# PHYSICIAN AND RESIDENT STAFFING IN AN ACADEMIC EMERGENCY DEPARTMENT

**By**

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# Physician And Resident Staffing In An Academic Emergency Department

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## ABSTRACT

Rising demands and market competition have forced many emergency departments to improve their quality of service. This improvement is usually achieved at the cost of increasing resources in the emergency department in order to increase the patient satisfaction.

This research deals in part with both problems, i.e., increasing patient satisfaction and keeping costs in the ED to a minimum. The research has schedules designed on the patient contacts for physicians and residents in the academic emergency department at York hospital such that the resource costs and patient waiting costs are kept at a minimum. The emergency department is simulated using Arena 7.0 and the minimum cost objective is achieved by running OptQuest for Arena to get the near optimal number of staff working the designed schedules in order to achieve the objective.

Efficiently scheduling doctors and residents resulted in waiting cost reductions of almost 80%. There was also an increase in patient satisfaction, considering the time taken by patients to see a doctor or resident for the first time. The time was reduced by 33% for critical patients and was reduced by almost 29% for intermediate care patients with the schedules designed herein.

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# Chapter 1

## INTRODUCTION

The health care industry is one of the leading industries in the United States. National health expenditures are projected to reach $3.1 trillion in 2012, growing at an average annual rate of 7.3 percent during the period 2002-2012. As a share of gross domestic product (GDP), health spending is projected to reach 17.7 percent by 2012, up from its 2001 level of 14.1 percent. (National Health Care Expenditures Projections Web Resource).

Emergency departments (EDs) constitute a major portion of this health care system. McCaig et al. (2002, pp. 326) define ED the as "An emergency department (ED) is a hospital facility for the provision of unscheduled outpatient services to patients whose conditions require immediate care and is staffed 24 hours a day."

An effective healthcare system should ensure that patients receive the right care, at the right time, and in an appropriate setting. While hospitals are the venue for a significant amount of care, they have less control over how and where it gets provided. The place where problems elsewhere in the system are most apparent is in the hospital ED (The Association of Maryland Hospitals and Health Systems Web Resource). EDs have to cope with increasing pressures from competition, reimbursement problems, and healthcare reform. The hospital's customers are less willing to accept long waits in any department, but especially so in the ED. Hence, as the pressures increase, hospitals must accelerate their search for ways to reduce costs and increase customer satisfaction. Thus, EDs indirectly share a vital impact on the American economy as a whole.

McCaig et al. (2002) present statistical data for several aspects of an ED. According to their report, from 1997 through 2000 ED utilization increased by 14 percent, from 94.9 million to 108.0 million visits annually. The mean waiting times for non-urgent visits increased from 51.1 minutes to 67.7 minutes.

The rising demands have led to an increasing number of patient complaints because of excessive waiting times. The statistics clearly indicate this. This situation not only presents a medical problem due to the time-sensitive nature of many treatment regimens, but it also provides a potentially serious business problem. If patient satisfaction continues to deteriorate, the ED will surely develop a poor reputation, and patients will ultimately choose a different medical center or ED for their treatment purposes. On the other hand, the rising demands provide the ED with a financial opportunity. If the ED can identify ways to increase its ability to regulate quality service to the patients on a daily basis, it can improve patient throughput and profitability.

### 1.1 Research Motivation

Due to the large size and varied use of an ED, it is necessary to maintain close control of all operations and processes that take place in them. Most ED health care providers are profit-seeking organizations. In the current environment of increasing demands, EDs can be profitable only when reimbursements exceed their costs (Kershaw, 2000). If the amount of revenue per patient is fixed or declining, the ED managers need to reduce costs or increase patient volume if they want to maintain or increase profits. That is why this research tries to analyze the objective of cost minimization of an ED. The research will not only help in reducing costs of the ED, but also try to improve the patient satisfaction.

### 1.2 Research Goals

The research presented herein deals with an application of simulation to an ED setting of a hospital in York, PA. A simulation model of the current ED system is constructed for the purpose of studying certain performance measures. The primary areas of focus of this research will be minimization of costs to the ED along with the improvement in patient satisfaction. These improvement factors and the reduction in costs will be achieved under certain conditions, which will involve perturbing the following two variables.

a. number of doctors, and
b. number of residents

This research makes use of simulation using Arena and OptQuest. The following chapter deals with the literature review of simulation as applied to the healthcare field.

# Chapter 2
# LITERATURE REVIEW

This chapter provides a brief review of the extensive, relevant literature that exists in the area of simulation for healthcare applications. The chapter starts with the common operations research tools used in healthcare and their implementation issues. The literature review then focuses on simulation modeling applied in the healthcare setting, specifically to an ED. In the area of simulation modeling, a review of types of simulation models is provided first, followed by a review of simulation models used in the emergency department environment. Subsequently, the review focuses on simulation models in emergency departments used in conjunction with neural networks or optimization to determine optimal staffing patterns or scheduling emergency staff.

As described earlier, the ED constitutes a major component of the healthcare industry. To efficiently manage this component, decision makers must make use of many different methodologies and tools. Operations Research (OR) deals with a scientific approach to solving problems faced by decision makers. Broadly defined, this field deals with the efficient design and operation of person machine systems, usually seeking to determine an optimal or effective utilization and allocation of scarce resources. The tools of OR lie in mathematical modeling and analysis of physical or economic systems, and its scope of applications arise in varied walks of life; business, industry, government and national defense (Industrial and Systems Engineering Department, Virginia Tech Web Resource).

## 2.1 Different OR Tools Used in Healthcare Industry

In the past decade, the literature on the use of OR tools in the health care industry implies a slow but steady rise in the implementation of statistical and operational research tools. The various OR tools that are currently applied for a better and more efficient health care system are listed below (Carter, 2002).

a. Simulation - Simulation can be used in health care to analyze issues like patient waiting times, queueing problems, and resource utilization problems. Simulation can also be used to visualize the impact of local decisions to the system as a whole. The major limitation is the availability of data for simulation modeling in health care.
b. Linear or Goal Programming - Linear programming / Goal programming can be applied in health care situations like staff scheduling and case mix management. It can be shown that these problems are analogous to such problems in the manufacturing industry. The bottleneck in implementing this is that the operations research specialist needs to define the case mix after analyzing the service, because health care personnel are not conversant enough with this kind of problem formulation.
c. Queueing Models - The hospital waiting lists and allocation of beds in a hospital is also a major concern. Queueing models can very well be deployed for such problems.
d. Data Envelopment Analysis - The quality of health care systems can be evaluated by these techniques. A lack of data may again be a problem in this case.

Apart from the above tools there are various other tools used in health care. Even though the above tools are most widely used in the health care industry, there are some difficulties in implementing these tools (Carter, 2002). Hence it might take a bit longer to implement these in a health care setting rather than any other industry.

### 2.2 Problems in Implementation

The potential utilization of OR tools in the health care industry still needs to be exploited fully. This potential has not been realized mainly due to the following factors as mentioned by Carter (2002).

a. Lack of Knowledge - Personnel in the health care industry are mostly unaware of OR tools and their effective utilization in health care. They have little or no knowledge about the OR domain of applicability. Hence the thought processes of health care personnel do not exhibit a holistic view of the applicability of OR.

b. Inefficient and Inadequate Data and Information Collection Systems - Hospitals and emergency departments in most cases utilize computerized databases for data and information storage. These systems collect less data than required for meaningful statistics, so the data are of little or of no use for most statistical analyses.
c. Not Worth the Effort and Money - Some health care managers look at these tools as an unnecessary investment. They find it more convenient and fruitful to invest the funds allocated to them in health facilities or improvement related expenditures. This is again due to the fact that the health care managers have very little or no knowledge of the OR field.

Despite the difficulties involved in the implementation of OR tools, they are time and again used in the healthcare industry due to their powerful analysis capabilities. Simulation in particular has been used by ED managers to aid them in their decision making process. By using simulation in an ED setting, managers have been able to evaluate "what-if" scenarios without actually having to interrupt the daily operations of the facility (Alvarez et al., 1999). Presented below is an extensive literature review of simulation in health care.

### 2.3 Types of Simulation Models

Simulation models can be classified according to the following general categories (Lieberman and Rathi, 1992):

a. Microscopic, mesoscopic, and macroscopic simulation models - These classifications are done based on the level of detail with which the models represent the system to be studied. A *microscopic* model describes both the system entities and their interactions at a high level of detail while a *mesoscopic* model generally represents most entities at a high level of detail but describes their activities and interactions at a much lower level of detail than would a *microscopic* model. A *macroscopic* model describes entities and their activities and interactions at a low level of detail.

b. Deterministic and stochastic simulation models – This classification addresses the processes represented by the model. *Deterministic* models have no random variables; all entity interactions are defined by exact relationships (mathematical, statistical or logical). *Stochastic* models have processes that include probability functions.

c. Discrete and continuous simulation models - Discrete simulation models represent a system by asserting that the states of the system elements change abruptly at discrete points in time. Continuous simulation models represent the system by changing state variables continuously over time (Law and Kelton, 1991). Typically, continuous simulation models involve differential equations giving relationships for the rates of change of the state variables with time. If the differential equation is simple enough to be solved analytically, the solution provides the values of the state variables at any given time as a function of the values of the state variables at time zero. Because continuous models frequently are not tractable using an analytical approach, numerical analysis techniques (e.g., Runge-Kutta integration) are used to integrate the differential equations. Hence, regardless of the nature of the real system, which might be either discrete or continuous, two types of discrete simulation models are typically applied in practice,

i. discrete time simulation and

ii. discrete event simulation.

For systems where most entities experience a continuous change in state and where the model objectives require very detailed descriptions, discrete time models are likely to be the better choice (Lieberman and Rathi, 1992).

## 2.4 Simulation in Healthcare

The health care industry has adopted simulation modeling methodology in various segments of its operations. Seila (2000) examines the medical education system in the United States and proposes it as a model for an education structure for professional systems analysts. The objectives and requirements of simulation education are examined and a curriculum structure is proposed. According to him, the proposed system would not only help improve the development of simulation models but also help reduce the time for development.

Simulation in health care is often restricted to problems such as facility design, staffing levels and scheduling, new policy evaluation, scheduling of patient admissions and disease and epidemic control.

Simulation is a basic tool of health systems engineering, helping to design systems that meet customer needs while reducing costs and improving quality (Dasbach and Gustafson, 1989). Simulation has been used in planning the number of hospital beds and allocating them among different departments (medical, surgical, coronary, etc.) (Wright, 1987; Vissilacopoulos, 1985; Dumas, 1985). Patient scheduling has been addressed using simulation (Kwak et al., 1976; Robinson et al., 1968). Simulation can be used to evaluate alternative patient care policies (Butler et al., 1992).

### 2.4.1 Simulation Models for Reduction in Admission Delays or Average Waiting Times of Patients

Freedman (1994) describes the use of discrete event simulation to study the effects of changing operations on the average length of stay in an emergency department at two different hospitals. This new system reduced the admission delay of patients from the emergency room to the hospital, which also reduced the patient's average length of stay.

Siddharthan et al. (1996), investigate the increased waiting time costs imposed on society due to inappropriate use of the emergency department by patients seeking non-emergency or primary care. They propose a simple economic model to illustrate the effect of this misuse at a public hospital. They found that the non-emergency patients contribute to lengthy delays in emergency departments for all classes of patients. They also propose a queueing model as an analysis tool to help reduce average waiting times.

### 2.4.2 Simulation Models for Healthcare in Conjunction with Neural Networks

Harrel and Price (2000) present a model developed in Medmodel that provides a basis for the comprehensive evaluation of large, complex problems that are representative of healthcare systems in general. They have designed independent arrivals and scheduled appointments as well as new statements and functions to solve unique hospital and healthcare specific simulation problems.

Kilmer et al. (1997) describe a discrete event stochastic simulation of a hospital emergency department, and the development of a metamodel of that simulation. The metamodeling technique used is artificial neural networks, which are trained using the output of the simulation. The performance of the neural network metamodel is compared to the simulation performance for estimating the mean and variance of patient time in the emergency department.

### 2.4.3 Simulation for Physician Demand or Patient Appointments

Fetter and Thompson (1965) analyze the physician utilization rate with respect to patient waiting time by using different input variables. Their results indicate that if a physician's appointments increase from 60% of capacity to 90% of capacity, the total physician idle time decreases by 160 hours and the average patient waiting time increases by 1600 hours over a fifty day period, then the physician's time would have to be worth ten times the patient's time to justify such a shift in patient scheduling and admission policies.

Rising et al. (1973) attempt to smooth physician demand by increasing the number of appointments slots in an outpatient clinic on those days that have the least number of walk-ins. Their results show a 13.4% increase in patient throughput and decreased clinic overtime.

Klassen and Rohleder (1996) identify the most efficient means of scheduling patients in medical offices to minimize the wait for patients and maximize the efficiency of physicians. They find that the patients with large treatment service time variances should be scheduled at the end of the appointment session. This minimizes the patient's waiting time and the physician's idle time.

Walter (1973) attempts to study the effect of using several different appointment schemes in a radiology department. He shows that a considerable amount of staff time is saved by segregating patients with similar examination time distributions into inpatient and outpatient sessions. He also shows that the practice of overbooking for a given appointment time yields a small increase in staff utilization while substantially increasing the patient waiting time.

Goitein (1990) proposes a simple example of waiting time analysis with Monte Carlo simulation. The author states that although many factors must play a part in determining whether and for how long patients wait, the predictability of the length of consultation is certainly a major factor. When the consultation can be kept to a fixed time, patients can be confident that their appointment will start on schedule.

### 2.4.4 Simulation for Scheduling of Resources/Servers

Most of the healthcare studies have focused on scheduling patients. However, some studies have taken into account scheduling the hospital staff. Such studies have analyzed the effects of variable staffing patterns on patient waiting times and other measures. The work done in this regard is to schedule the hospital staff in such a way that the demand of patients is met.

Kittell and Pallin (1992) describe the development of a simulation study at Mercy Hospital in Miami, FL. Their study evaluated several alternatives with the intent of getting more patients through the emergency department while making more efficient use of the department's resources, and still provide good quality services. The study found that a reduction of 50% in resources could be accomplished by implementing a fast track lane in the emergency department without risking the quality of services provided to patients.

Alvarez and Centeno (1999) present a simulation model of an emergency department that has enhanced VBA subroutines so that it can use real world data. These subroutines use a hierarchical approach to organize various scenarios under which the model may run and to partially reconfigure the ARENA model at run time.

Rossetti et al. (1999) discuss the efficient allocation and utilization of staff resources facing emergency department administrators. The paper discusses the use of computer simulation to test alternative emergency department (ED) attending physician staffing schedules and to analyze the corresponding impacts on patient throughput and resource utilization. The development of this model was based on the emergency department at the University of Virginia medical center.

Blake and Carter (2002) describe a methodology for allocating resources in hospitals. Their methodology uses two linear goal programming models. One model sets case mix and volume for physicians, while holding service costs fixed, while the other model translates case mix decisions into a commensurate set of practice changes for physicians. The models also allow investigation of trade-offs between case mix and physician practice parameters. The problem definition consists of an objective function of the case selection problem for a hospital and is stated as follows.

Determine the volume and mix of cases that

a. ensures the hospital is able to generate enough revenue to recoup the fixed and variable costs of production,
b. ensures physicians are able to generate a preferred level of income,
c. is feasible, given the productive capability of the hospital, and
d. allows physicians to perform a preferred mix and volume of cases.

The two models, case mix model and cost model, are validated using a three phase approach. Model results indicate that the economic goals of both the hospital and its associated medical staff could be jointly achieved through targeted change to case mix or physician practice, after budget reductions of 5% or 11%. Model results also suggest it is not always possible to satisfy jointly the economic objectives of both physicians and hospitals through a case mix based resource allocation.

Saunders et al. (1989) developed a computer simulation model of emergency department operations with the SIMAN language. A discrete event simulation model is developed in which patients' resources change at discrete points in time. This system uses multiple levels of preemptive patient priority. Each patient is assigned an individual nurse and physician. All standard tests, procedures, and treatments are incorporated. During the simulation, selected input data, including the number of physicians, nurses, treatment beds, and blood test turnaround time are varied to determine their simulated effect on patient throughput time, selected queue sizes, and rates of resource utilization. The dynamics of the emergency department care process are modeled by means of a flow diagram depicting patient movement among stations or events. At each substation in the emergency department, the duration of each wait is randomly distributed. Input data probability distributions are based on past data. Only one factor at a time is varied in the simulation. The authors demonstrate the model's ability to estimate output data such as patient throughput times, patient queues, and resource utilization rates.

