49	54.04
Pediatric Doctor	7.77	8.71
Nurse	23.48	29.61
Technician	2.52	2.69

Figure #15: *Resource Values*

6.0 Alternative Model Experiments

From the analysis above it was clear to the group that the main objects under control were the resources. The group also investigated the effects of changing server capacities. Many other variables could not be altered, such as historical service rates and arrival times provided by the client. Task sequencing was very difficult to implement and thankfully cannot be changed. Much of the experimentation done below focuses on server and resource utilization values, as well as the average time in system. These variables give a higher-level view of the system's overall effectiveness and efficiency. The series of experiments that will be discussed below focus on the following central ideas:

1. Adding additional doctors to decrease time in system and increase server utilization
2. Removing nurses to increase nurse utilization while decreasing scheduling costs
3. Removing a technician to increase technician utilization while decreasing scheduling costs
4. Increasing server capacities to decrease wait times and increase resource utilization

6.1 Adding Doctors

Scenario		Replications		Responses						
Name	Status	Required	Completed	EX_DOC_UTL	INT_DOC_UTL	PED_DOC_UTL	TIS	EX_DIAG_UTL	INT_DIAG_UTL	PED_DIAG_UTL
Initial	Compl...	25	25 of 25	47.313	40.2472	8.03036	0.451463	34.8457	29.6087	5.5336
2 of each	Compl...	25	25 of 25	23.7419	20.1199	3.91821	0.318482	29.8944	26.7107	5.35511
2 EXT	Compl...	25	25 of 25	23.7114	40.2881	7.76022	0.370451	29.8638	29.6992	5.3573

Figure 16: *Doctor Experiment*

The results of the experiment show the initial model compared to alterations. Doctor utilization, time in system, as well as the diagnostic serving stations were chosen as response variables to understand how the number of doctors affects system performance. The first deviation from the initial model was to add one additional doctor to the external, internal, and pediatric doctor resources, giving each a value of 2. As expected, all doctor utilization values were cut in half but the average time in system dropped dramatically from 27 to 19.2 minutes. Also worth noting is that server utilization values dropped which was unexpected. Because doctors are the most expensive resource, the group did not believe that adding additional doctors to all categories was feasible since their initial utilizations were not too high to begin with. Also, it makes no sense to increase the number of pediatric doctors at all because they are rarely used in this emergency department. To mediate this issue while still striving to decrease the time in system, the group decided to test adding only an additional external doctor since this doctor was utilized the most and also received the largest portion of patients. The result of this trial was a decrease in the average time in system, although not as significant as the first trial, while holding all other utilization values near their initial levels. The average time in system of this trial was 22.2 minutes, which is about an 18% improvement from the initial value.

6.2 Removing Nurses

Scenario		Replications		Responses		
Name	Status	Required	Completed	Utilization	Time_In_System	Max_TIS
Initial Nurse	Compl...	25	25 of 25	23.7389	0.451463	2.10761
4 Nurses	Compl...	25	25 of 25	35.4423	0.45504	2.1402
3 Nurses	Compl...	25	25 of 25	46.0381	0.468846	2.13793

Figure 17: *Nurse Experiment*

The results of the experiment show the initial model compared to alterations. The group decided to study nurses more closely because of their low initial utilization values. In the base model, six nurses are used with a utilization of about 24%. This corresponds to an average time in system of about 27minutes. The first trial decreased the number of nurses to 4 and improvements were seen in nurse utilization without any significant increase in the average time in the system. The second trial used only 3 nurses and utilization increased without a major increase to the time in system. The group decided not to implement a strategy with only two nurses for several reasons. One being that each of the three doctors (internal, external, and pediatric) must have a nurse accompany them at all times. The second being that nurses performs many of the additional tests that must be performed in the diagnostics station. Spreading nurses too thin would decrease doctor and server utilizations values at the expense of incremental improvements to nurse utilization. Clearly decreasing the overhead from 6 nurses to 3 is a noticeable improvement considering it does not seem to have a strong relationship with the time in system and increases utilization by 100%.

6.3 Decreasing Technicians

Design | Response Results | Pivot Grid | Reports | Input Analysis

Scenario		Replications		Responses	
Name	Status	Required	Completed	UTL	TIS
Initial	Compl...	25	25 of 25	2.46735	0.451463
1 Tech	Compl...	25	25 of 25	4.98059	0.452985

Figure 18: *Technician Experiment*

The results of the experiment show the initial model compared to alterations. Initially technicians have a utilization of about 2.5%. Because the x-ray department is used sparingly, the group decided to test what would happen if two technicians were decreased to only one. The increase in waiting time at the x-ray department would be minimal to the reduction in overhead by one technician. The results of the experiment prove this theory. In much the same way as reducing the number of nurses, reducing the number of technicians doubles the utilization rate and does not have a significant impact on the average time in system.

6.4 Increasing Server Capacities

Design | Response Results | Pivot Grid | Reports | Input Analysis

Scenario		tions		Responses									
Name	Status	ed	Completed	EXT_DIAG_Util	INT_DIAG_Util	PED_DIAG_Util	EXT_OBS_util	INT_OBS_Util	PED_OBS_Util	EXT_DOC_UTL	INT_DOC_Util	PED_DOC_Util	TIS
Initial	Compl...	25	25 of 25	34.8457	29.6087	5.5336	29.9549	22.7653	2.89023	47.313	40.2472	8.03036	0.451463
Cap=2	Compl...	25	25 of 25	22.1947	18.1952	2.83204	19.7421	14.632	1.50238	47.4588	40.6341	7.97604	0.465832

Figure 19: *Capacity Experiment, Utilization Values*

The results of the experiment show the initial model compared to alterations. The group hypothesized that increasing the capacity of the serving stations from one to two could increase the station and doctor utilization values (Figure #19) as well as decrease the waiting times at each server (Figure #20).

Design | Response Results | Pivot Grid | Reports | Input Analysis

Scenario		Replications		Responses						
Name	Status	Required	Completed	EXT_DIAG_Wait	INT_DIAG_Wait	PED_DIAG_Wait	EXT_OBS_Wait	INT_OBS_Wait	PED_OBS_Wait	TIS
Scenario1	Compl...	25	25 of 25	0.107668	0.0639971	0.00667857	0.104983	0.0774239	0.0155313	0.451463
Cap=2	Compl...	25	25 of 25	0.0977272	0.0615239	0.00877512	0.127085	0.0922017	0.0163928	0.465832

Figure 20: *Capacity Experiment, Wait Time Values*

Clearly this logic was incorrect. Increasing capacities decreased each server's utilization while actually increasing the time in system. Although doctor utilization increased for external and internal doctors it was not by any significant amount and does not justify expanding the sections of the emergency department. Increasing capacities also increased nearly all-waiting times at the servers, which was not expected. Clearly, altering the capacity levels is detrimental to the system.

7.0 Results and Recommendations

The main findings from model experiments will be implemented in this section to produce a more effective and efficient system. Results from experimentation were found to be as follows:

- Adding doctors decreases the average time in system at the expense of resource utilization and increases in scheduling overhead. There were no substantial improvements to server utilization.
- Removing nurses increases nurse utilization without having any significant effects on the average time in system
- Removing a technician increases technician utilization without having any significant effects on the average time in system
- Increasing server capacities does not increase server or doctor utilization rates and does not reduce server-waiting times. It actually increases the average time in system.

For these reasons the group recommends:

- Adding only an external doctor because it is the most worked and receives the most patients
- Scheduling 3 nurses instead of 6
- Scheduling 1 technician instead of 2

The results of this implementation can be seen below in figure #. This recommendation decreases the average time in system from 27 minutes to 22.8 minutes, about a 16% improvement. It also decreases the maximum time in system from 126.6 to 102.6, about a 19% improvement. External doctor's utilization is cut in half because of the additional doctor scheduled while all other doctor's utilization values remain about constant. The nurse's utilization increases by 42% and the technician's utilization increases by 100%.

Design | Response Results | Pivot Grid | Reports | Input Analysis

Scenario		Replications		Responses						
Name	Status	Required	Completed	TIS	MAX_TIME	EXT_DOC_UTL	INT_DOC_UTL	PED_DOC_UTL	Nurse_UTL	Tech_UTL
Initial	Compl...	25	25 of 25	0.451...	2.10761	47.313	40.2472	8.03036	23.7389	2.46735
Improv.	Compl...	25	25 of 25	0.38667	1.71423	24.6841	40.4343	8.22261	41.06	4.93807

Figure 21: *Results Experiment*

In conclusion, it is the group's proposal that the emergency department employ 3 nurses, 1 technician, 2 external doctors, 1 internal doctor, and 1 pediatric doctor at a time. Removing three nurses and one technician while adding one external doctor actually increases the efficiency of the system all while reducing overhead. These changes decrease the average time in system by 16% while saving the emergency department money in the form of worker salaries.

Other options worth exploring are the cross training of employees. Throughout the project the pediatric doctor's utilization is so low that it is almost not worthwhile to employ him. If one or both of the other doctors could be cross-trained to cover pediatric medicine it would increase resource utilization while removing the salary of one doctor from overhead costs. Also, the triage nurse's utilization never exceeds 20%. If her job description could be altered to include other "normal" nursing responsibilities more money could be saved all while increasing this nurse's utilization value.

Case 5

This emergency department (ED) is a part of a specialized hospital. It is divided into two sections: General section for all patients and Chest Pain Unit (CPU) for patients with heart problems only. This CPU was created because 40% of patients visiting the ED have hearts problem, and they need quick and different services.

When patients enter the ED, they will go directly to the triage area where a triage nurse categorized them based on the Emergency Severity Index (ESI) from 1 to 5 (1 is most urgent, and 5 is least urgent). At this triage section, conditions of patients and the path they will follow in the ED and the required resources are identified. Patients with ESI 1 have urgent conditions and usually come to the ED with an ambulance and go to the Cardio-Pulmonary Resuscitation (CPR) to receive needed services and then proceed to get further treatments. All other patients go to the triage area, and the triage nurse assesses their acuity. Patients with ESI 2 skip the reception and go to the CPU. Patients with ESI 3, 4, and 5 go to the reception area to complete the registration step. After that, patients with ESI 3 and 4 go to the CPU. Patients with ESI 5 leave the ED after receiving required treatment in the General section.

At the CPU, each patient will be assigned a bed and a nurse takes Electrocardiography (ECG). Then, a heart resident comes and decide whether more treatment is needed or not. Several patients will not need more treatment and leave the ED. Patients that need more treatment would have one of the following: lab test, medical advice, monitoring, and another ECG. After that,

patients will see the heart resident again and then leave the ED (either discharged or admitted to the hospital).

Questions

1- Develop a simulation model in SIMIO for this ED.

2- Improve the productivity of this system taking into consideration costs associated with adding new resources.

Data

Patients arrival rate		
52,000 patients /year	145 patients/day	6 patients/hour
Resources	**Number**	
Beds	7	
Receptionists	2	
Nurses	3	
Triage nurses	1	
Heart residents	1	
Probabilities	**%**	
Patients with heart problems	40	
ESI 1 patients	2	
ESI 2 patients	20	
ESI 3 & 4 patients	35	
ESI 5 patients	43	
Patients that need more treatments	50	
Lab tests	25	
Medical advice	25	
Monitoring	25	
Another ECG	25	

Service times in minutes		
Triage	**Reception**	**Monitoring**
Uniform (2,5)	Uniform (3,5)	Uniform (30,60)
CPR	**ECG**	**Test Process (1st evaluation by heart resident)**
Triangular (30,45,60)	Triangular (5,10,15)	Triangular (10,15,20)
Visit process (2nd evaluation by heart resident)	**Lab test**	**Medical advice**
Triangular (10,15,20)	Triangular (45,90,180)	Triangular (15,45,90)

Group's Solution

Emergency Department Case 5
Team 2: Simulating Success

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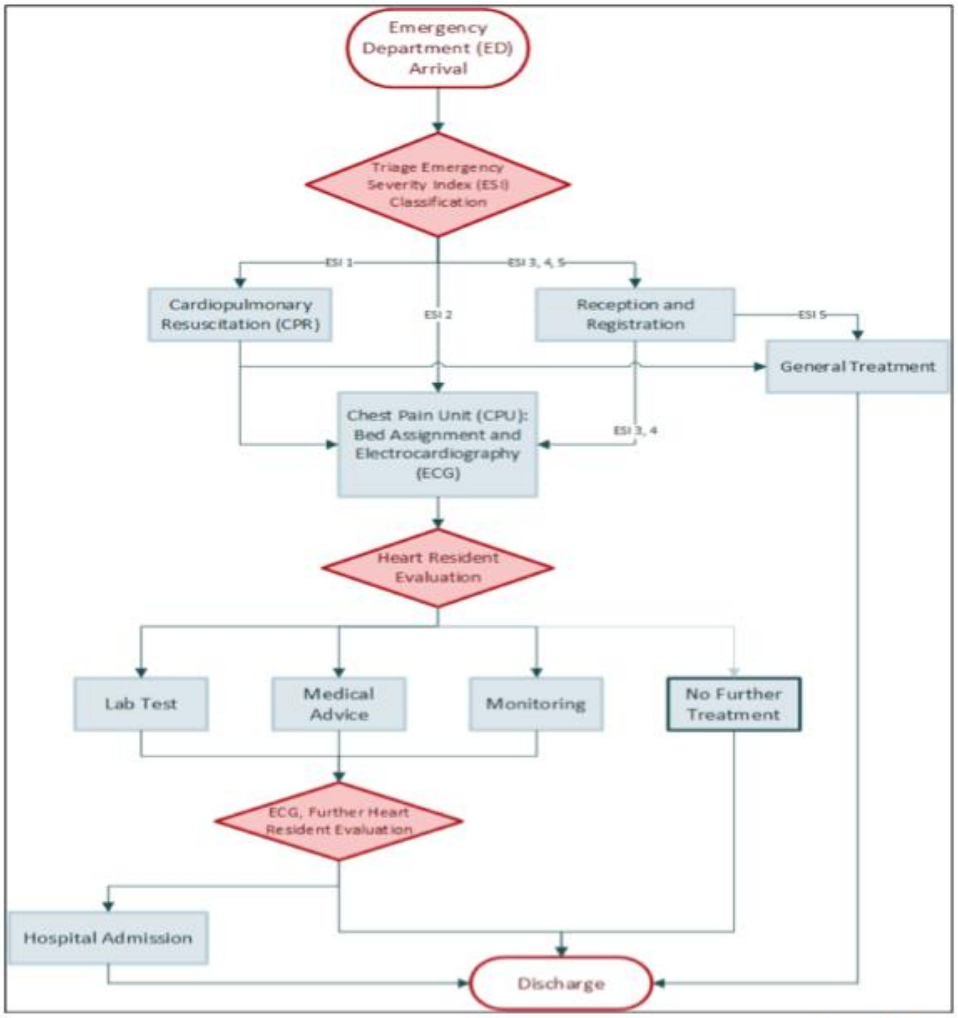

Figure 1.1: Process Map

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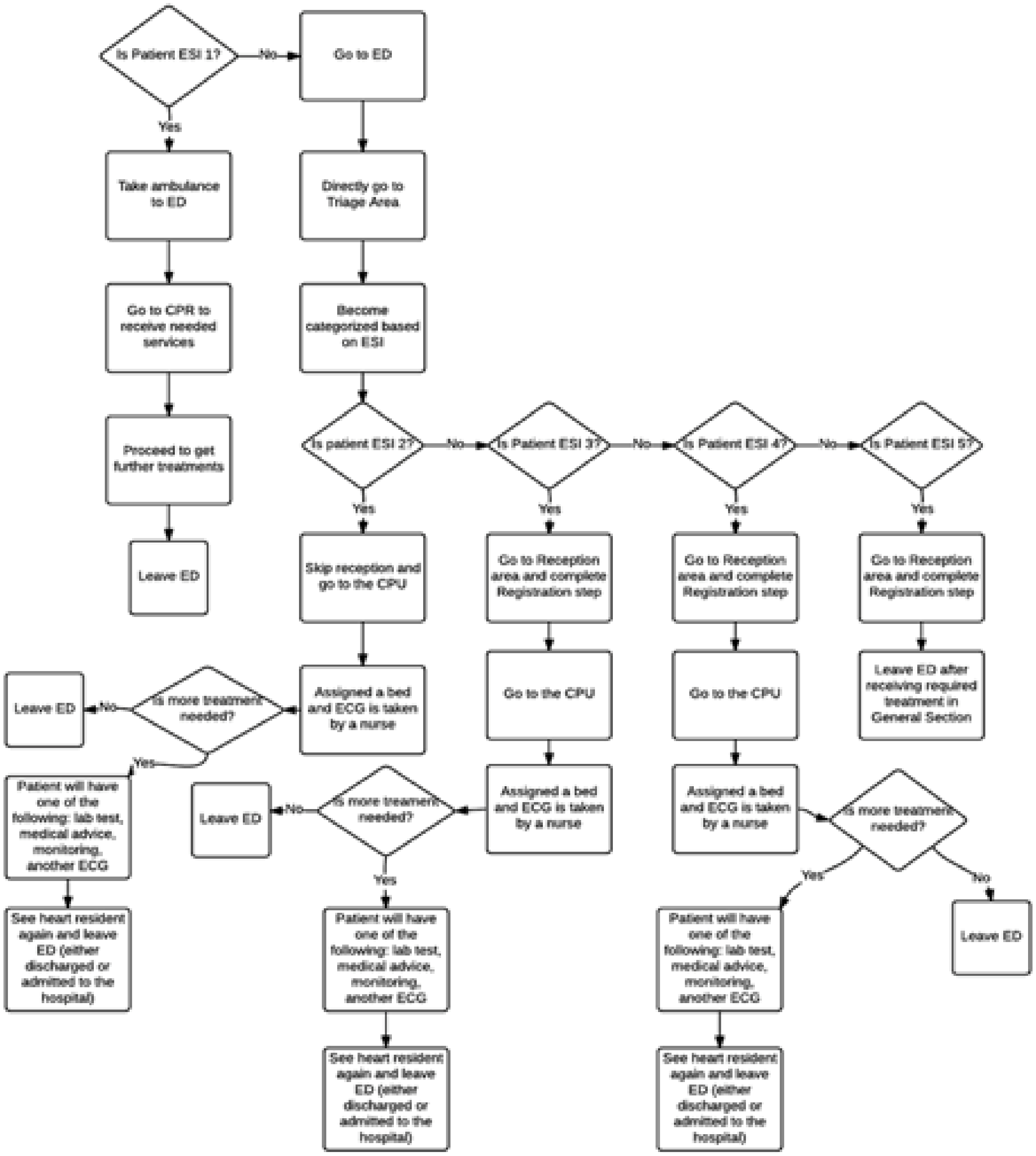

