A Simulation-Based Approach for Optimal Nurse Scheduling in an Emergency Department

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(ABSTRACT)

The purpose of this research is to determine an appropriate nurse staffing strategy for the Intermediate Care Unit (ICU) and the Critical Care Unit (CCU) of the Emergency Department at York Hospital in York, Pennsylvania. This strategy must adhere to certain administrative policies while keeping patient waiting times within allowable limits. Determining the proper number of resources in an emergency department is a difficult problem because while assistance must be provided without delay at any time, the available resources are restricted by the hospital budget. This research involves simulating the operations of the Emergency Department at York Hospital using the software package Arena 7.0 to evaluate how the system is impacted by various nurse staffing strategies. A microcomputer-based decision support system (DSS) for nurse scheduling that was first developed by Sitompul in 1991 has been implemented using Turbo Pascal 6.0 to generate twenty possible nurse staffing plans. The best alternative staffing plan has been evaluated by the simulation model to determine its effect on waiting times for patients. Specifically, patients are divided into five ESI levels, where ESI-1 patients are the most serious and ESI-5 patients are the least serious, and waiting times are provided for each patient type.

While the DSS approach is useful in generating specific working schedules that are acceptable to the nurses' requirements, it is limited when developing an overall staffing plan. Specifically, the DSS requires a user-defined ratio of nurses working the various shifts, and this ratio must remain constant throughout each month even if patient arrival rates are known to be time dependent. As an alternative approach, OptQuest for Arena was employed to search for an overall nurse staffing plan. After providing Arena with 50 DSS-generated schedules that satisfy the nurses' requirements, OptQuest was used to determine the best schedule for each nurse to follow in order to minimize the average waiting time in the system for patients.

Although the average waiting time obtained by the OptQuest staffing plan decreased from the current staffing plan for all patient types, a paired-t comparison determined using Arena's Output Analyzer indicated no statistical difference (at the 95% confidence level) between the DSS and OptQuest scenarios, in terms of the average waiting time for ESI-1 and ESI-2 patients. Further analysis indicated that a system bottleneck occurred in the triage area of the emergency department during evening hours. After adding one additional triage nurse in the evening shift, the OptQuest-generated staffing plan was re-evaluated. The results indicate that the suggested staffing plan reduced the average waiting time in the current staffing plan by 34.33%, 32.73%, 47.87%, 54.92%, and 52.41% for ESI-1, ESI-2, ESI-3, ESI-4, and ESI-5 patients, respectively. In addition, the average waiting time of ESI-1, ESI-2, ESI-3, ESI-4, and ESI-5 patients for the suggested staffing plan was 19.27%, 19.36%, 39.37%, 48.55%, and 46.64%, respectively, less than for the staffing plan determined when using the DSS approach alone.

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Chapter 1 Introduction

Throughout the past few decades, the public concern over rising health care costs has caused many insurance and medical companies to explore new alternatives for increasing the efficiency with which they deal with patients. One important area of health care that can be improved upon is the emergency department of a hospital. This research studies the operation of the emergency department at York Hospital in York, Pennsylvania, in order to search for nurse schedules that can increase the efficiency of its entire system, and thereby improve patient satisfaction.

1.1 Emergency Departments

The changing terminology for emergency departments demonstrates the changes that have taken place within them over the past century. Originally, these departments were termed “receiving wards” because they were set up as the channel that patients had to pass through before being admitted to the hospital. Prior to World War II, these departments were frequently housed in a single room, even in large hospitals. They were also called “accident rooms” or “accident dispensaries” since they were geared toward trauma care for those who survived long enough to reach the hospital. More recently, they have been named “emergency rooms,” “emergency departments,” and sometimes even “emergency units” (Cameron, 1980). These departments consist of several rooms, contain great quantities of modern equipment, and are staffed by skilled, fully–trained physicians, nurses, and technicians. They provide services not only for those with conditions needing urgent medical attention, but also for those who feel that they must have immediate attention to their problems, whether medical or not. A statement issued by the Committee on Trauma and approved by the Board of Regents of the American College of Surgeons states that

> *“The function of an emergency department is to give adequate appraisal and initial treatment or advice to any person who considers himself acutely ill or injured and presents himself at the emergency department door.”*
> (Spencer, 1972)

Unlike other hospital units, emergency departments are like hospitals within hospitals, since they are called upon to treat a large number of patients who present a great variety of medical problems. Moreover, these patients typically require immediate action, or at least rapid response, by the medical staff. Therefore, the atmosphere of an emergency department is often busier and more crowded than other hospital units. The emergency department waiting room adds to the confusion, since it is often noisy due to the crowd of ill adults and children. The emergency department staff, which includes a variety of professional workers (such as medical specialists, technicians, and administrative personnel) can be organized in one of several ways. The physician staffing pattern varies from having individual physicians (in some cases only on a part-time basis), through rotating staff arrangements, to non-hospital-based group practices. Frequently, a hospital has little or no direct control over the physicians in its emergency unit (Spencer, 1972). The nursing staff, on the other hand, is typically provided by the parent hospital and is under direct control of the hospital's nursing department. All of these aspects make the emergency department a challenging unit to operate efficiently (Soskis, 1985).

In the last two decades, visits to emergency departments in the United States have increased dramatically. This increase has been so spectacular that it has led to a new medical specialty known as emergency medicine. There are four main reasons for the increase in emergency department visits (Cameron, 1980). First, more people with severe trauma and serious illnesses survive until they reach the emergency department and have a better chance of staying alive once they get there. Second, in spite of advances in the care of the seriously ill and injured, most people coming into emergency departments suffer from problems and conditions that are important to them, but not urgent in medical terms. Third, a small but substantial number of people coming to emergency departments use it as their regular source of primary care, even when efforts are made to provide alternatives. Fourth, a sizable portion of people come to the emergency department because the emergency department is always open, because they can usually get there by police, fire rescue, or similar transports, and because they know that they will be seen.

Clearly, the emergency department staff is under a great deal of stress due to the immediate attention required by most patients. The large increase in visits to the emergency department has only served to increase that stress. At the same time, it has caused patients to become more frustrated as their waiting times have increased. As a result, most hospitals have been begun to explore ways to treat patients more quickly without incurring large costs. In particular, effective resource scheduling is one such area that has received a great deal of research attention.

1.2 Research Objectives

This research studies the operation of the Emergency Department at York Hospital, a medium–sized teaching hospital whose emergency department provides emergency service to both trauma and non–trauma patients in the York, Pennsylvania area. However, this study concentrates on only non-trauma patients. During peak hours, patients arrive at the average rate of ten per hour on weekdays and eleven per hour on weekends. The Emergency Department is staffed 24 hours each day by nurses, technicians, upper-level and lower-level residents, physician extenders, and doctors.

The goal of this research is to determine operational improvements that will decrease the average amount of time patients spend in the emergency department while maintaining current staffing levels. Specifically, the objective is to create an overall nurse staffing plan that will improve the performance of the emergency department. In particular, we will focus on nurse scheduling in order to reduce patient waiting times and therefore their total time in the system. Large waiting times not only increase the number of complaints voiced by patients, but also increase the cost of operation, since the overall cost is determined entirely by hourly throughput (i.e., the number of patients seen by department in an hour). As a result, smaller waiting times can lead to improved patient satisfaction and potentially increased revenues. The alternative nursing schedules are evaluated through an Arena simulation model, and the resulting patient waiting times are compared. It is hoped that the suggested nurse schedules will lead to improved service and a noticeably better atmosphere in the York Hospital Emergency Department.

1.3 Thesis Organization

The remainder of this thesis is organized as follows. Chapter 2 provides an overview of simulation and its use in the health care industry. An overview of the

Arena software package and OptQuest, an optimization tool used within Arena, are also demonstrated. Following that, a survey of the relevant literature in the application of simulation to hospital emergency departments is presented. Chapter 2 concludes with an introduction to nurse scheduling approaches and the development of a Decision Support System (DSS) model for nurse scheduling. Chapter 3 details the development of an Arena simulation model for the emergency department model at York Hospital. A general overview of the emergency department operation, the use of input data, a description of the Arena model components, and the results of current system model are presented. Chapter 4 describes the procedures, including a microcomputer-based DSS and OptQuest for Arena, that have been used to search for the solutions that meet the given research objectives. Chapter 4 also presents the results provided by the DSS-generated schedules and OptQuest, including the suggested nurse schedules for York Hospital. Finally, Chapter 5 summarizes the conclusions of this research.

Chapter 2 Literature Review

This chapter contains a review of the literature that is relevant to the current research problem, including general information on simulation, as well as specific information on software and relevant applications. It also presents an overview of solution approaches for the nurse scheduling problem.

2.1 Simulation

In recent years, economic pressures have led individual organizations and industries to improve their products or services in order to remain competitive with rival companies. Many strategies and tools have been employed to increase efficiency, but the complexity of these systems makes simulation a particularly useful tool. Simulation is one of many methodologies for studying dynamic systems, where a system is defined as a group of units that operate in some interrelated manner. In particular, simulation can be used to obtain an understanding of overall operation by designing a model that describes system behavior over time. Throughout the remainder of this document, the term simulation will refer to *computer simulation*, which is a specific type of mathematical simulation. While simulation does not necessarily require a computer, the widespread availability of computers has been the main reason that simulation modeling has become so popular. Kelton et al. (2002) state that

> *"Computer simulation refers to methods for studying a wide variety of models of real world systems by numerical evaluation using software designed to imitate the system's operations or characteristics, often over time."*

In general, simulation refers to a wide variety of activities, including the development of mathematical relationships that describe the system, the formulation of a suitable computer model that encorporates these relationships, and the execution of the computer model to evaluate system performance under a variety of settings.

Simulation can be used to study almost any type of problem. In general, it is suitable for models that cannot be adequately analyzed by exact mathematical techniques. In practice, simulation is most commonly used to analyze the behavior of complex queuing systems. While exact analysis techniques are available for some small queuing applications, often the complex systems that arise in manufacturing and service applications cannot be analyzed through exact methods. In addition, simulation can be used to quickly evaluate how the system responds to changes. Due to its widespread application areas, as well as the ability to analyze a system without physically building or modifying it, simulation is now a powerful tool for analyzing many types of systems. When models are developed effectively and results are analyzed correctly, simulation can help users draw accurate conclusions about how a system behaves. Many organizations have employed simulation to study a particular objective, including power planning, financial processes, economic systems, planning and operation of manufacturing plants, flood control, and others. Specifically, simulation is the quantitative tool that is utilized in business more than most other methods including queuing theory, dynamic programming, and linear programming (Payne, 1982).

In order to determine whether or not the simulation model accurately represents the real system, the model must be validated and verified. Validation is the process of determining how well the model represents the real system for the particular objectives of the study (Fishman and Kiviat, 1968). While validation refers to the modeling aspect, verification concerns the computer code. Law and Kelton (2000) define verification as the process of determining whether the conceptual simulation model has been correctly translated into a computer program. In other words, verification is concerned with debugging the computer program. A conceptual picture of the relationship between validation and verification can be found in *Simulation Modeling and Analysis* , 3 rd ed. by Law, A.M., and Kelton, W.D.(2000)

2.2 Arena Software Package

This section highlights the features and functions of a SIMAN/Cinema-based modeling/animation system, named Arena, that was developed by Systems Modeling Corporation and is currently distributed by Rockwell Software (Hammann and Markovitch, 1995). Arena represents a major advance in simulation technology, providing the capability to model quickly and easily without being limited to only specific problem domains. Arena is a popular piece of simulation software that merges the capability found in high-level simulation packages with the flexibility of simulation languages across a wide range of problem domains. Arena is an extension of the SIMAN and Cinema packages (Drevna and Kasales, 1994). The SIMAN language (Pegden, 1982) is a general-purpose SIMulation ANalysis program used to model complex systems. Cinema (Systems Modeling, 1994) is a flexible animation module which accompanies SIMAN and is used to design and run realistic graphical depictions of a SIMAN model. Arena is the latest addition to the SIMAN/Cinema family (Profozich and Sturrock, 1995). It supports all the basic procedures in a simulation study, including data analysis, model building, interactive execution, tracing, verification, and output analysis (Drevna and Kasales, 1994). In addition, Arena includes a graphical modeling animation system in the same work environment. This dynamic animation is based on concepts from object-oriented programming and hierarchical modeling (Kelton et al., 2002). Arena also includes an Input Analyzer as a tool for fitting an appropriate statistical distribution to input data. Similarly, the Output Analyzer can be used to perform statistical tests on the output data obtained from various simulation runs.

A practical software system called OptQuest, which comes with the Arena package, is a recent innovation from OptTek Systems Inc. (Kelton et al., 2002). This system helps decision makers to efficiently determine optimal parameters within a variety of software packages, including Arena and the Excel-based Crystal Ball software package. OptQuest integrates metaheuristics, classical optimization, and artificial intelligence and has the capability to guide the series of simulations in order to determine optimal or near optimal solution scenarios (Glover et al., 1999). Law and Kelton (2000) describe OptQuest for Arena as follows:

> *“OptQuest for Arena is an application that decides how to change model inputs that you choose and then runs a sequence of simulations to search for a combination of these inputs that optimizes (maximizes or minimizes) output performance measures that you designate.”*

OptQuest uses sampling techniques and advanced error control to quickly identify improved solutions. It combines the metaheuristics of scatter search, tabu search, and neural networks into a single, composite search algorithm to provide maximum efficiency in identifying new scenarios (Bapat and Swets, 2000). OptQuest allows the user to specify controls (input parameters) for a model, which include the resource levels and all variables in the model, and to set a lower bound, upper bound, and a suggested initial value for each control. Controls can also be restricted to integer values. The user can specify constraints to limit combinations of input controls and variables using linear equations and inequalities. These constraints can represent budget limits, space restrictions, and workforce allocations, for example. In addition, users can include logical conditions to better refine the search process (Bapat and Swets, 2000). Similarly, the user can specify an objective and requirements. The quantity to be optimized is known as the objective, and is given in the form of a linear function of controls. A requirement is nearly the same as a constraint, except that a requirement operates on outputs from the simulation to identify the feasible solutions, while constraints operate on inputs. The user also specifies computational limits and procedures for performing the search.