Alessandra et al. (1978) study both medical staffing levels and patient arrival rates to improve patient throughput. Several alternatives involving varying the staffing pattern and the patient scheduling schemes are analyzed. They show that the best alternative is keeping the staffing level and patient arrival rate the same, but distributing the current morning appointment patients to the afternoon shift.

Kumar and Kapur (1989) inspect ten different alternatives for nurse scheduling. They then select and implement the policy that yields the highest nurse utilization rate.

### 2.4.5 Simulation for Patient Routing and Flows

There is some work in the area of patient flows in an emergency setting. Patient routing and flow systems are required because patients arrive without appointments and require treatment. This arrival of patients is highly unpredictable, but patients can be routed to minimize waiting times and maximize medical staff utilization.

Kolesar (1970) presents a Markovian model for hospital admission scheduling. He suggests various queueing models for hospital scheduling and also puts forth a Markovian decision model for the same. He discusses some mathematical approaches to the problem of prescheduling elective admissions, and proposes a new Markovian decision model for treating the problem. He assumes that inpatient admissions fall into two mutually exclusive categories, elective admissions and mandatory admissions. He further presents two queueing models of the admissions system developed by John P. Young of the John Hopkins University. These are parallel input stream queueing models. Later he presents his Markovian model for admissions to the hospital. He also explores some optimization problems related to admissions scheduling and proposes various objective functions and constraints.

Kirtland et al. (1995) describe a project to improve the operation of Peninsula Regional Medical Center’s (PRMC) Emergency Department (ED) and to decrease patient dissatisfaction with length of stay. The other goal of the project is to reduce patient throughput times and determine appropriate staffing levels. They determined the average patient transit time through the department and the confidence intervals using UniFitII, a statistical analysis package. Also they used the trace validation function from the MedModel program to validate the model. The project examined 11 different alternatives to improve patient flow and determined the appropriate staffing mix based on patient volume. The top three alternatives were: using a fast track system in minor care, staging patients to the next available treatment room, and using point-of-care testing. The impact of changes is a reduction in patient turnaround time by 38 minutes.

McGuire (1994) describes how a team at one emergency services department in a SunHealth Alliance hospital used simulation technology to test alternatives and choose a solution to significantly reduce the length of stay for patients in the emergency department. His work identified which alternatives had the greatest impact on patient’s length of stay and which ones had no significant impact. He concludes by saying that the successful simulation studies are dependent on the cooperation of each department that is affected by the study and that affects the objective of the study. Also, careful planning is necessary to reduce delays and make the data collection as smooth as possible.

Edwards et al. (1994) compare the results of simulation studies in two medical clinics that use different queueing systems: serial processing, where patients wait in a single queue, and quasi-parallel processing, where patients are directed to the shortest queue to maintain flow. They show that patient waiting times can be reduced by up to 30% using quasi-parallel processing.

### 2.4.6 Simulation for Staff Sizing and Planning

To improve the quality of service, the most important resource that might make a significant difference is the staff. Hence, to provide efficient and timely healthcare service the staff size should be such that the quality of healthcare is above some threshold. The two main reasons for staff size planning are the inefficient utilization of available staff and the shortage of staff to meet the demand.

Klafehn and Connolly (1993) model an outpatient hematology department using Proof Animation from Wolverine Software. They analyzed different staffing patterns and found that if the staff is cross-trained or becomes multifunctional, patient waiting times can be reduced. Hashimoto and Bell (1996) conducted a time study to show that increasing the number of physicians, and consequently the number of patients, can significantly increase the total time spent at the clinic for patients. By limiting the number of physicians to four and increasing the number of dischargers to two, they were able to decrease the average patient total time at the clinic by roughly 25%.

Swisher et al. (1997) present a simulation model of a family practice outpatient clinic. According to their observations, adding additional medical staff members has a negligible effect on the average patient total time at the clinic and clinic overtime. McHugh (1989) examines various staffing policies for nurses and analyzes the effects of this on cost, understaffing, and overstaffing. Her analysis shows that 55% of the maximum workload produces a good balance between the three measures. Wilt and Goddin (1989) evaluate patient waiting times to determine appropriate staffing levels in an outpatient clinic.

Ishimoto et al. (1990) use simulation to explore the operations of a pharmacy unit in a hospital. They find the optimal medical staff size and a mix that reduces patient waiting times.
Lopez-Valcarcel and Perez (1994) analyze eight different scenarios in an emergency department simulation by varying the number of staff, the patient arrival rates, and the service times of

diagnostic equipment. They recommend that the patient arrival rate should not exceed twelve patients per hour for a certain staffing pattern. Moreover, they recommend that investments in human resources would be more effective than investments in newer equipment.

Weng et al. (1999) present a case study for an outpatient clinic at a local hospital in the Cincinnati area. Their paper is a systems analysis of the clinic using the performance measures of patient throughput, time in system, queue times and lengths, and total cash flow. They ran various scenario tests for second year residents and medical assistants to meet their objective. Based on the simulation run for scenarios, they found that six residents and two medical assistants make an optimal staff size. But they could not achieve the set level of patient throughput with this staff size and hence suggest lowering the expected number of patients.

Bretthauer et al. (1998) present a general model and solution methodology for planning capacity requirements in health care organizations. They apply the model to two specific applications, a blood bank and a health maintenance organization. They develop an optimization/queueing network model that minimizes capacity costs while controlling customer service by enforcing a set of performance constraints, such as setting an upper limit on the expected time a patient spends in the system. Their model also captures the stochastic behavior of health care systems within the optimization framework.

Isken et al. (1999) present a general framework for modeling resource allocation problems in outpatient obstetrical clinics. The objective behind modeling such a framework was for the purpose of exploring questions related to demand, appointment scheduling, exam room allocation, patient flow patterns, and staffing. They say that the important resources for which allocation decisions must be made include staffing (physicians, nurse practitioners, nurses, other support staff), exam rooms, and available appointment slots. The paper focuses on the use of discrete event computer simulation to support decisions related primarily to facility sizing and staffing. The model is divided into three related submodels: demand, appointment scheduling, and clinic operations. They have provided certain approaches for these submodels like characterizing demand, allocating specific exam rooms to specific physicians, and creating appointment schedules. Their framework provides a good starting point for would-be modelers and a reference for guiding the model development process.

## 2.5 Summary

An extensive amount of literature exists in the field of simulation and its applications in the healthcare industry. While this broad field is explored by many researchers, little work appears on the application of simulation in healthcare for the purpose of cost analysis.

Hence the problem that this research considers has been addressed very little. Also, this research examines the problem for the York Hospital ED and, hence, is limited to the constraints of that facility.

# Chapter 3

# York Hospital ED and Simulation Model

## 3.1 The York Hospital Emergency Department

York Hospital is consistently recognized as one of the top 100 hospitals in the nation, and is the region's leader in advanced specialty care. What began in 1880 has become a 558-bed community teaching hospital that employs more than 4,300 people and serves a population of 350,000 in south central Pennsylvania. York Hospital offers services and programs that feature highly skilled clinical staff, life-saving technology, and state-of-the-art facilities to address some of the most complex medical, surgical, and behavioral conditions (WellSpan Health Web Resource). The simple patient flow at the York ED is shown in Figure 3.2.

## 3.2 ED Functionality

The ED at York Hospital provides emergency care for patients. It is an ESI 5-level Triage unit as described below. The ED also has a trauma center. The ED treats as many as 60,000 patients per year and has many resources including physicians, residents, nurses, technicians, physician extenders, and diagnostic testing technicians.

A flow for the typical patient's process is as follows.

a. A patient enters the ED and goes to the triage station.

b. The triage nurse classifies the patient into the appropriate ESI level. The patients that arrive to the emergency room are classified according to the severity of their medical condition and the resources needed to treat them. There are five levels of severity as defined by the York emergency department. They are called ESI levels, which stand for "Emergency Severity Index." Figure 3.1 shows a description of the ESI classification process.

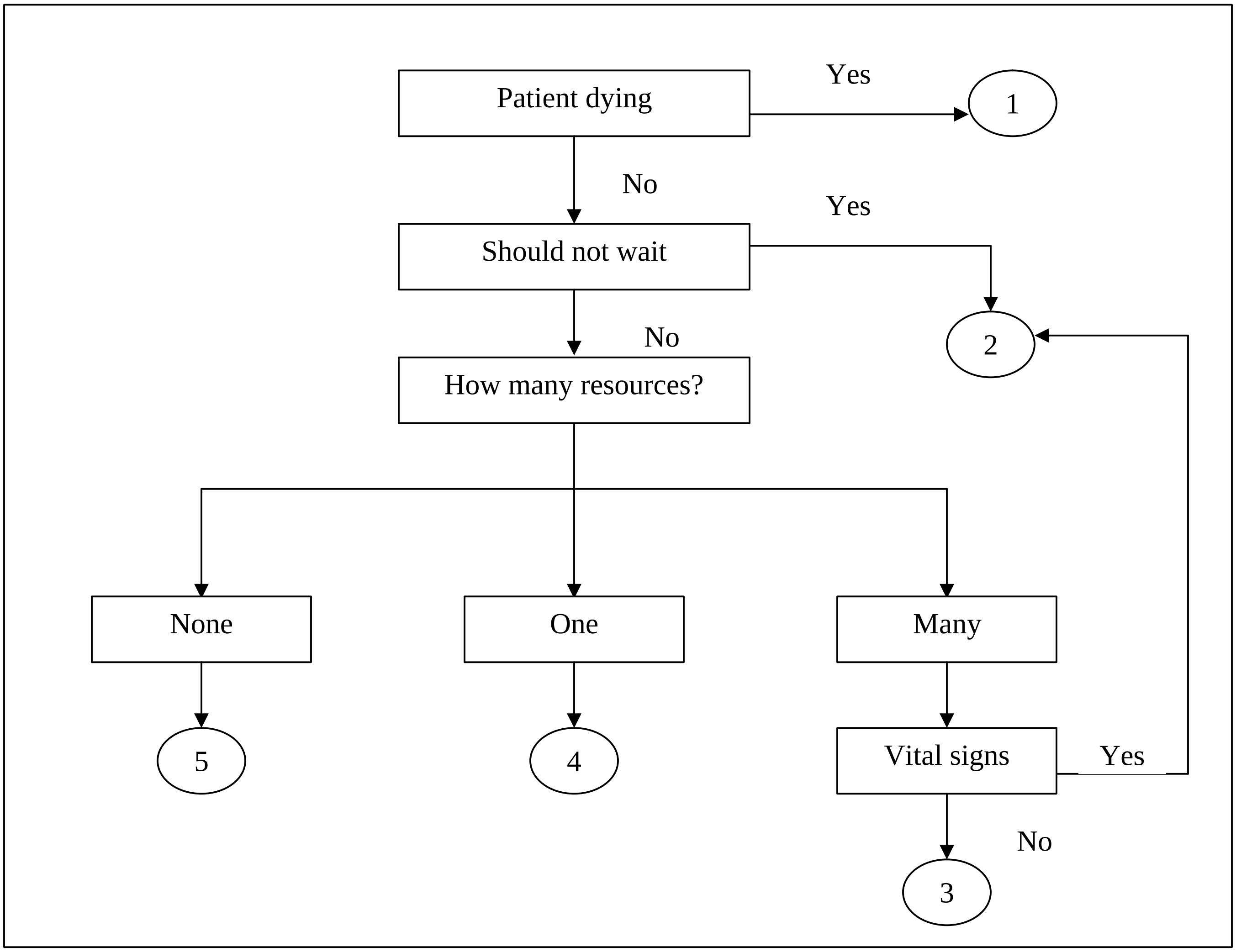


**Figure 3.1: Emergency Severity Index (ESI) Classification**

c. After the triage classification, the patient is routed to critical care (CC), intermediate care (IC) or alterna care (AC). This routing depends on the ESI level and also on the unit's working times, in the case of AC. Typically, the ESI levels 1 and 2 plus the geriatric patients (greater than 65 years of age) for ESI level 3 are routed to CC, while the ESI levels 4 and 5 are routed to IC and AC, with priority being given to AC, if available.
d. The patient proceeds to consultation with the doctor or the resident.
e. After the initial diagnosis, the consulting physician decides if the patient needs any lab or imaging tests. Usually, the ESI level 5 patients do not need any tests and hence receive the necessary treatment before they are billed for the service and discharged.

f. After the lab tests or diagnostic tests, the patient then meets the same physician to get the test results reviewed. The physician or resident then decides if the patient should be admitted to the hospital or discharged.

A detailed flowchart of this patient process is depicted in Figure 3.2.

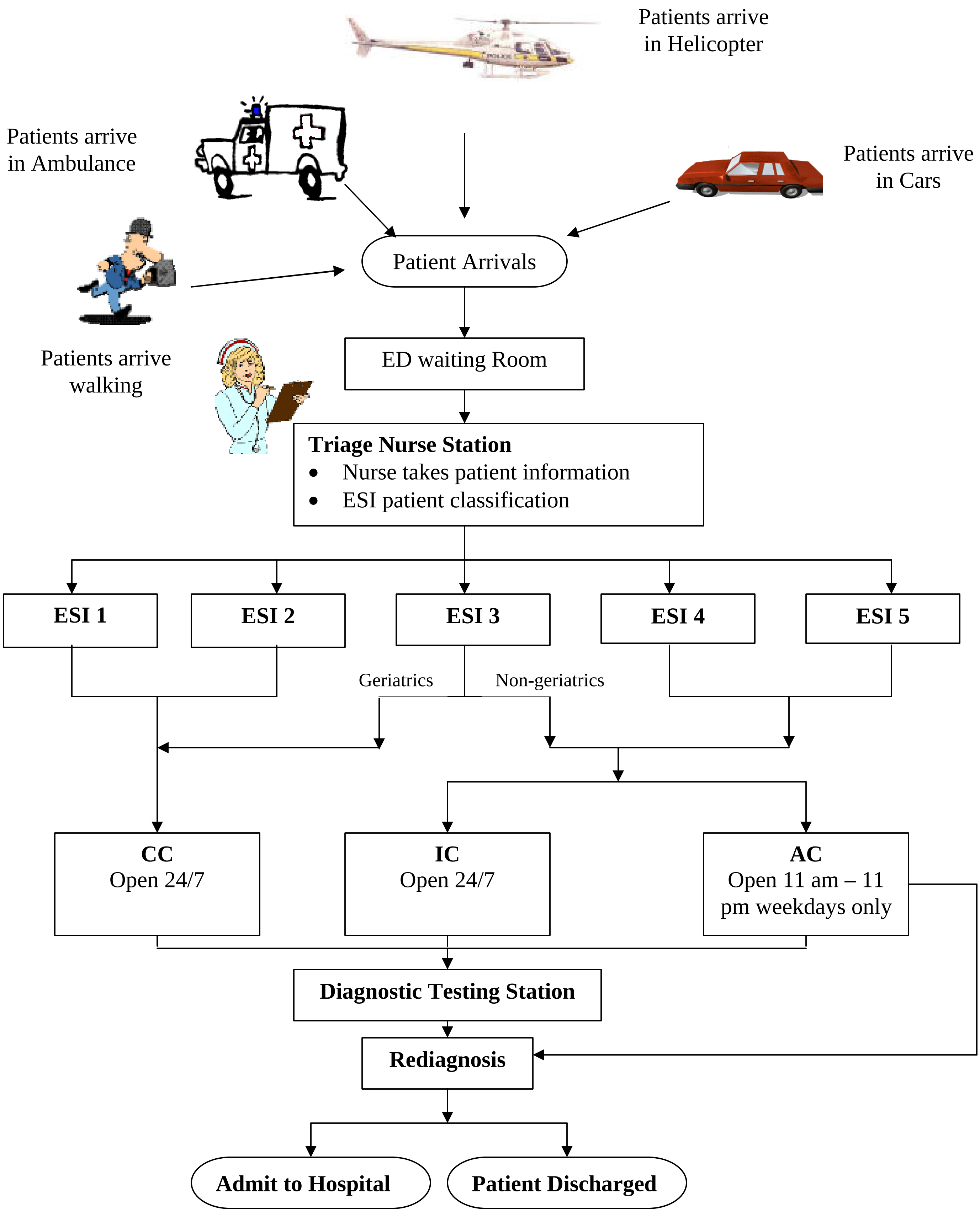


**Figure 3.2: Flowchart for York ED Functionality**

### 3.3 Selection of Software

This research used Arena, a simulation software package provided by Rockwell Software Inc. Opt Quest, a component of Arena, was used to determine the near optimal staffing needs.