Figure 2.1: Detailed Process Map

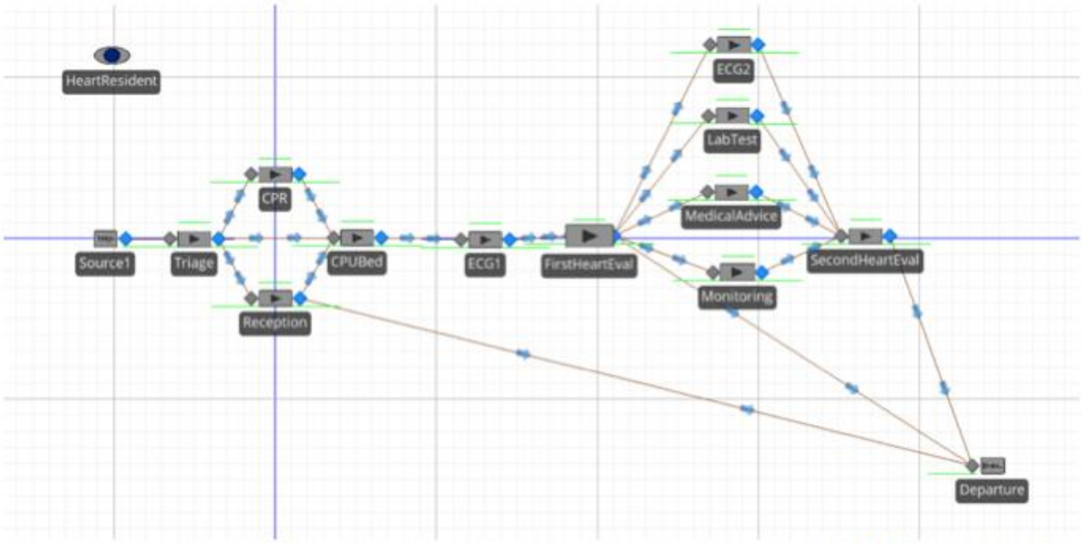

Figure 5.1. 2-D layout of current facility.

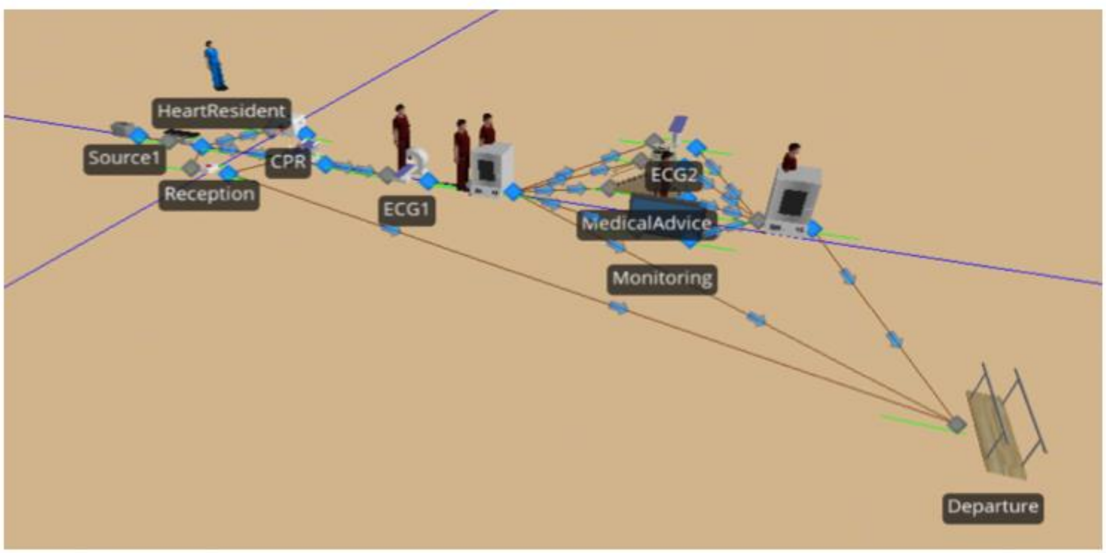

Figure 5.2. Final demonstrated 3-D model.

6. Results and Recommendations

Our simulation highlighted multiple issues. Among the most important were low utilization issues and a large amount of time spent in queues or waiting lines. For example, our results discovered a utilization of 6.8% in the ECG 2 area and 27.4% in the ECG 1 area. There was also a low utilization in the reception area tallying in at 15.5%. Currently the hospital is paying for staff in these areas, but the works are waiting around for work for over two-thirds of their scheduled work time.

Another issue that was discovered through the simulation was a large amount of time spent in queuing lines. Nearly two hours are spent at the lab testing area and nearly an hour is spent in the first heart evaluation area. These two issues have room for improvement as patients do not want to spend three hours of their time waiting around for service. Furthermore, with a higher capacity for service in these areas, the doctors and nurses would be able to pass more patients through the system. This would be especially helpful in an area where time is of the utmost importance. An example of this would be in the first heart evaluation area where a short diagnosis time is quite important.

Some of our proposed alternatives have now shown their faces as being effective solutions for the hospital. Our first alternative focuses on reducing staff:

Alternatives:

1. Reduce the number of ECG Nurses from three to two
    a. Objectives:
        i. Cost savings
        ii. Improved efficiency
2. Reduce the number of receptionists from two to one
    a. Objectives:
        i. Cost savings
        ii. Improved efficiency
3. Increase the lab test capacity
    a. Objectives
        i. Reduce wait time
        ii. Increase customer satisfaction
4. Hire an additional heart resident
    a. Objectives
        i. Reduce wait time
        ii. Increase customer satisfaction
5. New training and/or advanced technology retrofit
    a. Objectives:
        i. Reduce processing time and resources needed

						ECGReduction			
Object Type	Object Name	Data Source	Category	Data Item	Statistic	Average	Minimum	Maximum	Half Width
Server	CPR	[Resource]	Capacity	ScheduledUtilization	Percent	8.7499	8.5627	8.9879	0.0573
	CPUBed	[Resource]	Capacity	ScheduledUtilization	Percent	0.1620	0.1612	0.1629	0.0002
	ECG1	[Resource]	Capacity	ScheduledUtilization	Percent	54.8173	54.4606	55.0950	0.0702
	ECG2	[Resource]	Capacity	ScheduledUtilization	Percent	6.8270	6.6468	7.0162	0.0360
	FirstHeartEval	[Resource]	Capacity	ScheduledUtilization	Percent	83.3461	82.9234	83.7511	0.0994
	LabTest	[Resource]	Capacity	ScheduledUtilization	Percent	69.0980	67.9777	70.1237	0.2519
	MedicalAdvice	[Resource]	Capacity	ScheduledUtilization	Percent	35.1420	34.1970	36.1523	0.1770
	Monitoring	[Resource]	Capacity	ScheduledUtilization	Percent	31.9813	31.4118	32.7419	0.1292
	Reception	[Resource]	Capacity	ScheduledUtilization	Percent	15.4890	15.3859	15.5589	0.0192
	SecondHeartEval	[Resource]	Capacity	ScheduledUtilization	Percent	41.6436	41.3546	42.2256	0.0877
	Triage	[Resource]	Capacity	ScheduledUtilization	Percent	34.6347	34.5077	34.7724	0.0329

Figure 6.1. Server capacity results after alternative one implemented in SIMIO pivot grid.

Object Type	Object Name	Data Source	Category	Data Item	Statistic	ReceptionReduction			
						Average	Minimum	Maximum	Half Width
Server	CPR	[Resource]	Capacity	ScheduledUtilization	Percent	8.7657	8.4618	9.1036	0.0663
	CPUBed	[Resource]	Capacity	ScheduledUtilization	Percent	0.1618	0.1606	0.1630	0.0003
	ECG1	[Resource]	Capacity	ScheduledUtilization	Percent	27.3638	27.1446	27.5748	0.0462
	ECG2	[Resource]	Capacity	ScheduledUtilization	Percent	6.8320	6.6726	7.0408	0.0388
	FirstHeartEval	[Resource]	Capacity	ScheduledUtilization	Percent	83.2421	82.5450	83.8927	0.1369
	LabTest	[Resource]	Capacity	ScheduledUtilization	Percent	69.0152	67.1777	70.4920	0.2996
	MedicalAdvice	[Resource]	Capacity	ScheduledUtilization	Percent	35.2867	34.5158	35.8223	0.1364
	Monitoring	[Resource]	Capacity	ScheduledUtilization	Percent	31.7806	30.8896	32.4047	0.1643
	Reception	[Resource]	Capacity	ScheduledUtilization	Percent	30.9486	30.7386	31.1825	0.0427
	SecondHeartEval	[Resource]	Capacity	ScheduledUtilization	Percent	41.6286	40.9261	42.0711	0.1064
	Triage	[Resource]	Capacity	ScheduledUtilization	Percent	34.6102	34.3438	34.7806	0.0427

Figure 6.2. Server capacity results after alternative two implemented in SIMIO pivot grid.

If the hospital follows through with our first alternative, utilization will effectively double. Utilization will go from 27.4% to 54.8% (Figure 6.1). This is a major benefit to the hospital as they will be able to lower costs by reducing staff. Efficiency will improve with this alternative as well. With reduced costs, the hospital may use the extra money for implementing more costly alternatives. Our second alternative is similar to the first alternative in its benefits. The original utilization is 15.5% and we expect it to nearly double to 30.9% according to our simulations (Figure 6.2).

Object Type	Object Name	Data Source	Category	Data Item	Statistic	LabTestIncrease			
						Average	Minimum	Maximum	Half Width
ModelEntity	DefaultEntity	[Population]	FlowTime	TimeInSystem	Average (Ho...	1.1854	1.1657	1.2108	0.0054
Server	CPR	InputBuffer	HoldingTime	TimeInStation	Average (Ho...	0.0394	0.0325	0.0446	0.0014
	ECG1	InputBuffer	HoldingTime	TimeInStation	Average (Ho...	0.0074	0.0072	0.0076	0.0001
	ECG2	InputBuffer	HoldingTime	TimeInStation	Average (Ho...	0.0000	0.0000	0.0000	0.0000
	FirstHeartEval	InputBuffer	HoldingTime	TimeInStation	Average (Ho...	0.7802	0.7474	0.8186	0.0082
	LabTest	InputBuffer	HoldingTime	TimeInStation	Average (Ho...	0.0976	0.0877	0.1109	0.0027
	MedicalAdvice	InputBuffer	HoldingTime	TimeInStation	Average (Ho...	0.1836	0.1751	0.1919	0.0021
	Monitoring	InputBuffer	HoldingTime	TimeInStation	Average (Ho...	0.1391	0.1277	0.1482	0.0024
	Reception	InputBuffer	HoldingTime	TimeInStation	Average (Ho...	0.0000	0.0000	0.0000	0.0000
	SecondHeartEval	InputBuffer	HoldingTime	TimeInStation	Average (Ho...	0.0579	0.0555	0.0594	0.0004
	Triage	InputBuffer	HoldingTime	TimeInStation	Average (Ho...	0.0225	0.0222	0.0228	0.0001
Sink	Departure	[DestroyedObjects]	FlowTime	TimeInSystem	Average (Ho...	1.1854	1.1657	1.2108	0.0054

Figure 6.3. Time in station results after alternative three implemented in SIMIO pivot grid.

Object Type	Object Name	Data Source	Category	Data Item	Statistic	HeartResIncrease			
						Average	Minimum	Maximum	Half Width
ModelEntity	DefaultEntity	[Population]	FlowTime	TimeInSystem	Average (Ho...	0.8990	0.8849	0.9136	0.0031
Server	CPR	InputBuffer	HoldingTime	TimeInStation	Average (Ho...	0.0386	0.0322	0.0495	0.0015
	ECG1	InputBuffer	HoldingTime	TimeInStation	Average (Ho...	0.0074	0.0071	0.0077	0.0001
	ECG2	InputBuffer	HoldingTime	TimeInStation	Average (Ho...	0.0042	0.0035	0.0045	0.0001
	FirstHeartEval	InputBuffer	HoldingTime	TimeInStation	Average (Ho...	0.0297	0.0283	0.0311	0.0003
	LabTest	InputBuffer	HoldingTime	TimeInStation	Average (Ho...	1.9420	1.7800	2.1162	0.0365
	MedicalAdvice	InputBuffer	HoldingTime	TimeInStation	Average (Ho...	0.2476	0.2320	0.2681	0.0035
	Monitoring	InputBuffer	HoldingTime	TimeInStation	Average (Ho...	0.1928	0.1778	0.2125	0.0035
	Reception	InputBuffer	HoldingTime	TimeInStation	Average (Ho...	0.0000	0.0000	0.0000	0.0000
	SecondHeartEval	InputBuffer	HoldingTime	TimeInStation	Average (Ho...	0.0607	0.0585	0.0630	0.0004
	Triage	InputBuffer	HoldingTime	TimeInStation	Average (Ho...	0.0225	0.0222	0.0230	0.0001
Sink	Departure	[DestroyedObjects]	FlowTime	TimeInSystem	Average (Ho...	0.8990	0.8849	0.9136	0.0031

Figure 6.4. Time in station results after alternative four implemented in SIMIO pivot grid.

Our next two alternatives focus on reducing wait times and increasing customer satisfaction. This improvement will be beneficial to the hospital in keeping patients who are in a stable-enough situation to choose which hospital to go to. By increasing the lab test capacity, we can achieve a wait time about 20 times as short as usual (Figure 6.3). By hiring an additional heart resident, we can achieve a wait time about 25 times as short (Figure 6.4). The wait times

are drastically shorter and are bound to keep customers in a better mood. Not only will we be able to reduce the wait time, but we will also be able to increase the number of patients that we can push through the system at one time. The only limit would be demand considering we would now be able to service 20 or 25 people in the time that it originally took to work with one.

Another solution that we considered was the implementation of training and even advanced technology retrofits. While these would definitely prove beneficial to any environment, it is hard to determine the effectiveness of it or the profitability. While simulating new retrofits is out of the scope, we are able to assume that it would assist the hospital. For this reason, we included these as an alternative. Unfortunately, we are hardly able to place a monetary value to this solution.

We chose to use a PICK (possible, implement, challenge, and kill) chart to aid the hospital in choosing which alternatives to implement. While some alternatives are quite beneficial, this does not cover monetary costs. A benefit that is very helpful to the hospital, but expensive to implement may be placed on the backburner. Alternatively, a benefit with little use to the hospital but a large cost will be removed from the improvements list. This alternative would be placed in the Kill category of the PICK chart. We created a PICK chart for the hospital to use for our alternatives. The benefit in PICK charts is the ability to include projects from a number of areas. This allows the hospital to choose whether or not to implement one of our alternatives over their current list of additions or changes to the hospital by comparing them on an equal basis. Our pick chart is as follows:

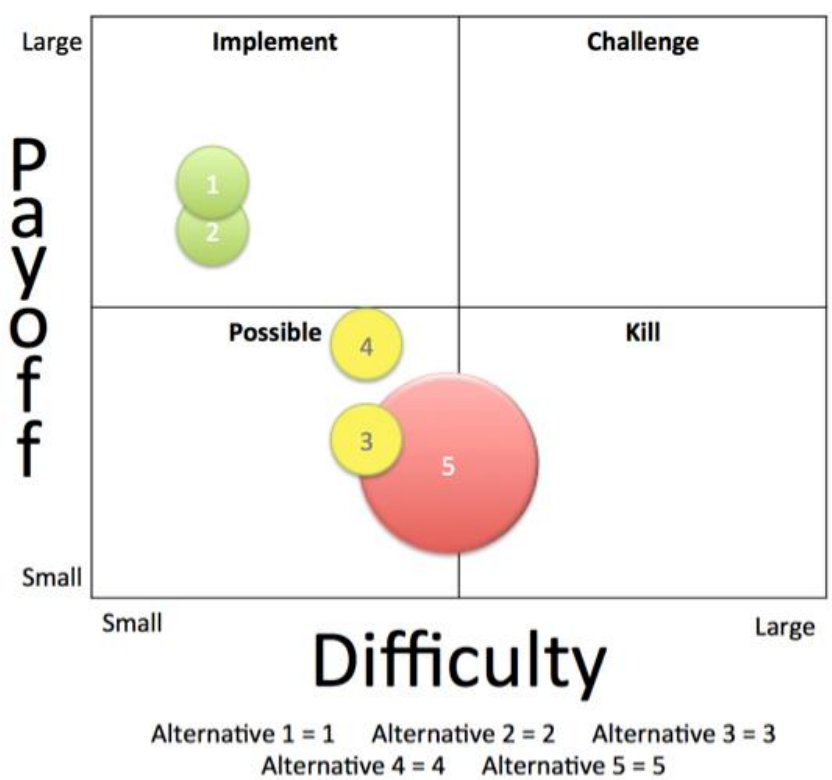

Figure 6.5: Alternatives PICK Chart

We feel that alternatives 1 and 2 are the most beneficial to the hospital while alternatives 3 and 4 are beneficial, but not nearly as significant as the first two. We recommend that the hospital consider the fifth alternative, but at their discretion because of our inability to attach a monetary value to the improvement.