OptQuest guides the search process by selecting system inputs and then running the model through a user-specified number of replications for each set of inputs in order to determine the system outputs. When OptQuest determines the results for a particular set of input conditions, it uses this output as a self-learning aid to search for the next set of input alternatives. If an alternative does not satisfy all the constraints, the system automatically eliminates such an alternative and continues searching for the next alternative that satisfies the user's needs (Bapat and Swets, 2000). While the search is in progress, the results of the search process are displayed visually in the form of a results table and graph. Once the process is completed, OptQuest displays the "optimal" configuration, along with its associated objective value. Due to the nature of simulation optimization, OptQuest cannot guarantee with certainty that it is finding the exact optimum in every case (Law and Kelton, 2000). However, the suggested solutions are often of high quality. For more information on how to use OptQuest in modeling, see Law and Kelton (2000).

2.3 Simulation in Hospital Emergency Departments

This section contains a review of simulation research that pertains to hospital emergency departments. We begin with conceptual models and then summarize some recent research efforts focusing on the simulation of emergency departments.

2.3.1 Conceptual Models of Emergency Departments

Increased pressure to control costs, as well as increased competition, has prompted health care managers to seek tools to effectively operate their institutions. The emergency department is a significant part of a hospital, since working conditions require that urgent services be provided without delay, even in peak conditions. Therefore, it is essential that close attention be paid to decisions regarding the number of resources at the disposal of the department at any given time. The resources include both physical resources (such as beds, laboratories, instruments, special equipment, etc.) and human resources (such as medical doctors, nurses, technicians, residents, medical students, etc.). The problem of providing the proper number of resources in an emergency department is a difficult one because while assistance must be provided without delay at any time, the available resources are restricted by the hospital budget. Moreover, the system behavior of an emergency department has several unique characteristics that can cause difficulties when constructing a model, as detailed below (Bressan et al., 1989):

1) Patient arrivals are characteristically random and the probability distribution of inter-arrival times is often ruled by time-dependent parameters. For instance, the arrival pattern of patients during the day may be different from that at night.
2) The number of required resources, either physical or human, might vary according to time-dependent parameters. For instance, the number of working staff differs between the morning, the afternoon, and the night.

3) Patients have conditions of varying severity, and the severity of the patients determine the priority with which they are dealt. For instance, the service of a low-priority patient may need to be interrupted if a patient with a higher priority arrives.
4) To evaluate the system behavior, it is essential to receive not only the average, but also the maximum waiting time, for every queue. This is important because in addition to customer satisfaction, the patient's condition may actually be affected by an unusually long waiting time.

In modeling an emergency department, the basic elements that need to be taken into account are assistance or service requests, employed resources, and patients (Bressan et al., 1989). First, every *request* is described by all the resources that are required to execute a particular service and treatment. Generally, requests are grouped into similar classes. It is implied that all requests requiring the same service are grouped in the same class. For example, the requests of an extremely urgent class may require two medical doctors for a time randomly distributed according to an exponential distribution with a mean of 45 minutes. Second, every *resource* is characterized by the period of time during which it is employed, as well as its ability to serve particular types of requests. All resources in an emergency department are either human (such as doctors, nurses, medical students, etc.) or physical (such as beds, equipment, etc.). Third, *patients* are the source of requests. Generally, a patient arrives in the system, which includes the departments and services, and presents a sequence of service requests. For example, a patient with a broken leg first needs a specialized visit (resource: an orthopedist), then a series of radiographs (resources: a radiological set and a technician) and a second visit (resource: an orthopedist), and finally a plastering (resources: an orthopedist and a nurse) (Bressan et al., 1989). During the time in system, a patient must obey certain rules for seizing and releasing resources. For instance, a resource, such as a nurse, is seized when a patient arrives in the system and is released only at the end of the service. The resources deal with each type of request according to a given priority list.

A block diagram of an emergency department model can be found from the title of "A Generalized Model to Simulate Urgent Hospital Departments" in *System*

Modelling and Simulation by Bressan, C., Facchin, P., and Jacur, G.R. (1989). This framework consists of two interdependent sections: patient flow and resource flow. A set of patient generators describe patient arrivals to the facility by ambulance, car, and other means of transport. Usually, the highest priority is assigned to patients arriving in an ambulance or rescue vehicle and critical patients arriving by car. In addition, patient arrivals can follow either a deterministic or a stochastic arrival pattern. Generally, patients arrive according to a time-dependent Poisson process (Jacur and Facchin, 1984). Once in the system, every patient presents a sequence of service requests based upon his/her particular condition. The request sequence and the patient's priority are determined by a triage nurse who makes this assessment based on their patient's vital signs and symptoms. When a patient moves up to first place in the queue, the resources (such as beds, nurses, doctor, etc.) needed by the request are seized. The service times for each type of request may be given either as deterministic values or as random variables. At the end of each service, the patient releases the resources and either leaves the system or rejoins the queue based upon the priority of his/her next request. In addition, a patient's treatment may be interrupted, in which case he/she needs to re-enter the queue. A patient leaves the emergency department either by being admitted to the hospital or discharged from the facility.

2.3.2 Some Recent Simulation Studies of Emergency Departments

Since simulation is a powerful tool for analyzing and improving operations, emergency department managers frequently use computer simulation to assist them in their decision-making processes. Many simulation models have been used to support operational decision-making in a variety of hospital departments. Simulation has been employed to address problems in areas such as new policy evaluation, staffing levels and scheduling, scheduling of patient admissions, facility design and development, and disease and epidemic control. The most common objectives of these studies have included the reduction of a patient's time in the system, improvement of customer service, better resource utilization, and reduction of operating costs (Alvarez and Centeno,1999).The following are some example applications of the use of simulation modeling in emergency departments.

At the Sunhealth Alliance Hospital in Charlotte, North Carolina, a simulation model was used to test several operating alternatives with the purpose of reducing the length of stay for patients who visited an emergency department (Mcquire, 1994). Since the average patient waiting time in the current system was 157 minutes, which was greater than the acceptable level of 120 minutes, the emergency department considered several possible ways to reduce patient waiting time. The emergency department managers decided to use simulation to test these alternatives, and the MedModel software package was chosen for the study. Five alternatives were tested and evaluated for effectiveness with the simulation model. The results of each alternative showed that the system can reduce the length of stay for all patients as follows:

Improvement 1: *Adding an additional registration clerk during peak hours (3:00 p.m. to 11:00 p.m.).* This configuration can reduce the length of stay by twelve minutes per patient.

Improvement 2: *Extending the hours of operation of the fast track area and pediatric clinic.* Originally, the fast-track hours were 5:00PM-10:30PM during the week and 3:00PM-11:00PM on the weekend. The pediatric clinic's hours were 6:00PM-10:00PM seven days a week. When the operating hours were extended to 11:00AM-11:00PM on the weekends for both areas, and for the pediatric clinic during the week, the simulation yielded an improvement of sixteen minutes per patient.

Improvement 3: *Reducing turnaround times in the ancillary department.* The turnaround time represents the time from placing the order until the results are ready. By reducing the turnaround time to 45 minutes, the average length of stay could be reduced by 24 minutes.

Improvement 4: *Dividing the holding rooms with curtains to increase the number of spaces for admitted patients.* The simulation showed that the emergency department saved patients an average of 22 minutes if the four rooms were divided by a curtain to accommodate eight patients.

Improvement 5: *Using emergency department physicians instead of residents in the fast track area.* Using the new operating time detailed in Improvement 2, the simulation showed that the length of stay for all patients was reduced by an average of fourteen minutes, without a reduction in treatment and service quality. In addition, the average length of stay for patients in the regular emergency department was reduced by 50 minutes (from 157 to 107 minutes).

In St. Luke Episcopal Health System in Houston, Texas, the ProModel simulation software was employed to model and analyze its entire emergency department system. Since the current facility and operational design resulted in long patient waiting times, the research objective assessed the impact of this design on patient care in order to reduce the average length of stay. The results showed that the length of stay was reduced by 40 percent by implementing a new system for triage that was called the Triage Plus System (Lange, 1997). Similarly, the ProModel software was used in Baystate Hospital in Springfield, Massachusetts, to model the impact of an emergency department expansion project. The simulation model helped managers see which changes could be made within the existing facility, without the expansion. The hospital used simulation to test several alternatives with the objectives to increase patient throughput and reduce waiting time. The model showed that reallocating beds and reducing backlogs, which kept the emergency department beds full and led to long waiting times, resulted in an increase in patient throughput of five to nine percent without requiring additional staff, while significantly reducing the average waiting time per patient. These changes in the existing emergency department allowed the hospital to avoid a major expansion project, saving the hospital an approximately $1.2 million investment. (www.medmodel.com, 2003).

At the Washington Adventist Hospital, in Takoma Park, Maryland, a simulation model was used to evaluate an expansion in the number of beds in the emergency department, which led to a reduction of 36 minutes in the average length of a patient's stay (Alvarez and Centeno, 1999). Kirtland et al. (1995) used a simulation in the Peninsula Regional Medical Center (PRMC) in Salisbury, Maryland, to reduce the patient's time in the system and determine appropriate staffing levels. The background information was entered into the MedModel simulation software to develop a model of the PRMC's emergency department. The simulation was run for a minimum of twenty replications to validate the model using historical data. The project examined a total of eleven different alternatives. The top three alternatives included establishing a fast track care in the minor care area, placing patients in the treatment area when beds are available instead of sending them back to waiting room, and using point-of-care lab testing. Implementation of these alternatives resulted in a reduction of patients' time in the system by 38 minutes, or 24 percent, on the average.

At Mercy Hospital in Miami, Florida, Kittell and Pallin (1992) described the use of a simulation model in order to evaluate several alternatives with the objective of maximizing the number of patients treated in the emergency department, while making more efficient use of the resources and maintaining quality service. The study revealed that a fast track policy allowed a 50 percent reduction in resources without negatively affecting the quality of service provided to its customers. In 1995, this hospital used simulation to study reducing time in an emergency department via a fast track lane. The fast tack lane was designed to serve non-urgent patients with ailments such as headaches, abrasions, wound checks, etc. The simulation model was developed using SIMAN language and evaluated several alternatives. The results suggested that a fast track area should be opened, and recommendations were also provided for staffing. After implementing the fast track lane, the patients with low priority served by the emergency department experienced a 25 percent reduction in their length of stay without negatively affecting the times of patients with higher priority. It was recommended that non-urgent patients be sent to the fast track area, but they could be treated by the regular emergency department if resources in the fast track were busy and the emergency department had available resources (Centeno et al., 1995).

The preceding examples illustrate that simulation has been successfully used to improve the operations in several emergency departments. Significant reductions in patient waiting times have been achieved, which in turn lead to better patient satisfaction. The goal of this research is to provide York Hospital with similar results through effective scheduling of the nursing staff.

2.4 Nurse Scheduling

Efficient allocation of nurse staff resources is an important issue facing nursing department administrators today. Imbalances between nurses' available hours and patient care demands have been a concern since at least the 1940's (Giovanetti, 1978). The scheduling of nursing services is relatively complex due to the variety of conflicting interests or objectives between hospitals and nurses. There are different levels of skill in the nursing pool, and each nurse has different capabilities. In addition, the demand for nursing services varies widely throughout the week and is hard to forecast. The final schedule must also meet certain hospital requirements or policies, such as day off policies, work pattern expectations, etc. (Sitompul, 1990). Therefore, nurse scheduling is a difficult and time consuming task. The schedule must assign each nurse to a series of shifts over a specified period of time, while maintaining certain standards of patient care and satisfying nurse work preferences. Many solution techniques (including heuristics, optimization models, artificial intelligence-based approaches, constraint-based programming, and decision support systems) have been developed for the nurse scheduling problem with the objectives of using minimum staffing to avoid wasted manpower, providing adequate patient care, ensuring continuity in service, and satisfying organizational policies (Sitompul and Randhawa, 1990). These solution approaches can often lead to significant operational savings. For instance, Cosneau (1993) showed that computerized nurse scheduling saved eight hours of labor each month in the Rouen University Hospital, France (Darmoni et al., 1995).

2.4.1 Types of Scheduling Problems

The nurse scheduling problem may be considered a multi-stage problem that includes determining a set of feasible schedules that satisfy the system constraints for a specified time, selecting the best schedule based on the given criteria, fine-tuning the schedule to meet changes in staffing levels and patient demands, and making specific shift assignments for each nurse. The general goal of workforce scheduling in hospitals is to develop a systematic method for assigning nurses to work shifts and work days while maintaining continuous high quality service. Sitompul and Randhawa (1990) have developed a classification scheme for nurse scheduling models based on the type of schedules that are generated (cyclical or non-cyclical) and the solution procedure that is used (optimization or heuristic). In cyclical scheduling, each nurse's work pattern is repeated in a cycle of *n* weeks. With this scheduling type, it is relatively simple to generate a consistent schedule. Additionally, the number of nurses that work a particular pattern from its solution is constantly reused. This means that as long as the staffing requirements remain unchanged, the entire scheduling problem needs to be solved only once. However, the cyclical scheduling approach is rigid in the face of variation in supply and demand. On the contrary, in non-cyclical scheduling, a new schedule is generated to meet a given set of constraints for each scheduling period. Usually, this approach is time-consuming, but it is flexible in dealing with variations in supply and demand.