The Arena graphics simulation system is a complete and flexible modeling environment combined with an easy-to-use graphical user interface. It is designed for building computer models that accurately represent an existing or proposed application.

"Arena integrates all simulation-related functions--animation, input data analysis, model verification, and output analysis--into a single simulation-modeling environment. Its flexible flow-charting objects can capture the essence of systems of all kinds, and its Windows-compatible interface is easy to learn and use because it is certified Microsoft Office compatible" (Information Technology and Engineering Computer Services (ITECS) Web Resource). Arena Professional Edition is used to create customized simulation products, i.e. templates focused on specific applications or industries. With Arena Professional Edition, one can develop custom templates that consist of "libraries" of modeling objects that make it significantly easier and faster to develop models that require repeating logic (Source: Arena Help Topics, Rockwell Software Inc.).

OptQuest is a computer software system that allows users to automatically search for optimal solutions to complex systems. One can easily define the variables to control, the objectives to maximize or minimize, and any conditions required to be met, and then let OptQuest search for the best solution. OptQuest intelligently chooses possible scenarios, presents them to your model for evaluation, and then uses the results to find even better possibilities. OptQuest gets to the best scenarios quickly. Its state-of-the-art algorithms, which are based on tabu search, scatter search, integer programming, and neural networks, can handle very complex models with ease. "OptQuest for Arena is an optimization tool (solver) customized for analyzing the results of simulation runs conducted in Arena (experimentation). OptQuest includes sampling techniques and advanced error control to find better answers faster" (Information Technology and Engineering Computer Services (ITECS) Web Resource).

## 3.4 Simulation Model Construction

The simulation model for York Hospital ED is built using ARENA 7.01. Following is the detailed analysis of the model development process in Arena.

### 3.4.1 General Steps in Simulation Modeling Using Arena

The basic steps for simulation using Arena are given below.

**a. Create a basic model**

A basic model is built in Arena using the intuitive, flowchart-style environment provided by Arena for building an "as-is" model of the process. Arena's modules are dragged and dropped —the shapes in the flowchart—into the model window and later connected to define process flow.

**b. Refine the model**

After building the basic model, real-world data like process times, resource requirements, staff levels are added to the model by double-clicking on modules and adding information to Arena's data forms. It is also possible to create a more realistic picture of the system under consideration by replacing the animation icons that Arena automatically supplies with custom built graphics like the ones from ClipArt or other drawing packages.

**c. Simulate the model**

The refined simulation model is run to verify that the model properly reflects the actual system. Bottlenecks are identified during this process and communicated with others using Arena's graphical animation.

**d. Analyze simulation results**

Arena provides automatic reports on common decision criteria, such as resource utilization and waiting times. Reports for customized statistics can be designed to meet system analysis requirements.

**e. Select the best alternative**

Changes are made to the model to capture the possible scenarios pertinent to the research, and then the results are compared to find the best solution.

### 3.5 York Hospital ED Simulation Model

The main objective for modeling the York Hospital ED is to study different scenarios of staffing patterns for doctors and residents with the objective of minimizing ED costs. The simulation model representing the current system at York ED is used for comparative analysis of performance measures with the staffing pattern generated using OptQuest.

The simulation modeling is done using Arena's modular interfacing facility, which enables one to divide the simulation model into several modules that can be connected and run in conjunction, a system as a whole.

**Assumptions**

a. The Arena model assumes that the simulation starts at 12:00 am Sunday.
b. There are six doctors scheduled to work in the ED. At any given time at least two doctors are always present.
c. Service time data are assumed in some places with the help of expert opinion. These include service times at all the processes in the diagnostic testing department.
d. A physician extender in AC works on Thursdays and Fridays, while the AC doctor works Monday through Wednesday. The AC is closed on Saturdays and on Sundays.
e. The diagnostic testing unit requires various resources for operating the machines like X-ray machines or conducting the lab tests. The current system at the ED employs technicians for this purpose. These technicians can be modeled as resources in the Arena model. Also the machines themselves can be considered as resources in the model. But, these resources in the diagnostic testing center are not modeled in this Arena model because of lack of data and also are not covered in the scope of this research.
f. In the real system, medical students work in IC. These medical students are not modeled as resources, instead a delay for the time they use is assumed in the IC treatment process.
g. In the actual system the AC nurse routes some patients to the diagnostic testing station before they even consult the doctor in AC, although this is rare. This patient flow is not considered in this research model, and hence every patient has to consult the respective AC doctor or physician extender before the patient goes to diagnostic testing.
h. One simulation run covers seven days.
i. Initial consultation by the doctor and the rediagnosis consultation times are different.
j. All resources considered in the model have predefined schedules.

The following are the main modules in the Arena model for York Hospital.

### 3.5.1 Patient Arrivals

This module deals with the arrival of patients to the ED. Arrivals are typically via four modes: walk–ins, ambulance, cars, and helicopters. Arrivals via different modes of transportation are not taken into account in this model.

The patient arrivals are designed as per the ESI levels. Each ESI level is treated as a different type of entity. Each ESI level patient arrival has a defined arrival schedule which is derived from the mean inter-arrival times data available as shown in Table 3.1. The arrivals are modeled as time dependent poisson processes. Arrivals are divided into two batches in a 24-hour day. They are divided as patients arriving from 12 am to 12 pm and the second batch of the patients arriving at the remaining time. The arrivals are also split differently according to weekday and weekend arrivals.

The patients first go to the triage nurse station (unless the case is a severe trauma center case). The patients are split according to their ESI level for the percent utilizing the resources in imaging, ultrasound, etc.

**Table 3.1: Mean Inter-Arrival Times for Different ESI Levels**

| ESI Level | 12:00 AM – 12:00 PM | | 12:00 PM – 12:00 AM | |
|---|---|---|---|---|
| | **Weekdays** | **Weekends** | **Weekdays** | **Weekends** |
| **ESI-1** | 323 | 289 | 239 | 270 |
| **ESI-2** | 93.2 | 96.4 | 67.3 | 67.3 |
| **ESI-3** | 38 | 34.1 | 21.2 | 20.2 |
| **ESI-4** | 88.8 | 69.5 | 40.4 | 32.8 |
| **ESI-5** | 199 | 171 | 142 | 120 |

### 3.5.2 Triage Nurse Station

This is a station that serves as a patient check-in station. The resources in this department are shown in Table 3.2 and the service time for them is as shown in Table 3.3. There is one nurse at any given time. In the real system, the nurse divides the patients according to the severity index. The patients are divided into the five ESI levels as explained above.

**Table 3.2: Resources at Triage Nurse Station**

| Resource | Number |
| --- | --- |
| Triage Nurse | 4 |

The ESI level 3 patients are further classified as geriatric or old (patient age greater than 65 years) and non-geriatric or young patients. The geriatric patients are routed to critical care while the young patients are directed to intermediate care. The following is a short representation of the routings:

i. Critical Care: ESI levels 1 and 2, ESI level 3 (old)

ii. Intermediate Care: ESI level 3 (young) and ESI levels 4 and 5.

iii. Alterna Care (when open): ESI levels 4 and 5 (priority given to Alterna Care)

**Table 3.3: Service Times for Triage Nurse**

| Activity | Service Time Distribution (min) |
| --- | --- |
| Patient evaluation by triage nurse | Uniform(2,7) |

There is some time involved for transporting patients from the triage to the respective department (critical, intermediate or alterna care) and also from the respective departments to the diagnostic testing center. This patient transportation time is included in the model and the distribution is as shown in Table 3.4.

**Table 3.4: Patient Transportation Times**

| Route Patients | Transportation Time Distribution (min) |
|---|---|
| From waiting room to CC, IC, or AC | Triangular (3,4,5) |
| Between either CC, IC, or AC and diagnostic testing | Triangular (5,6,7) |

### 3.5.3 Critical Care (CC)

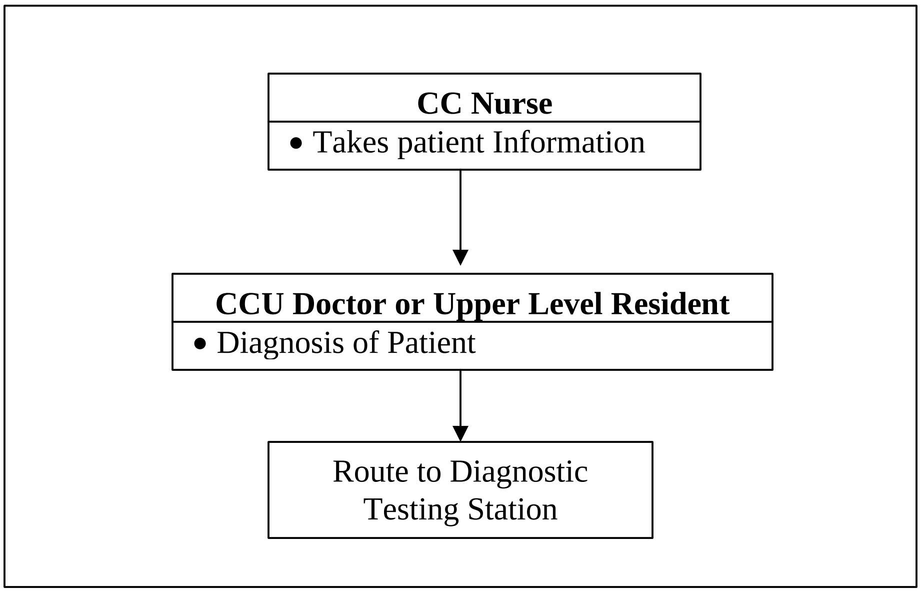


**Figure 3.3: Flowchart for CC Arena Design Model**

Critical Care is where the most severe cases are directed. These include ESI levels 1 and 2, and also geriatric patients belonging to ESI level 3. Figure 3.3 shows a typical patient flow process in the CC. Table 3.5 shows the resources available in CC.

**Table 3.5: Resources in CC**

| Resource | Total Number |
|---|---|
| CC Nurse | 24 |
| CC Bed | 15 |
| Upper Level Resident | 5 |

The flow of patients here is that the patient first occupies a bed, and the nurse takes patient information. The patient is then evaluated by the upper level resident who decides the course of action to be taken for treatment. Sometimes the doctor is consulted in complicated cases. The service time distribution for various processes in the CC is as shown in Table 3.6.

The nurses, physicians and residents work as per schedules shown in appendix A.

**Table 3.6: Service Times in CC**

| Activity | Service Time Distribution (min) |
|---|---|
| Patient evaluation by CC nurse | Triangular (10,12,15) |
| Patient evaluation by upper level resident or doctor | Triangular (5,10,15) |
| Follow-up treatment by doctor or upper level resident and nurse after reviewing diagnostic reports | Uniform (8,20) |
| Additional time for admission/ discharge<br>- Admitted patient<br>- Discharged patient | <br>Triangular (25,35,180)<br>Uniform (5,25) |

The patient is routed to the diagnostic testing station for tests. After these tests, the patient is again reevaluated or rediagnosed depending on the test results. An important aspect here in Arena modeling is that the patient seizes the same nurse and evaluator after the tests are conducted.

The ED pays approximately $200 per hour to a physician and $10.20 per hour to an upper level resident is. These costs are utilized in the model to calculate the staffing costs.

### 3.5.4 Intermediate Care (IC)

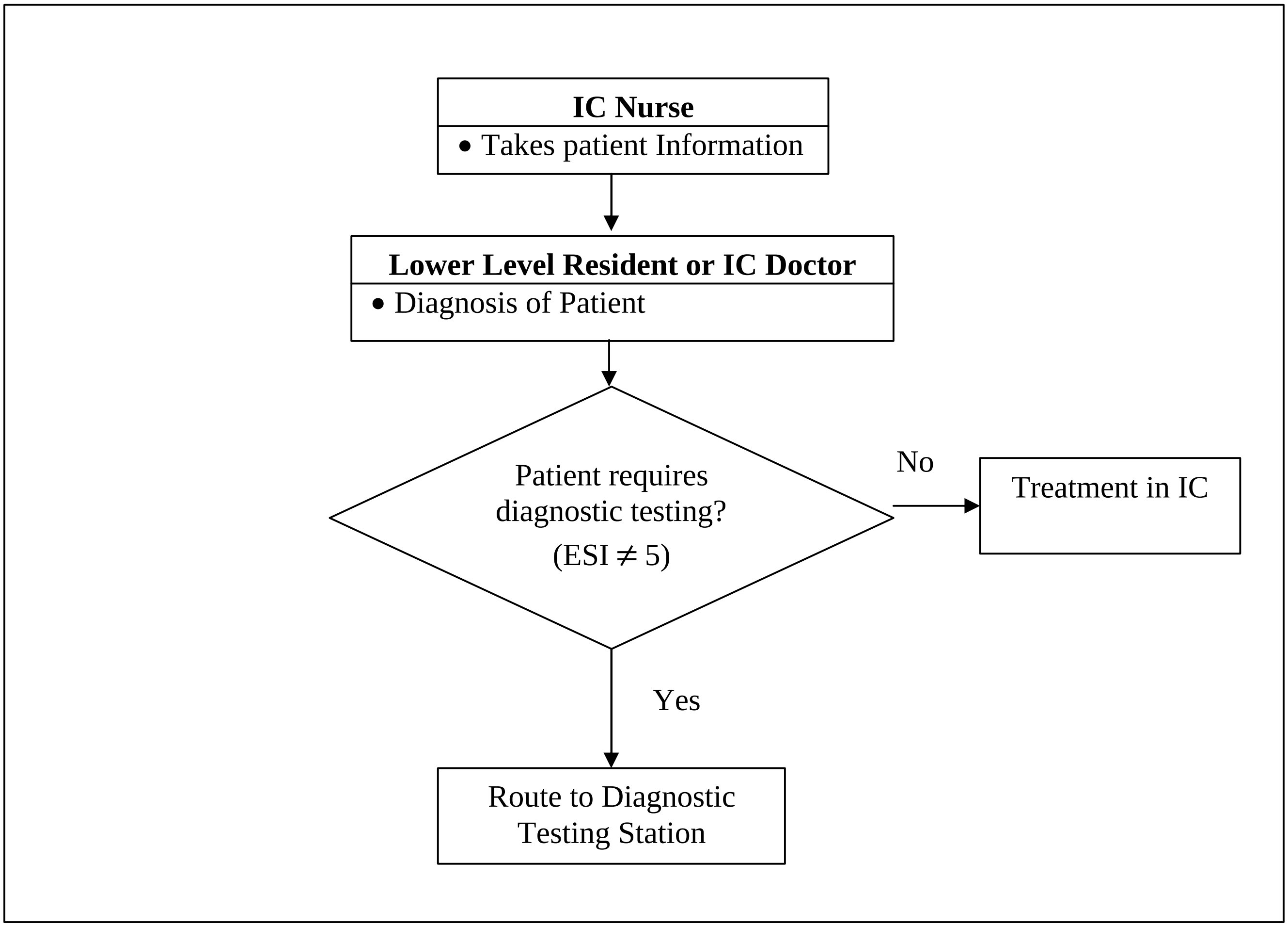


**Figure 3.4: Flowchart for IC Arena Design**

Intermediate Care is, as the name implies, a unit that takes care of the less serious cases. The categories of patients assigned to IC are ESI levels 4 and 5 and also the young patients belonging to ESI level 3. Figure 3.4 shows the Arena logic for IC. The unit operates 24 hours a day. The resources in IC are as shown in Table 3.7.

**Table 3.7: Resources in IC**

| Resource | Total Number |
|---|---|
| IC Nurse | 21 |
| IC Bed | 16 |
| Lower Level Residents | 4 |

The flow of patients in the model is similar to the CC. In the IC evaluation is done by a lower level resident or IC doctor. Finally, patients go to diagnostic testing. The ESI level 5 patients do not go to diagnostic testing at all and are discharged from the ED after this consultation. The service time distribution for various processes in the IC is as shown in Table 3.8. The lower level residents are paid $6.00 per hour. The lower level residents and IC nurses also work according to a fixed schedule as in appendix A.