7. Conclusion

Many possible/beneficial solutions exist outside of those we recommended, but we stand by our recommendations and the capability to aid in the emergency rooms. The best situation would be that they incorporate as many alternatives as possible from the given list based on the decisions in the PICK chart. The purpose of the PICK chart would be to prioritize the different alternatives with any other changes that they have been planning. The PICK chart will assist them in labeling a change as [P]ossible, [I]mplement now, [C]hallenge, or [K]ill. This is often a strong visual method of choosing which projects to follow through with as it assists groups with deciding which adjustments are most important to them.

Working with programs such as StatFit and SIMIO, our team has designed, modeled, and offered multiple improvements for the functions and uses of a hospital and its subsidiaries. The programs each had a strong role in the completion of this project and were each useful tools for their individual purposes. StatFit was useful in making sense of data and inputting usable data into SIMIO. SIMIO was useful in designing and simulating a real-life hospital environment with different Emergency Severity Index (ESI) levels.

This project has been a learning experience for the entire team as we have had the chance to work with a real-life situation and build a real-life simulation model. We, as a team, have worked hard for the past four months to learn to use multiple programs that are all new to us. These programs may come in handy down the road for each of us, and we are now more qualified to take control of simulation situations in the future.

Case 6

This emergency department (ED) is a part of a mid-sized hospital. It works 24 hours and gets patients by ambulances or as walk-ins. In this ED, patients are classified as critical (level 1) and noncritical (levels 2 and 3) based on their conditions. All ambulance patients are considered level 1 and go directly to the emergency room. Walk-in patients go to the reception area to give their information to receptionists. Then, they go to the examination room where a doctor assesses the acuity of their illnesses and decide whether extra tests (such as lab tests and X-rays) are needed or not. Some patients will need these extra tests and technicians at the laboratories area will do them. After that, patients will go back for reexamination by the doctor in the examination room. Level 3 patients receive their medications and leave the ED. Level 2 patients will go to the treatment room where a nurse perform minor treatments and then leave the ED. Level 1 patients will be assigned a bed in the emergency room and receive treatment by a doctor with the assistance of a nurse. After that, those patients will leave the ED (either discharged or admitted to the hospital).

Questions

1- Develop a simulation model in SIMIO for this ED.
2- Improve the productivity of this system taking into consideration costs associated with adding new resources.

Data

Resources	Number
ER nurses	9
TR nurses	1
Doctors	2
Lab technicians	3
Receptionists	2

Probabilities	%
Walk-in patients	90
Ambulance Patients	10
Level 1 patients	30
Level 2 patients	50
Level 3 patients	20
Patients that need extra tests	50

Service times in minutes

Reception	Lab tests	Examination room
Uniform (5,10)	Triangular (10,20,30)	Uniform (10,20)
Reexamination process	**Treatment room**	**Emergency room**
Uniform (7,12)	Uniform (20,30)	Uniform (60,120)

Patients arrival rates (patients/hour)

Time	Rate
12 am- 1 am	5.39
1 am – 2 am	4.23
2 am – 3 am	3.88
3 am – 4 am	2.64
4 am – 5 am	2.22
5 am – 6 am	5.57
6 am – 7 am	5.73

7 am – 8 am	6.31	
8 am – 9 am	7.62	
9 am – 10 am	8.56	
10 am – 11 am	9.22	
11 am – 12 pm	9.89	
12 pm- 1 pm	9.08	
1 pm – 2 pm	8.55	
2 pm – 3 pm	7.82	
3 pm – 4 pm	7.37	
4 pm – 5 pm	8.23	
5 pm – 6 pm	6.92	
6 pm – 7 pm	8.16	
7 pm – 8 pm	7.63	
8 pm – 9 pm	6.49	
9 pm – 10 am	5.03	
10 pm – 11 pm	3.94	
11 pm – 12 am	2.46	

Group's Solution

Undergraduate Simulators

Case 6 - ESI 4523

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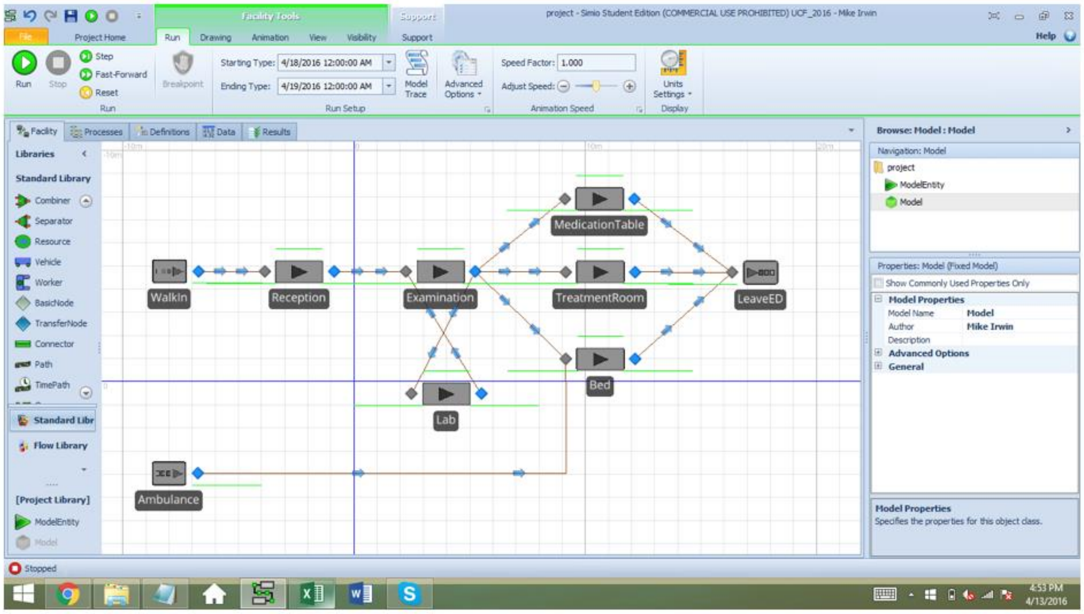

Figure 1: First Simio model.

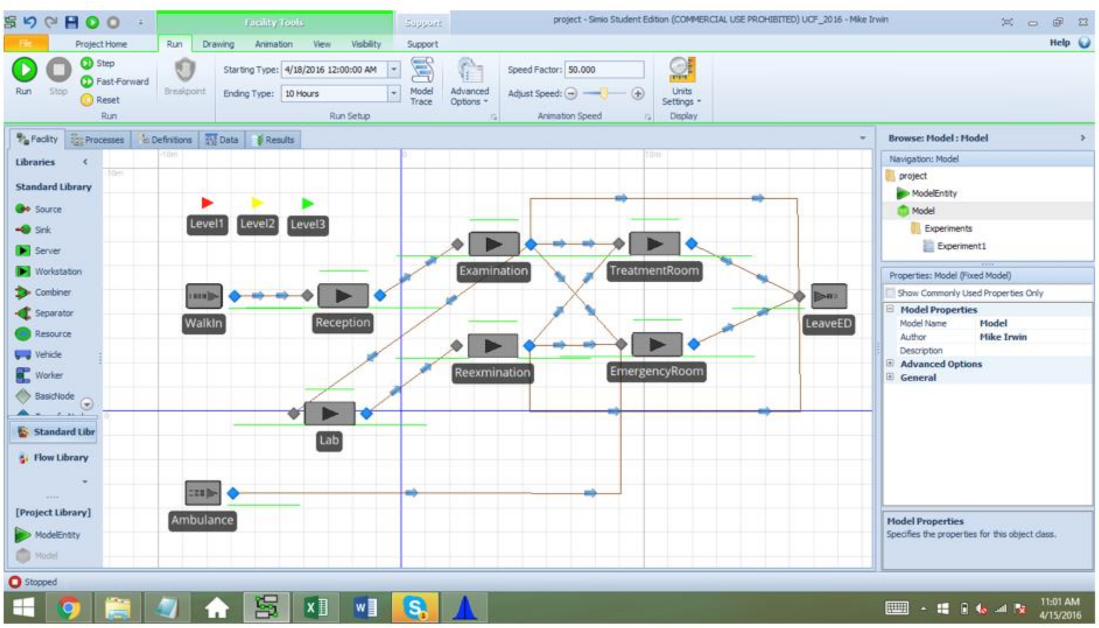

Figure 2: Second Simio model with Reexamination Room included.

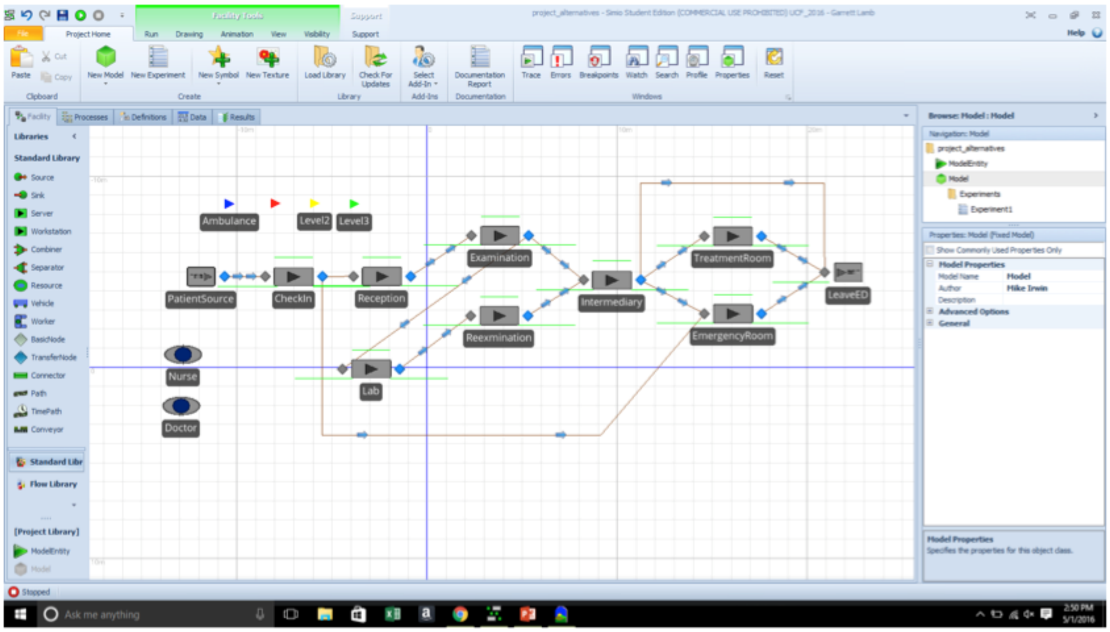

Figure 3: Third Simio model with Ambulance entity and movable resources.

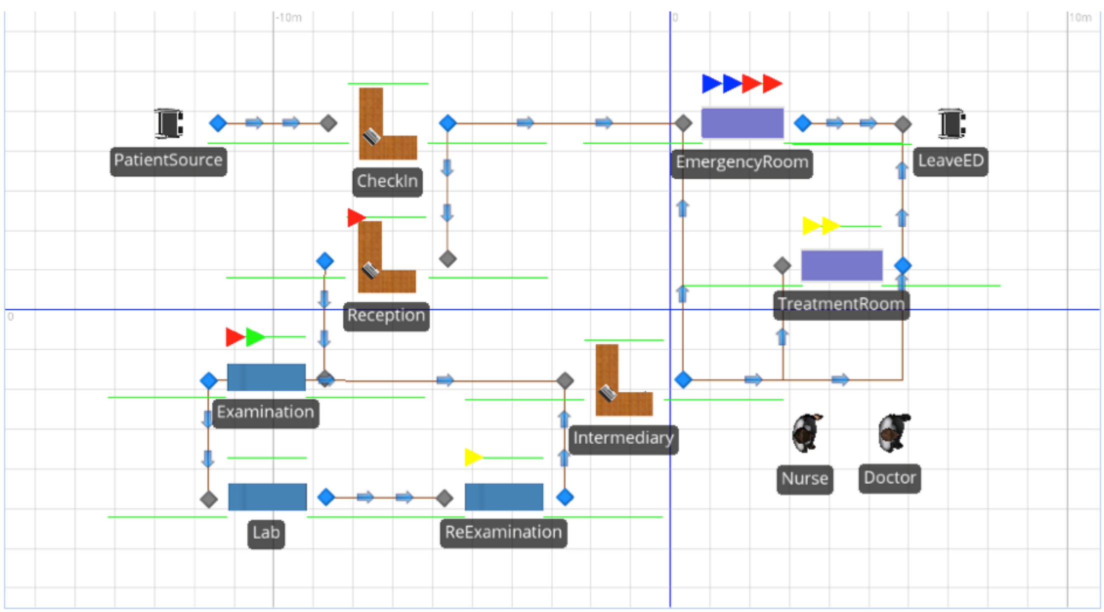

Figure 5: Final Simio model with updated design, animation, and graphics.

Alternative Models

There are a few different ways to help remedy our situation of long wait times for the walk in patients. We may be able to come up with some other alternatives after collecting and analyzing more data, but with the preliminary information that we have, these are our first suggestions.

The first idea is to use some of the doctors and nurses from the emergency room when and if there is downtime in the ER. With an extra doctor or nurse helping in the non-emergency exam room or lab room, they will be able to see more patients and treat them quicker and be able to send them to the treatment nurse or on their way with their medications.

Another plan would be to add one or 2 more exam rooms. While one patient is being cared for by a doctor in one room, in another a nurse can be taking the patient's vitals. Also, waiting in an exam room is more comforting than waiting in a reception area. The patients will know that they are about to be examined.

Our final preliminary remedy would be to send the patients that go for extra test and lab work straight to the treatment nurse or home with medication after being seen in the lab room. The lab work usually takes a while to be worked, so the lab technicians can do lab work and send the patients to the treatment nurse or on their way home. The doctor then can call the patients when the results come in and schedule a follow up visit, instead of waiting around and taking up an exam room.

We met with the client and received data about the system regarding a variety of processing times, arrival rates, available resources, and other useful information. Once we had the data, we were able to use Stat::Fit and find distributions of the service times of each server. Upon finding these distributions, we were able to model the system using Simio based on the data we were given by our client.

Table 1: Resources allocated in the current system.

Resources	Number
ER nurses	9
TR nurses	1
Doctors	2
Lab Technicians	3
Receptionists	2

While running simulations of the initial model, the team noticed several issues with how we didn't have enough of some resources yet an abundance of other resources. We knew from the beginning that more doctors would be need to be added to the process because they are needed in 3 different servers. We also knew that patients were moving very easily through the lab, and being stopped by a bottleneck in the Reexamination server. This led us to believe that a possible solution would be to decrease the number of lab techs the emergency department employed by at least one.

Later on after we had already implemented some of our remedies, we thought of the idea that nurses could be able to perform examinations in the exam room. This would potentially allow the emergency department to process patients faster while needing less resources. Doctors would be able to focus more on reexamination as well as treating patients in the emergency room, while at the same time nurses would be utilized more because they would have the ability to move to the exam room if they weren't busy in the treatment or emergency rooms.

The following remedies will be thoroughly tested and analyzed:

1. Cutting lab techs

    a. We found that cutting technicians improved upon the utilization of the lab without sacrificing much speed of processing. However, when we reduced the number of technicians to 1, patients started to get backed up waiting to be processed by the lab. After all, we dropped the number of lab technicians to 2.

2. Cross training nurses
    a. When we initially made nurses a joint resource instead of being separated by treatment room and emergency room, it took much of the burden off of the one nurse that was manning the treatment room. Now, ten nurses were able to move to perform treatments and work with doctors in the ER if they were needed there. We knew that either the number of nurses would need to drop or the number of doctors would need to increase.
3. Lowering the number of nurses
    a. We tested lowing the number of nurses carefully while simultaneously increasing the number of doctors to find a balance that would yield relatively high utilization of both resources without sacrificing patient speed through the system. Our target was to get the average patient through the system in 3 hours or less while taking into account the costs of adding certain resources.
4. Adding more doctors
    a. Again, we knew from the beginning that the emergency department would need more doctors in the system. Two doctors needed at three servers was not going to yield positive results within the process. The question at the beginning was just how many doctors would the department need that could potentially maximize the productivity of the given system. After several experiments, the team found that a balance of 6 doctors with 6 nurses processed patients at the most efficient rate for the current configuration of the system.