The optimization approach finds a globally optimal solution that maximizes an objective function subject to a set of constraints. Optimization models require large computational resources because of the large number of objectives and constraints that are used to represent real-time operations. The structure of these models can also lead to inflexibility, which can fail to accommodate the dynamics involved in scheduling (Sitompul and Randhawa, 1990). A heuristic technique, however, provides a good solution without guaranteeing that it is the best. Typically, heuristic models generate an initial schedule to satisfy predicted workload and then refine the initial schedule to meet hospital policy constraints and to fit individual work preferences (Sitompul and Randhawa, 1990). Heuristics are used to avoid the excessive cost encountered in optimization approaches. While most heuristic models have focused on solving the cyclical scheduling problems, optimization models are most often used for non-cyclical problems.

2.4.2 Historical Approaches to Nurse Scheduling

Until the 1960s, nurse scheduling tools consisted mainly of graphical devices (Giglio, 1991). In 1966, Howell presented a cyclical nurse scheduling tool, and Ahuju and Sheppard (1975) proposed an alternative model for the same problem. Several researchers have approached this problem using linear programming problem

(Abernathy, 1973). Mathematical programming approaches have also been developed that modify linear programming concepts to allow preferences of individual nurses to be included in a large mutliple-choice programming problem (Warner, 1976). Although mathematical models are powerful, they often lack flexibility. Arthur and Ravindran (1981) used goal programming to permit more flexible priority choices for determining nurse schedules. To visualize this solution process, Bell et al. (1986) developed a new nurse scheduling tool that coupled computer graphics technology with sophisticated and flexible visual interactive modeling (VIM) software. In 1987, Rosenbloom and Goertzen presented an algorithm for the cyclical nurse scheduling problem that allows a wide variety of possible labor constraints. Their approach can easily be implemented on a computer and guarantees optimal solutions. After first being applied to nurse scheduling by Arthur and Ravindran (1981), goal programming (GP) was reused by Ozkarahan (1989) to allow for a wide variety of schedule preferences. Linear goal programming was used to generate alternative-based schedules, and the schedules were then assigned to individuals according to their preferences. This model was called a flexible nurse scheduling support system. Computer simulation has also been used to determine optimal nurse staffing levels in hospitals. McHugh (1989) used computer simulation to examine the effect of varying nurse staffing levels on wage costs and staffing adequacy. The optimal nurse staffing was proposed as the level of staffing that jointly minimized wage costs, overstaffing, and understaffing. In the current research project for York Hospital, we use a similar strategy to search for suggested nurse schedules.

2.4.3 Recent Nurse Scheduling Approaches

More recently, modern operations research techniques have been applied to the nurse scheduling problem. For example, Aickelin and Dowsland (2003) used genetic algorithms for manpower scheduling at major UK hospitals. The results from this approach showed that this algorithm was fast, flexible, and able to find high quality solutions. Artificial Intelligence (AI) is another methodology that has been used to solve the nurse scheduling problem. The AI-based computer system uses an abstraction of a human scheduler’s knowledge and information in formulating the schedule and monitoring its execution (Lukman, 1986). Lukman (1986) presented a AI model for the nurse scheduling problem, where a series of decision-making rules are made within the form where *if* a condition is satisfied, *then* action is taken. For example, we can revise the current schedule if it suits our intention. The model includes nurse's schedule requests, continuity of previous schedules, minimum coverage level, and the preferred working pattern of each nurse. All possible schedules were generated based on these considerations. Another approach, constraint-based programming (CBP), was also developed to avoid the complexity in combinatorial optimization. CBP reduces the search space because it defines a set of values to indicate that all constraints are satisfied (Darmoni et al., 1995). The CBP technology has been successfully applied to the nurse scheduling problems in some Japanese facilities (Astier et al., 1993).

Several computerized nurse scheduling systems have been developed. Generally, these systems are computer versions of scheduling heuristics because the heuristic methods are more appropriate and more flexible than are mathematical methods (Darmoni et al., 1995). For example, Darmoni et al. (1995) developed the computer-assisted nurse scheduling program called Horoplan for Rouen University Hospital in France. Horoplan uses heuristics to solve non-cyclical constraint-based scheduling problems, and it builds a complete nurse schedule within the foundation of many constraints that were defined as parameters in order to optimize scheduling flexibility. A core set of constraints are provided to represent general concerns of most French hospitals, and users can easily add or modify constraints to meet their particular needs. One hundred schedules were generated for Rouen University Hospital and these schedules then were evaluated by the six head nurses of the project group.

The use of a decision support system (DSS) in computerized nurse scheduling systems is a management information systems approach that is user-interactive (Nutt, 1984). Mann and Watson (1984) gave the following definition of a DSS:

> *"A decision support system is an interactive system that provides the user with easy access to decision models and data in order to support semi-structures decision-making tasks."*

The DSS has been used in many management decisions such as when to hire part-time help, how to schedule vacation and personal holidays, etc. (Bell et al., 1986). It has also been applied successfully to the nurse scheduling problem.

While most research into nurse scheduling only incorporates isolated elements of the nurse scheduling problem, a DSS can encompass all elements of the problem for more effective analysis (Nutt, 1984). By implementing an algorithm with a DSS, a scheduler can quickly and easily review and modify the schedule that meets the quantitative criteria for optimality, as well as additional managerial concerns as understood by the scheduler (Bell et al., 1986). Sitompul and Randhawa (1990) state that a DSS focuses on supporting decision-making and shifts attention from the operational level toward the issues of managerial problem solving. The key characteristics of a DSS for the nurse scheduling problem concentrate on a less well-structured problem, an integration of analysis techniques with database access and retrieval functions, a simple method of using an interactive model, and flexibility in the face of changes in the environment.

In 1993, Sitompul and Randhawa presented a heuristic-based computerized nurse scheduling system that uses a DSS approach. There were two objectives of this research, including designing a DSS framework for nurse scheduling in hospitals and developing a heuristic procedure for generating nurse schedules using the proposed DSS framework. Figure 2.1 represents the conceptual framework for the DSS model that was re-created based on the original figure, which can be found from a title of “A Heuristic-Based Computerized Nurse Scheduling System” in *Computers and Operations Research* (Vol. 20, No. 8) by Sitompul, D., and Randhawa, S.U. (1993). The model includes five elements, including a pattern generator, schedule generator, schedule processor, system database, and user interface. The pattern generator generates a group of work and shift patterns. The schedule generator combines work and shift patterns to form working schedules, and the schedule processor assigns a schedule to each nurse. These three elements send the information (including shift patterns, working schedules, and nurse assignments) to storage within the system database. The user interface is a front-end program that allows the user to tailor the model to the specific needs of the hospital. The program was successfully used to generate nursing schedules for the Samaritan Hospital in Corvallis, Oregon. In the current research problem at York Hospital, we implement this DSS model and evaluate how the schedules it provides impact patient waiting times.

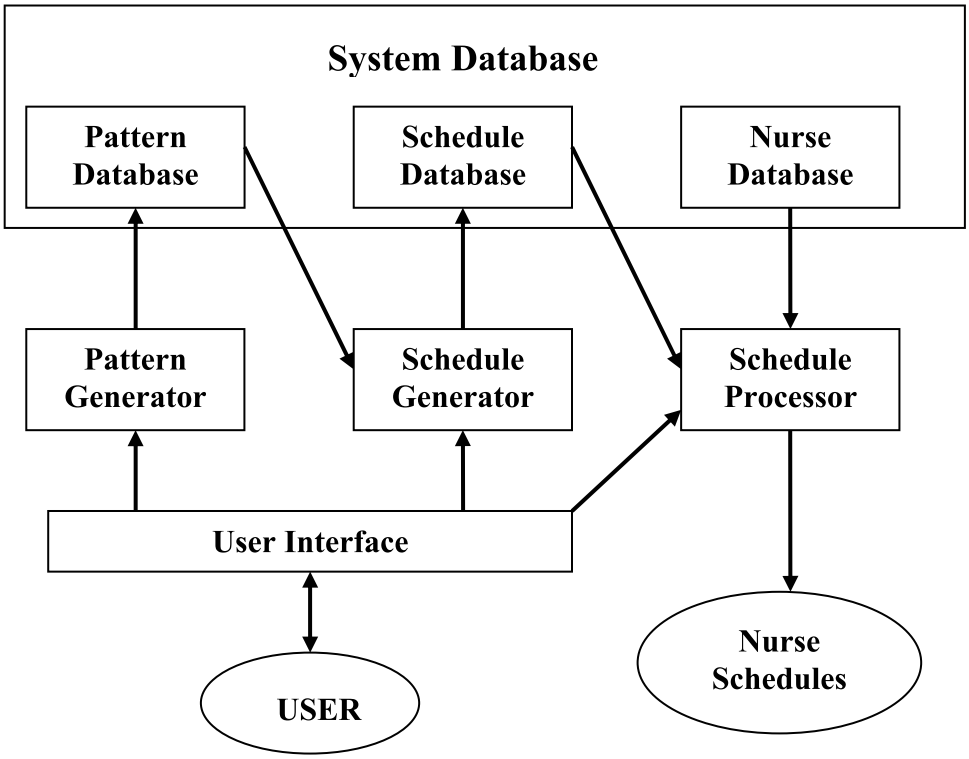


Figure 2.1: The Conceptual Framework for the DSS Model

Chapter 3 Simulation Model Development

This chapter describes the activities in the emergency department at York Hospital in York, Pennsylvania, as well as the development of a simulation model for this system. The first section provides an overview of the operations and the patient flow through the emergency department, including the input data used in the simulation model. We then present a brief description of the simulation model that is used to analyze the scheduling alternatives. The last section describes the methodology used to validate the simulation model.

3.1 Emergency Department at York Hospital

Efficient allocation and utilization of staff resources is an important issue facing all emergency department administrators, including those at York Hospital. In order to evaluate possible changes to operational policies and procedures without disturbing the actual system, a simulation model of the emergency department was commissioned by the hospital. The problem addressed in this study is the development and analysis of a simulation model for the emergency department at York Hospital in York, Pennsylvania. The main interest of this study is to identify process inefficiencies and to evaluate how the system is impacted by various nurse staffing strategies.

The emergency department at York Hospital provides emergency service for both trauma and non–trauma patients 24 hours a day. The emergency department of the hospital, therefore, is a busy area which deals with people who are suffering from a wide range of illnesses. At present, a total of about 60,000 patients are seen in the department each year. The unit is staffed around the clock by doctors, physician extenders, residents, technicians, and nurses with full specialist backup. This study focuses on the non-trauma patient process. There are a total of 35 beds for patient care divided into three individual areas. Specifically, these are the Critical Care Unit (CCU) with fifteen beds, the Intermediate Care Unit (ICU) with sixteen beds, and Alterna Care (AC) with four beds. The CCU treats patients with urgent injuries and illnesses, while the ICU deals with less severe conditions. Both of these units operate seven days a week, 24 hours a day. Alterna Care is a relatively new addition to the emergency department, and it treats only minor injuries and illnesses during the weekday hours of 11:00 AM to 11:00 PM. The purpose of Alterna Care is to remove patients with minor conditions from the ICU in order to decrease treatment time for all patients.

Although it is impossible to precisely classify the flow of all emergency department patients through the system, a general flow process for a typical emergency department patient is presented in Figure 3.1. The following subsections provide a more detailed description of patient flow in the York Hospital Emergency Department. These descriptions include a summary of the input data for the simulation model. Service times for all procedures were provided by a panel of experts familiar with the system, while the arrival rates and the proportion of patients falling into various categories were obtained from data collected from patient records over the past two years.