**Table 3.8: Service Times in IC**

| Activity | Service Time Distribution (min) |
|---|---|
| Patient evaluation by IC nurse | Triangular (4,5,6) |
| Patient evaluation<br>- lower-level resident<br>- Doctor | <br>Triangular (5,10,15)<br>Triangular(4,7,15) |
| Follow-up treatment by doctor and nurse after reviewing diagnostic reports | Triangular (7,8,9) |
| Additional time for admission/ discharge<br>- Admitted patient<br>- Discharged patient | <br>Triangular (25,35,180)<br>Uniform (5,25) |

### 3.5.5 Alterna Care (AC)

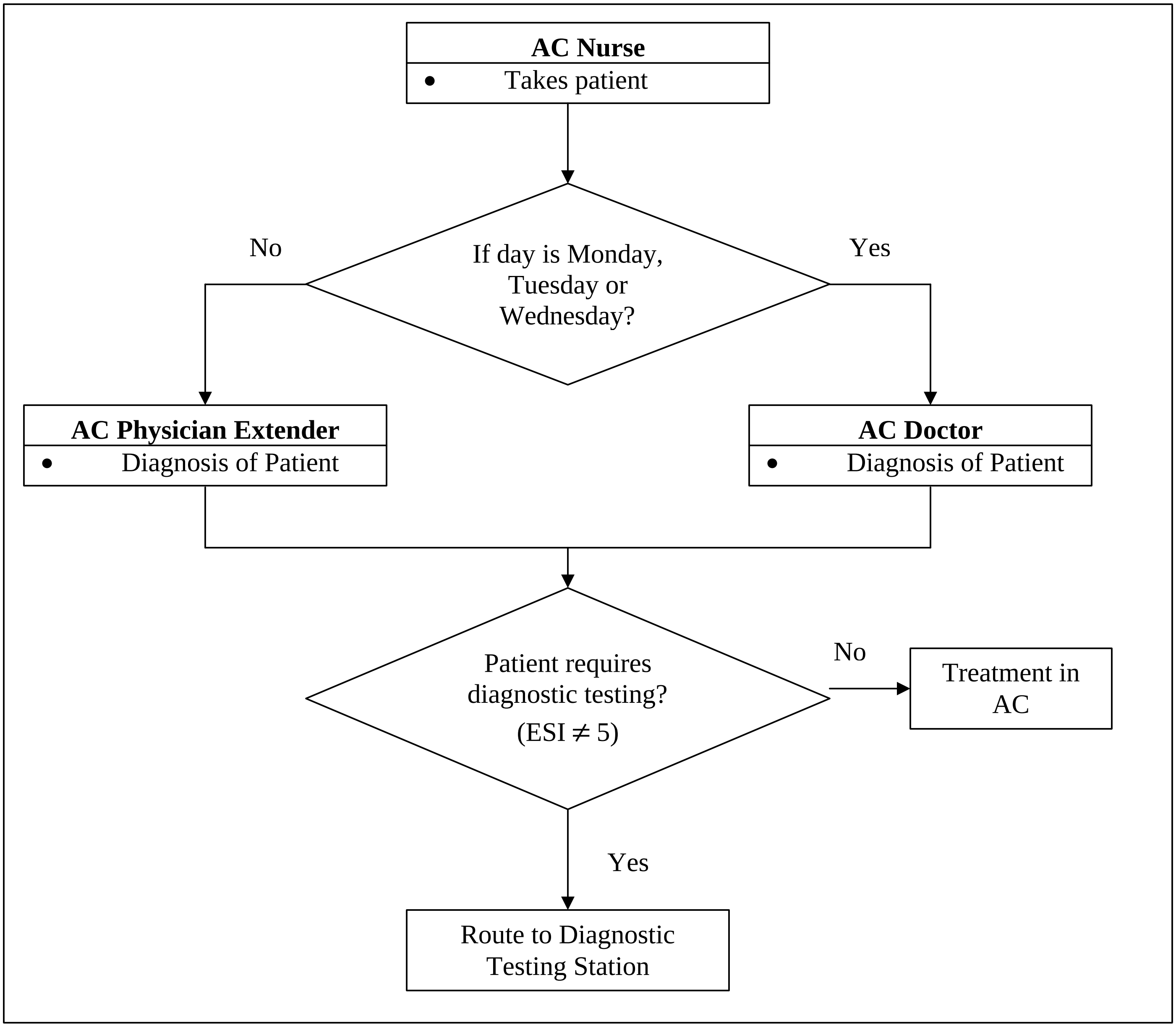


**Figure 3.5: Flowchart for AC Arena Design Model**

Alterna Care is where the patients of ESI levels 4 and 5 are directed if it is open. This facility runs only on weekdays and is open from 11 am to 11 pm. Table 3.9 lists the resources in AC.

**Table 3.9: Resources in AC**

| Resource | Total Number |
|---|---|
| AC Nurse | 1 |
| AC Bed | 4 |
| Physician Extender | 1 |
| AC Doctor | 1 |
| Technician | 1 |

The main evaluator is either a physician extender or a doctor. Either one of them works on any given day. In this model, it is assumed that a doctor works from Monday to Wednesday while a physician extender works on Thursdays and Fridays. The patient flow in Alterna Care is similar to the flow in IC, except that there is no lower level resident present. Figure 3.5 is a flowchart representation of the Arena model for AC. The service time distribution of various processes in the AC is as shown in Table 3.10.

**Table 3.10: Service Times in AC**

| Activity | Service Time Distribution (min) |
|---|---|
| Patient evaluation by AC nurse | Triangular (1,5,9) |
| Patient evaluation<br>- AC doctor<br>- AC physician extender | <br>Triangular (1,4,5)<br>Triangular(4,6,10) |
| Follow-up treatment by AC technician or Physician extender and nurse after reviewing diagnostic reports | Uniform (3,8) |
| Additional time for admission/ discharge<br>- Admitted patient<br>- Discharged patient | <br>Triangular (25,35,180)<br>Uniform (3,21) |

### 3.5.6 Diagnostic Testing

The diagnostic testing station is a submodel that encompasses two major testing units: the imaging and lab tests. The imaging subunit consists of X-ray equipment (portable and fixed), Computer Aided Tomography (CAT) machines, Magnetic Resonance Imaging (MRI), and ultrasound. The lab testing unit performs various tests like blood and urine tests. The tests are conducted by technicians who work in this department. The service time distributions for various processes in the diagnostic testing center are as shown in Table 3.11.

**Table 3.11: Service Times for Diagnostic Tests**

| Activity | Service Time Distribution (min) |
|---|---|
| Imaging | |
| - Portable x-ray | Triangular (10,15,30) |
| - Stationary x-ray | Triangular (30,45,60) |
| Ultrasound | Triangular (45,60,85) |
| CAT scan | Triangular (80,90,120) |
| Lab Testing | Uniform (45,60) |

The patient continues to occupy his or her respective bed in AC or IC or CC while at the diagnostic testing unit. After testing the patient returns to the care unit he came from earlier and waits for the doctor to reexamine.

The model does not use any resources in this testing station because the research is not concerned about the technicians who work here and also there are no data regarding them. To incorporate the process times for various processes in this unit, delays are assigned to various processes. Figure 3.6 depicts the Arena design model for the diagnostic testing center.

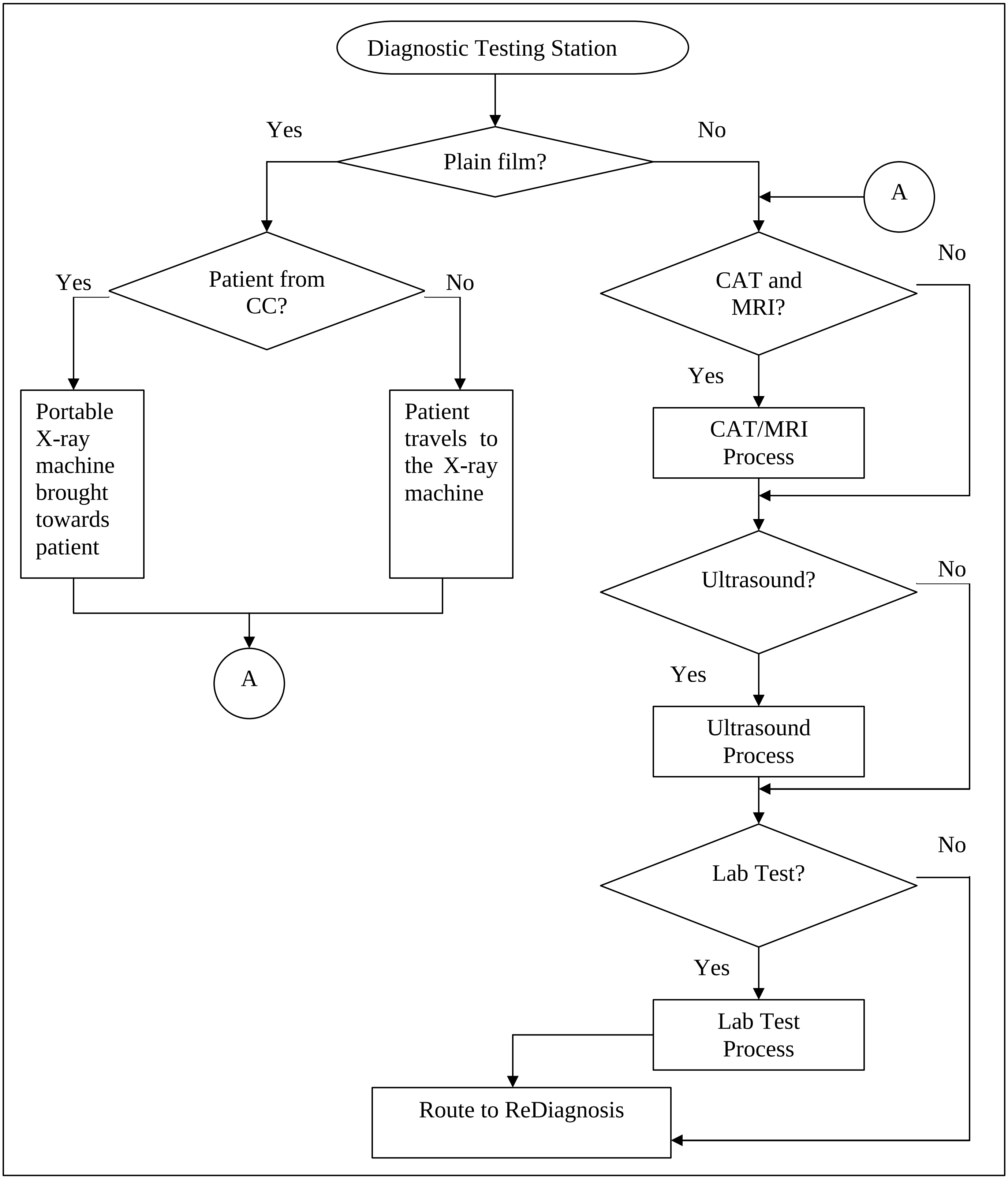


**Figure 3.6: Flowchart for Diagnostic Testing Arena Design Model**

### 3.5.7 Rediagnosis

After the required imaging tests or lab tests, the patient has to see the doctor for reevaluation based on the test results. The patient seizes the same resource (i.e. doctor and nurse) if they are available, else seizes other similar resource if the resource is off duty. The flow of patients in this module is designed such that the patient first is separated as per the department that he was first routed at the triage station and then seizes the nurse in that respective department. The next step that the patient follows is to seize the doctor for reevaluation. The doctor then determines if the patient is to be admitted to the hospital or discharged. After this decision the patient is given some assistance from patient representatives. The model uses a delay for this functionality because of a lack of data for the patient representatives. This sub model also checks if the AC is closed and clears all the queues in AC and releases resources if the AC is closed.

### 3.5.8 Time Period and Day Sub-model

This sub model is used to keep track of the actual time and also the day of week at any given time in the simulation run. The submodel also does the task of keeping track of the costs in the system at any given time.

## 3.6 Cost Inclusions in Arena Model

This research looks at two basic costs; staffing costs (only for doctors/physicians and residents) and patient waiting costs. The staffing costs are easily tangible costs and can be easily measured, while the patient waiting costs are less tangible and hard to quantify. These costs are implemented in Arena model for the current ED system, referred to actual system hereafter, as explained in the sections below.

### 3.6.1 Staff Costs

The ED incurs a cost for the resources used. Since this research is concerned only with the resources of physicians and residents, other resource costs are ignored and it is assumed that they remain constant.

Available data reveal the ED pays approximately $200 per hour for a physician, $ 10.20 per hour to a ULR and $6 per hour to a LLR. The schedule for physicians, upper level residents and lower level residents in the actual system at York ED is as shown in appendix A. Using the cost rate ($/Hour) and the schedule, the total staffing cost for a particular physician or a resident is calculated as

Physician cost = number of hours scheduled in a day * cost rate for physician

The cost for residents is calculated similarly. The total staff cost is calculated as the sum of the physician costs and resident costs. A variable *Totalstaffcost* is defined in the arena model and its value is set as

*Totalstaffcost* = *Totalstaffcost* + Total daily physician cost + Total daily upper level residents cost + Total daily lower level residents cost

This variable is updated at the end of each day during runtime in order to get runtime costs for staff.

### 3.6.2 Patient Waiting Costs

There is another aspect of costs relevant to this research, the costs incurred by making the patients wait. Clearly these costs trade off against the resource and staffing costs. In practice the patient dissatisfaction costs are difficult to quantify. The average total times for the patients in the model representing the current ED system are used to help calculate these waiting costs per patient type.

#### 3.6.2.1 Waiting Cost Rates

The waiting costs depend on the satisfactory waiting time in the system for the patients. Assume that the opportunity cost of the ED is the waiting cost incurred due to patient dissatisfaction. This cost is calculated based on the amount of revenue earned by the ED per unit time of the patient in the system. This amount of revenue earned per total time of the patient in the system is used to calculate the cost rates. In short,

Patient wait cost = Average profit contribution lost due to patient dissatisfaction

Average revenue is the revenue gained by the ED from a patient for the average amount of total time spent by the patient in the system (as per ESI type). Thus for each ESI level,

Cost rate for patient of ESI level ‘x’ ($/Min) = Average Revenue to ED from a patient of ESI level ‘x’ ($) / Average Total Time spent in system by a patient of ESI level ‘x’ (Min)

Thus cost rate is in effect the value (in $) for patient time in the system. The data for revenues from different ESI levels is as shown in Table 3.12.

**Table 3.12: Average Revenue earned by ED from Different ESI Patients**

| Patient Type | Revenue ($) |
|---|---|
| ESI 1 | 5000 |
| ESI 2 | 3000 |
| ESI 3 | 2000 |
| ESI 4 | 1000 |
| ESI 5 | 400 |

In addition, the average total time in the model representing the current ED system as per various ESI levels is as shown in Table 3.13.

**Table 3.13: Average Total Time in Model for Current ED for Different ESI Patients**

| Patient Type | Average Total Time (min) | Half Width |
|---|---|---|
| ESI 1 | 312.48 | 4.14 |
| ESI 2 | 300.87 | 4.57 |
| ESI 3 | 243.51 | 8.05 |
| ESI 4 | 86.18 | 4.1 |
| ESI 5 | 47 | 2.1 |

Hence using the above data in Tables 3.12 and 3.13, the cost/minute or the cost rate is calculated for different ESI patient types. Table 3.14 shows the waiting cost per minute or cost rates for different patient types.

**Table 3.14: Waiting Cost/min or Cost Rates for Different ESI Patients**

| Patient Type | Waiting Cost/Minute ($/min)= Average revenue/Average total time in system |
|---|---|
| ESI 1 | 16 |
| ESI 2 | 9.97 |
| ESI 3 | 8.21 |
| ESI 4 | 11.60 |
| ESI 5 | 8.52 |

The cost rate for ESI 4 and 5 are more than the cost rates for ESI 3. This is because there is no correlation between a patient's health condition and revenue earned. The ED does not charge depending on the time spent but charges on the treatment process. In our research, what we are calculating is the amount of money the ED loses on an average per minute if they lose a patient of a specific ESI type. Hence the variation in cost rates.

### 3.6.2.2 Calculation of Waiting Costs

A patient is dissatisfied if the waiting time of the patient in the ED exceeds a certain threshold wait time limit or a satisfactory wait time. This threshold time is different for each ESI patient type. Hence, the waiting cost for a patient is then calculated as per the flowchart in Figure 3.7.