5. Reducing number of receptionists
    a. Given two receptionists worked in the system, we tried to reduce the number of receptionists to see if this would affect the rest of the system adversely. If we could reduce the number of receptionists, this could save the department several thousands of dollars yearly. However, when we ran the simulation with only one receptionist, the average time in system for patients rose to a level that the team was not comfortable with. After all, the number of receptionists in the system remained at two.
6. Training nurses to perform examinations
    a. This remedy would require the way the system functioned to be altered. When we implemented this change, we needed to find a balance in the available resources of doctors and nurses again. We found that we could reduce the number of doctors to five, but we would need to increase the number of nurses to seven in order to show an improvement upon average patient time in system. This option would prove to yield the lowest average patient time in system, and it could potentially prove to be more cost effective for the department. However, there are also potential issues with having the department configured this way.
    b. We were able to implement this in Simio by making an object list, which we called DoctorNurse. The list was simply two rows, the first row being "Doctor" and the second row being "Nurse". It's important that this list is an object list, and these names match exactly to the names of the resources. Once the list was created, we were able to seize the list by changing the object type to be "FromList", then we simply selected Doctor Nurse for the Object List Name.

Results

Our approach to testing alternative solutions was to start off with the base model and then increment or decrement the resources one at a time to measure how much impact each resource had on the system. We tested a total amount of almost twenty different combinations and shown below is a condensed version of that journey. We chose to highlight the points at which the system changed dramatically or produced a new bottleneck. At one point during our tests, we wanted to test if two lab technicians could do the job as well as three, and they could, so we stuck with that adjustment throughout. We didn't deem this change important enough to document in detail, so we chose not to list it below in a table. We also tested if we could reduce the amount of receptionists down to one and found that the system would build up a massive queue in reception if we did so, so we decided to stick with two receptionists throughout our testing.

	Current	10 Doctors	10 Doctors 10 Merged Nurses
Cost ($/year)	1840000	3840000	3840000
Time in System (min.)	17167	3476.82	74.79
Doctor Utilization (%)	100	47.62	47.66
TR Nurse Utilization (%)	37.35	100	42.09
ER Nurse Utilization (%)	21.90	31.98	42.09
Exam Queue Time (min.)	23330.4	0.0042	0.0010
ReExam Queue Time (min.)	0.0002	0.5502	0.5289
Lab Queue Time (min.)	3.5188	0	0
Treatment Queue Time (min.)	7.6757	7904.97	0
Emergency Queue Time (min.)	859.33	0.0168	0.0240

Table 2: Test runs for the extremes compared against the current system.

Given that the system was operating at ludicrously unacceptable levels of processing time, we wanted to test some extremes to ensure that the system was actually fixable. We started by adding eight doctors – for a total of ten – resulting in an approximate two-million-dollar increase in investment. This reduced the time in the system significantly, but produced another bottleneck in the system: The treatment room. Because the treatment room is only allocated a single nurse, it starts to build up an extremely long queue when the pressure is relieved from the examination room. This is also reflected in the jump of the treatment room nurse utilization from 37.35% to a full 100%. The hospital is currently allocating nine nurses to the emergency room and only one to the treatment room, which results in very high utilization for the treatment room nurse and very low utilization for the emergency room nurses. One solution may be to simply reallocate some emergency room nurses to the treatment room, but this results in a hard-coded system that handles the extremes poorly (e.g., during a period where there's a large queue in the emergency room and no queue in the treatment room, the treatment room nurses will be severely underutilized). Instead, we want to cross-train the nurses to be able to work in either the treatment room or the emergency room. The cost required is minimal, considering emergency room nurses are generally more specialized treatment room nurses, and the hospital currently has an abundance of emergency room nurses. This creates a much more flexible system that handles both normal and extreme operations extremely well. After both of these changes (ten doctors and cross-trained nurses), the total time in the system went down from nearly twelve days to just over an hour. However, the investment is extreme (two million dollars), and the queue times are practically non-existent for all of the rooms, which would suggest that the system is overstaffed.

Table 3: Test runs for decreasing the amount of doctors, nurses, and technicians.

	10 Doctors 10 Nurses	6 Doctors 10 Nurses	6 Doctors 6 Nurses
Cost ($/year)	3840000	2760000	2360000
Time in System (min.)	74.79	116.75	121.32
Doctor Utilization (%)	47.66	79.28	73.81
Nurse Utilization (%)	42.09	46.76	79.28
Exam Queue Time (min.)	0.0010	15.50	15.27
ReExam Queue Time (min.)	0.5289	3.14	3.18
Lab Queue Time (min.)	0	0.0193	0.0281
Treatment Queue Time (min.)	0	0	0.1752
Emergency Queue Time (min.)	0.0240	5.91	5.50

We decreased the amount of doctors in increments of one until we settled on a reasonable value of time in system (i.e., around two hours). We found that if we decreased the number of doctors from six to five, the time in system would increase to approximately three hours, which was deemed unacceptable by the team. Once we settled on six doctors, we also found that we could decrease the amount of lab technicians from three to two with almost no effect to the system whatsoever, so we opted for that change as well, as reflected in the cost above. After adjusting the amount of doctors, we found that the nurses were being underutilized, which would suggest that they are currently overstaffed. We decremented the amount of nurses down one at a time until we settled on six nurses, which appeared to be the happy medium between cost and performance. Compared to the original system, the cost is increased by approximately $520,000, but the overall efficiency of the system is increased dramatically, with time in system down from nearly twelve days to a mere two hours, in addition to very reasonable queue times (fifteen minutes for examination and five minutes for emergency room) and balanced utilization of doctors and nurses.

Table 4: Test runs for six doctors, six nurses, and two technicians, with nurses in or out of the examination room.

	No Nurses in Exam Room	Nurses in Exam Room
Cost ($/year)	2360000	2360000
Time in System (min.)	121.32	112.54
Doctor Utilization (%)	73.81	76.60
Nurse Utilization (%)	79.28	75.06
Exam Queue Time (min.)	15.27	8.43
ReExam Queue Time (min.)	3.18	3.92
Lab Queue Time (min.)	0.0281	0.0168
Treatment Queue Time (min.)	0.1752	0.9774
Emergency Queue Time (min.)	5.50	6.88

We noticed that the examination queue time was consistently the limiting factor of the system, so we wanted to explore some ways to fix the problem without simply adding more doctors. In the same vein as our change to cross-train the nurses, we wanted to see what effect allowing nurses in the examination room would have on the system. We programmed the model to require a "doctor or nurse, with doctor preferred" in the examination room and noticed that the time in the system only went down by nine minutes. However, the utilization for doctors did increase, and the queue times became more balanced – only eight minutes for examination and seven minutes for the emergency room, versus fifteen and five minutes respectively. There's no change in the investment for these

increases in efficiency, but it does increase the risk of the system because nurses are more likely to misdiagnose patients than doctors are.

Table 5: Test runs for nurses in the examination room.

	6 Doctors 6 Nurses	5 Doctors 7 Nurses
Cost ($/year)	2360000	2210000
Time in System (min.)	112.54	104.55
Doctor Utilization (%)	76.60	81.11
Nurse Utilization (%)	75.06	71.56
Exam Queue Time (min.)	8.43	1.28
ReExam Queue Time (min.)	3.92	3.68
Lab Queue Time (min.)	0.0168	0.2058
Treatment Queue Time (min.)	0.9774	0.1466
Emergency Queue Time (min.)	6.88	20.15

We wanted to experiment further with having nurses in the examination room, so we fidgeted with the amount of doctors and nurses until we found a potentially more appealing alternative. Decreasing the amount of doctors to five and increasing the amount of nurses to seven decreases the yearly cost by $150,000, decreases the overall time in system by eight minutes, increases doctor utilization, and decreases examination queue time by seven minutes, but it also increases the queue time for the emergency room by thirteen minutes. Given that the emergency room is likely the most important room, it may be unacceptable for the queue time to be an average of twenty minutes, but this is a decision to be made by the hospital.

Table 6: Test runs of the most promising models compared against the current system. Constants include cross-trained nurses, two receptionists, and two lab technicians.

	Current	6 Doctors 6 Nurses	5 Doctors 7 Nurses in ExRoom
Cost ($)	1840000	2360000	2210000
Time in System (min.)	17167	121.32	104.55
Doctor Utilization (%)	100	73.81	81.11
TR Nurse Utilization (%)	37.35	79.28	71.56
ER Nurse Utilization (%)	21.90	79.28	71.56
Exam Queue Time (min.)	23330.4	15.27	1.28
ReExam Queue Time (min.)	0.0002	3.18	3.68
Lab Queue Time (min.)	3.5188	0.0281	0.2058
Treatment Queue Time (min.)	7.6757	0.1752	0.1466
Emergency Queue Time (min.)	859.33	5.50	20.15

The most promising models both include an increase in cost, but this is to be expected with the catastrophic levels of operation of the current system. Given that the alternative models have a significant increase in throughput, the increase in cost is negligible to the increase in profits, as shown later in the document. As stated before, having nurses examine patients in the examination room is the riskier option, but it increases patient throughput by a significant margin. However, it also increases the emergency room queue time by a considerable amount, which is not ideal considering it's the most important room to have operating quickly. If this is a significant problem but having nurses in the examination room is not, the hospital may consider six doctors and six nurses in the

examination room instead, as shown in Table 5. The difference between the two alternatives is clearly risk vs. reward and the advantages for each will be shown later in the document.

Cost Analysis

After finalizing the results, a cost analysis was done to approximate the revenue gained through each of the alternatives. We wanted to understand which changes really provided the biggest growth in revenue while still maintaining a high patient throughput and reasonable utilizations for the workforce. This analysis was extremely important because we planned to increase the staff of doctors significantly in most of the simulations and the only way to justify the increase in cost would be to increase patient throughput which would in turn increase revenue. These values are subject to change and can be altered to fit the budget of the emergency department and to compete with competing emergency departments. These values were used in order to calculate the average revenue the hospital makes as well the potential revenue can make with the options we recommend.

First we had to determine which costs could be reasonably estimated and the costs we focused on were the different costs of the workforce and then the revenue each patient provides on average. In order to get these averages, we researched baseline salaries for all the positions the emergency department currently offers. These numbers were all found from various online sources located in our references and they include benefits that the company has to pay the employees. A doctor on average has a yearly salary of $250,000, a nurse has an average yearly salary of $100,000, a lab technician has an average yearly salary of $80,000, and a receptionist has an average yearly salary of $50,000. With the costs of the workforce we then proceeded to calculate how much revenue the emergency department makes.

By researching the average amount of revenue a patient brings to the hospital ($350), we were able to calculate how much profit the hospital makes per year currently and how much profit the hospital could potential make with the changes we have in mind. Once we had the average revenue each individual patient brings to the hospital we then had to calculate the throughput of patients currently and in each of our options. The average number of patients for the current state of the hospital is 19,467 patients per year. In the first option we recommend, the patient throughput increases substantially to 111,515 patients per year. Finally, with our second option the number of patients the hospital helps per year increases to 111,798 per year. These options resulted in revenue of $6,796,708.38, $38,934,347.10, and $39,033,153.72 respectively.

With the revenue calculated we then had to calculate the different costs each option had in order to make sure the hospital was still making profits even with the changes we suggest. We compared these numbers to the baseline or current state of the emergency department in order to properly compare the options and ensure our recommendations result in positive outcomes for the hospital. The cost of the current workforce is about $1,840,000 per year, the option 1 cost is about $2,360,000 and the last option costs $2,210,000. With the costs and the revenue, we could calculate per option, as shown in Table 7.

With these analyses we were able to ensure that our recommendations are not only cost effective, but are justified. These recommendations mentioned below all increase cost, but significantly increase profit, so much so that the change in cost seems minimal. If the emergency hospital has the budget to make these changes, they will be able to reach unheard of profit levels and will continue to grow substantial and help thousands of more patients per year.

Table 7: Cost analysis of the current system vs. the most promising models.

	Current	Option 1	Option 2
Cost	$ 1,840,000.00	$ 2,360,000.00	$ 2,210,000.00
Revenue	$ 6,796,708.38	$ 38,934,347.10	$ 39,033,153.72
Profit	$ 4,956,708.38	$ 36,574,347.10	$ 36,823,153.72

Recommendations

Table 8: Important aspects of Option 1 vs. Option 2.

	Option 1	Option 2
Cost	$ 2,360,000.00	$ 2,210,000.00
Revenue	$ 38,934,347.10	$ 39,033,153.72
Profit	$ 36,574,347.10	$ 36,823,153.72
Time in System (min.)	121.32	104.55
Doctor Utilization (%)	73.81	81.11
Nurse Utilization (%)	79.28	71.56
Exam Queue Time (min.)	15.27	1.28
Emergency Queue Time (min.)	5.50	20.15

After running many different scenarios through Simio, two clear options presented themselves: Option 1 includes six doctors and six nurses, while Option 2 includes five doctors and seven nurses. Both options included two technicians (down from three), as well as two receptionists. The difference is that Option 1 does not allow nurses to perform examinations in the examination room, while Option 2 does. Option 2 profits approximately $248,806 per year more than Option 1, but the hospital may leave itself open to higher insurance costs or lawsuits due to the increased risk of having a nurse examine patients.

Option 1 had remarkable results in throughput and exam room queue times, with 121 minutes and 15 minutes respectively. They are a significant decrease from the current times of 17,167 minutes for the throughput and 23,330 minutes for the exam room queue time, which was growing at an exponential rate due to a bottleneck in the system. These times for Option 1 are relatively close to Option 2's results, but Option 1 has a preferable doctor and nurse utilization percentages.

This option has an estimated yearly profit of $36,574,347.10, which includes the cost of the additional doctors that are needed to fulfill the positions so that the estimated time a patient stays in the system is at 2 hours. Option 2 does achieve a higher revenue by a difference of $248,806.60 but it also comes with the risk of letting a nurse treat level 3 patients and potentially make a mistake like not sending the patient to the emergency room for further treatments or lab work. This could potentially lead to higher insurance costs and even malpractice lawsuits. We believe the risks of Option 2 are not worth the meager difference in revenue.

Option 1 also has the potential to process 111,515 patients per year, which is a significant increase over the current numbers. Option 2 only has an increase of 283 people per year, but that comes with the risk of letting a nurse make a costly mistake.

In our opinion, Option 1 is the clear best option. The patient exam room wait times and total time are drastically reduced to a reasonable amount of time while keeping the doctors and nurses engaged in their jobs. The revenue it provides is outstanding since Option 1 can handle a great deal more patients throughout the year. With all of these improvements and the reduced risk of not having nurses able to treat patients without a doctor, Option 1 is the perfect plan for the Emergency Department.

Case 7

This emergency department (ED) is a part of a local hospital and it works 24 hours a day. Patients arrive to this ED by ambulance or as a walk-in and then go to the triage directly. A triage nurse will do the triage process, and then the clerk will register patients' information. After that, patients have to wait for a free bed and an available nurse to be admitted to this ED or wait in the waiting room. Some patients might leave the ED when the waiting time is long. After being admitted, patients will be assessed by the nurse according to their acuity level and then directed to see a physician or a delegate. Patients in this ED are classified based on the Canadian Triage and Acuity Scale (CTAS) into five levels. In this scale, level 1 is the most urgent and level 5 is non-urgent. In this system, levels 1 and 2 are treated the same way and considered as high acuity categories and levels 3, 4, and 5 are treated similarly and considered as low acuity categories. Physicians treat high acuity patients and low acuity patients are treated by delegates.

Once a physician is available, the patient will be assessed and an order will be produced. These orders could be: treat, send to the lab (blood work), or send for diagnostics (radiology). When going to the lab, a nurse should come and draw the blood sample. However, when patients are sent for diagnostics, they go to the radiology room. After all this, patients will go back, and a doctor will treat them, and then they leave the ED (either discharged or admitted to the hospital).

Questions

1- Develop a simulation model in SIMIO for this ED.

2- Improve the productivity of this system taking into consideration costs associated with adding new resources.