3.1.1 Arrival Process

Typically, a patient enters the emergency department through one of three modes: walk-in, ambulance, or helicopter. This section gives a brief overview of each activity in the general patient arrival process. When a walk-in patient arrives at the hospital and enters the emergency department, the patient is sent to the waiting room until a triage nurse to become available. The term “ambulance patient” is used to describe any patient who arrives at the emergency department by ambulance, as well as by any rescue vehicle or police car. Ambulance patients can be categorized as trauma or non-trauma. Non-trauma ambulance patients are processed via the same procedure as walk-in patients when they arrive in the emergency department. The only difference is that the non-trauma ambulance patient will skip registration by the triage nurse in the event they are unconscious. Trauma patients who arrive by ambulance are immediately sent to a separate trauma station that is not considered in our analysis. Nearly all patients who arrive by helicopter are classified as trauma patients. Similar to trauma ambulance patients, trauma helicopter patients are immediately sent to the trauma unit upon arrival. Generally, the process of the non-

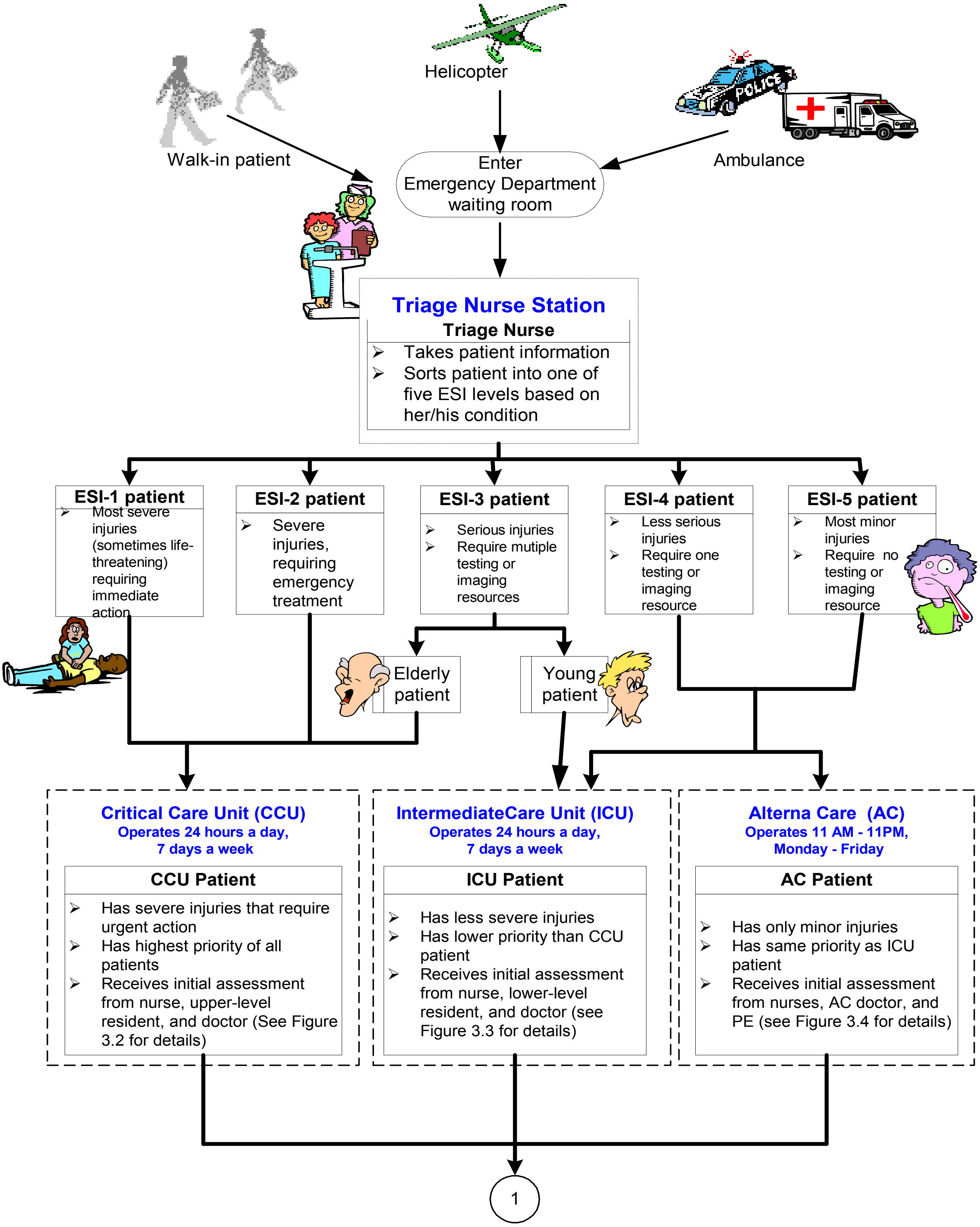


Figure 3.1: Flowchart of Patient Care for the Emergency Department at York Hospital

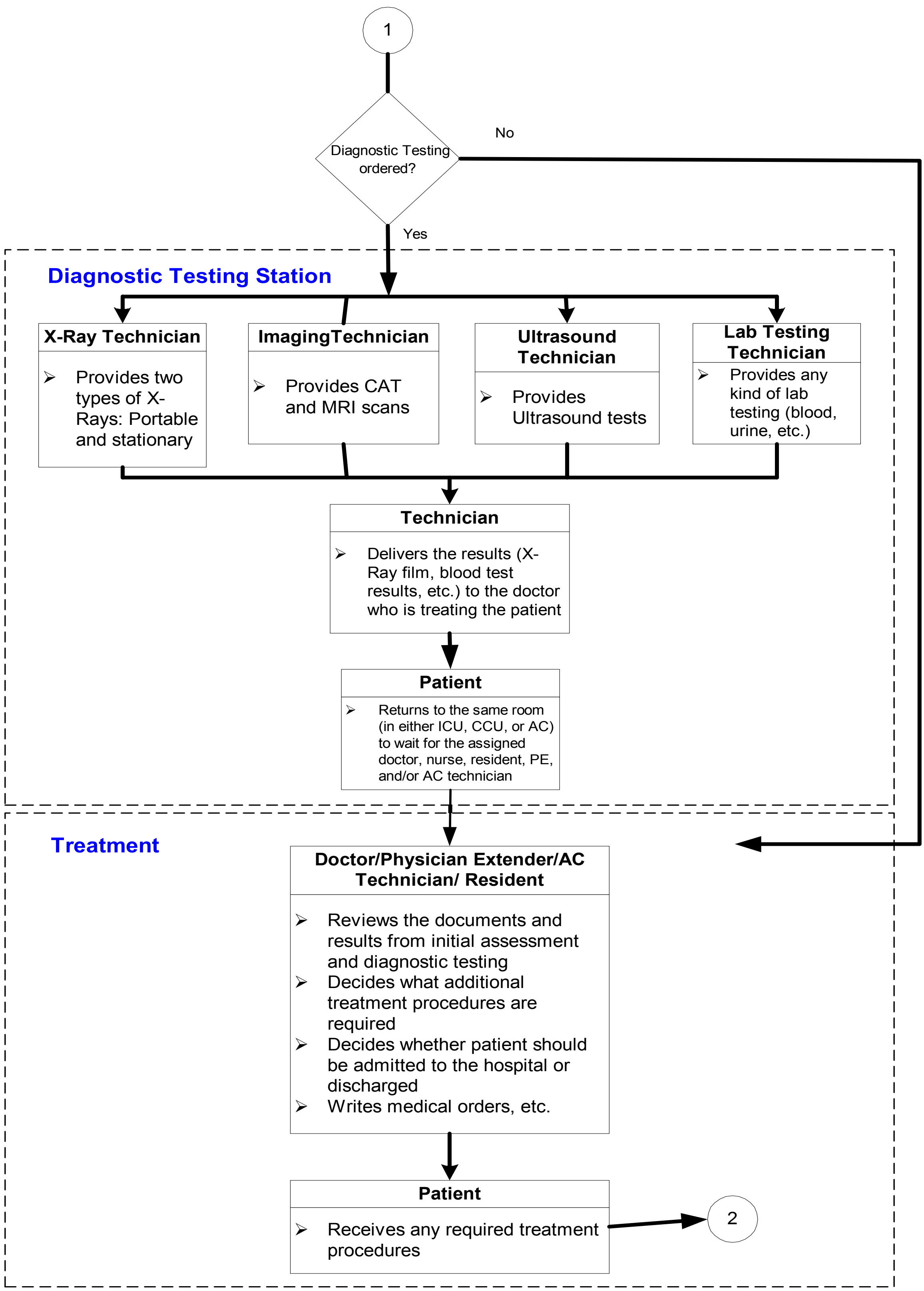


Figure 3.1: Flowchart of Patient Care for the Emergency Department at York Hospital (cont.)

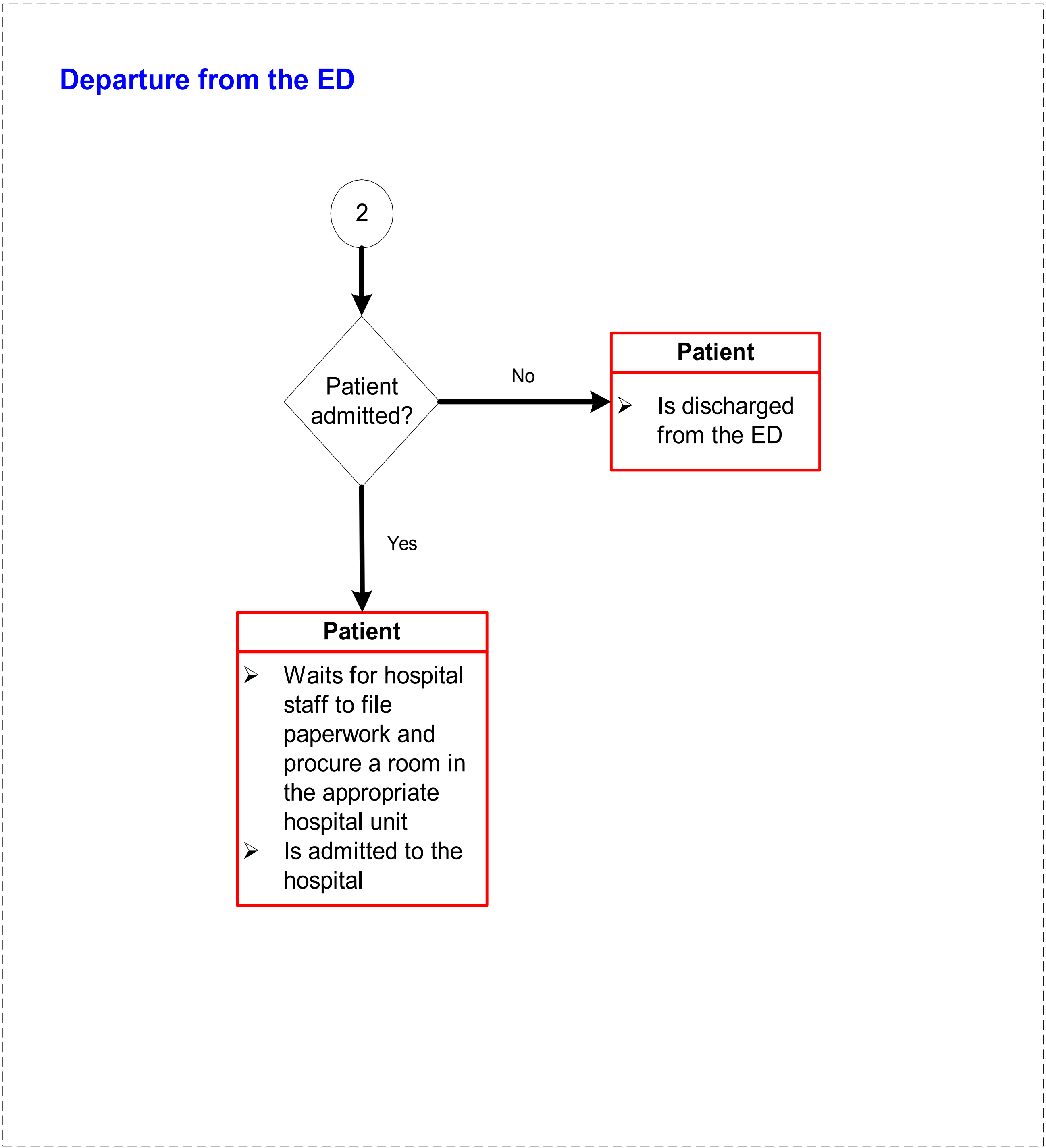


Figure 3.1: Flowchart of Patient Care for the Emergency Department at York Hospital (cont.)

trauma patient who arrives by helicopter is identical to that of the non-trauma ambulance patient.

While York Hospital was unable to provide data on the number of arrivals for these three types of transportation, they were able to provide data for the average number of patients who arrive in each ESI level throughout the day (For more details on ESI levels, see Section 3.1.2). Therefore, our model does not directly consider the mode of transportation to the emergency department. The data on patient arrivals was collected for each day of the week and time of day. The data was grouped into weekday (Monday – Friday) and weekend (Saturday – Sunday) arrivals, and each of these groups was further separated into two time periods: midnight to midday (12:00 AM-12:00 PM) and midday to midnight (12:00PM-12:00 AM). Arrival rates for each ESI level, according to day of the week and time of day, were then estimated from the data. These arrival processes have been modeled as time-dependent Poisson processes, where the mean inter-arrival time (in minutes) is shown in Table 3.1.

Table 3.1: Mean Inter-Arrival Times (in minutes) for Patient Classes throughout the Week

	12:00 AM – 12:00 PM		12:00 PM – 12:00 AM	
ESI Level	**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

3.1.2 Triage Nurse Station

The triage nurse registers the patient by taking personal information and creating a file for this specific visit. To ensure that patients with more life-threatening or painful conditions receive immediate attention, the emergency department uses a new five-level triage system, known as the Emergency Severity Index (ESI) system. It is the job of the triage nurse to determine the ESI level of incoming patients by assessing their conditions. There is a total of three triage nurses throughout the week to handle of all patients who come to the emergency department. One triage nurse is scheduled throughout each of the three shifts daily. Upon a patient's arrival, he or she will be seen and assessed by the triage nurse, who will evaluate the patient's condition on a scale of 1 to 5. The service time for this process is provided below in Table 3.2.

Table 3.2: Service Times for the Triage Nurse

Activity	Service Time Distribution (min)
Initial assessment by triage nurse	Uniform (2,7)

At the ESI-1 level, most patients have suffered a severe injury or are in severe pain that requires immediate action. They may be intubated or unresponsive. An ESI-2 patient is also considered an emergency patient who, for instance, may be confused or lethargic, in severe pain, in respiratory distress, or may have unstable vital signs. Those assessed as ESI level 3, 4 or 5 are of decreasing urgency and generally have stable vital signs. However, the classification of these three levels is based on the expected need for treatment resources as follows (Bohrn, Ferraro and Eitel, 2001):

Level Three: Multiple resources will be needed (x-rays, labs, etc.)

Level Four: A single resource will be needed (x-ray, consultation, etc.)

Level Five: Only require a medical history and physical, and no physical resources

ESI-1 and ESI-2 patients are immediately transported into the Critical Care Unit (CCU) to receive treatment from upper-level residents, doctors, and CCU nurses. By contrast, ESI-4 and ESI-5 patients are sent to Alterna Care (AC), a unit that works with the less urgent patients unit that works with the less urgent patients, whenever it is available. When Alterna Care is unavailable, these patients are sent to the Intermediate Care Unit (ICU). The patients in ESI level 3 are routed to either the ICU or the CCU, depending on their age. Younger patients (less than 65 years old) are moved to the ICU, while the CCU provides treatment for the elderly patients.