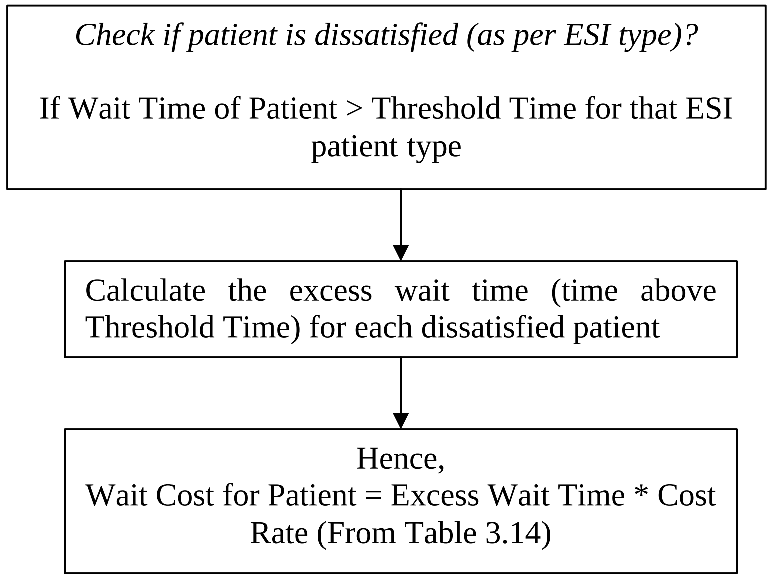


**Figure 3.7: Flowchart for Calculation of Patient Waiting Cost**

#### 3.6.2.3 Arena Model Changes for Waiting Costs

To incorporate the waiting costs in the arena model, it is necessary to have the data for the satisfactory total wait times in the system for each ESI level. If a patient has to wait for more than this satisfactory time, the ED incurs an opportunity cost. Hence, any excess wait time above this satisfactory time will be the time which calls for waiting cost to the ED.

Table 3.15 shows the satisfactory wait times in the system for the patient as per ESI level. This data is obtained from the personnel at York Hospital ED.

**Table 3.15: Satisfactory Wait Times in System for Different ESI Patients**

| **ESI Level** | **Satisfactory Total Waiting time in system (Tolerance limits on waiting times) Minutes** |
|---|---|
| ESI 1 | 0 |
| ESI 2 | 10 |
| ESI 3 | 100 |
| ESI 4 | 150 |
| ESI 5 | 180 |

Beyond these tolerance times, the system will incur a cost of respective waiting cost/min for each ESI type as calculated in Table 3.14. The waiting costs as per ESI type are stored in variables called *ESI1WaitCost*, *ESI2WaitCost*, *ESI3WaitCost*, *ESI4WaitCost*, and *ESI5WaitCost* respectively. These variables are updated at runtime at each queue where the patient has to wait. The variables are defined as,

*ESI1WaitingCost*= *ESI1WaitingCost* + (Excess Wait Time for ESI1 * Waiting Cost/Min for ESI1)

Similarly, the remaining waiting cost variables for different ESI types are calculated.

A variable *TotalWaitCost* is defined to hold the total wait costs during runtime for all the five ESI patient types. This total waiting cost is calculated as

*TotalWaitCost* = *ESI1WaitCost* + *ESI2WaitCost* + *ESI3WaitCost* + *ESI4WaitCost* + *ESI5WaitCost*

This variable for total waiting cost is updated during runtime by a dummy entity flow in arena.

### 3.6.3 Total Costs

A variable called *TotalCost* is defined in the arena model, which stores the total costs for waiting and staffing as described above. The value of this variable is also updated during runtime using a dummy entity creation module in arena. The value of total costs is given as

*TotalCost* = *TotalStaffCost* + *TotalWaitCost*

## 3.7 Model Verification and Validation

Verification is the process of ensuring that the Arena model behaves in the way it was intended according to modeling assumptions made (Kelton et al., 2002).

The ED model was verified by allowing a single entity to enter the system and following the entity to be sure that the model logic and data are correct. The step feature in Arena found on the Run toolbar was used to control the model execution and step the entity through the system. Also the model was tested by replacing input data by constants instead of a scheduled arrival. Thus deterministic data was used to predict the system behavior. Arena break and watch options were also used to perform model verification.

Validation is the task of ensuring that the model behaves the same as the real system (Kelton et al., 2002).

Several steps were taken throughout the research development cycle to validate the model. These included identifying elements to be included in the model, and determining appropriate level of detail. After initial validation, the ED personnel and faculty advisors were presented with the model flow, assumptions and details, and output of the current model. Expert opinion from the ED personnel was sought on the model outputs in regards of mean waiting times of patients and total time in system for different ESI patients. Animation of the system was used as one of the validation methods.

### 3.8 Arena Model Runtime

The system under study is a steady state system because the ED is a unit that operates 24 hours everyday without any stops or restarts. A steady-state system is one in which the quantities to be estimated are defined in the long run (Kelton et al., 2002).

#### 3.8.1 Warm-up period determination

Since, this system is a steady state system it cannot be designed to start in an empty or idle state. Even in a steady state system simulation, the system has to be initialized. If the system is initialized as empty and idle in a simulation where things eventually become congested, the output data for some period of time after initialization will tend to understate the eventual congestion, i.e. will be biased toward low values of typical performance measures. To overcome this problem, we initialize empty and idle, realizing that this is unrepresentative of steady state, but then let the model warm up for a while until it appears that the effect of the artificial initial conditions have dissipated. At that time, the statistical accumulators are cleared and the simulation gathers statistics from then on (Kelton et al., 2002).

There are various methods for determining the warm up period. This research makes use of the Welsch test for determining the warm up. Plots of the key variables like average total time in system and mean waiting time for each ESI level for ten replications and each replication of 100 days were obtained. Then output analyzer was used to eyeball the plots and see where they appear to stabilize.

From all such plots, the warm up period was determined to be 2000 minutes. In addition, the moving average plots of these key variables were looked upon and the maximum time after which the system appears to be stabilized was considered as the warm up period. The total run length was determined to be 50 days.

### 3.9 Current ED Model Simulation Results

The Arena model representing the current ED was run as explained in the above section along with the warm up period of 2000 minutes. The following are the results that were obtained. These were confirmed to be correct by expert opinion.

**Table3.16: Average Total Waiting Times in Current ED Model Simulation Run**

| Patient Type | Average Total Wait Time (Mins) | Half Width |
|---|---|---|
| ESI 1 | 26.3 | 1.20 |
| ESI 2 | 33.55 | 1.42 |
| ESI 3 | 33.03 | 1.31 |
| ESI 4 | 15 | 1.03 |
| ESI 5 | 22.80 | 1.12 |

**Table 3.17: Average Total Time in System in Current ED Model Simulation Run**

| Patient Type | Average Total Time (mins) | Half Width |
|---|---|---|
| ESI 1 | 312.48 | 4.14 |
| ESI 2 | 300.87 | 4.57 |
| ESI 3 | 243.51 | 8.05 |
| ESI 4 | 86.18 | 4.1 |
| ESI 5 | 47 | 2.1 |

**Table 3.18: Average Total Time to Physician in Current ED Model Simulation Run**

| Physician | Average Time to Physician (Mins) | Half width |
|---|---|---|
| Time to CC Evaluator | 34.93 | 1.5 |
| Time to IC Evaluator | 28.0 | 1.83 |
| Time to AC Doctor | 23.3 | 1.2 |

# Chapter 4

# Analysis

This chapter focuses on the methodology implemented in the research and analyses the results obtained. It starts with the analysis of sensitivity of waiting cost rates in the research. This is followed by the design of schedules for doctors and residents depending on the patient contacts. It further delves into the details of the OptQuest model and the results obtained from it. A comparative analysis of the results from the new schedules is presented.

## 4.1 Sensitivity Analysis of Patient Waiting Costs

The total cost that this research looks into is a function of the patient waiting costs. Since the system seems to be driven by the patient waiting costs, a sensitivity analysis study is done for these costs. Average patient waiting cost is calculated for various cost rates. The change in the average patient waiting cost is observed for three different cost rates for the five ESI types. These cost rates are perturbed from their actual values which were calculated in Table 3.14.

Figure 4.1 shows the fluctuation in average waiting costs calculated for the cost rates as defined in Table 3.14, for a 50 days run of simulation. The statistics are reset to 0 at the end of warm up period. The collection of statistics starts from here onwards. Figure 4.2 is the graph of the fluctuations in the average total costs for the actual cost rates.

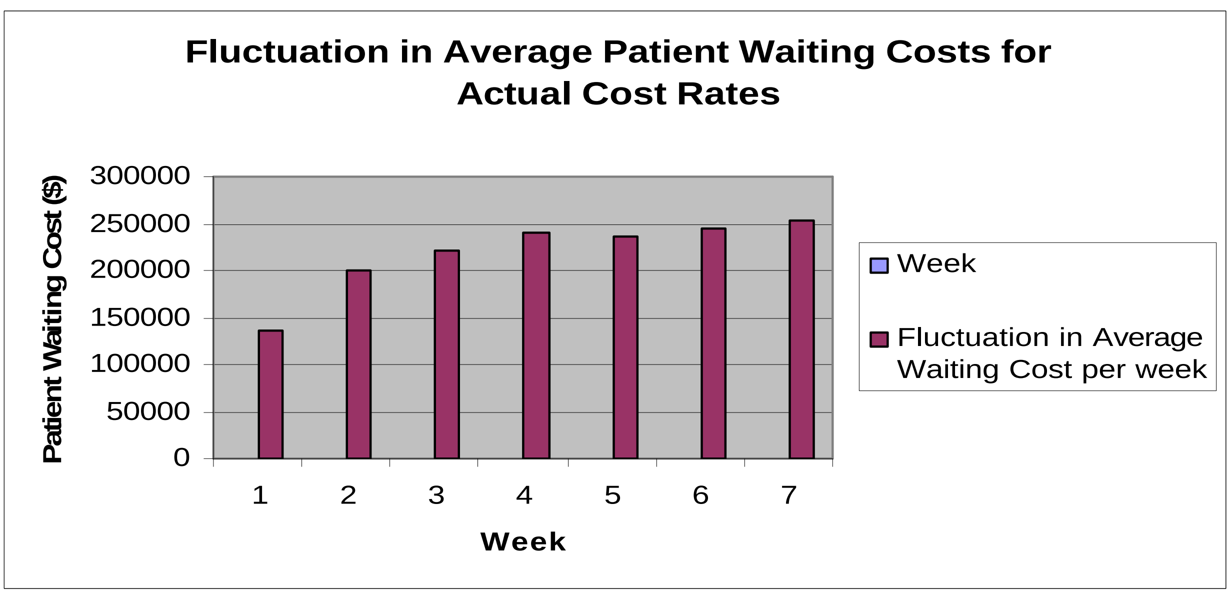


**Figure 4.1: Fluctuation in Average Patient Waiting Costs per Week for Actual Cost Rates**

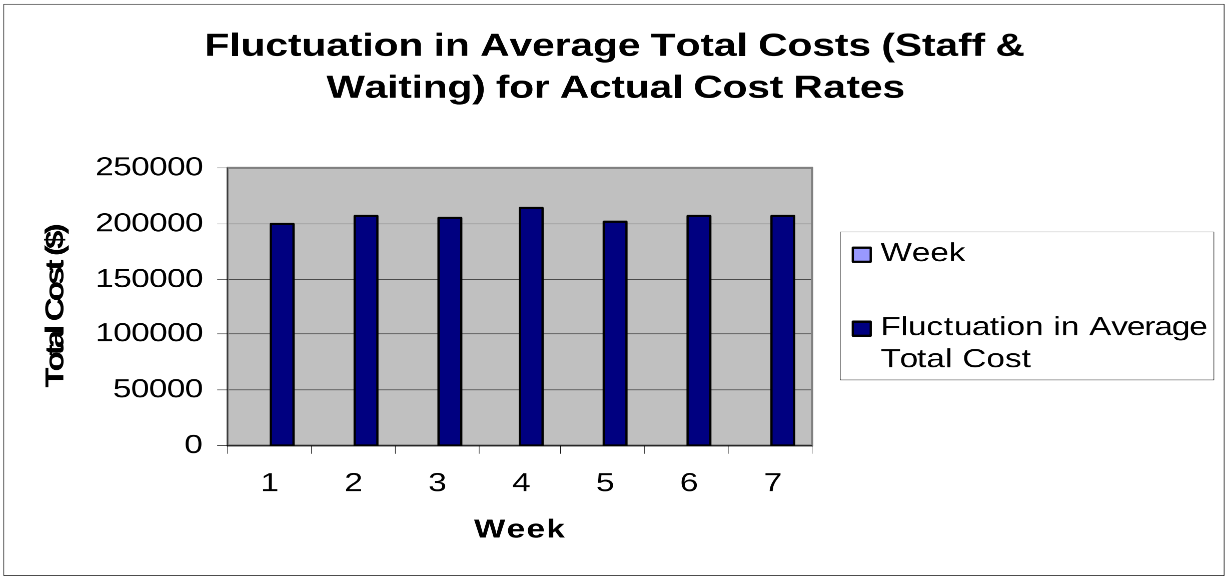


**Figure 4.2: Fluctuation in Average Total Costs per Week for Actual Cost Rates**

The cost rates used in the second case shown in Table 4.1 were raised by 50% from their actual values in Table 3.14.

**Table 4.1: Waiting Cost/min or Cost rates for Different ESI Patients (50% increase from the actual cost rates)**

| ESI Level | Waiting Cost/Minute ($/min)= Average revenue/Average total time in system |
|---|---|
| ESI 1 | 24 |
| ESI 2 | 14.95 |
| ESI 3 | 12.30 |
| ESI 4 | 17.4 |
| ESI 5 | 12.72 |

Figure 4.3 is the graph of average cumulative waiting costs per week when the cost rates for all ESI levels are as in Table 4.1.

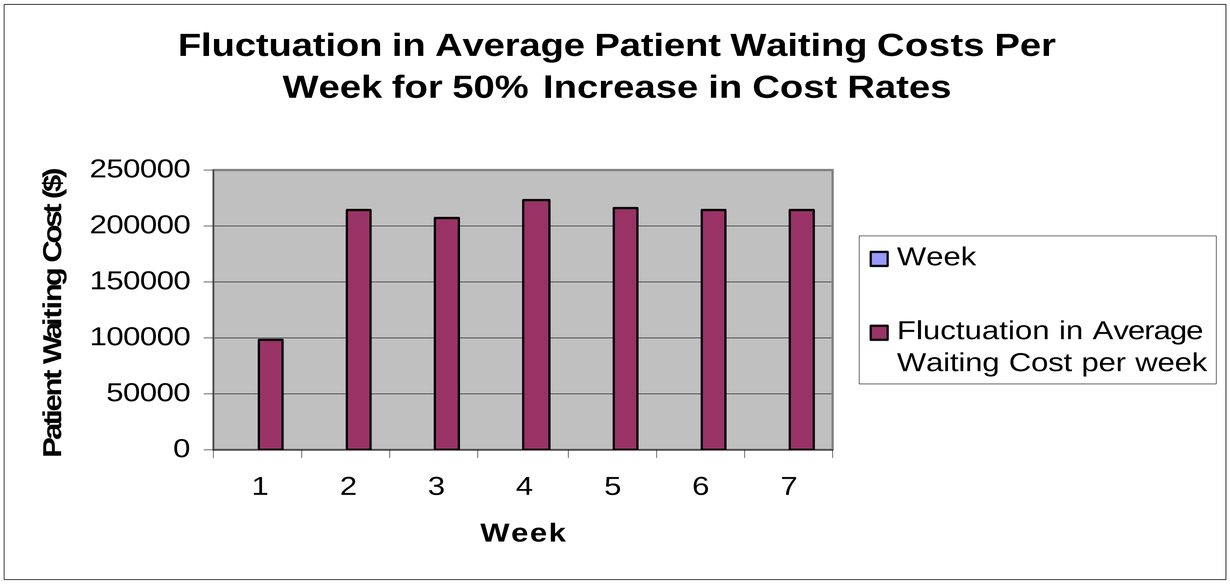


**Figure 4.3: Fluctuation in Average Patient Waiting Costs per Week for 50% Increase in Cost Rates**

Figure 4.4 is the fluctuation in the average total costs per week for the cost rates in Table 4.1.