Data

Resources	**Number**	
Nurses	3	
Triage nurses	1	
Physicians	1	
Delegates	1	
Radiology technicians	1	
Receptionists	1	
Probabilities	**%**	
Patients leaving from the waiting room	5	

Probabilities	**Level 1**	**Level 2**	**Level 3**	**Level 4**	**Level 5**
Patients condition	0.01	0.16	0.56	0.25	0.02
Patients receiving radiology	0.82	0.07	0.48	0.28	0.18
Patients having blood work	0.85	0.73	0.51	0.19	0.01

Service times in minutes			
Triage nurse (TR)	**Registration**	**Nurse assessment**	**Radiology**
Poisson (10)	Lognormal (2)	Beta (10)	Beta (9)
Draw blood	**Physician treatment**	**Delegate treatment**	
Triangular (2,4,6)	Triangular (4,6,9)	Triangular (4,5,6)	

Patients arrival rates (patients/hour)		
12 am - 1 am	3.5	
1 am – 2 am	2.7	
2 am – 3 am	2.2	
3 am – 4 am	1.7	
4 am – 5 am	1.9	
5 am – 6 am	3.3	
6 am – 7 am	3.8	
7 am – 8 am	4.4	
8 am – 9 am	6.5	
9 am – 10 am	10.1	
10 am – 11 am	12.4	
11 am – 12 pm	11.7	
12 pm - 1 pm	8.5	
1 pm – 2 pm	8.3	
2 pm – 3 pm	7.7	
3 pm – 4 pm	6.8	
4 pm – 5 pm	6.6	
5 pm – 6 pm	5.8	
6 pm – 7 pm	5.9	

7 pm – 8 pm	4.6	
8 pm – 9 pm	4.3	
9 pm – 10 am	3.5	
10 pm – 11 pm	3.3	
11 pm – 12 am	3.1	

Group's Solution

ED Sim Cases – Case 7
ESI 4523C – Systems Simulation

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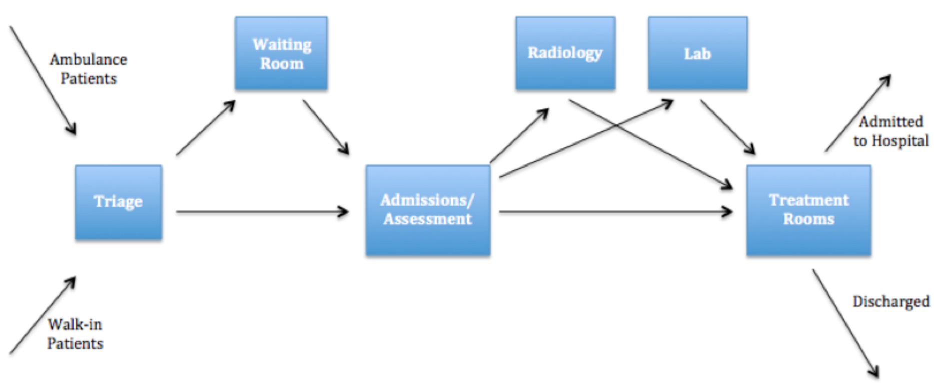
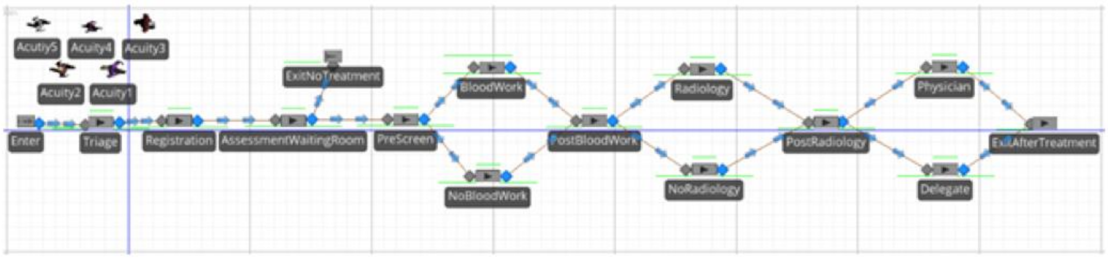
Figure 1: Original Layout of Emergency Department



Model Created - Initial Layout

As described above, our team determined that the layout of the model for the initial simulation should be created as shown in Figure 2.

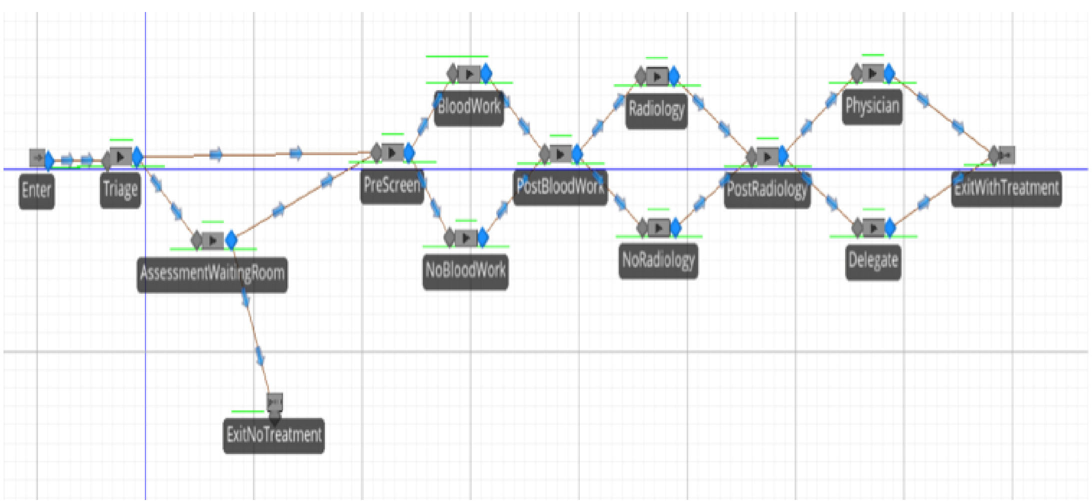
Figure 2



Model Created - Alternative 1

Alternative 1 focuses on the beginning stages of being assessed within the emergency room. Triage and registration were initially two separate locations, where a patient would have to arrive to the ER, enter the triage to be assigned a trauma level from 1 to 5, and then proceed to the registration room. Alternative 1 combined these two tasks in order to eliminate the transportation time between the triage and registration. Another change involved a priority path from the triage, directly to the pre-screen. These changes are seen below:

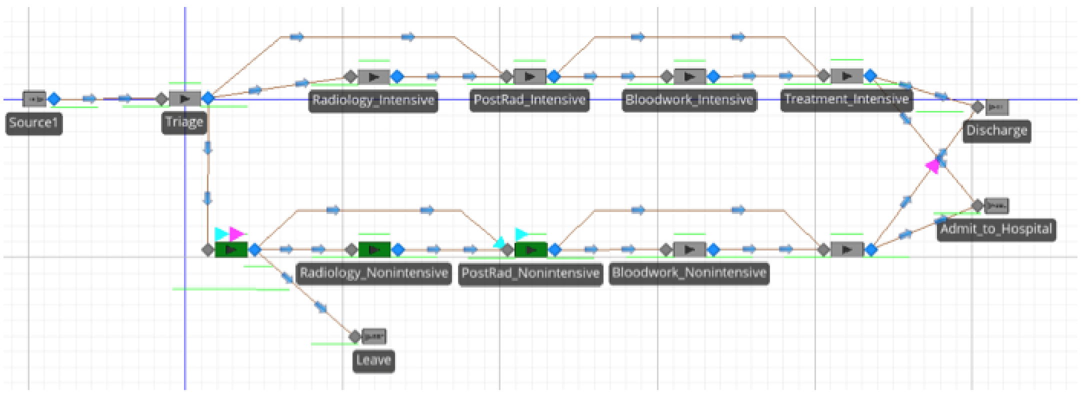
Figure 8



Model Created - Alternative 2

Alternative 2 explores the option of dedicating resources based on trauma level- levels 1 and 2 are given exclusive access to machinery and doctors, while level 3, 4, and 5 are limited to nurse consultations and treatments. Although it does not fully utilize the available resources, the goal is to treat urgent patients as quickly as possible. Shown below is the overview of proposed alternative 2:

Figure 10



Results and Recommendations

Figure 11

Intensive	Patient Waiting Time (Hours)	Staff Work Time (Hours) Radiology	Bloodwork	Treatment	Triage	Registration	Staff Down Time (Hours)
Initial	0.0923	0.0685	0.0651	0.1091	16.1657	1.2404	1.1664
Alternative 1	0.0764	0.0656	0.0601	0.1019	20.3195	0	1.9277
Alternative 2	0	0	0	0	0	0	336

Nonintensive	Patient Waiting Time (Hours)	Staff Work Time (Hours) Radiology	Bloodwork	Treatment	Triage	Registration	Staff Down Time (Hours)
Initial				0.1217			0.2253
Alternative 1				0.0869			0.3432
Alternative 2	0.0538	0.0565	0.033	0	0	0	336

Overall	Patient Waiting Time (Hours)	Staff Work Time (Hours) Radiology	Bloodwork	Treatment	Triage	Registration	Staff Down Time (Hours)
Initial	0.0923	0.0685	0.0651	0.1154	16.1657	1.2404	
Alternative 1	0.0764	0.0656	0.0601	0.0944	20.3195	0	
Alternative 2	0.0269	0.02825	0.0165	0	0	0	

Intensive		
0		
0	Patient Utilization	Staff Utilization
Initial	98.51%	93.80%
Alternative 1	98.79%	91.42%
Alternative 2	100.00%	0.00%
0		
Nonintensive		
0		
0	Patient Utilization	Staff Utilization
Initial	41.02%	35.07%
Alternative 1	33.18%	20.20%
Alternative 2	28.12%	0.03%
0		
Overall		
0		
0	Patient Utilization	Staff Utilization
Initial	98.51%	64.44%
Alternative 1	98.79%	55.81%
Alternative 2	64.06%	0.01%

Referring back to the Discrete Simulation Project Proposal, we chose Patient Wait Time, Staff Work Time, Patient Utilization, and Staff Utilization as our performance measures. These measures were used to evaluate and compare each of the different models. Patient Wait Time is the time a patient spends waiting in the system. Staff Work Time is the time spent by the staff working in each server in the system. Patient Utilization is the percentage of Patient Waiting Time to the total operation time. Staff Utilization is the percentage of Staff Work Time to the total operation time.

Looking at the Intensive patients, the initial model had a Patient Wait Time of .0923 hours whereas Alternative 1was .0764 hours and Alternative 2 was 0 hours. These statistics prove that intensive care patients on average have a lower waiting time in Alternative 2. We unfortunately had to disregard the calculations for Alternative 2 because the simulation didn't work as planned. According to the results for Alternative 2, there is no Patient Wait Time and the staff doesn't work at all for the patients in intensive care. For these reason, we chose to disregard the results of Alternative 2. Therefore, Alternative 1 had the least Patient Wait Time for the Intensive patients. The Staff Utilization rate for the Intensive care patients was highest in the initial model. Alternative 2 provided 100% Patient Utilization because again there was no Patient Wait Time, so all patients were being utilized in the system.

The Overall chart, shows the averages of the Intensive and Non Intensive patients. In general, Alternative 1 provided results that were better than the initial model. Since Alternative 1 combined the Triage and Registration into one server, the Staff Work Time for Triage is significantly higher than the Initial model. That was to be expected because we combined two servers into one. We realized that the Initial model proved to have the best Staff Utilization of 64% and Alternative 1 proved to have the best Patient Utilization of 98.79%.

We recommend implementing Alternative 1 because it produced the most positive outcomes. Patients will have to wait less time in the system and they will be utilized the best. We also recommend combining the Physician and Delegate servers into one, or possibly training the Delegates to be equal to the Physician. By doing so, it will allow the doctors to be used a resource in the system. If there was an increase in patients in the blood work, then all doctors would report to the Bloodwork, but once the crowd goes down, a doctor could leave Bloodwork and move to another server in the system that needs help.

Case 8

This emergency department is a part of a large hospital. It consists of four sections that deal with patients according to their conditions and have all the necessary requirements to help in the treatment process. Section 1 contains four fully equipped rooms with a capacity of 18 beds to provide cares for patients with most critical conditions. Section 2 is similar to Section 1 with less equipment, and it is for urgent patients and has a capacity of 4 beds. Section 3 is for patients with low acuity levels (ESI 3, 4, and 5) and it has a capacity of 6 beds. Section 4 is similar to Section 3 with a capacity of 12 beds.

Patients arrive at this ED in two ways: as walk-in patients or by an ambulance. Walk-in patients will go to the nurse' station for the signing in process and then to the triage station. However, Ambulance patients will go directly to the triage station for the initial assessment by triage nurses. In the triage station, triage nurses assess patients' conditions using Emergency Severity Index (ESI) to classify patients' urgency. The scale of this index is from 1 to 5 where is the most critical. ESI 1 patients need immediate cares and have a high risk of life loss while ESI 5 patients have the least risk of life loss. Most walk-in patients will be classified between ESI 3 to ESI 5, whereas ambulance patients could be anywhere between ESI 1 and ESI 4.

The treatment process is almost the same in all sections with some differences due to patients' conditions and urgency. It starts with an assessment by the treatment team that usually consists of a doctor and a nurse. Some patients will need to have extra tests and will be sent to the lab and

technicians will do these tests. Patients that do not need extra test will leave the ED. After these tests, patients will have another assessment by the treatment team before leaving the ED (either discharged or admitted to the hospital). In this ED, every patient will be assigned one nurse all the time.

Questions

1- Develop a simulation model in SIMIO for this ED.
2- Improve the productivity of this system taking into consideration costs associated with adding new resources.

Data

Resources	**Number**	
Nurses at triage	1	
Nurses at Reception	1	
Nurses	3	
Doctors	2	
Lab technicians	2	

Probabilities	%
Walk-in patients	90
Ambulance patients	10
ESI 1 patients	10
ESI 2 patients	20
ESI 3 patients	30
ESI 4 patients	35
ESI 5 patients	5
Patients that need extra tests	40

Service times in minutes		
Signing in process	**Triage**	
Triangular (3,5,7)	Uniform (1,2) for ESI 1 & 2	Uniform (10,15) for ESI 3, 4 &5
1st Assessment	**Lab tests**	**2nd Assessment**
Triangular (20,30,40)	Triangular (20,40,60)	Triangular (10,15,20)

Patients arrival rates (patients/hour)	
Time	**Rate**
12 am- 1 am	5.39
1 am – 2 am	4.23
2 am – 3 am	3.88
3 am – 4 am	2.64
4 am – 5 am	2.22
5 am – 6 am	5.57
6 am – 7 am	5.73
7 am – 8 am	6.31
8 am – 9 am	7.62
9 am – 10 am	8.56
10 am – 11 am	9.22
11 am – 12 pm	9.89
12 pm- 1 pm	9.08
1 pm – 2 pm	8.55
2 pm – 3 pm	7.82
3 pm – 4 pm	7.37

4 pm – 5 pm	8.23	
5 pm – 6 pm	6.92	
6 pm – 7 pm	8.16	
7 pm – 8 pm	7.63	
8 pm – 9 pm	6.49	
9 pm – 10 am	5.03	
10 pm – 11 pm	3.94	
11 pm – 12 am	2.46	

Group's Solution

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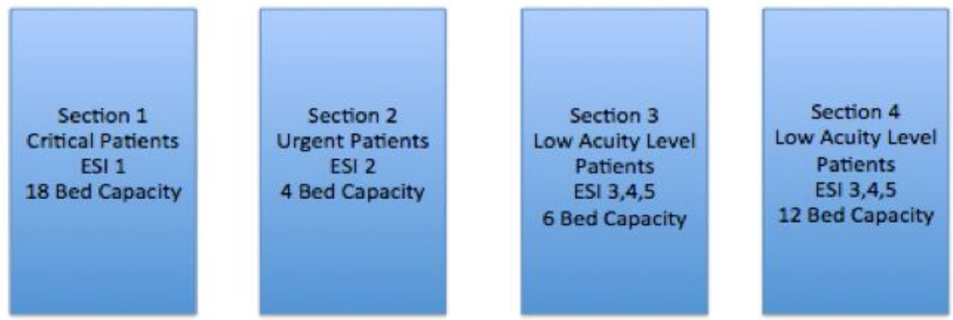