3.1.3 Critical Care Unit (CCU)

CCU is a unit that works with the most severe patients, specifically those in ESI levels 1 and 2, and elderly patients in ESI level 3. This unit is staffed 24 hours a day and seven days a week by CCU nurses, upper level residents, and doctors. There are a total of 21 full-time CCU nurses, three part-time CCU nurses, and five upper-level residents, and their specific working schedule that has been provided by York Hospital is shown in Appendix A. The typical CCU patient flow process, shown in Figure 3.2, is initiated by the initial assessment from the CCU nurse. The CCU nurse gathers relevant information from the patient and performs an initial assessment. After the CCU nurse completes the initial assessment, an upper level resident or a doctor continues treatment of the patient and makes decisions as to whether or not the patient requires additional testing, such as x-ray, ultrasound, etc. If diagnostic testing is required, the patient is transported to the appropriate testing area and then returned to his/her original room in CCU. Based upon any test results or the doctor's assessment, the patient then receives any other necessary medical procedures. Finally, the patient is either discharged from the emergency department or must be admitted to the hospital, based on the decision of the doctor or resident. A summary of service times for the CCU activities is shown in Table 3.3.

Table 3.3: Service Times for the Critical Care Unit (CCU)

Activity	Service Time Distribution (min)
Patient evaluation by CCU nurse	Triangular (11,12,13)
Patient evaluation by upper-level resident	Triangular (5,10,15)
Initial treatment of patient by doctor	Triangular (5,10,15)
Follow-up treatment by doctor or upper-level resident and nurse after reviewing diagnostic testing	Uniform (8,20)
Additional time for treatment after releasing doctor and nurse - Admitted patient - Discharged patient	 Triangular (25,35,180) Uniform (5,25)

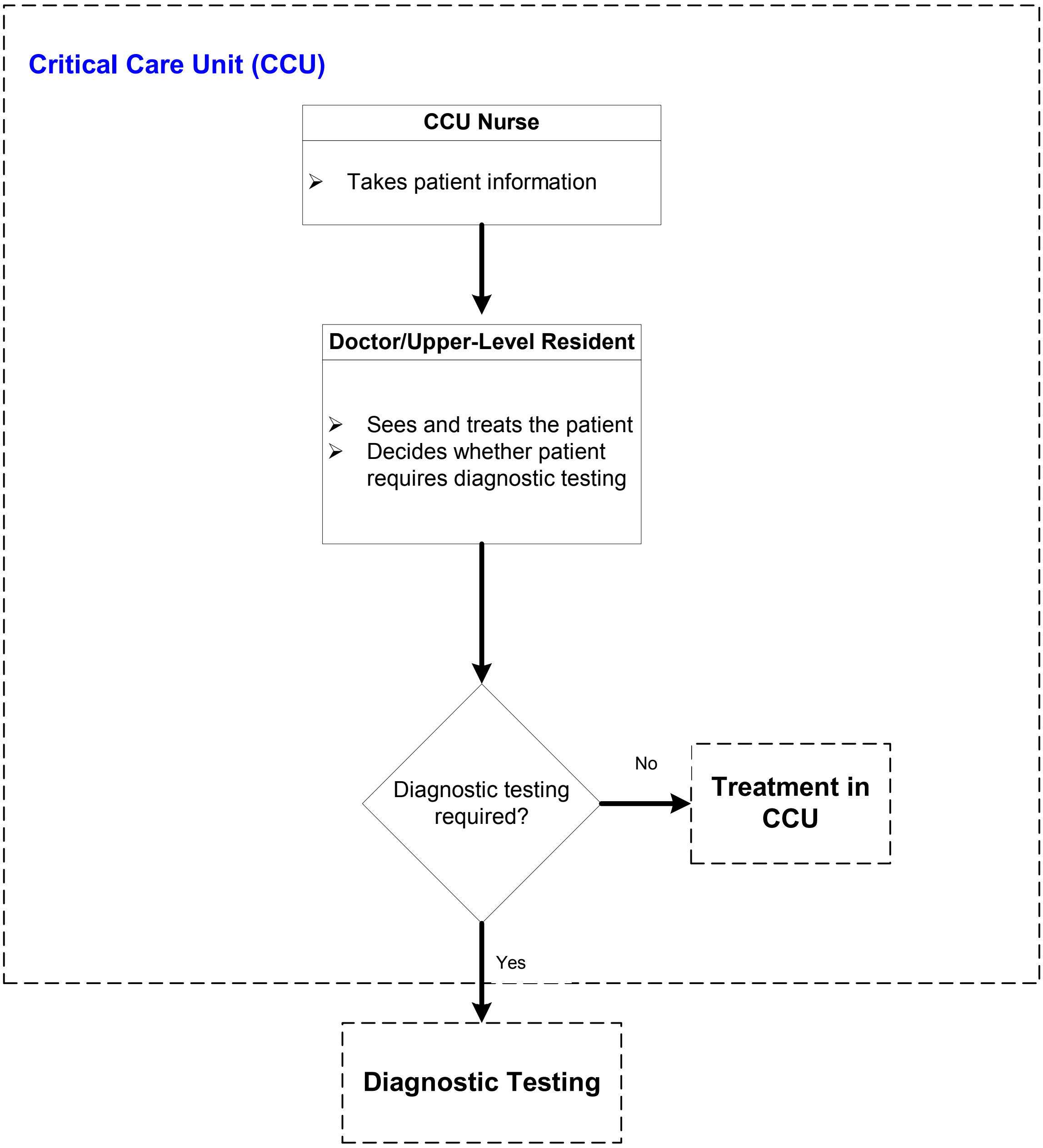


Figure 3.2: Flowchart of CCU Operation

3.1.4 Intermediate Care Unit (ICU)

ICU is a unit that works with the less urgent patients (those in ESI level 4 and 5, as well as the younger patients in ESI level 3). This unit is staffed 24 hours a day, seven days a week by ICU nurses, lower-level residents, and doctors. There are a total of seventeen full-time ICU nurses, four part-time nurses, and four lower-level residents. The working schedules that have been provided by York Hospital are shown in Appendix A. The flow through the ICU, shown in Figure 3.3, is similar to the patient flow through the CCU. The ICU patient care cycle begins with a visit from the ICU nurse. Following this initial assessment, the patient is evaluated by a lower-level resident. After the lower-level resident completes the initial evaluation process, the doctor performs an assessment and continues treatment of the patient. Note that in the ICU, the lower-level residents provide a preliminary assessment to the doctor, while the upper-level residents in the ICU basically function in place of the doctor. Similar to the CCU, the doctor then decides whether diagnostic testing is required. The patient then receives appropriate tests and treatment, and finally the patient is either discharged or admitted to the hospital. The service times for these ICU activities are summarized in Table 3.4.

Table 3.4: Service Times for the Intermediate Care Unit (ICU)

Activity	Service Time Distribution (min)
Patient evaluation by ICU nurse	Triangular (4,6,10)
Patient evaluation by lower-level resident	Triangular (5,10,15)
Initial treatment of patient by doctor	Triangular (4,7,15)
Follow-up treatment by doctor and nurse after reviewing diagnostic testing	Uniform (4,12)
Additional time for treatment after releasing doctor and nurse - Admitted patient - Discharged patient	 Triangular (25,35,180) Uniform (5,25)

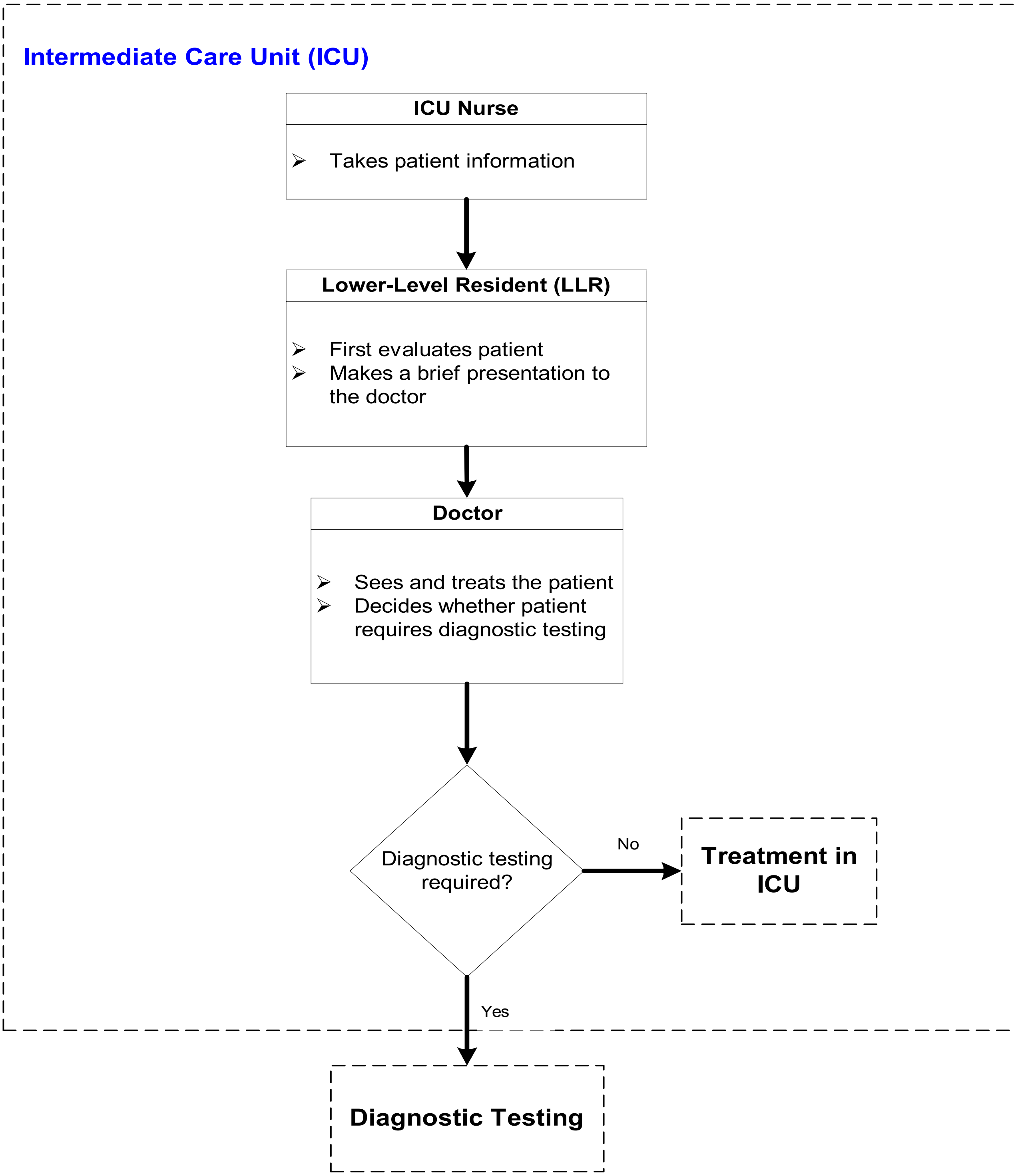


Figure 3.3: Flowchart of ICU Operation

3.1.5 Alterna Care (AC)

Like the ICU, AC is used to treat patients with a low level of severity (those in ESI levels 4 and 5). AC accepts patients from 11:00 AM – 10:30 PM on weekdays for assessment by AC nurses, AC doctors, and Physician Extenders (PE). We use the term PE to refer to those professionals (such as highly trained nurses) who can provide treatment normally associated with a doctor for minor patients. When the AC is not in operation, patients who would normally be assigned to the AC are sent to the ICU for treatment. The AC is staffed by one nurse, as well as either one doctor or one PE. The doctor is scheduled three days a week (Monday-Wednesday), while the PE works the remaining two days. The AC doctor and PE are dedicated to work only in the AC and are not shared with the ICU or CCU. In addition, the AC has an AC technician who works four days a week (Monday-Thursday). When the AC technician is working, he or she provides the follow-up treatment normally provided by the AC doctor or PE. The AC technician does not, however, perform the initial assessment, as this must be performed only by the AC doctor or PE.

The flowchart of AC operation, shown in Figure 3.4, begins with an initial assessment by the AC nurse. The patient is then treated by either the doctor or the PE, based on who is scheduled to work. The doctor or physician extender decides whether the patient requires any diagnostic tests. Once the doctor has received any necessary test results, the doctor provides any appropriate treatment and finally discharges the patient from the emergency department. In nearly all cases, the patient is discharged home, but in rare cases, the patient may be admitted to the hospital. The service times for activities in Alterna Care are summarized in Table 3.5.

Table 3.5: Service Times for Alterna Care (AC)

Activity	Service Time Distribution (min)
Patient evaluation by AC nurse	Triangular (1,5,9)
Treatment of patient by AC doctor	Triangular (1,4,5)
Treatment of patient by physician extender (PE)	Triangular (4,6,10)
Follow-up treatment by AC technician or PE and nurse after reviewing diagnostic testing	Uniform (3,8)
Additional time for treatment after releasing doctor and nurse - Admitted patient - Discharged patient	 Triangular (25,35,180) Uniform (3,21)

3.1.6 Diagnostic Testing

As previously described, a patient's treatment may require some additional testing alternatives, for example x-ray, ultrasound, etc. Diagnostic testing is a unit that provides these additional tests, and it is divided into two areas: imaging and lab testing. The imaging department provides traditional X-ray equipment, a portable X-ray machine, Computer Aided Tomography (CAT), Magnetic Resonance Imaging (MRI), and ultrasound. The lab testing area performs tests on a variety of patient specimens, including blood and urine. It is possible that a patient requires multiple types of tests. The service time distribution for each area is presented in Table 3.6. The diagnostic testing unit is staffed by technicians who perform the above types of tests. Throughout the testing process, the patient continues to occupy the bed assigned to him/her in the treatment unit (CCU, ICU, AC). At the completion of testing, the patient is returned to his or her room to wait for the doctor, resident, PE, AC technician and/or nurse to continue treatment.