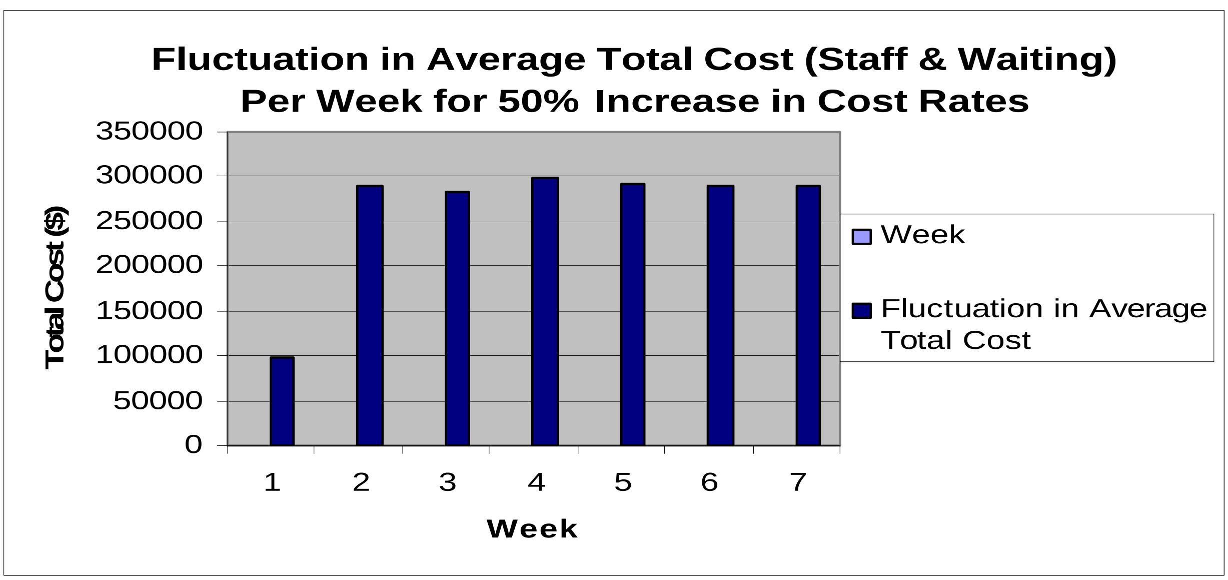


**Figure 4.4: Fluctuation in Average Patient Total Costs per Week for 50% Increase in Cost Rates**

In the third case as shown in Table 4.2, the cost rates were reduced by 50% from their actual values in Table 3.14.

**Table 4.2: Waiting Cost/min or Cost rates for Different ESI Patients (50% reduction from the actual cost rates)**

| ESI Level | Waiting Cost/Minute ($/min)= Average revenue/Average total time in system |
|---|---|
| ESI 1 | 8 |
| ESI 2 | 4.97 |
| ESI 3 | 4.10 |
| ESI 4 | 5.80 |
| ESI 5 | 4.26 |

Figure 4.5 shows the fluctuation in average waiting costs per week for the cost rates in Table 4.2, when the cost rates for all ESI levels are reduced by 50% of the actual values. Figure 4.6 is the fluctuation in average total cost per week for these cost rates.

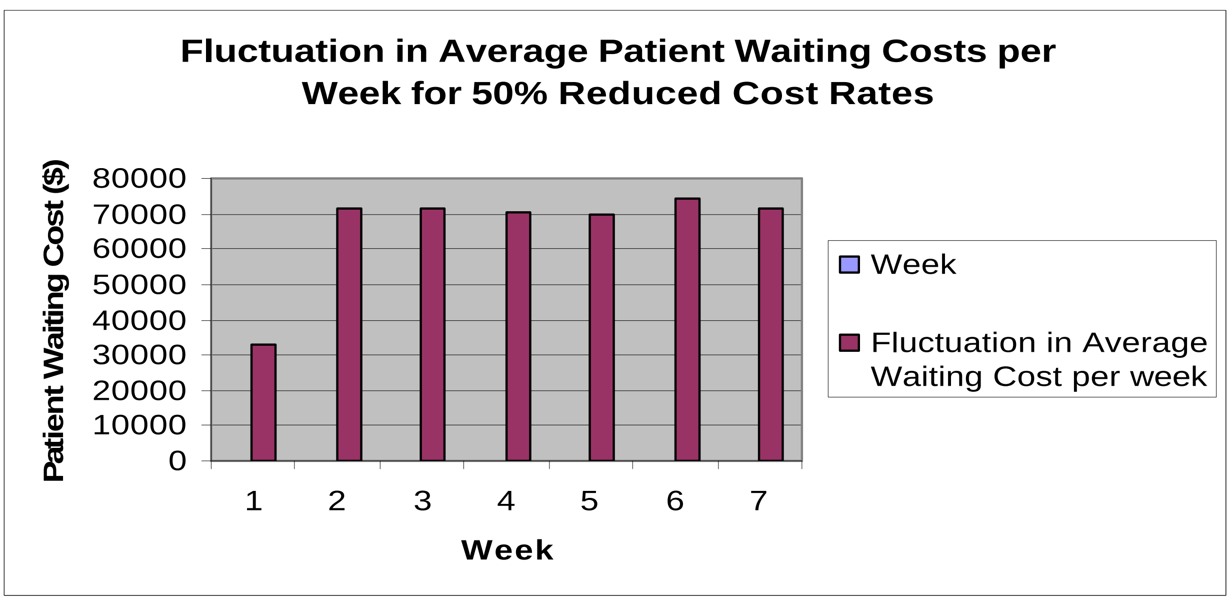


**Figure 4.5: Fluctuation in Average Patient Waiting Costs per Week for 50% Reduction in Cost Rates**

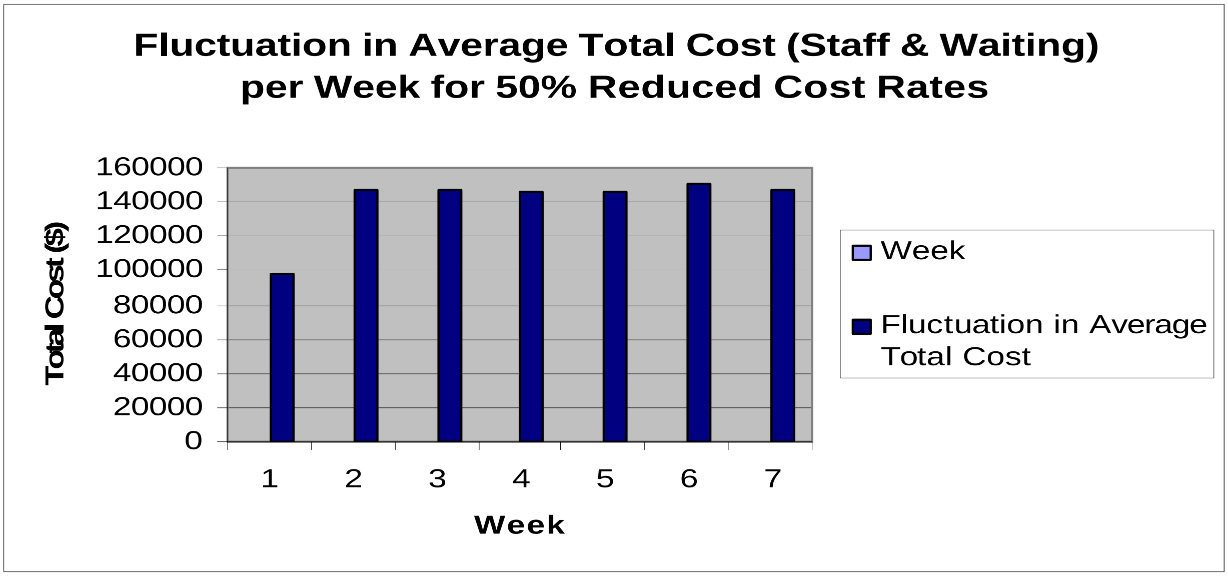


**Figure 4.6: Fluctuation in Average Patient Total Costs per Week for 50% Reduction in Cost Rates**

Thus, the waiting cost is observed to behave similarly with different cost rates for patient waiting, with the model runtime conditions remaining same as explained in section 3.8 for all three cases. Figure 4.7 shows that the total cost increases linearly as the patient waiting cost rates are raised and hence there is a linear relationship between the cost rates and total costs.

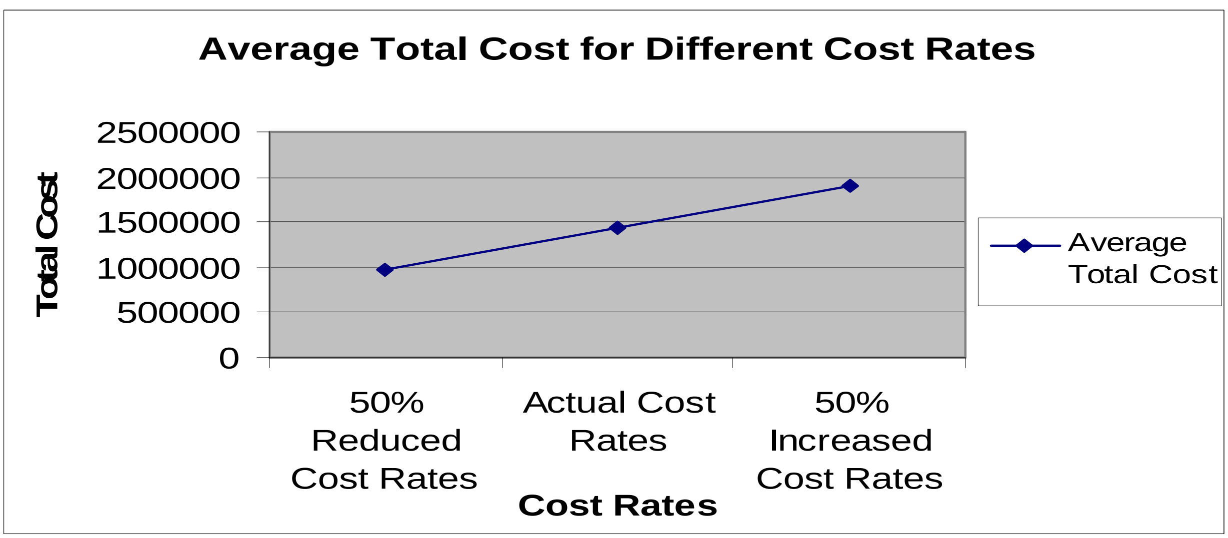


**Figure 4.7: Average Patient Total Costs with Increasing Waiting Cost Rates**

## 4.2 Determination of Schedules for Physicians and Residents

The model was run to determine the number of patient contacts with an evaluator (doctor or resident) or the load on the doctors and residents in the critical care and intermediate care at any given time of the day. An average was taken over all the replications to determine the average patient contacts with an evaluator at any given time period within each day of a week. Figure 4.8 shows a graph of patient contacts with the CC evaluator.

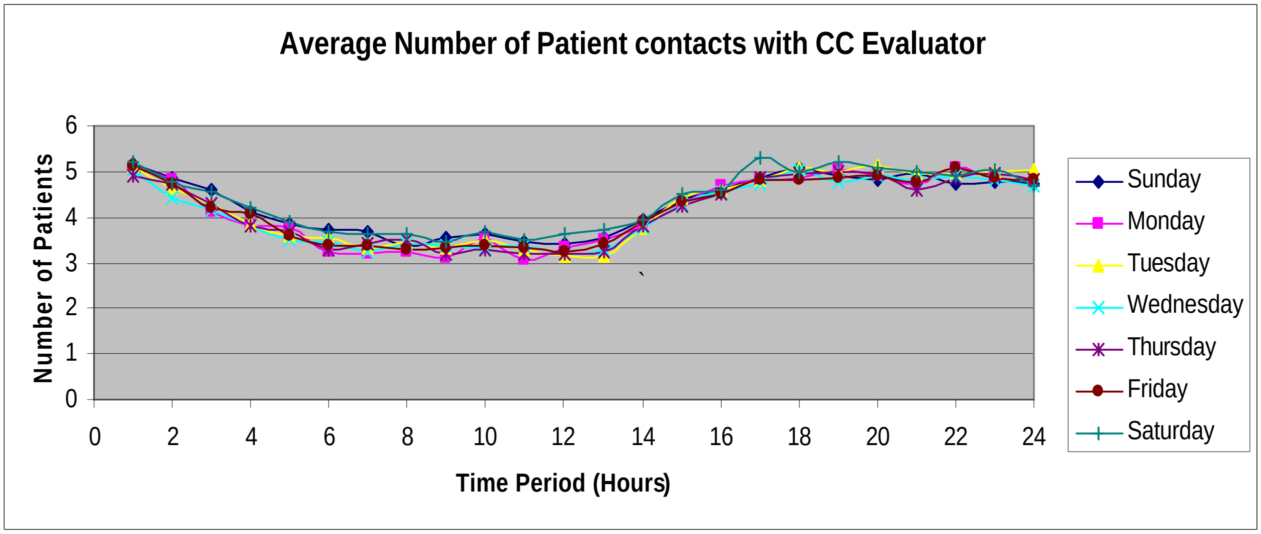


**Figure 4.8: Average Number of Patient Contacts or Load on the CC Evaluator**

From Figure 4.8, a schedule can be determined for the doctors and residents in critical care. A schedule is for an entire day and has three shifts with each shift of eight hours. The schedule is designed in such a way that the same number of doctors or residents work throughout each eight hour shift. Since the same number of resources work throughout the shift it is critical to determine the correct shift so that resources may be best utilized. Keeping this in mind the following schedule in Table 4.3 was determined for the upper level residents in critical care. This schedule was designed such that each shift considers the variable patient contact loads in an entire day. Similar loads within a day were designed to form one shift so as to best utilize the number of resources in that shift.

**Table 4.3: Schedule for ULRs**

| Shifts | Weekday | Weekend |
|---|---|---|
| Shift 1 | 12 am – 8 am | 12 am – 8 am |
| Shift 2 | 8am – 4 pm | 8am – 4 pm |
| Shift 3 | 4pm – 12 am | 4pm – 12 am |

Similarly a schedule for LLR's in the IC was determined from the graph in Figure 4.9, which is a representation of the number of patient contacts with the IC evaluator or the load on the IC evaluator. The peak loads of patient contacts show that two different schedules were possible for the LLR's as shown in Table 4.4 and Table 4.5. These were determined so that the LLR's can be best utilized in a shift.

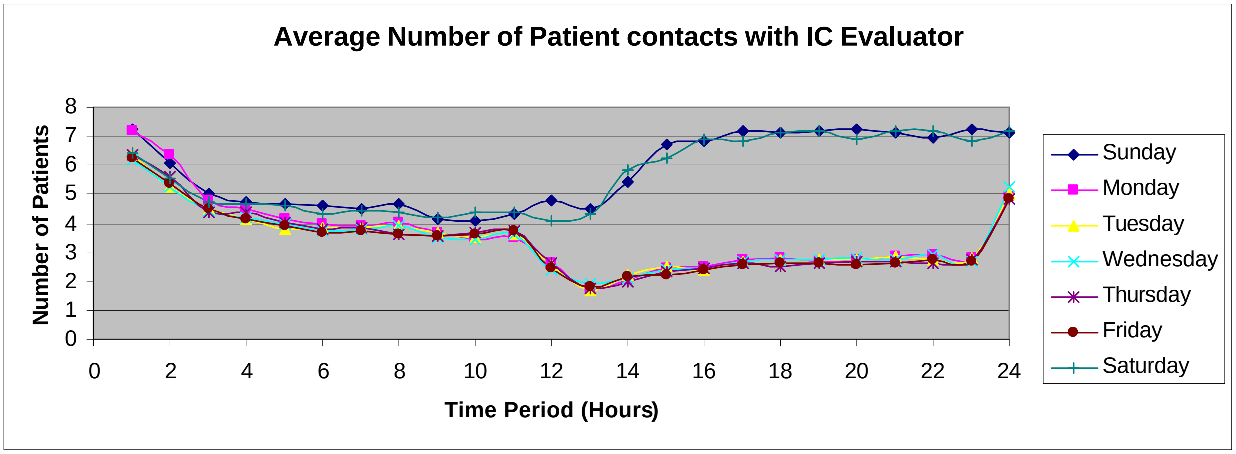


**Figure 4.9: Average Number of Patient Contacts or Load on the IC Evaluator**

**Table 4.4: Schedule I for LLR's**

| Shifts | Weekday | Weekend |
|---|---|---|
| Shift 1 | 12 am – 8 am | 12 am – 8 am |
| Shift 2 | 8am – 4 pm | 8am – 4 pm |
| Shift 3 | 4pm – 12 am | 4pm – 12 am |

**Table 4.5: Schedule II for LLR's**

| Shifts | Sunday | Monday – Friday | Saturday |
|---|---|---|---|
| Shift 1 | 12 am – 7 am | 11 pm – 7 am | 11 pm – 7 am |
| Shift 2 | 7am – 3 pm | 7am – 3 pm | 7am – 3 pm |
| Shift 3 | 3pm – 11 pm | 3pm – 11 pm | 3pm – 12 am |

Since the physicians work in both CC and IC, the shifts had to be designed using both Figure 4.8 and 4.9. The following shifts in Table 4.6 were designed for the physicians.