Figure 2.1: ED Sections

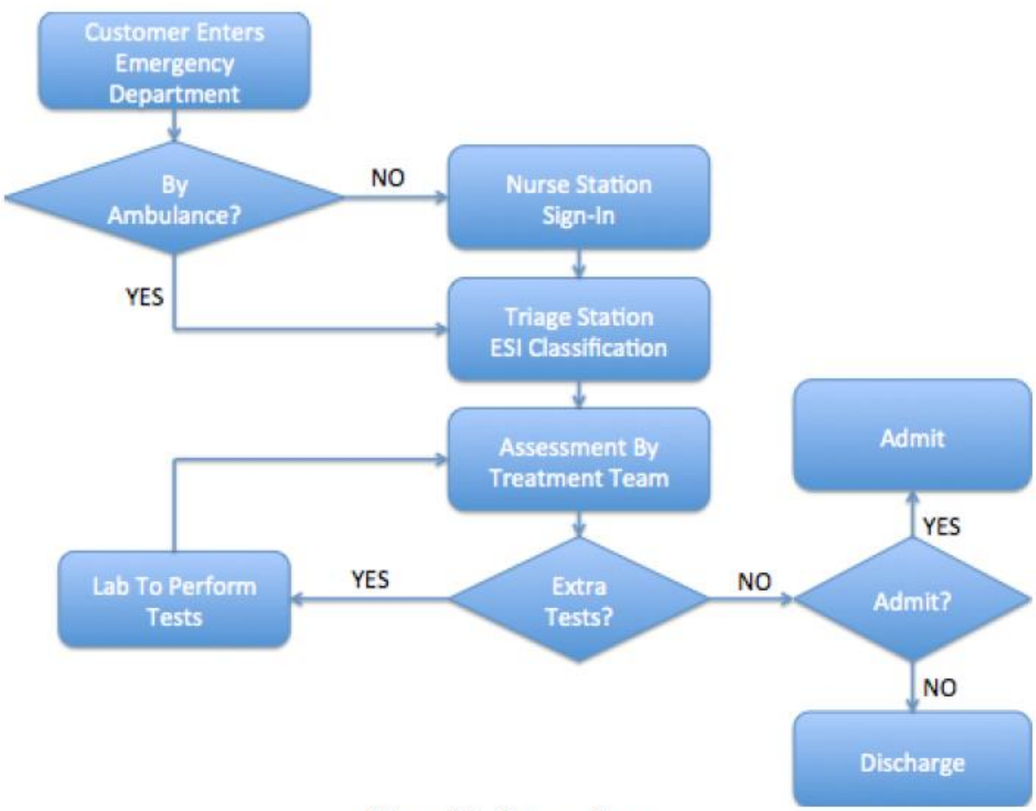

Figure 2.2: Process chart

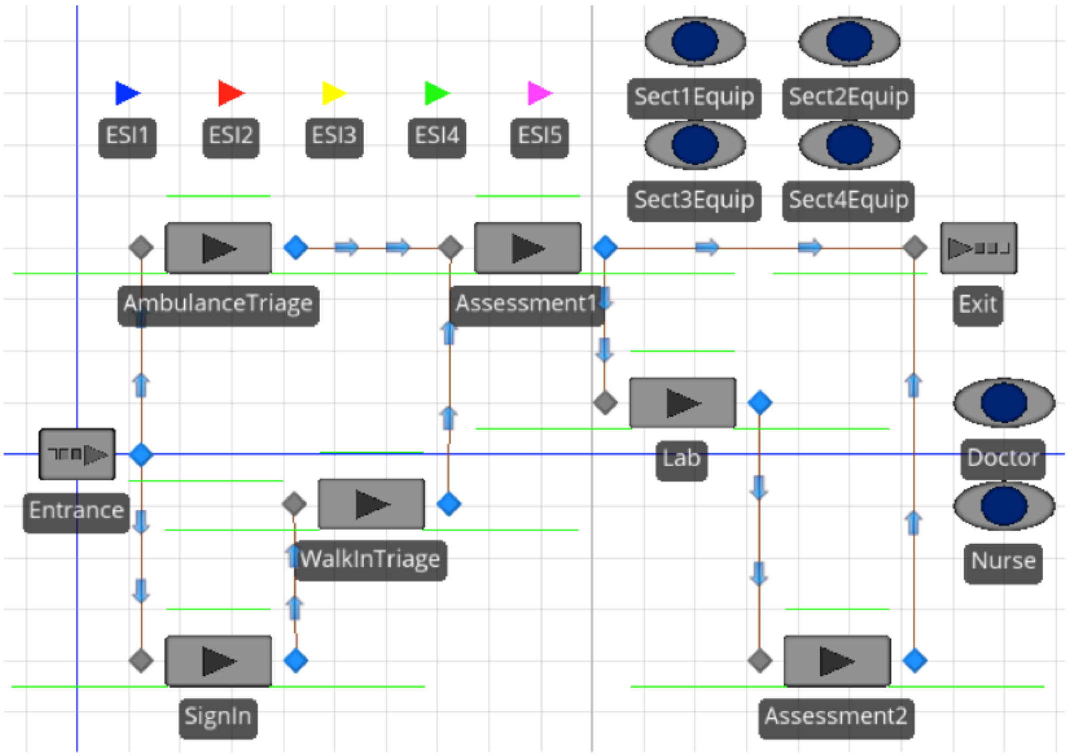

Figure 5.1: Base model

4 Alternatives

4.1 Flexible Sections for Treatment

The authors took three alternatives into consideration. The first is to increase flexibility in the assignment of beds for patients in each of the four sections. What is meant by this is that Section 1, which has eighteen beds, is never at full capacity because 10% of the patient mix that goes through that section are classified ESI level 1. Moving beds from this section is would not be the ideal solution because the equipment with in this section is important for those who are in need of them but the equipment within this section should be able to accommodate for those of ESI levels 3, 4 and 5. Section 2 having only four beds and Section 3 having six beds, those patients entering these sections would have the respective patients. Section 4, the last section, has a total capacity of twelve beds and would still receive patients of the the lower level of priority. With this alternative, the authors saw to reduce the wait time by allowing an increase capacity of patients to be seen. Allowing the patients to be able to use any available beds would allow patients to spend less time within in the system and their wait times would be decreased as well.

4.2 Designated Nurse for ESI 5 Patients

Due to the fact that each patient requires a nurse but not all patients are required to see a doctor, the team thought about the idea of ESI level 5 patients to only be seen by a nurse because these patients are the closest to being in a stable condition. This way, these patients can be in and out of the system in a quick and efficient manner. Their wait time would be reduced and the amount of time in their system would also be reduced. With the implementation of this alternative,the team hopes that all other ESI levels as well as ESI level 5 patients will make it through the system in less time.

4.3 Additional Doctor on Staff

After a few thought processes and meetings, the team came to an agreement that a system with varying priority levels and an uneven staff only decrease efficiency. Since the system only required 3 nurses and only 2 doctors, the team's thoughts were to add an additional doctor to have an even staff. This way each patient being seen gets to be seen by both and the workload on each staff decreases. The doctors and nurses can work together in an efficient manner to have the patients treated quickly but make sure that they are treated in order to be fully healed and in a stable condition. The addition of a doctor might be able to prove this theory and also support the idea of more doctors and nurses being hired for this particular emergency department.

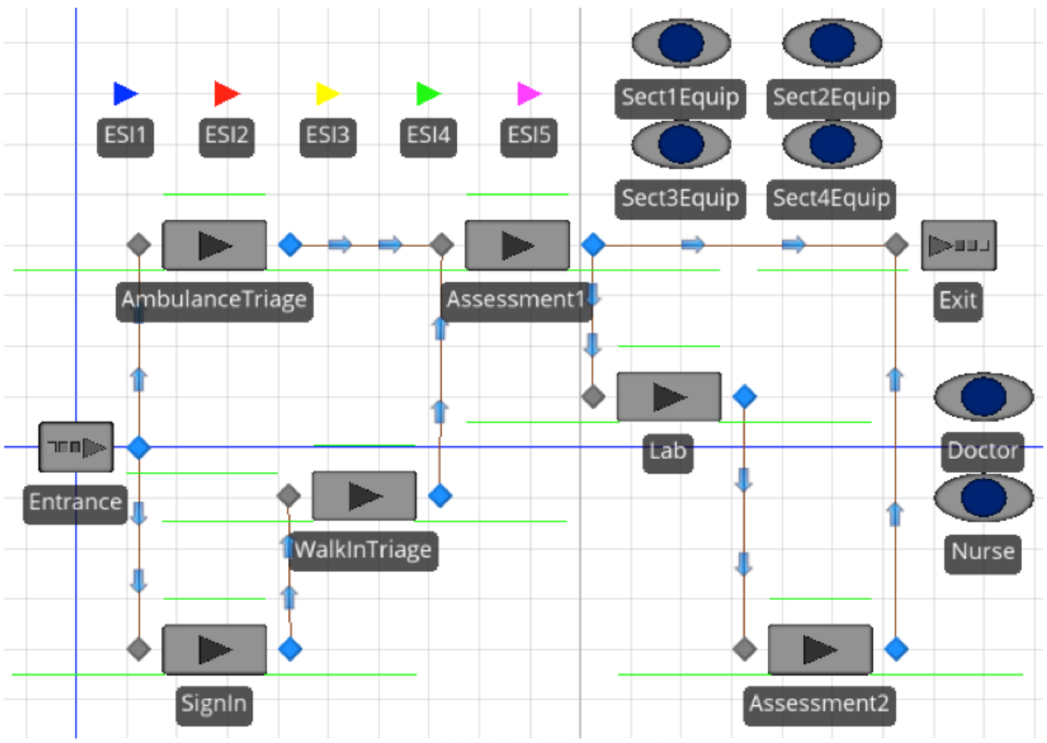

Figure 5.4: Model with Flexible Sections Alternative

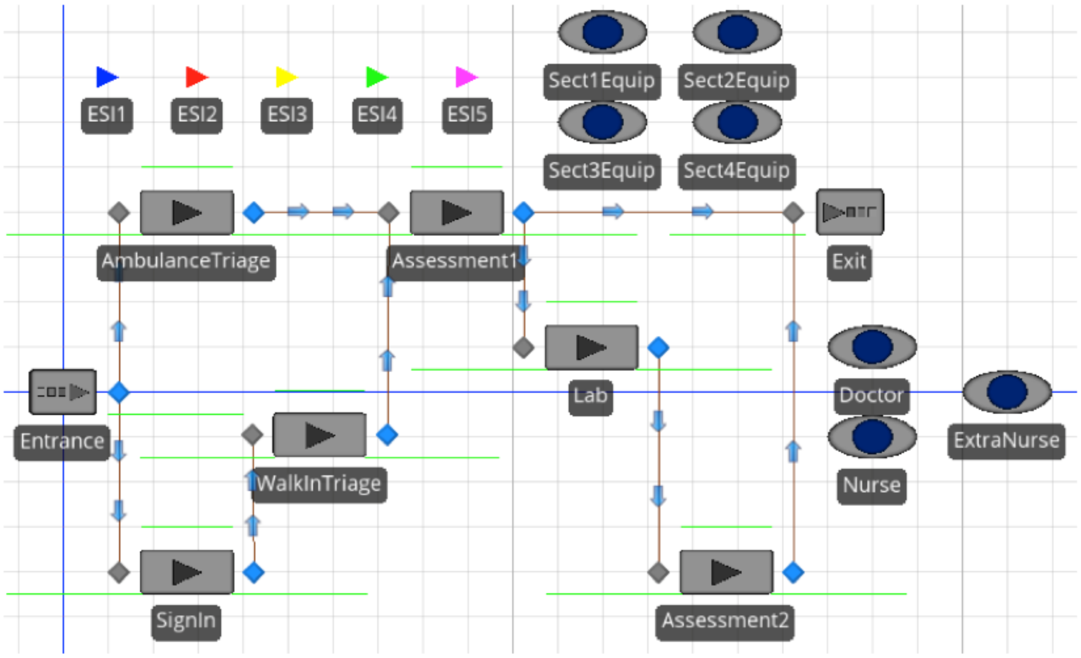

Figure 5.5: Model with ESI 5 Nurse Alternative

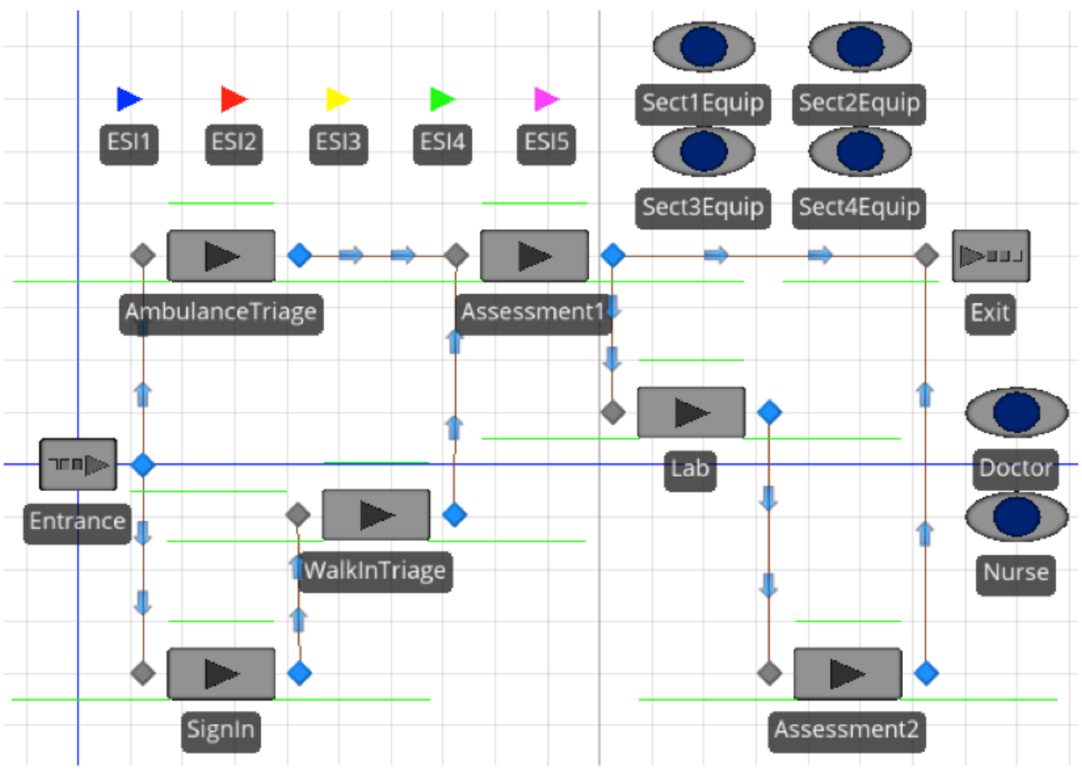

Figure 7: Model with Additional Doctor Alternative

6 Results

6.1 Final Results

The final results of this experiment are detailed in the following Table 6.1:

Table 6.1: Final Results

Key Performance Indicator	Base Model	Flexible Sections	ESI 5 Nurse	Add Doctor
Staff Wait Time (hours)	2.97	6.63	∞	0.56
Sections 1 and 2 Wait Time (hours)	< 1 minute	42.64	< 1 minute	< 1 minute
Sections 3 and 4 Wait Time (hours)	68.84	76.72	69.00	0.13
Doctor Utilization (percent)	100	100	100	91.96
Nurse Utilization (percent)	100	100	100	92.92
ESI 1 In-System Time (hours)	2.02	2.56	2.18	2.02
ESI 2 In-System Time (hours)	2.14	2.98	2.24	2.07
ESI 3 In-System Time (hours)	4.05	15.97	4.06	2.14
ESI 4 In-System Time (hours)	305.49	∞	304.56	3.00
ESI 5 In-System Time (hours)	∞	∞	∞	9.54

6.3 Recommendations

After all testing out the different alternatives, the final recommendation for this particular ED to add another doctor to help out with the patients and even perhaps add more doctors and nurses. The increase of staff could decrease the wait times to minutes and decrease the average times of patients being in the system from lengthy hours to much less hours. The team agreed that as long as the staffing numbers are equal, there will not be issues of long wait times for the patients and the amount of time the patients spend with in the system. This would increase the efficiency with in the ED.

Case 9

This Primary Care Clinic (PCC) is a part of Student Health Services (SHS) in a governmental university. It provides medical cares for students attending the University. This PCC receives walk-in patients, and patients with appointments and works from 8 am to 5 pm Monday through Friday.

When patients arrive at this PCC, they go to the front desk for registration. After that, they go to the triage station. Patients that need urgent care will be taken directly to see a doctor or a nurse practitioner. At the triage, a triage nurse will do an initial assessment of the condition of the patient to decide whether a doctor or a nurse practitioner should see the patient for treatment. Patients that need to see a doctor will be directed to a medical assistant. The medical assistant will check patient's vital signs and request lab tests (when needed) before meeting the doctor. After that, the patient meets the doctor for treatment and then leaves the PCC. Similarly, patients that meet the nurse practitioner get the needed treatment and leave the PCC.

Questions

1- Develop a simulation model in SIMIO for this PCC.
2- Improve the productivity of this system taking into consideration costs associated with adding new resources.