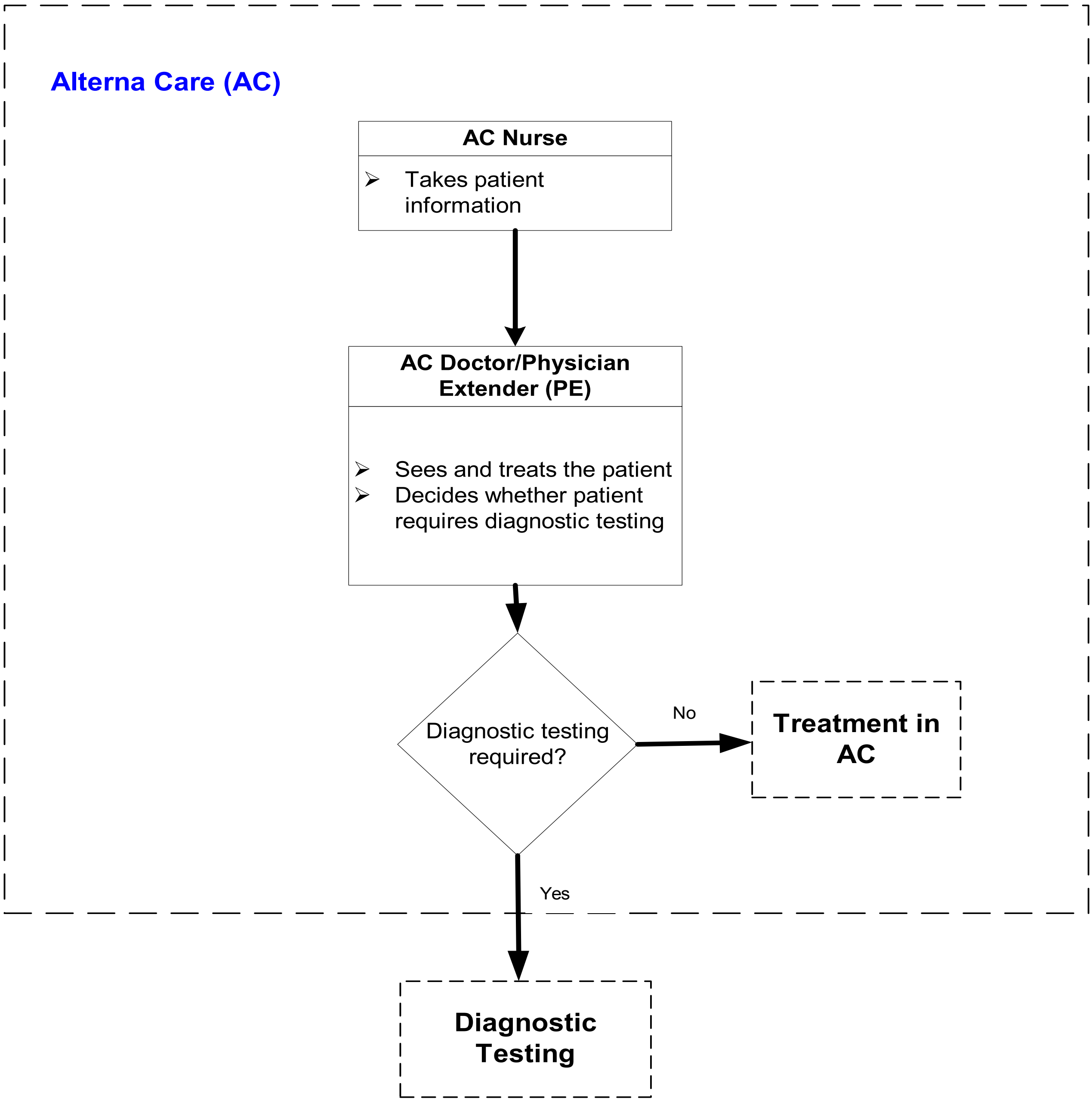


Figure 3.4: Flowchart of AC Operation

Table 3.6: Service Times for Diagnostic Testing

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

3.1.7 Treatment and Departure from the ED

Following any necessary diagnostic tests, the patient returns to his or her room to wait for further treatment. When the testing results are returned to the doctor, resident, PE, or AC technician, he or she reviews all documents and analyzes them. In the AC, this task is performed by the AC technician when available. The gathered information is used to determine what type of further treatment is required. The doctor then provides necessary medical orders to the staff, and the patient receives the ordered treatment. Finally, the patient is either discharged from the emergency department or admitted to the hospital depending upon the doctor's orders. If the patient is ordered to be admitted to the hospital, he/she is transported to the appropriate hospital ward after the hospital admissions staff completes the necessary paper work to procure a room.

3.1.8 Treatment Resources

This section focuses on emergency department resources, both human and physical, that provide treatment services to patients. These resources include residents (upper-level residents and lower-level residents), doctors, nurses (in the triage, CCU, ICU, and AC units), physician extenders, AC technicians and beds (in the CCU, ICU, and AC). Since the diagnostic testing unit is a treatment area that is shared with other hospital departments, we cannot identify these resources as belonging to the emergency department. Therefore, the technicians and instruments in diagnostic testing are excluded from the definition of these resources. The time for this service represents the entire time that the patient is away from the emergency department, and is therefore assumed to approximate the waiting process without specific resources. The number of available resources for each resource type is shown in Tables 3.7 and 3.8.

Table 3.7: Staff in the Emergency Department

Resource	Number Available**
Upper-Level Residents	5
Lower-Level Residents	4
Doctors (shared by ICU and CCU)	6
Triage Nurses	3
ICU Nurses	18 full-time 3 part-time
CCU Nurses	21 full-time 3 part-time
AC Nurses	1
AC Technicians	1
Physician Extenders Or AC Doctors	1

** Specific working schedules for all employees have been provided by the hospital

Table 3.8: Physical Resources of the Emergency Department

Resource	Number Available
AC beds	4
ICU beds	16
CCU beds	15

3.1.9 Patient Classifications

This section describes the percentage of patients who are sent to diagnostic testing for each type of test and who are admitted to the hospital. The data in this section were obtained from patient records provided by the emergency department at the York Hospital. The percentage of patients in each ESI level who require each of the various diagnostic procedures was provided by the emergency department administrators, and this information is provided in Table 3.9. This table shows the proportion of patients in each ESI level requiring a particular diagnostic test, regardless of the sequence that they were taken. For example, a patient can have the CAT scan before the ultrasound, or he/she can do otherwise. The percentage of admitted patients is shown for each ESI level in Table 3.10. This data was collected by the emergency department from November 1999 through June 2002, based on a total of 144,326 patient visit data sheets.

Table 3.9: Percentage of Patients that Require Each Diagnostic Test

ESI Level	Imaging			Lab Testing
	X-Ray	CAT/MRI	Ultrasound	
ESI-1	81	96	30	83
ESI-2	76	95	28	79
ESI-3	56	40	20	51
ESI-4	37	8	0	9
ESI-5	0	0	0	0

Table 3.10: Percentage of Patients Admitted to the Hospital

ESI Level	Percentage of ESI Level Patients Admitted to the Hospital
ESI-1	76.06
ESI-2	56.05
ESI-3	80.70
ESI-4	0.87
ESI-5	0.48

In addition, it is assumed that 50 percent of ESI-3 patients are classified as elderly (over 65 years old).

3.1.10 Transportation and Routing Times

The simulation model includes transportation times for patients and caregivers to move from the waiting area to the emergency department units and between different areas within the emergency department. Specifically, the model includes the route from the triage nurse station to either ICU, CCU, or AC, and from either ICU, CCU, or AC to diagnostic testing and vice versa. A team of emergency department experts estimated these transportation times, which are summarized in Table 3.11.

Table 3.11: Transportation Times

Route	Transportation Time Distribution (Min)
From waiting room to CCU, ICU, or AC	Triangular (3,4,5)
Between either CCU, ICU, or AC and diagnostic testing	Triangular (5,6,7)

3.2 Arena Model

In this research, the emergency department of York Hospital has been modeled using the Arena 7.0 simulation package. The main objective of the simulation model is to develop an understanding of system performance. Then, the various nurse staffing plans will be evaluated to determine a schedule that best suits hospital goals. All other employees in the model have been given specific working schedules that correspond to information provided by York Hospital. The simulation model follows the patient flow process described in Section 3.1, including the input data presented there. The Arena simulation model developed for this thesis is available upon request by contacting Lisa Patvivatsiri at plisa@vt.edu.

The model has been animated to provide an overall view of the emergency department system as the simulation is running. This animation not only helps the modeler determine whether the model is working correctly (Law and Kelton, 2000), but it also allows the decision maker to view a snapshot of the entire simulated. The animation of the emergency department model at York Hospital is shown in Figure 3.5. The upper portion of the animation provides the date and time, as well as the status (busy, idle, or inactive) of the triage nurse. The central portion shows the status of the nurses and resources (including the upper-level residents in the CCU, the lower-level residents in ICU, and physician extender, AC technician, and AC doctor in the AC) in each of the three care units, while the ICU/CCU doctors are shown in the lower portion. The bottom of the animation indicates whether or not each piece of diagnostic testing equipment is in use. On the far right, a display shows the number beds in use for each unit (CCU, ICU, and AC). Counters display the total number of patients who have been admitted to the hospital or discharged over the course of the day. Finally, counters on the far left display the number of patients who have arrived in each ESI level throughout the day.

The model has been separated into several sub-models for ease of use, as well as for verification and validation purpose. These sub-models include Triage Nurse Station, Critical Care Unit (CCU) Station, Intermediate Care Unit (ICU) Station, Alterna Care (AC) Station, Diagnostic Testing Station, and Treatment Station. Each of these sub-models is described in the following sections. In addition, several sub-models have been developed to help with operational logic of the system and

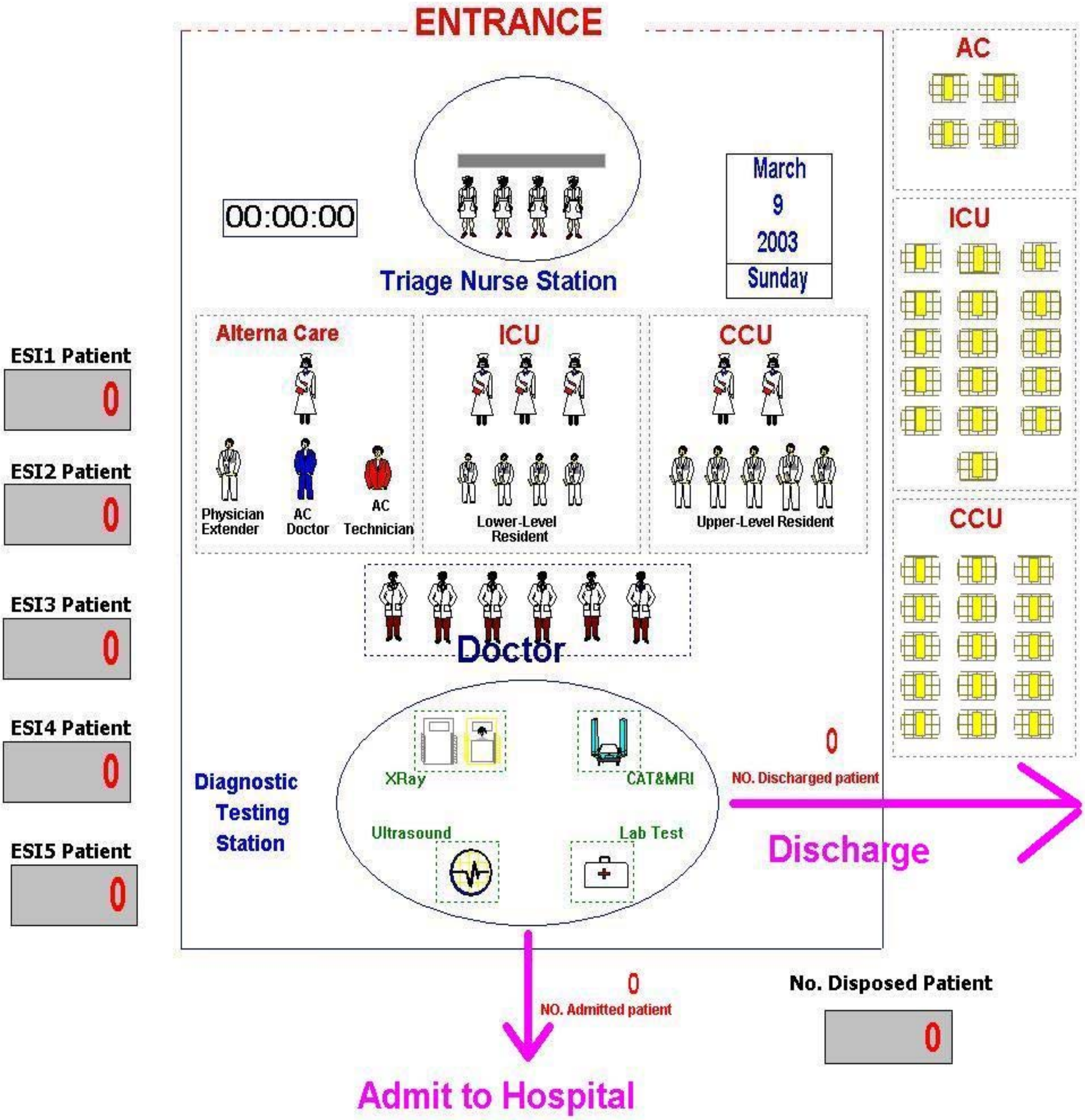


Figure 3.5: Animation of ED Model at York Hospital

statistical collection. For details on these sub-models, see the documentation provided directly in the Arena model itself.