**Table 4.6: Schedule for Physicians**

| Shifts | Weekday | Weekend |
|---|---|---|
| Shift 1 | 12 am – 8 am | 12 am – 8 am |
| Shift 2 | 8am – 4 pm | 8am – 4 pm |
| Shift 3 | 4pm – 12 am | 4pm – 12 am |

### 4.3 Determining Near Optimal Staffing using OptQuest

The actual system reflects that the mean waiting times of patients of all ESI types is higher than the acceptable times as in Table 3.15. Hence OptQuest is used to determine the near optimal number of staff as per the above schedules, such that the staffing and the patient waiting costs are minimized and the patient satisfaction is improved. Two different arena models were constructed, one to include LLR schedule I from Table 4.4 and the other to include LLR schedule II from Table 4.6.

#### 4.3.1 Arena Model Changes to Include Staffing Variables

The actual system Arena model is generalized to allow for variation in the number of staff (doctors and residents in CC and IC), with the ability to add resources during these shifts. To add an easily controlled variable number of physicians, define the variables *VarDoctors1*, *VarDoctors2*, and *VarDoctors3* to be the number of doctors working shift1, shift2, and shift3 as defined in Table 4.6 above. Only three variables for physician capacity are required because the weekday and weekend shifts are the same. A resource called *NewDoctor* is defined in the resource spreadsheet in Arena and a schedule for this resource is defined in the schedules section called *NewDoctorSchedule*. This schedule comprises of the variable capacities of doctors *VarDoctors1*, *VarDoctors2* and *VarDoctors3*, working on the three shifts (shift1, shift2 and shift3) every day over a whole week. This schedule is assigned to the *NewDoctor* resource.

Similarly, three upper level resident capacity variables *VarUlr1*, *VarUlr2*, and *VarUlr3* are defined to work in shift1, shift2 and shift3 as per Table 4.3. Also, a schedule *NewUlrSchedule* is defined and is assigned to a new resource called *NewUlr*. Variables for LLR capacities are added as *VarLlr1*, *VarLlr2*, and *VarLlr3* for shift1, shift2 and shift3. A schedule called *NewLlrSchedule* is defined for the new resource *NewLlr*. In the second arena model for LLR schedule II we include two more variables *VarLlr4* and *VarLlr5* along with the other variables defined herein. The variable *VarLlr4* is the number of LLR's working the first shift on Sundays and *VarLlr5* is the number of LLR's working the shift3 on Saturday as in Table 4.5

#### 4.3.1.1 Staffing Costs

As described in Chapter 3, to calculate the total cost for a physician the number of hours a physician works in a day should be known. The total cost of a physician to the ED can then be calculated as,

Total Cost of physician = Number of hours worked * 200

Since, there are three shifts defined for a physician and each shift is of 8 hours, only the capacity working per shift should be known in order to calculate the total cost of physicians. A variable named *VarTotalPhysicianCost* is defined to hold the total value of physician cost per day. Since the ED pays $200/Hour to a physician, the value of this variable is calculated as,

*VarTotalPhysicianCost* = *VarDoctors1**200*8 + *VarDoctors2** 200*8 + *VarDoctors3**200*8

The ED pays approximately $10.2 per hour to the upper level residents and $6/hour to the lower level residents. Similar to the physician cost calculations, variables for calculating the total cost for ULR's and LLR's are defined for one day with the respective values as below:

*VarTotalUlrCost* = *VarUlr1**10.2* 8 + *VarUlr2**10.2* 8 + *VarUlr3**10.2* 8

For LLR schedule I,

$$VarTotalLlrCost = VarLlr1*6*8 + VarLlr2*6*8 + VarLlr3*6*8$$

And for the second Arena model with LLR schedule II,

$$VarTotalLlrCost = VarLlr1*6*8 + VarLlr2*6*8 + VarLlr3*6*8 + VarLlr4*6*7 + VarLlr5*6*9$$

Hence, to calculate the total cost due to the staff, a variable called *VarTotalStaffCost* is defined. This will be the sum of the costs due to physicians, upper level residents and lower level residents and is calculated as,

$$VarTotalStaffCost = VarTotalStaffCost + VarTotalPhysicianCost + VarTotalUlrCost + VarTotalLlrCost$$

This variable is updated during runtime in order to get runtime costs for staff.

**4.3.1.2 Waiting Costs**

Similar to the actual system model, variables are defined to store waiting costs for patients of each ESI level at runtime. These variables are updated at each stage where an entity waits above the threshold wait time. These variables are called *ESI1WaitingCost*, *ESI2WaitingCost*, *ESI3WaitingCost*, *ESI4WaitingCost*, and *ESI5WaitingCost* respectively. These variables store the costs due to excess waiting and hence are defined as,

*ESI1WaitingCost* = *ESI1WaitingCost* + (Excess Wait Time for ESI1*Waiting Cost/Min ESI1)

The cost rates for different ESI patient types are as defined in Table 3.14.The remaining waiting cost variables are calculated similar to the above calculation. A variable called *VarTotalWaitCost* is defined to hold the sum of the total waiting costs of all the different ESI patients during runtime. This variable is calculated as,

$$VarTotalWaitCost = VarTotalWaitCost + ESI1WaitingCost + ESI2WaitingCost + ESI3WaitingCost + ESI4WaitingCost + ESI5WaitingCost$$

This waiting cost is continuously updated during runtime by using a dummy entity creation sub model in Arena.

#### 4.3.1.3 Total Cost

To calculate the total costs due to the staff and patient waiting during runtime, a variable called *VarTotalCost* is defined as shown below,

$$VarTotalCost = VarTotalStaffCost + VarTotalWaitCost$$

This cost is updated during runtime.

## 4.4 Setting up the OptQuest Model

Arena comes with a package called OptQuest that uses heuristics tabu search and scatted search to move intelligently around the input-control space in an attempt to converge quickly and reliably to a near optimal point. Two different optquest models were constructed in order to handle the two different schedules for LLR's as described in Section 4.2. The following sections explain the OptQuest models used in this research. All conditions remain same for both the models unless explicitly stated in the section.

### 4.4.1 Input Controls for the ED OptQuest Model

It is necessary to first define the input parameters or controls for the ED model. Table 4.7 shows the settings for the input parameters for this model.

**Table 4.7: Input Parameters or Controls for the OptQuest Model of the ED**

| Control (Capacities of doctors and residents in various shifts) | Lower Bound | Upper Bound | Type (Increment) | Category |
|---|---|---|---|---|
| *VarDoctors1* | 0 | 6 | Discrete(1) | Variable |
| *VarDoctors2* | 0 | 6 | Discrete(1) | Variable |
| *VarDoctors3* | 0 | 6 | Discrete(1) | Variable |
| *VarUlr1* | 0 | 5 | Discrete(1) | Variable |
| *VarUlr2* | 0 | 5 | Discrete(1) | Variable |
| *VarUlr3* | 0 | 5 | Discrete(1) | Variable |
| *VarLlr1* | 0 | 4 | Discrete(1) | Variable |
| *VarLlr2* | 0 | 4 | Discrete(1) | Variable |
| *VarLlr3* | 0 | 4 | Discrete(1) | Variable |

The variables selected are the capacities of the physicians, upper level residents and the lower level residents as defined in the modified arena model. The upper bounds for the variable *VarDoctors1*, *VarDoctors2*, and *VarDoctors3* are set to 6 because the current actual system has 6 doctors working at the most. Similarly the upper level bounds are set for the other controls depending on the actual real life system. The increment column is set to Discrete (1), which helps OptQuest identify that the optimization problem is to be run with discrete values of the controls with an input step size of 1.

Two additional variables *VarLlr4* and *VarLlr5* are selected as input controls for the second optquest model.

### 4.4.2 Constraints for the ED OptQuest Model

Constraints are the limits to be placed on the combinations of input control variables. Table 4.8 shows the various constraints placed on the OptQuest model.

**Table 4.8: Constraints on the OptQuest Model for ED**

| Constraint Number | Constraint |
|---|---|
| 1 | *VarDoctors1* >= 2, *VarDoctors2* >= 2, *VarDoctors3* >= 2 |
| 2 | *VarUlr1* >= 1, *VarUlr2* >= 1, *VarUlr3* >= 1 |
| 3 | *VarLlr3* >= 1, *VarLlr3* >= 1, *VarLlr3* >= 1 |

Constraint 1 is placed because in the actual system at any given time there are two physicians working. Constraints 2 and 3 are placed since, this being an academic ED, residents are trained and hence at any given time at least one upper level resident and one lower level resident should be present.

The constraint 3 in the second optquest model will have two additional variables *VarLlr4* and *VarLlr5*.

### 4.4.3 Objective and Requirements for the ED OptQuest Model

The objective and requirements specify what is to be optimized (either minimize or maximize) and also sets requirements on the output. A requirement is similar to a constraint except that it operates on an output from the simulation as opposed to an input, and serves basically to identify as infeasible any scenarios that don't meet the requirements.

The ED OptQuest model objective is as shown in Table 4.9.

**Table 4.9: Objective for the ED OptQuest Model**

| Type | Response | Lower Bound | Upper Bound |
|---|---|---|---|
| Minimize Objective | *VarTotalCost* | - | - |

The objective for this research is to minimize the total cost, assuming all costs remain constant except physician & resident staffing costs and patient waiting costs. Hence, the objective is to minimize the variable *VarTotalCost*, which includes all required costs.

### 4.4.4 Run Conditions for the ED OptQuest Model

The time required to run the model can vary from certain hours to certain number of days. The two different models were run for a period of 48 hours to get the best results in that runtime.

## 4.5 Results from Optquest Model for the ED

The following are two different result sets for the two different OptQuest models which incorporated the two different schedules for LLR's as explained in Section 4.2.

### 4.5.1 Results for OptQuest Model with LLR Schedule I

The following are the results for the OptQuest Model designed for LLR schedule I as in Table 4.4.

**Table 4.10: Staff Variables for First OptQuest Model**

| Staff Variables | Value |
|---|---|
| *VarDoctors1* | 2 |
| *VarDoctors2* | 2 |
| *VarDoctors3* | 2 |
| *VarUlr1* | 3 |
| *VarUlr2* | 3 |
| *VarUlr3* | 2 |
| *VarLlr1* | 2 |
| *VarLlr2* | 2 |
| *VarLlr3* | 2 |

The objective value for minimum cost for this OptQuest model is as shown in Table 4.11.

**Table 4.11: Objective Value for First OptQuest Model**

| Staff Variables | Value ($) |
|---|---|
| *VarTotalCost* | 657648.75 ± 16305.5 |

### 4.5.2 Results for OptQuest Model with LLR Schedule II

The following are the results for the OptQuest Model designed for LLR schedule II as in Table 4.5.

**Table 4.12: Staff Variables for Second OptQuest Model**

| Staff Variables | Value |
|---|---|
| *VarDoctors1* | 2 |
| *VarDoctors2* | 2 |
| *VarDoctors3* | 2 |
| *VarUlr1* | 1 |
| *VarUlr2* | 1 |
| *VarUlr3* | 2 |
| *VarLlr1* | 1 |
| *VarLlr2* | 1 |
| *VarLlr3* | 1 |
| *VarLlr4* | 2 |
| *VarLlr5* | 1 |

The objective value for minimum cost for this OptQuest model is as shown in Table 4.13.

**Table 4.13: Objective Value for Second OptQuest Model**

| Staff Variables | Value ($) |
|---|---|
| *VarTotalCost* | 669125.85 ± 16421.30 |

## 4.6 Recommended Staffing Pattern and Schedules

Thus from the results the following are the recommended number of staff working in the shifts as shown in Tables 4.14 and 4.15.

**Table 4.14: Schedule I and Staffing Pattern**

| Staff | Weekdays | | | Weekends | | |
|---|---|---|---|---|---|---|
| | 12am – 8am | 8am – 4pm | 4pm – 12am | 12am – 8am | 8am – 4pm | 4pm – 12am |
| Doctors | 2 | 2 | 2 | 2 | 2 | 2 |
| ULR | 3 | 3 | 2 | 3 | 3 | 2 |
| LLR | 2 | 2 | 2 | 2 | 2 | 2 |

**Table 4.15: Schedule II and Staffing Pattern**

| Staff | Weekdays | | |
|---|---|---|---|
| | 11pm – 7am | 7am – 3pm | 3pm – 11pm |
| Doctors | 2 | 2 | 2 |
| ULR | 1 | 1 | 2 |
| LLR | 1 | 1 | 1 |

| Staff | Sunday | | |
|---|---|---|---|
| | 12am – 7am | 7am – 3pm | 3pm – 11pm |
| Doctors | 2 | 2 | 2 |
| ULR | 1 | 1 | 2 |
| LLR | 2 | 1 | 1 |

| Staff | Saturday | | |
|---|---|---|---|
| | 11pm – 7am | 7am – 3pm | 3pm – 12am |
| Doctors | 2 | 2 | 2 |
| ULR | 1 | 1 | 2 |
| LLR | 1 | 1 | 1 |

### 4.7 Comparative Analysis

The two new Arena models for the schedules in Tables 4.14 and 4.15 were run to get the performance metrics for costs and patient satisfaction as compared to the actual system. The following sections describe these metrics in detail.

#### 4.7.1 Costing

The total costs to the ED for the actual system and the system with the two different schedules with variable staff, for 50 ED days run, are as shown in the Table 4.16.

**Table 4.16: Costs in the Actual System and the New Proposed Staffing Systems (For 50 Days)**

| System | Total Waiting Cost ($) | Total Staff Cost ($) | Total Cost ($) |
|---|---|---|---|
| Actual System | 924129.0 | 520715.8 | 1444844.8 ± 47512.3 |
| System with Schedule I (Table 4.14) | 151690.3 | 505958.4 | 657648.7 ± 16305.5 |
| System with Schedule II (Table 4.15) | 179122.6 | 490003.2 | 669125.8 ± 16421.30 |

It can be seen from Table 4.16, that the patient waiting costs form a large part of the total cost. The two schedules that were designed show a reduction of almost 83.5% and 80.6% respectively from the actual system. This can be attributed to the fact that the new schedules designed take into consideration the peak loads of patient contacts with the physicians and residents during a day. This reduces the waiting times for patients, which in turn reduces the waiting costs. The cost rate used for calculations as shown in Table 3.14 is far greater than the staff cost rate which in turn drives the total cost mostly on waiting time of patients. Also, the total scheduled hours for the physicians and residents are increased by almost 30 hours per week. But an important aspect here is that OptQuest has increased the resource hours for resources costing less (residents) rather than costly resources (physicians) which were kept at the bare minimum requirement by OptQuest, as can be seen in Figure 4.10. Even though an 80% reduction in costs may not be the exact reduction due to assumptions made for the research.

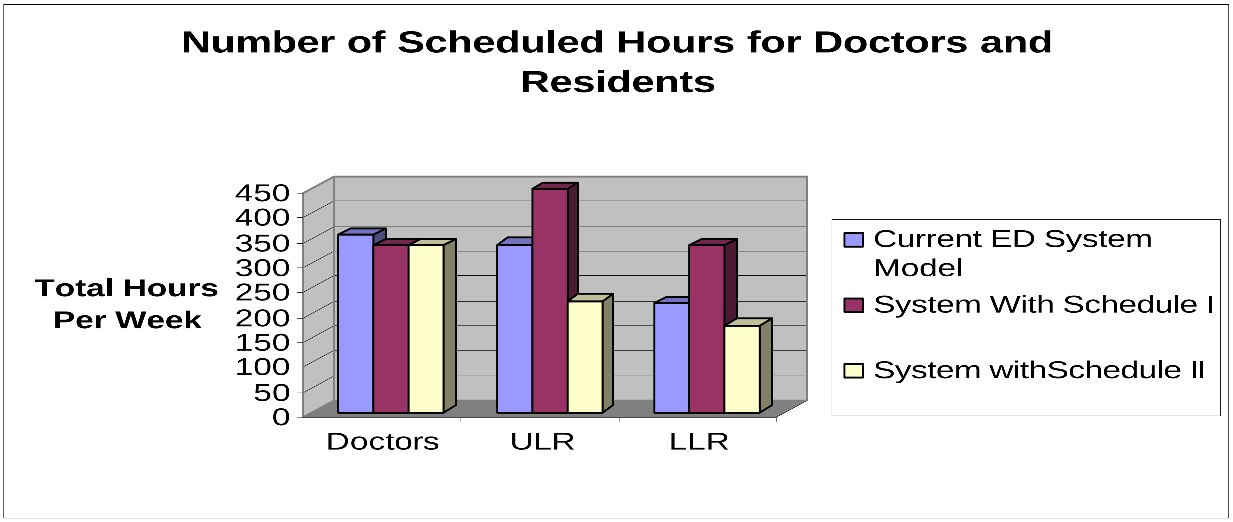


**Figure 4.10: Number of Scheduled Hours for Doctors and Residents in One week**

### 4.7.2 Patient Satisfaction

Patient satisfaction is usually referred to in terms of time in a business setting such as an emergency department. This research looks at the time for a patient to see a physician or resident in the ED for the first time as a performance measure for patient satisfaction. Patient satisfaction in this regard improved over the actual system as shown in Table 4.17.