Data

Resources	Number		
Nurse Practioners	3		
Physicians	3		
Medical assistants	2		
Supporting staff	1		
Lab technicians	1		
Probabilities	**%**		
Patients with critical conditions	8		
Patients treated by nurse practitioners	33		
Patients that need lab tests	26		
Service times in minutes			
Registration	**Triage**	**Check-up**	
Uniform (4,8)	Triangular (3,5,7)	Triangular (2,4,6)	

Treatment		
Physicians	**Nurse Practitioners**	**Lab tests**
Triangular (15,20,25)	Triangular (12,16,20)	Triangular (20,40,60)

Patients arrival rates (patients/hour)

Time	**Monday**	**Tuesday**	**Wednesday**	**Thursday**	**Friday**
8 - 9 am	13	13	12	11	10
9 - 10 am	12	12	11	10	9
10 - 11 am	12	12	10	9	8
11 - 12 pm	12	12	11	10	9
12 - 1 pm	Closed	Closed	Closed	Closed	Closed
1 - 2 pm	13	12	11	10	10
2 - 3 pm	12	12	10	10	9
3 - 4 pm	8	8	7	7	7
4 - 5 pm	3	3	3	2	2

Group's Solution

UCF Simulation Novices - Team 15

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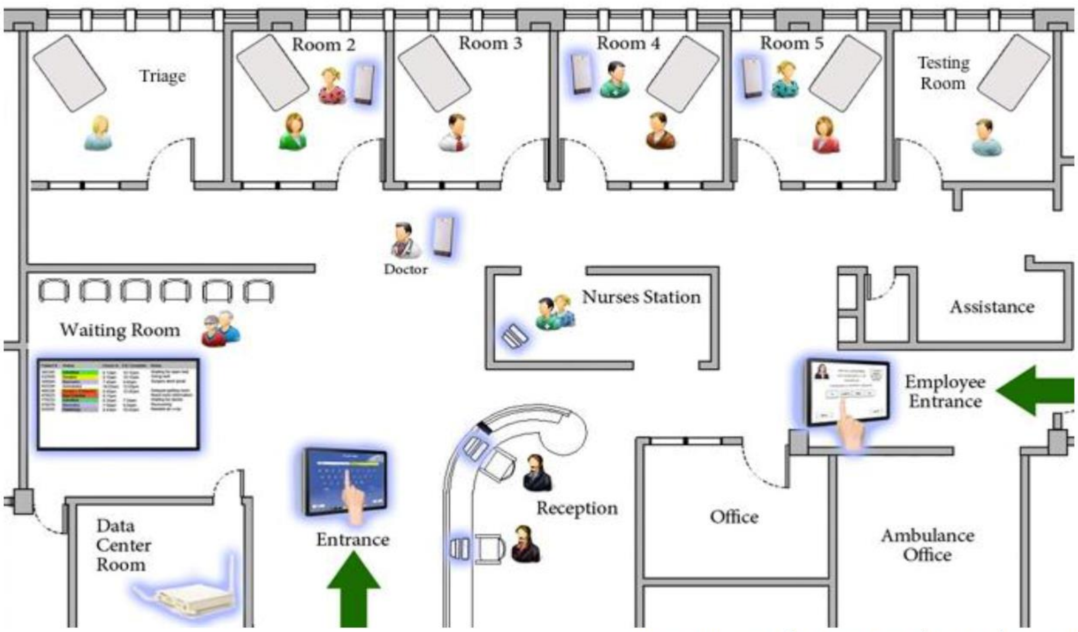


Figure 1: Projected Primary Care Clinic Facility Layout

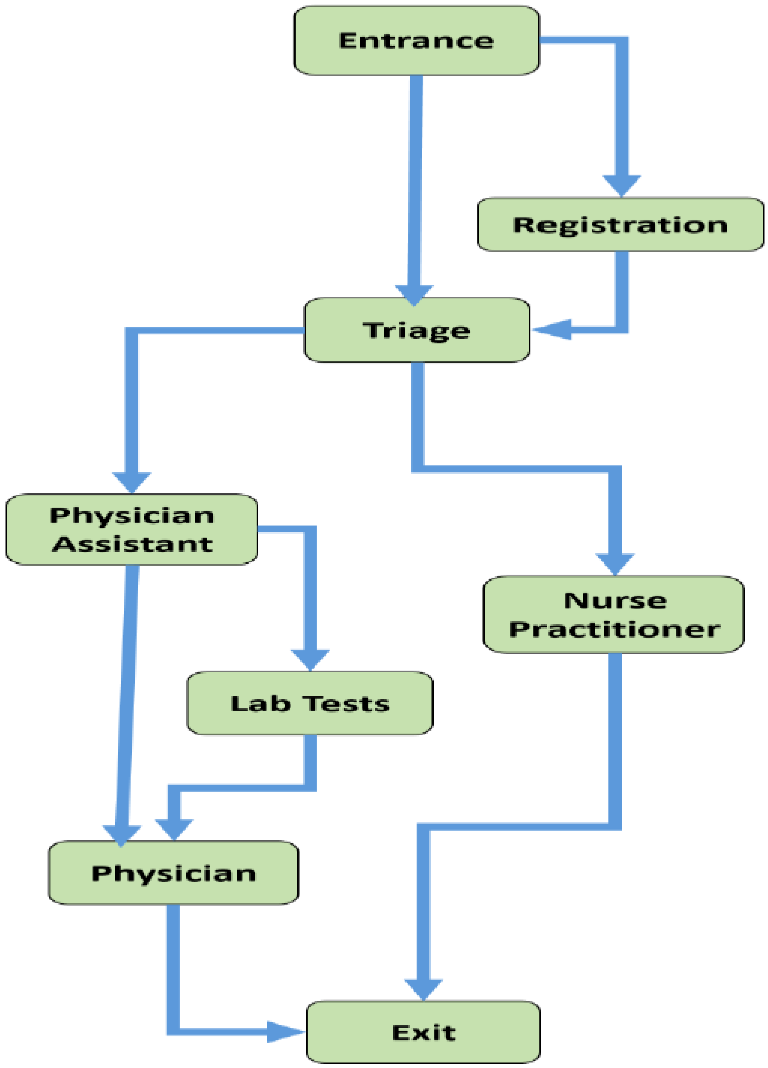
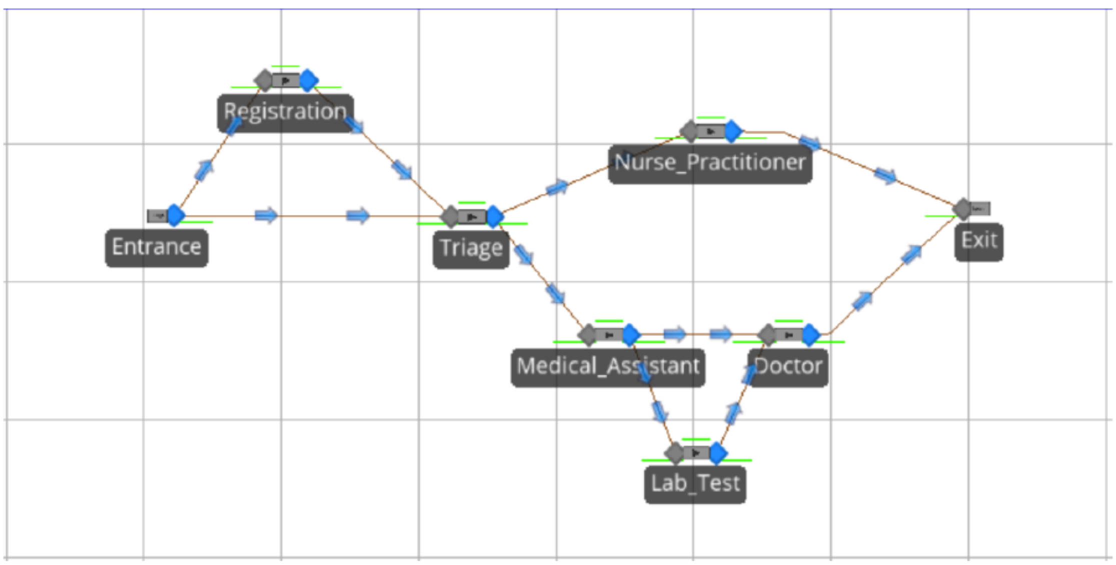


Figure 2: Primary Care Clinic Process Flow

Simulation Layout and Flow



Simulation Results

The results of the simulation showed that the Doctor, Lab Tests, and Nurse Practitioner had the highest average time in their station. The Lab Tests in particular had by far the highest of the three. This is partially due to the fact that the Medical Assistant in charge of the initial evaluation after the Triage is also responsible for helping the patient go through lab testing and evaluating them before they can see the Doctor. This is causing the Medical Assistant to support two roles in the system and can cause a backup in their area if not properly staffed for the days patient traffic.

Data Item	Object Name	Data Source	Category	Statistic	Object Type	Average
TimeInStation	Doctor	Processing	HoldingTime	Average (Hours)	Server	0.6567
				Maximum (Hours)	Server	0.7363
				Minimum (Hours)	Server	0.5024
		InputBuffer	HoldingTime	Average (Hours)	Server	0.0852
				Maximum (Hours)	Server	1.2995
				Minimum (Hours)	Server	0.0000
	Lab_Test	Processing	HoldingTime	Average (Hours)	Server	1.2922
				Maximum (Hours)	Server	1.6047
				Minimum (Hours)	Server	0.6861
		InputBuffer	HoldingTime	Average (Hours)	Server	0.0201
				Maximum (Hours)	Server	1.0615
				Minimum (Hours)	Server	0.0000
	Medical_Assistant	Processing	HoldingTime	Average (Hours)	Server	0.1291
				Maximum (Hours)	Server	0.1606
				Minimum (Hours)	Server	0.0676
TimeInStation	Nurse_Practitioner	Processing	HoldingTime	Average (Hours)	Server	0.5254
				Maximum (Hours)	Server	0.5896
				Minimum (Hours)	Server	0.4036
		InputBuffer	HoldingTime	Average (Hours)	Server	0.0006
				Maximum (Hours)	Server	0.1541
				Minimum (Hours)	Server	0.0000
	Registration	Processing	HoldingTime	Average (Hours)	Server	0.1970
				Maximum (Hours)	Server	0.2607
				Minimum (Hours)	Server	0.1333
		InputBuffer	HoldingTime	Average (Hours)	Server	0.6191
				Maximum (Hours)	Server	4.6008
				Minimum (Hours)	Server	0.0000
	Triage	Processing	HoldingTime	Average (Hours)	Server	0.1629
				Maximum (Hours)	Server	0.1952
				Minimum (Hours)	Server	0.1008
		InputBuffer	HoldingTime	Average (Hours)	Server	0.0496
				Maximum (Hours)	Server	0.7611
				Minimum (Hours)	Server	0.0000

To go along with this information of time in station, the Doctors also have the highest average number of patients in their station. This would mean that the Doctor almost always has someone in their office or in queue to come into their office, creating a large backup in the Doctors section if not properly maintained.

Data Item	Object Name	Data Source	Category	Statistic	Object Type	Average
NumberInStation	Doctor	Processing	Content	Average	Server	0.9936
				Maximum	Server	6.0000
		InputBuffer	Content	Average	Server	0.1289
				Maximum	Server	12.9600

The time off shift shows that there is a large amount of time during the day where patients cannot be seen due to the staff all being off on break. This off time is necessary for the staff to be allowed to have, but this also creates a large amount of time where patient traffic can back up.

Data Item	Object Name	Data Source	Category	Statistic	Object Type	Average
TimeOffShift	Doctor	[Resource]	ResourceState	Average (Hours)	Server	2.0000
				Occurrences	Server	360.0000
				Percent	Server	8.3333
				Total (Hours)	Server	360.0000
	Lab_Test	[Resource]	ResourceState	Average (Hours)	Server	2.0000
				Occurrences	Server	360.0000
				Percent	Server	8.3333
				Total (Hours)	Server	360.0000
	Medical_Assistant	[Resource]	ResourceState	Average (Hours)	Server	2.0000
				Occurrences	Server	360.0000
				Percent	Server	8.3333
				Total (Hours)	Server	360.0000
	Nurse_Practitioner	[Resource]	ResourceState	Average (Hours)	Server	2.0000
				Occurrences	Server	360.0000
				Percent	Server	8.3333
				Total (Hours)	Server	360.0000
TimeOffShift	Registration	[Resource]	ResourceState	Average (Hours)	Server	2.0000
				Occurrences	Server	360.0000
				Percent	Server	8.3333
				Total (Hours)	Server	360.0000
	Triage	[Resource]	ResourceState	Average (Hours)	Server	2.0000
				Occurrences	Server	360.0000
				Percent	Server	8.3333
				Total (Hours)	Server	360.0000

Proposed Alternative Solutions

Due to there being a long break for lunch where the entire primary care clinic shuts down, there is a slight backlog created. Our proposed solution to this issue is to have their be shift work implemented into the set up. This would still allow for all operators to have their breaks

for lunch, but it would prevent the backup created by an entire clinic shut down. This would allow for there to always be at least a functioning level of staff available during lunch hours and for there to be a constant flow of patients during all hours of the day that the clinic is open.

A more expensive alternative would be to hire extra staff in all areas. Since there are no specific operators that have an extended wait time or long service times, the optimal solution would be to add staff in all areas to support any influx of patients. This could be particularly utilized during times when there is a large amount of patients that enter the system at one time. The additional staff will be capable of accommodating these patient quantity changes. In order to make this alternative the less expensive than just having the staff sitting around the office when not in use, there could be additional staff on call for all of these positions. This would allow for the staff to only be filled when there is a need for the extra staff around. The on call staff would be paid less during on call hours until they are called in to the office for support. This way there would always be sufficient staff available to handle any level of patient arrivals.

Based on our results, it would make the most sense to have extra staff on call for the particular operators in the system of the Doctor, someone for Lab Tests, and a Nurse Practitioner. These three positions are of the highest concern because they have the highest average time in their system and could end up causing a backup in the other areas of the primary care clinic if not properly staffed. By providing on call operators for these sections of the clinic, we can reasonably assume that the primary care clinic can handle an influx of patients.

Due to the Medical Assistant needing to support the role of evaluating the patient after they go through Triage and then taking them through Lab Testing and carrying out further evaluations if necessary, they can be stretched thin during times when there is a high level of patient flow through the primary care clinic. The best solution options to this would be to either have a Medical Assistant permanently staffed to do Lab Testing, or again add a Medical Assistant to the on call hours. Either option would keep the Medical Assistant from being overwhelmed with patients during times of high patient traffic, but the on call option would be the most cost effective.

Conclusion

After the results of using SIMIO to simulate the Primary Care Clinic were analyzed and all reasonable solutions were considered. The Simulation Novices decided that the solution to improve the productivity of this system, while taking into consideration costs associated with adding new resources, was to add in shift work to the schedule. This would allow for almost no costs to be added because no new resources would need to be added to the system to improve its productivity. Adding in shift work would eliminate the long stretch where the entire clinic shuts down for the staff to go on break, and instead have only some staff leave at certain times so the clinic could always be open and allowing patient traffic to continue to be processed.

Case 10

This emergency department (ED) is a part of a medical center that is located in a metropolitan area. It has 32 beds for main care, 6 for critical care, and 14 for minor emergency and all these beds are located in rooms. This ED employs 65 physicians, three assistant physicians, four nurse practitioners, and 75 nurses. It is divided into treatment and pretreatment area. The treatment area is used for the treatment process while the pretreatment area includes registration station, waiting room, and triage rooms.

Patients arrive at this ED in two ways: as walk-ins or in an ambulance. Ambulance patients go directly to the treatment area whereas walk-in patients go to the pretreatment area. In the pretreatment area, patients go through registration where nurses take their information. After that, they wait for an available nurse to perform the triage process to assess their conditions. After that patients wait for an available bed in the treatment area.

In the treatment area, ambulance patients will have a bedside registration done by a nurse. After that, all patients wait for a free medical assistant to perform an initial assessment and decide whether a physician or a nurse practitioner is needed to do the examination. Then, patients proceed to be examined by the proper person (physician/nurse practitioner). Some patients will need extra tests (like blood samples or x-rays), and they go to the lab area to do the required test. After that, they go back to have another examination and then leave the ED (either discharged or

admitted to the hospital). Similarly, patients that did not need extra tests leave the ED after the first examination.

Questions

1- Develop a simulation model in SIMIO for this ED.

2- Improve the productivity of this system taking into consideration costs associated with adding new resources.