3.2.1 Triage Nurse Sub-Model

The sub-model for the triage nurse represents the first area a patient encounters when entering the emergency department. Patients are represented as entities that flow through the simulation model. Although there are three modes of patient arrival to the emergency department (walk-in, ambulance, and helicopter), no data was available for each specific arrival mode. However, data was provided on the arrival rates for each of the five ESI levels. Each type of ESI patient arrives according to a time-dependent Poisson process, as previously shown in Table 3.1. Separate arrival processes are used for each ESI level, each with a specific arrival schedule, and patients are then assigned an attribute to represent their ESI level. Additionally, 50 percent of all patients in the ESI-3 level are labeled as young patients with the other 50 percent being elderly. While ESI-1, ESI-2, and elderly ESI-3 level patients are directed to one of 15 CCU beds, the young ESI-3 level patients are directed to one of 16 ICU beds. For ESI-4 and ESI-5 level patients, the model first checks whether the patient arrives in the system within the operating time of AC. If the AC is closed, these patients are directed to the ICU. If the AC is open, these patients are directed to either the AC or ICU, depending on which unit can serve them first. If both units are available, the ESI-4 and ESI-5 patients are sent to the AC. All patients retain their assigned bed throughout the duration of their stay in the emergency department. The patients are also assigned a patient status attribute (ICU, CCU, or AC) before exiting this sub-model.

3.2.2 Critical Care Unit (CCU) Sub-Model

Patients directed to the CCU by the triage nurse arrive to this sub-model. The four types of resources in this sub-model include CCU nurses, CCU beds, upper-level residents, and doctors. The number of resources is shown in Tables 3.7 and

3.8, and the CCU staff schedules are provided in Appendix A. Time distributions for all activities are presented in Section 3.2. Each resource type is grouped as a set, for example a CCU nurse set, CCU bed set, etc. Within this sub-model, the patient has an initial assessment from a CCU nurse, seizes a CCU bed, and is then evaluated by an upper-level resident or doctor. At this point in the model, the entity stores the identity of the doctor or upper-level resident as a specified attribute. This allows the entity to re-seize this same doctor or resident later, after completing the diagnostic tests. (A similar approach is also applied to the ICU and AC stations). Before leaving the sub-model for diagnostic testing, the patient releases all resources except for his or her bed, which is kept for his or her return from testing.

3.2.3 Intermediate Care Unit (ICU) Sub-Model

Patients who are sent to the ICU from the triage nurse arrive at this sub-model. There are four types of resources in this sub-model: ICU nurses, ICU beds, lower-level residents, and doctors. As in the CCU station, resources are defined as a set, for example ICU nurse set, ICU bed set, and others. However, the set of doctors in the ICU is shared with the CCU. That is, doctors in the emergency department can treat patients in both care units, based on where they are needed. The schedule for ICU workers is presented in Appendix A. The number of ICU resources is displayed in Tables 3.7 and 3.8, and Section 3.2 detailed service time distributions for each ICU activity. After being evaluated by an ICU nurse, the patient checks for an available lower-level resident. The patient then proceeds to a process module where a doctor is seized to treat the patient. Finally, the patient releases all resources, except for the ICU bed, before leaving the sub-model for diagnostic testing.

3.2.4 Alterna Care (AC) Sub-Model

Entities in this sub-model represent the patients who are sent to the AC by the triage nurse. AC nurses, AC beds, AC doctors, AC technicians and physician extenders are the resources within this area. Similar to the ICU and CCU stations, each resource type is grouped as a set. The number of resources is shown in Table

3.7 and 3.8, the staff schedule is presented in Appendix A, and the service distribution time is presented in Section 3.2. After being assessed by an AC nurse, the patient is then treated by an available AC doctor or physician extender. If the entity leaves this sub-model for diagnostic testing, it releases all resources except the AC bed.

3.2.5 Diagnostic Testing Sub-Model

All patients requiring diagnostic testing are logically routed to this sub-model, where they can undergo any of the testing procedures. The percentage of patients needing each type is presented in Table 3.9. The diagnostic testing area includes portable and stationary X-ray machines, CAT and MRI scanners, ultrasounds, and lab testing equipment. Since the diagnostic testing department is shared area with the overall hospital, the simulation model does not include specific resources for this area. The hospital was unable to provide data on how the demand for these resources from other departments impacted the availability of the resources for emergency department patients. However, they were able to estimate the overall time that emergency department patient spends for each type of test. Therefore, each testing procedure was modeled (using these appropriate time distributions) as a simple delay, with no resources being seized. For the purpose of animation, we seize resources from a set with a very large capacity. Each patient can proceed to each of the possible tests, based on generated probabilities that depend on the patient's ESI level. Upon completion of all required tests, the patient is returned to the CCU, ICU, or AC for further treatment.

3.2.6 Treatment Sub-Model

After diagnostic testing, all patients are routed to the treatment sub-model, where patients receive final treatment in the appropriate care unit (CCU, ICU, or AC). An attribute is assigned to each patient to ensure that they return to the same unit to which they were originally assigned. Upon returning to the original care unit, the patient must seize the same caregivers (nurse, doctor, resident, and physician extender) that previously provided treatment. One exception to this is that when an AC technician is working in the AC unit, the AC technician completes this treatment instead of the original AC doctor or PE. This caregiver reviews all documents and orders final treatment options. However, if the original nurse, doctor, resident, or physician extender has left for the day, the patient checks for another available nurse, doctor, resident, or physician extender to complete treatment. The service time distribution for final treatment is provided in Section 3.2. Once treatment is completed, the patient is either admitted to the hospital or discharged from the emergency department. Prior to being admitted to the hospital, the patient must wait for the admission staff to procure an appropriate room. When the patient leaves the emergency department (either by being discharged or admitted to the hospital), all associated resources (including the bed) are released for use with other patients.

3.3 Verification and Validation of the Model

We have used several methods for verifying and validating the simulation model to ensure accurate results. Throughout the modeling process, the research team remained in close contact with hospital administrators and received valuable input on ways to make the model more accurately reflect the real system. Each section of the model logic was discussed in detail with emergency department staff before construction of the model began. A coordinator of this study, who is knowledgeable about the actual system, reviewed the model and determined that its behavior was reasonably accurate. The data collection process was executed by the emergency department management and included data from all shifts. All modeling input for which data was unavailable was estimated by staff members familiar with these activities.

Verification is the process of ensuring that the computer program is operating correctly. The three following strategies have been used to perform model verification:

1) **Using the capability of the Arena 7.0 software package to find and fix model errors.** Examples include the Run/Check option, Edit/Find option, Break option, and others. The Run/Check option is used to check the model

while it runs. If some errors are detected during run time, an Arena Errors/Warnings window appears to inform the user. While checking for errors, the Edit/Find option helps the user track where a variable is used by locating all occurrences of a string of characters. The break option stops the simulation when a logical error occurs (Kelton, 2002).

2) **Building an animation of the simulation model.** The animation imitates the behavior of the actual system and helps the modeler verify the model by visualizing its performance. The animation of the emergency department at York Hospital is shown in Figure 3.5. This model was run many times while closely watching the animation which led to the discovery of several errors that were subsequently corrected.

3) **Group evaluation of the model.** The model logic was presented to the overall team of graduate students working on the York Hospital project. Each sub-model was discussed in detail, and suggested improvements were incorporated.

In order to validate the Arena model, the model was executed under the current hospital staffing policy. Run lengths and warm-up periods of 35 days and 7 days, respectively, were used for each replication to allow the system to reach realistic operating conditions before collecting the appropriate statistics. The model was run for twenty replications, and the average results were used to create 95% confidence intervals for several output categories. The number of replications performed was determined by performing a pilot study and calculating the number of observations needed to obtain a confidence interval half-width within 0.10. Tables 3.12 summarizes the results for the average waiting times a patient spent in the system.

Table 3.12: Simulation Results of the Average Waiting Times for Patients in the Current System

Entity	Number of Observations	Average Waiting Time(hrs)	95% Confidence Interval Half Width	Maximum Waiting Time (hrs)
ESI-1	144	0.50± 0.03	0.03	4.78
ESI-2	506	0.53± 0.02	0.02	4.61
ESI-3	1444	0.56± 0.03	0.03	4.92
ESI-4	777	0.59± 0.03	0.03	4.18
ESI-5	250	0.57± 0.04	0.04	4.11

These results were presented to the York Hospital research team for evaluation. The team concluded that these results accurately represent the actual systems and also agree with the results obtained from a previous simulation model of the system.

Chapter 4 Experimental Procedures and Results

After the simulation model was developed using Arena to reflect the current situation in the emergency department at York Hospital, then research focus shifted to improving the system performance through more effective nurse scheduling policies. Specifically, the experimental approaches focus on evaluating various nurse scheduling alternatives with respect to the waiting time spent in the system for emergency department patients. To determine nursing schedules that meet hospital requirements and provide acceptable waiting times for patients, a heuristic scheduling approach, known as a microcomputer-based decision support system (DSS), was utilized to search for good nursing schedules that can satisfy the nurse and hospital requirements. In addition, the Arena optimization tool known as OptQuest was also used to search for a nursing schedule that minimizes the average waiting time of patient stay in the emergency department. Both of these approaches are summarized in the following sections.

4.1 Microcomputer-Based Decision Support System (DSS)

The microcomputer-based DSS for nurse scheduling is a heuristic approach used for schedule generation and schedule assignment. Section 2.5 provides an overview of the DSS process. Additional details, including sample computer code, can be found in the dissertation by Sitompul (1991). The DSS program is interactive and user-friendly. For this research, the DSS nurse scheduling system has been implemented using Borland's Turbo Pascal Professional version 6.0 compilers produced by Borland International. Pascal is a high-level, general-purpose programming language that is suitable for a diverse range of applications (Savitch, 1993). Pascal was selected as the language for this system because it is a modular and very structured language. Moreover, it is easy to modify, extend, and expand the program in Pascal. The program developed in this research consists of three main components including schedule generation, screening, and matching. The computer code for this system generates schedules for four-week periods. The s*chedule generation process* begins by generating a series of work patterns. A work pattern is a daily pattern that must be followed by a nurse, and it also shows whether a nurse will work on a particular day or not. The set of work patterns is generated in terms of seven binaries for each week of a four-week period, where 1 represents a working day while 0 represents a day off. After the work patterns have been generated, the DSS next generates possible shift patterns using a specified hospital policy. This pattern shows the shift that a nurse must work in a particular week during a certain period. The shift pattern is generated in terms of a D (Day shift), E (Evening shift), and N (Night shift) combination. It is assumed for this research that D stands for 7:00AM-3:00PM, E stands for 3:00PM-11:00PM, and N stands for 11:00PM-7:00AM. Additionally, it is assumed that nurses must work the same shift for an entire week. That is, shift changes only occur at the beginning of the week, and the same shift is worked throughout the week. The combination of the work and shift patterns is therefore a complete scheduling pattern for the hospital. An example of a complete schedule for one nurse over a four-week period is shown in Figure 4.1.

```
     Schedule No.:      1
-----------------------------
  Day:          M T W T F S S
-----------------------------
  Week: 1   D:  1 1 1 0 0 1 1
  Week: 2   D:  1 0 0 1 1 1 1
  Week: 3   N:  1 1 0 0 1 1 1
  Week: 4   E:  1 1 1 1 0 0 1
=============================
```

Figure 4.1: Example of a Complete Scheduling Pattern for One Nurse over a Four-Week Period

The *screening process* screens all complete patterns against a set of common constraints to determine which scheduling patterns are acceptable to the hospital and the nurses. The two sets of constraints that are taken into account by this research consist of shift policy, as well as nurse and hospital requirements. The shift policy is a specific operating policy concerning the proportion of nurses working in different shifts within the emergency department. For example, a 4:3:1 shift policy indicates that the number of nurses working in the day shift is four times the number of nurses working in the night shift, and the number of nurses working in the evening shift is three times the number of nurses working in the night shift. There are nine ratios built into the program, namely 1:1:1, 2:1:1, 2:2:1, 3:2:1, 3:2:2, 3:3:1, 3:3:2, 4:3:1, and 4:3:2. However, the program allows the user to define other shift policy ratios. The nurse and hospital requirements constrain the number of consecutive days off, the number of consecutive working days, the assignment of single day off/on, and the scheduling pattern for the weekends. The performance measure used by this heuristic approach is the penalty cost that is associated with the violation of the constraints. Therefore, the dissatisfaction with a particular schedule can be measured by its resulting penalty cost. The user can choose default penalty costs built into the program or define specific penalty costs based on the particular hospital. The constraints with their associated default penalty costs are displayed in Figure 4.2. In addition, the user specifies the maximum allowable penalty cost, as well as the number of patterns to be generated and the number of schedules to be selected from the schedule database. During the process of pattern generation (work and shift patterns), there are a large number of possible patterns that can be generated. However, some of these different patterns are not feasible, meaning that they exceed the user-defined maximum allowable penalty cost. When the set of constraints is considered, the number of these patterns can be significantly reduced. The results from this screening process are stored in a schedule database comprised of a diverse set of feasible patterns.