**Table 4.17: Time to See a Doctor or Resident for the First Time**

| System | First Time to CC Evaluator (Min) | First Time to IC Evaluator (Min) | First Time to AC Evaluator (Min) |
|---|---|---|---|
| Actual System | 34.93 ± 1.5 | 28 ± 1.83 | 23.3 ± 1.2 |
| System with Schedule I (Table 4.14) | 23.4 ± 1.1 | 19.9 ± 0.8 | 18.5 ± 1.0 |
| System with Schedule II (Table 4.15) | 23.5 ± 0.95 | 19.8 + 0.85 | 17.3 ± 0.9 |

### 4.8 Effect of Waiting Cost Rate on Schedules

The underlying Arena models for the two OptQuest models were modified to incorporate the increased cost rates as shown in Table 4.1 and reduced cost rates as shown in Table 4.2. Thus four new OptQuest models, that included the two designed schedules for each case, were run in order to gain an insight into the effect of the change in waiting cost rates.

The results obtained from these OptQuest models for the number of doctors and residents that should work in the designed schedules are the same as shown in Tables 4.14 and 4.15. Hence, the designed schedules are valid for increased cost rates as well as decreased cost rates. This can be attributed to the fact that the waiting cost in the reduced cost rates case is still a lot higher as compared to the staff costs.

The costs obtained from the above designed models are shown in Table 4.18.

**Table 4.18: Costs for Designed Schedules with different Cost Rates**

| | System with Schedule I | | System with Schedule II | |
|---|---|---|---|---|
| **Cost Type** | **50% Increase In Actual Cost Rates** | **50% Reduction In Actual Cost Rates** | **50% Increase In Actual Cost Rates** | **50% Reduction In Actual Cost Rates** |
| **Wait Cost** | 227478.48 | 92394.50463 | 268614.7887 | 89492.13719 |
| **Staff Cost** | 505958.4 | 494208 | 490003.2 | 490003.2 |
| **Total Cost** | 733436.8886 | 586602.5046 | 758617.9887 | 579495.3372 |

Figure 4.11 shows a comparative graph for the total waiting costs for the actual system and the two designed schedules, for the different values of cost rates.

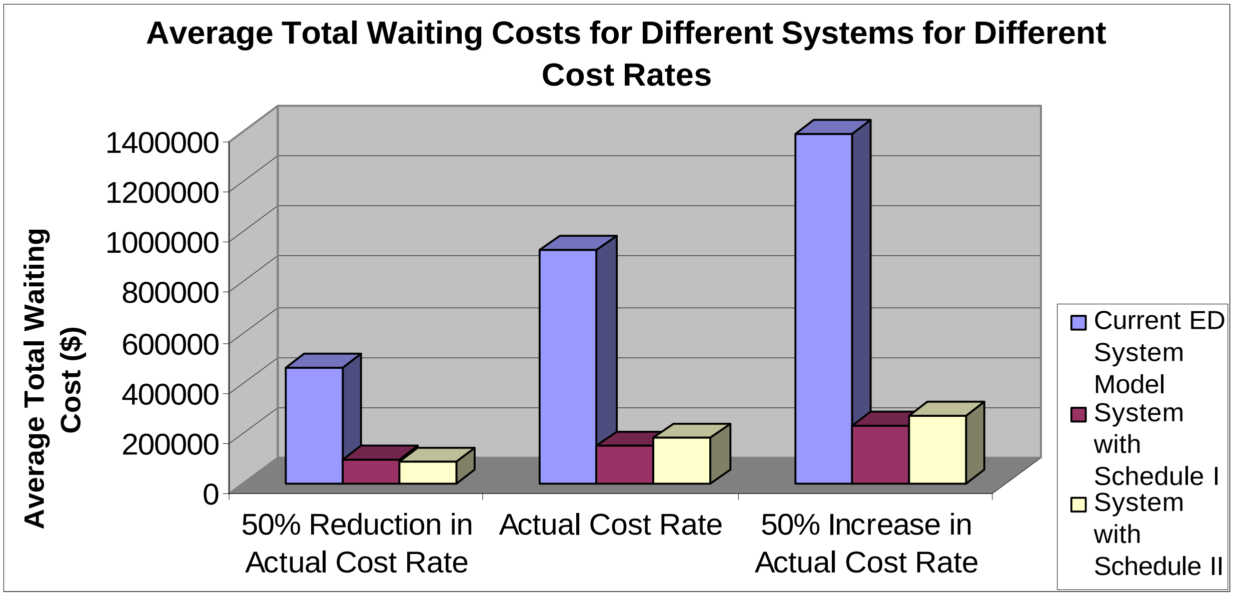


**Figure 4.11: Total Waiting Costs for Different Systems for Different Cost Rates**

# Chapter 5

# Conclusions

## 5.1 Summary

The goal of this research is to minimize costs for the ED at York Hospital by designing schedules for doctors and residents with variable staffing patterns depending on the number of patient contacts with the doctors and residents. The construction of a simulation model of the ED helps in understanding the basic functionality in the ED. It also helps to compare the results from the OptQuest model of the research to the actual performance measures.

The two new staffing patterns for doctors and residents, as shown in Tables 4.14 and 4.15, show that patient waiting costs are reduced by almost 80%. The factors contributing to this reduction in costs are also explained in Section 4.7.1. Thus the goal of cost reduction to the ED was achieved.

The second goal of this research was patient satisfaction in terms of the time to see a physician or a resident for the first time. Figure 5.1 shows the time required to see a physician for the first time in the three departments AC, CC and IC for the three models.

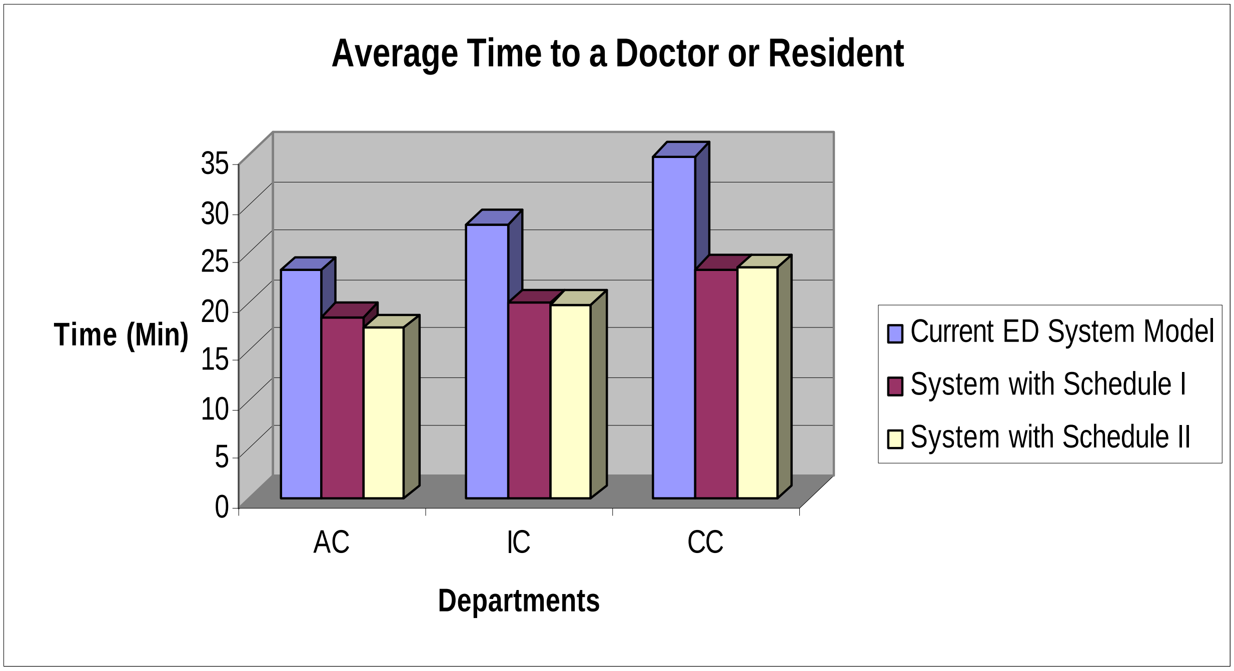


**Figure 5.1: Time to see a Doctor or Resident for the First Time**

The time to first see a physician or resident in the critical care unit is reduced by almost 33% and that for an intermediate care patient is reduced by almost 29%. The schedules designed for doctors and residents are dependent on the number of patient contacts. This research utilizes the fact that the opportunity cost to the ED is in fact the patient cost. Thus, in order to improve service while keeping costs to a minimum, the tradeoff is achieved

The simulation model for the ED in this research does not consider the trauma patients in the ED. Hence it is desirable to have some extra capacity of the doctors and residents scheduled for the designed shifts. Hence the schedule I designed in this research is a recommended staffing solution for reducing the costs to the ED.

### 5.2 Future Work

This research can be further enhanced to include costs for other resources, like nurses and technicians. The total cost of an ED can also include the cost due to allocation of resources like beds and equipment. Scheduling other resources depending on the number of patient contacts is also an approach that could lead to newer horizons in the costing scenario.

This research deals only with the costing aspect of an ED with respect to doctors, residents and patient waiting costs. Another way of approaching this problem would be to look at the ED as a profit center and try to maximize the profits to the ED. This can take into account the revenue obtained by the ED from each patient for each unique process.

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**APPENDIX A**

**Schedules for ED Staff**

## I. Doctor Schedules

| Resource | Sunday | Monday | Tuesday | Wednesday | Thursday | Friday | Saturday |
|---|---|---|---|---|---|---|---|
| **Doctor1** | 12 am – 4pm | 7am – 4pm | 7am – 1pm | 11pm-12am | 12am – 7am | 12am – 7am | 12am – 7am; 11pm – 12 am |
| **Doctor2** | 9am – 5pm | 9am – 5pm | 7am – 4pm | 7am – 4pm | 7am – 4pm | 7am – 4pm | 7am – 4pm |
| **Doctor3** | 1pm – 10 pm | 1pm – 10 pm | 9am – 5pm | 9am – 5pm | 9am – 5pm | 9am – 5pm | 9am – 5pm |
| **Doctor4** | 4pm – 12 am | 12am – 1am; 4pm – 12 am | 12am – 1am; 1pm – 10 pm | 1pm – 10 pm | 1pm – 10 pm | 1pm – 10 pm | 1pm – 10 pm |
| **Doctor5** | 12am – 1am; 5pm – 12 am | 12am – 1am; 5pm – 12am | 12am – 2 am; 4pm – 12 am | 12am – 2 am; 4pm – 12am | 12am – 1am; 4pm – 12am | 12am – 1am; 4pm – 12am | 12am – 1am; 4pm – 12am |
| **Doctor6** | 12am – 2am; 11pm - 12am | 12am – 2am; 11pm - 12am | 12am – 7am; 5pm – 12am | 12am – 7am; 5pm – 12am | 12am – 2am; 5pm – 12am | 12am – 2am; 5pm – 12am | 12am – 2am; 5pm – 12am |

## II. ULR Schedules

| Resource | Sunday | Monday | Tuesday | Wednesday | Thursday | Friday | Saturday |
|---|---|---|---|---|---|---|---|
| **ULR1** | 7am – 5pm | 7am – 5pm | - | 7am – 5pm | 7am – 5pm | 7am – 5pm | 7am – 5pm |
| **ULR2** | 8am – 6pm | 8am – 6pm | 12am – 7am | 8am – 6pm | 8am – 6pm | 8am – 6pm | 8am – 6pm |
| **ULR3** | 1pm – 11 pm | 1pm – 11 pm | 1pm – 11 pm | 1pm – 11 pm | 1pm – 11 pm | 1pm – 11 pm | 1pm – 11 pm |
| **ULR4** | 12am – 7am; 9pm – 12am | 12am – 7am; 9pm – 12am | 12am – 7am; 9pm – 12am | 12am – 7am; 9pm – 12am | 12am – 7am; 9pm – 12am | 12am – 7am; 9pm – 12am | 12am – 7am; 9pm – 12am |
| **ULR5** | 12am – 2am; 4pm – 12 am | 12am – 2am; 4pm – 12 am | 12am – 2am; 4pm – 12 am | 12am – 2am; 4pm – 12 am | 12am – 2am; 4pm – 12 am | 12am – 2am; 4pm – 12 am | 12am – 2am; 4pm – 12 am |

## III. LLR Schedules

| Resource | Sunday | Monday | Tuesday | Wednesday | Thursday | Friday | Saturday |
|---|---|---|---|---|---|---|---|
| **LLR1** | 12am – 7am; 9pm – 12am | 12am – 7am; 9pm – 12am | 12am – 7am; 9pm – 12am | 12am – 7am; 9pm – 12am | 12am – 7am; 9pm – 12am | 12am – 7am; 9pm – 12am | 12am – 7am; 9pm – 12am |
| **LLR2** | 12am – 1am; 5pm – 12am | 12am – 1am; 5pm – 12am | 12am – 1am; 5pm – 12am | 12am – 1am; 5pm – 12am | 12am – 1am; 5pm – 12am | 12am – 1am; 5pm – 12am | 12am – 1am; 5pm – 12am |
| **LLR3** | 1am – 7 am | 1am – 7 am | 1am – 7 am | 1am – 7 am | 1am – 7 am | 1am – 7 am | 1am–7am |
| **LLR4** | 9am – 5pm | 9am – 5pm | 9am – 5pm | 9am – 5pm | 9am – 5pm | 9am – 5pm | 9am – 5pm |

## IV. Nurse Schedules

| # of CC Nurses | # of IC Nurses | # of Triage Nurses | Sunday | Monday | Tuesday | Wednesday | Thursday | Friday | Saturday |
|---|---|---|---|---|---|---|---|---|---|
| 6 | 5 | 1 | 7am - 3pm | 7am - 3pm | 7am - 3pm | 7am - 3pm | 7am - 3pm | 7am - 3pm | 7am - 3pm |
| 7 | 8 | 2 | 3pm - 11pm | 3pm - 11pm | 3pm - 11pm | 3pm - 11pm | 3pm - 11pm | 3pm - 11pm | 3pm - 11pm |
| 5 | 4 | 1 | 11pm - 7pm | 11pm - 7pm | 11pm - 7pm | 11pm - 7pm | 11pm - 7pm | 11pm - 7pm | 11pm - 7pm |
| 4 | 3 | - | 11am - 3pm | 11am - 3pm | 11am - 3pm | 11am - 3pm | 11am - 3pm | 11am - 3pm | 11am - 3pm |
| 2 | 1 | - | 11pm - 3am | 11pm - 3am | 11pm - 3am | 11pm - 3am | 11pm - 3am | 11pm - 3am | 11pm - 3am |

## V. AC Nurse Schedule

| Resource | Sunday | Monday | Tuesday | Wednesday | Thursday | Friday | Saturday |
|---|---|---|---|---|---|---|---|
| **AC Nurse** | - | 11am – 11pm | 11am – 11pm | 11am – 11pm | 11am – 11pm | 11am – 11pm | - |

# Vita

Amar Sasture was born in Sholapur, India on 3rd July, 1977. He got his bachelors degree in 1999, in the field of Mechanical Engineering from Shivaji University, India. After completing his undergraduate degree, he worked as a Management trainee in Octon Technologies Ltd. Pune, India. He was promoted to the position of a Software Engineer within the first six months. After working here for about a year and a half he joined FirstPolicy.com, which was an insurance B2B portal firm in Pune, India, wherein he was working as a Project Leader and .a senior software engineer.

In the fall of 2001, he opted for a graduate program in the field of Industrial and Systems Engineering at Virginia Tech. His core concentration was Operations Research. He completed his MS in fall 2003 with a thesis option under the able guidance of his advisor, Dr. C.P. Koelling.

Amar is planning to work as an Analyst in the field of systems engineering and development.