Data

Patients arrival rate (patients/hour)		
Poisson (10)		
Resources	**Number**	
Beds	52	
Physicians	25	
Assistant Physicinas	3	
Nurse practitioners	4	
Nurses	75	

Probabilities	**%**	
Walk-in patients	91	
Ambulance patients	9	
Patients treated by physicians	68	
Patients treated by nurse practitioners	32	
Patients that need extra tests	44	
Service times in minutes		
Registration	**Triage**	**Bedside registration**
Triangular (3,5,7)	Triangular (10,15,20)	Triangular (1,2,3)
Initial assessment	**First examination**	
	Physicians	**Nurse practitioners**
Triangular (2,4,6)	Triangular (20,30,40)	Triangular (10,15,25)

Lab tests	**Second examination**	
	Physicians	**Nurse practitioners**
Triangular (20,40,60)	Triangular (10,15,20)	Triangular (5,10,20)

<u>Group's Solution</u>

Team 16

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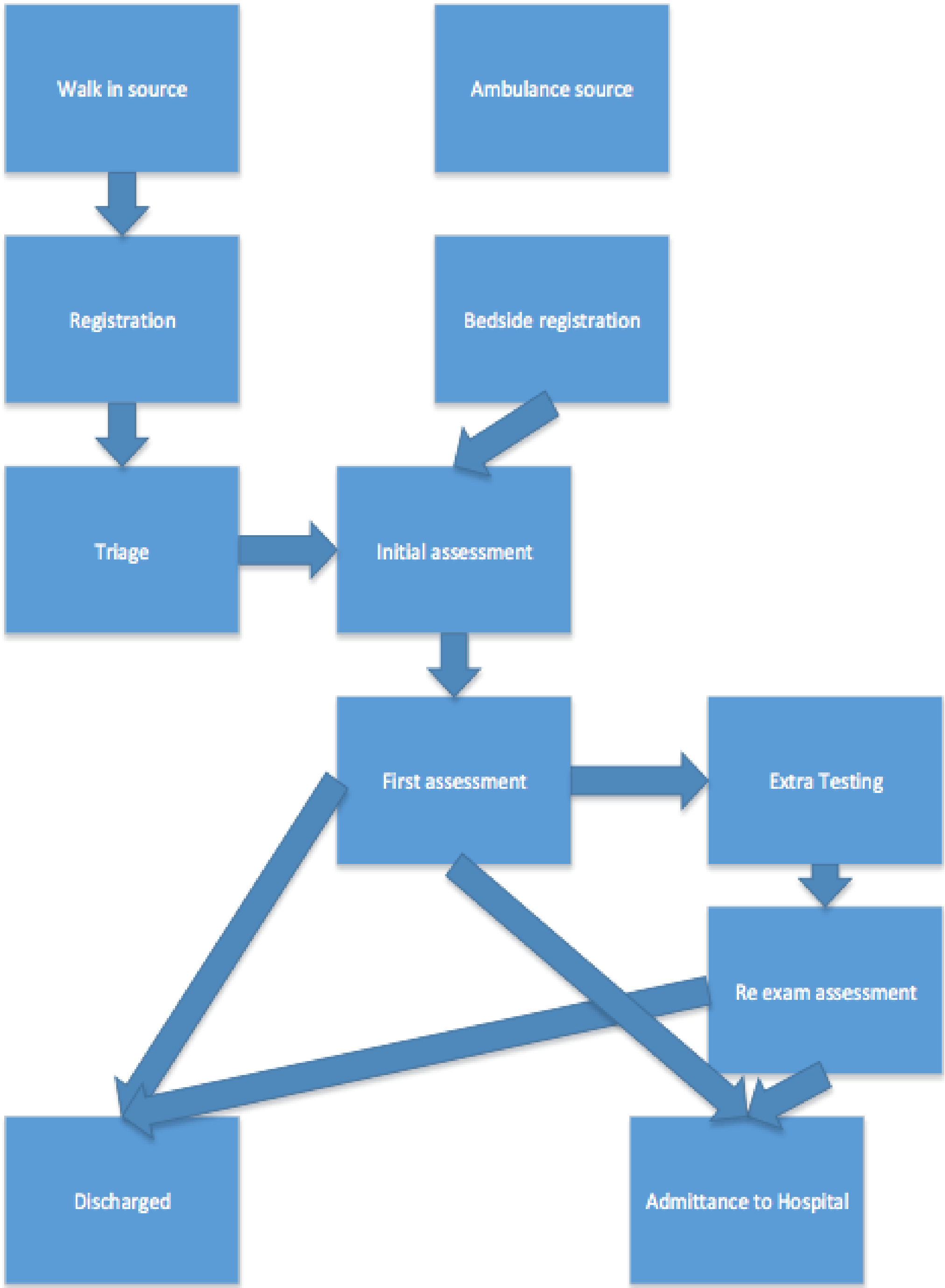
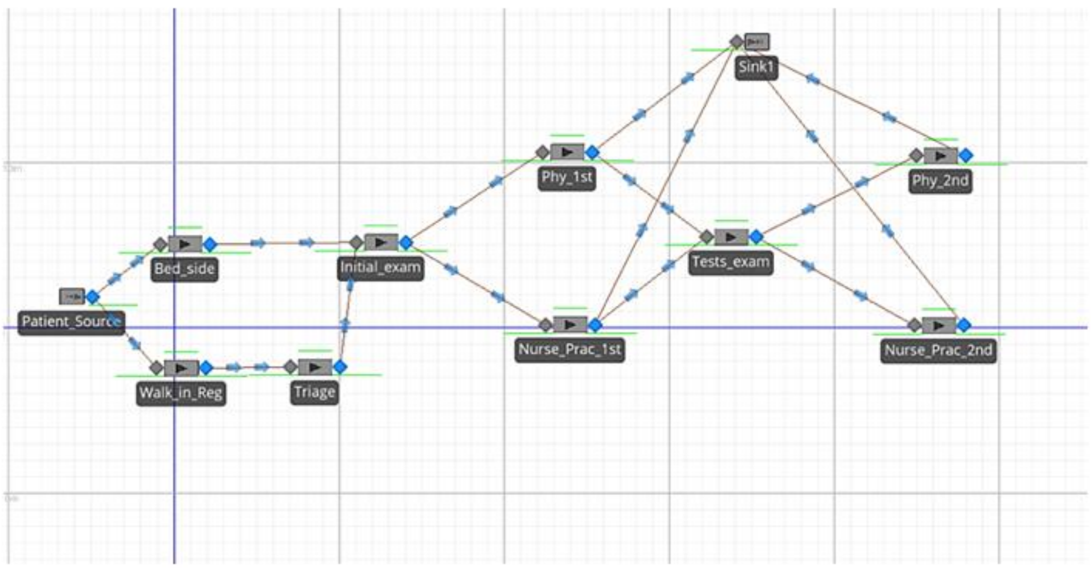
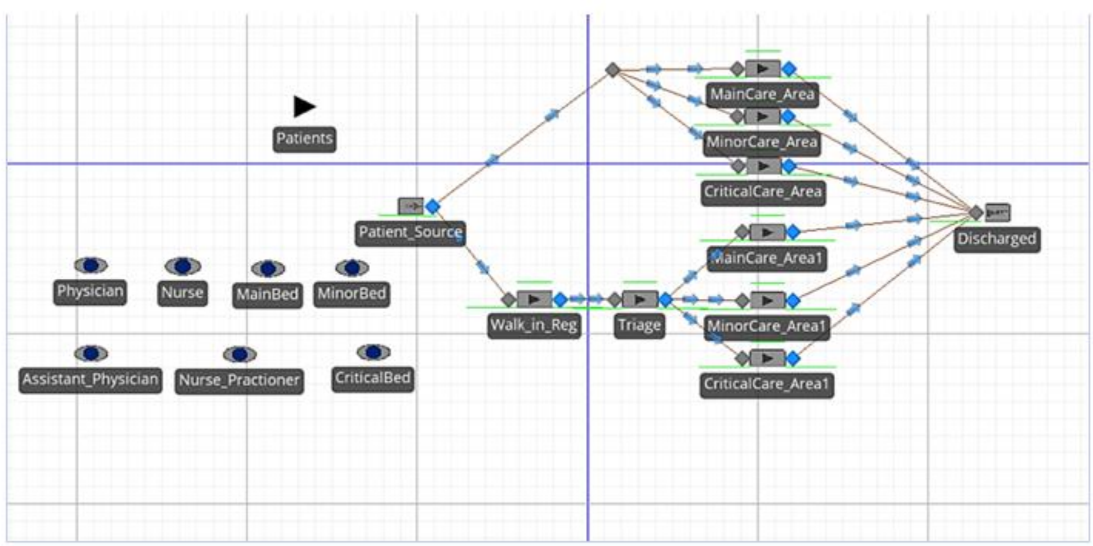

Walk in source
Ambulance source
Registration
Bedside registration
Triage
Initial assessment
First assessment
Extra Testing
Re exam assessment
Discharged
Admittance to Hospital

INITIAL MODEL



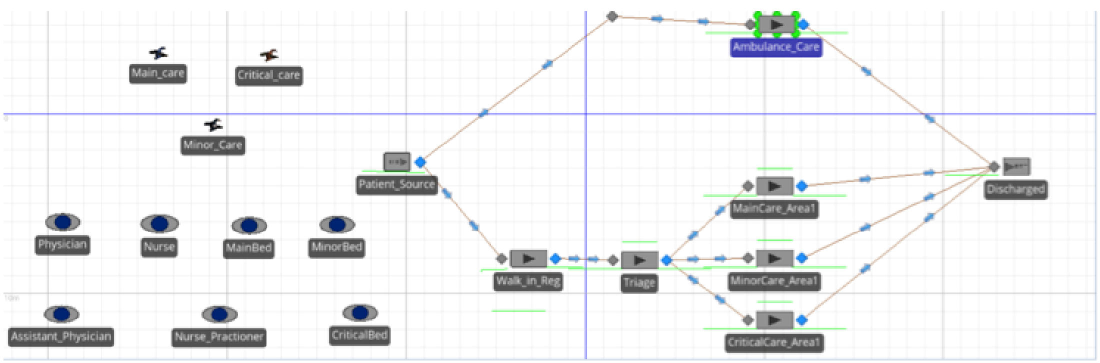
ALTERNATIVE MODEL



OPTIMAL FINAL MODEL

This model is the final model that was created for the emergency department. The first thing to notice in this model that it solves the problem that the previous models had. This model takes into account the three different types of patients that come into our system: main, critical, and minor care patients. The program does this by creating separate entities for each of the three types and designates them to their corresponding bed area. The other thing that you would like to note is the fact that there is now a server called ambulance care. Ambulance care pulls from the critical bed resource as we believed that those coming from an ambulance will more than likely be a critical care patient and must be treated right away. Thus it would render having separate types of patients useless and reduce waiting times for entities. The other reason why we decided to condense it is because that only 9% of patients come from an ambulance which is not significant enough to upset the balance of arrivals. This model is also the bases of our optimizations to the system and we used it to suggest improvements after analyzing the data and finding any bottlenecks. Changes to this model allows us to give the client options in order to improve the efficiency of the emergency department and shows how the changes would affect the system statistically.

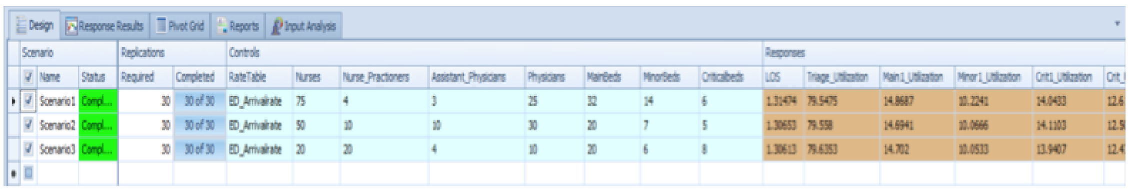
When compared to the initial model, the optimal model manages to use tasks sequences to represent the services provided to the patient by medical personnel, which is something that we initially didn't learn until after gaining more experience with the software.



RESULTS

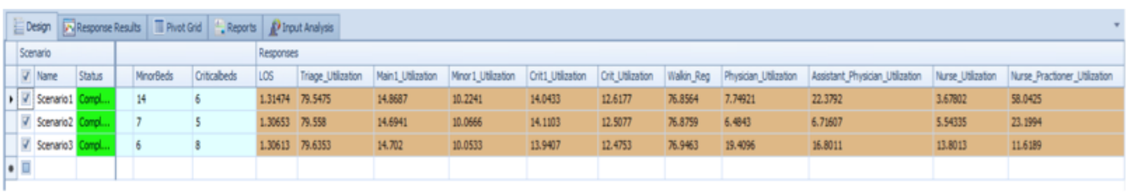
By running different scenarios in SIMIO, we were able to get results on how to further improve the Emergency Department. You will note that the level of service from our alternate model was about 1.43 hours in system. Even though this is actually very good for an Emergency Department, there is still room for improvement. The first thing that was noticed is that Nurse Practitioners have much lower processing time than Physicians, a mode of 18.6 minutes compared to 34 minutes for the main examination and 13.6 minutes compared to 17 minutes for second evaluation respectively. With this in mind, we were told that 68% of patients see a physician and 32% of patients see a nurse practitioner. This certainly slows down the service time for a patient and trying to speed things up we decided that the percentages should be flipped. Considering that both have roughly the same knowledge base and skill set, there would be no difference in actual care but a difference in the speed of care.

With this change done to the model, we ran three different scenarios that would change the resources that the model contained, tracked utilization and cost. Here are the scenario with the resource pool numbers:



Scenario		Replications		Controls								Responses					
Name	Status	Required	Completed	RateTable	Nurses	Nurse_Practioners	Assistant_Physicians	Physicians	MainBeds	MinorBeds	Criticalbeds	LOS	Triage_Utilization	Main1_Utilization	Minor1_Utilization	Crit1_Utilization	Crit_
Scenario1	Compl...	30	30 of 30	ED_Arrivalrate	75	4	3	25	32	14	6	1.31474	79.5475	14.8687	10.2241	14.0433	12.6
Scenario2	Compl...	30	30 of 30	ED_Arrivalrate	50	10	10	30	20	7	5	1.30653	79.558	14.6941	10.0666	14.1103	12.5
Scenario3	Compl...	30	30 of 30	ED_Arrivalrate	20	20	4	10	20	6	8	1.30613	79.6353	14.702	10.0533	13.9407	12.4

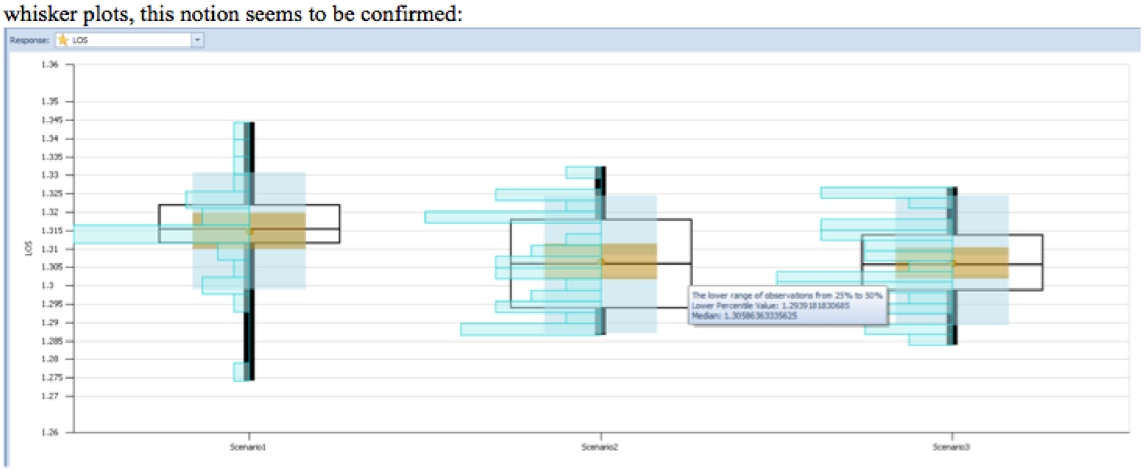
Note that scenario 1 is all of our original numbers and scenarios 2 and 3 where the modifications were made. The next image will show the utilizations of the resources, servers and the level of service of each scenario:



Scenario				Responses											
Name	Status	MinorBeds	Criticalbeds	LOS	Triage_Utilization	Main1_Utilization	Minor1_Utilization	Crit1_Utilization	Crit_Utilization	Walkin_Reg	Physician_Utilization	Assistant_Physician_Utilization	Nurse_Utilization	Nurse_Practioner_Utilization
Scenario1	Compl...	14	6	1.31474	79.5475	14.8687	10.2241	14.0433	12.6177	76.8564	7.74921	22.3792	3.67802	58.0425
Scenario2	Compl...	7	5	1.30653	79.558	14.6941	10.0666	14.1103	12.5077	76.8759	6.4843	6.71607	5.54335	23.1994
Scenario3	Compl...	6	8	1.30613	79.6353	14.702	10.0533	13.9407	12.4753	76.9463	19.4096	16.8011	13.8013	11.6189

The utilization varies across the board and the unfortunate thing is that we were not able to bring utilization up without taking big hits to the level of service. The good thing is that all of the level of service times are within .01 or less of each other which indicates that all are viable options according to the service times. More good news is that with the changes we were able to lower the average service time by about 7 minutes for each scenario which could definitely be the difference between life and death for a patient. Despite all this, it is hard to decide which option would be best.

At a glance, we would be inclined to suggest that scenario 3 is the best because of the low LOS and the reduction in resources which would indicate a lower cost of operation for the Emergency Department. Looking at the box and whisker plots, this notion seems to be confirmed:



Scenario 3 on average hit lower times than the previous two scenarios indicating that it is the best choice according to raw data alone. Though service time should not be the only criteria to judge which model will be ultimately used.

To further discriminate between the scenarios, we decided to calculate the average total cost of each scenario and their respective replications. Here are the results:

AVG Total cost Scenario 1	Avg Total Cost of Scenario 2	Avg Total cost of Scenario 3
$ 50,794,017.41	$ 50,816,060.37	$ 50,865,793.46

As you can see, scenario 3 is actually the most costly alternative which looking at the data it does not make sense. But if you take a closer look at the utilizations, specifically for nurse practitioners, it is going down which means that there are a lot of resources idle which is eating up cost for the emergency department. The original numbers with a higher percentage of patients going to see nurse practitioners is the most cost effective choice.

It will just depend on whether you value service time or cost more as the differences are very small but could make a major difference in the long run. In just cost, using scenario 1 would save you a maximum of $852,000 a year and that is quite a bit if you are looking to invest more into your Emergency Department.

RECOMMENDATION

Our recommendations to the emergency department, are to allow more patients to see nurse practitioners considering their lower processing times. The next thing is that all ambulance patients should be treated as critical care patients and just pull from the critical bed resource at any given time considering there is such a small percentage of them coming in. Third, allow the triage for a capacity of around 3 patients at a time since that is your bottleneck in your system. Increasing it to 3 will lower the utilization from 100% and reduce the service time significantly, 576 hours to 1.30 is a massive improvement. Lastly, we suggest with going with scenario 1 as it is the most cost effective and the time difference is .01 hours in the LOS. This is entirely up to you but it would be beneficial if you are planning to expand and improve your emergency department.

Considering our constraints we were not able to hit every type of configuration that is possible and there is a possibility of less cost and less time with a different configuration. Even though it was not modeled, we also want to suggest giving nurses more responsibilities to increase their utilization in your system and the same could be said for all other employees. This could greatly reduce service times and we would be more than happy to model it for you if you decide to employ our service again.

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