The *matching process* consists of two different matching operations: matching shift patterns to work patterns and matching nurses to specific work schedules. The first operation combines work patterns and shift patterns. The process starts by picking one weekly pattern and one shift pattern from the pattern database. Then the first character (D, E, or N) of the first shift pattern is assigned to the first seven digits of the work pattern, representing the work assignment for the first week. The second character of the shift pattern is then assigned to the second seven-digit set in the work pattern for second week assignment. The process continues through the last work pattern and shift pattern, which results in a working scheduling for one nurse. The procedure for accomplishing this process is shown in Figures 4.3 and 4.4, and the working schedules resulting from this combination are shown in Figure 4.5.

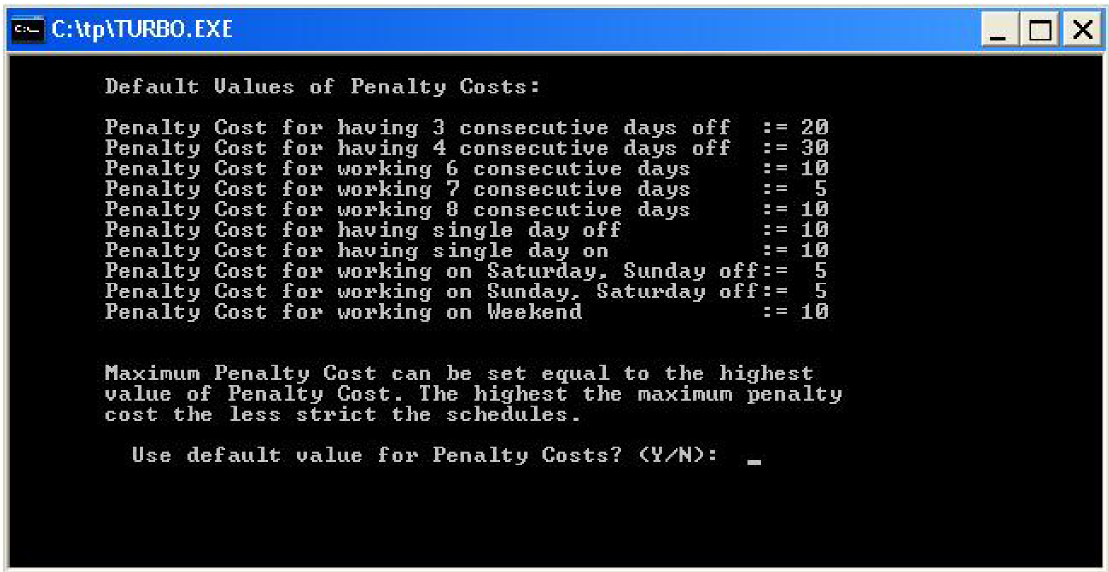


Figure 4.2: Default Penalty Costs for the DSS

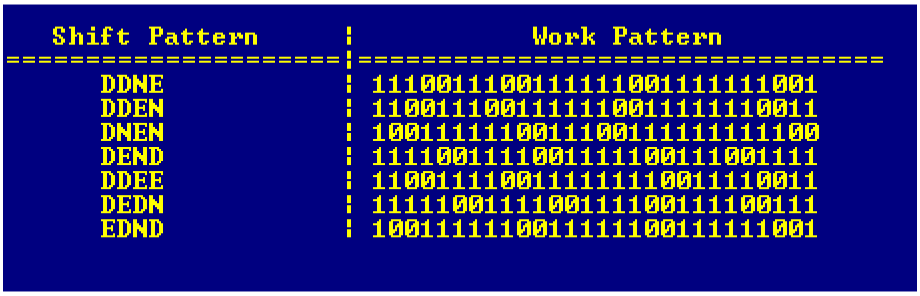


Figure 4.3: Example of Shift and Work Patterns

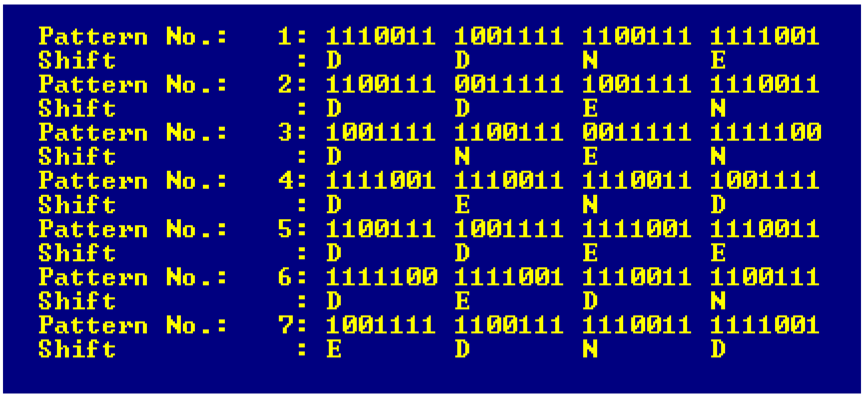


Figure 4.4: Matching Shift and Work Patterns

Schedule No.: 1

Day:		M	T	W	T	F	S	S
Week: 1	D:	1	1	1	0	0	1	1
Week: 2	D:	1	0	0	1	1	1	1
Week: 3	N:	1	1	0	0	1	1	1
Week: 4	E:	1	1	1	1	0	0	1

Schedule No.: 3

Day:		M	T	W	T	F	S	S
Week: 1	D:	1	0	0	1	1	1	1
Week: 2	N:	1	1	0	0	1	1	1
Week: 3	E:	0	0	1	1	1	1	1
Week: 4	N:	1	1	1	1	1	0	0

Schedule No.: 2

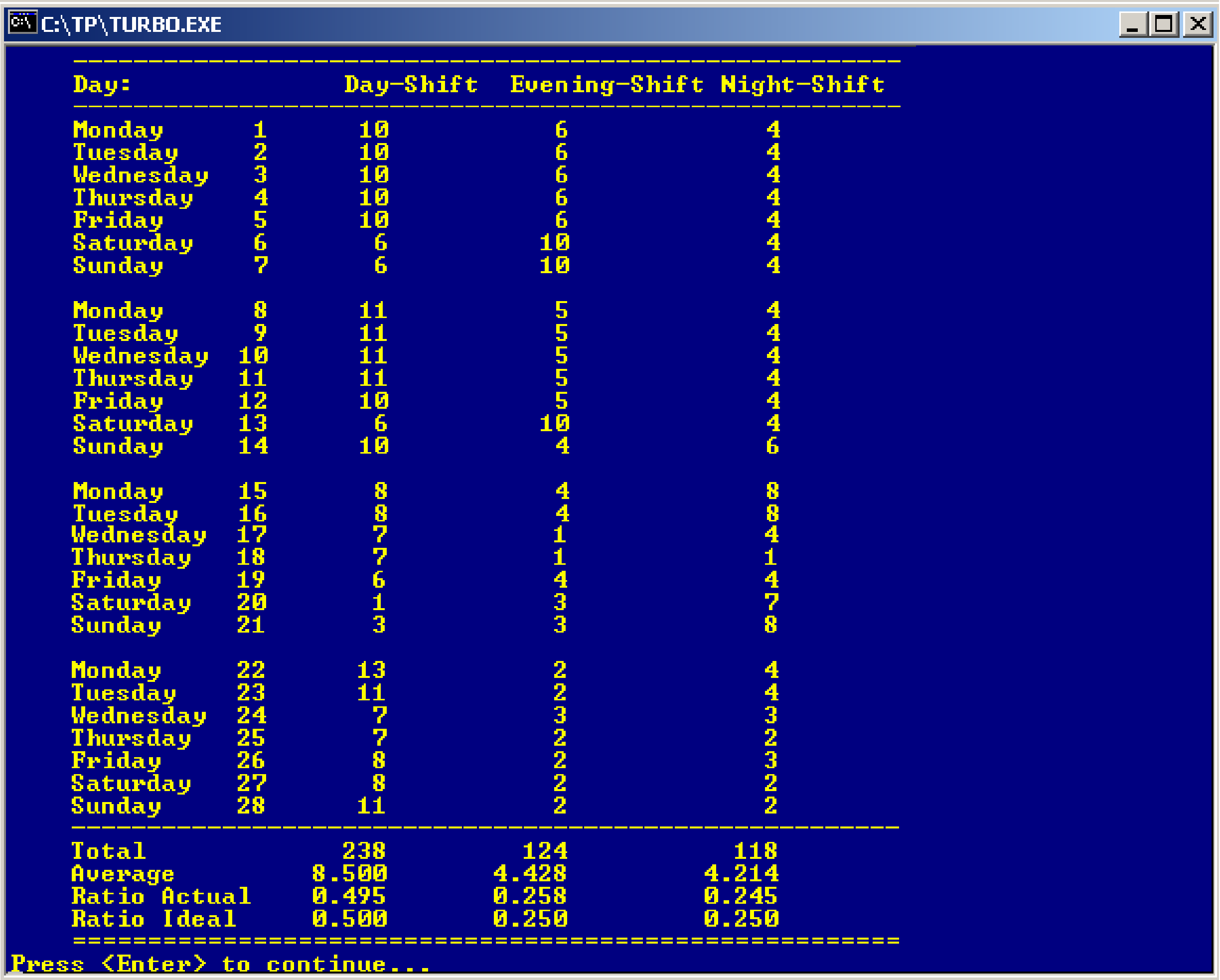
Day:		M	T	W	T	F	S	S
Week: 1	D:	1	1	0	0	1	1	1
Week: 2	D:	0	0	1	1	1	1	1
Week: 3	E:	1	0	0	1	1	1	1
Week: 4	N:	1	1	1	0	0	1	1

Schedule No.: 4

Day:		M	T	W	T	F	S	S
Week: 1	D:	1	1	1	1	0	0	1
Week: 2	E:	1	1	1	0	0	1	1
Week: 3	N:	1	1	1	0	0	1	1
Week: 4	D:	1	0	0	1	1	1	1

Figure 4.5: Example of Possible Nurse Schedules

The second matching operation is the process of assigning specific schedules to the individual nurses. This process is accomplished by matching the schedules from the schedule database with the nurse database. Once the program is executed, a feasible set of working schedules is provided, and a summary report is created. The reports generated by the program consist of individual work schedules as shown in Figure 4.5, as well as a staff summary report (shown in Figure 4.6) that displays the number of nurses working in each shift on each day of the scheduling period. In addition, the actual ratios (based on the generated schedules) and the ideal ratios (based on the specific shift policy) are also presented in this staff summary report. The administrator can use this report to assess whether or not the schedule generated meets the staffing requirements of the hospital. If the patterns generated do not satisfy the staffing requirements, the program generates other patterns and schedules. This process can be repeated until a desirable set of working schedules is obtained.



C:\TP\TURBO.EXE

Day:		Day-Shift	Evening-Shift	Night-Shift
Monday	1	10	6	4
Tuesday	2	10	6	4
Wednesday	3	10	6	4
Thursday	4	10	6	4
Friday	5	10	6	4
Saturday	6	6	10	4
Sunday	7	6	10	4
Monday	8	11	5	4
Tuesday	9	11	5	4
Wednesday	10	11	5	4
Thursday	11	11	5	4
Friday	12	10	5	4
Saturday	13	6	10	4
Sunday	14	10	4	6
Monday	15	8	4	8
Tuesday	16	8	4	8
Wednesday	17	7	1	4
Thursday	18	7	1	1
Friday	19	6	4	4
Saturday	20	1	3	7
Sunday	21	3	3	8
Monday	22	13	2	4
Tuesday	23	11	2	4
Wednesday	24	7	3	3
Thursday	25	7	2	2
Friday	26	8	2	3
Saturday	27	8	2	2
Sunday	28	11	2	2
Total		238	124	118
Average		8.500	4.428	4.214
Ratio Actual		0.495	0.258	0.245
Ratio Ideal		0.500	0.250	0.250

Press <Enter> to continue...

Figure 4.6: Example of the Staff Summary Report

As mentioned earlier, the DSS requires the user to provide a specific shift policy. In order to determine the current shift policy used at York Hospital, the current staffing plan was reviewed. The summary table of the number of CCU and ICU nurses working in each hour is displayed in Tables A.8 and A.9 in Appendix A. The hospital currently assigns 4 full-time CCU nurses in a day shift (7:00am-3:00pm), 6 full-time CCU nurses in an evening shift (3:00pm-11:00pm), and 5 full-time CCU nurses in a night shift (11:00pm-7:00am). In addition, 3 full-time ICU nurses, 6 full-time ICU nurses, and 4 full-time ICU nurses are assigned in the day, evening, and night shifts in the ICU treatment area, respectively. The emergency department employs a total of 39 full-time nurses, with each nurse having approximately two days off each week. In addition, the emergency department employs several part-time nurses. Specifically, the part-time nursing schedule is as follows: 2 CCU nurses between 11:00am-3:00pm, 1 CCU nurse between 11:00pm-3:00am, 2 ICU nurses between 11:00am-3:00pm, and 1 ICU nurse between 11:00pm-3:00am. Since this research focuses only an scheduling full-time nurses, the current part-time schedule was assumed to remain unchanged.

Based on this information, the number of full-time nurses working the day, evening, and night shifts is 7, 12, and 9 respectively. Therefore, the DSS generates nurse schedules with the shift policy of 0.77:1.33:1. The DSS program was run for twenty replications, using default penalty costs and a maximum penalty cost of 40. A nurse staffing plan with an actual ratio closest to the ideal ratio and with no zero-capacity shifts during 28 day period is considered an acceptable staffing plan. Since the DSS generates an entire staffing plan in the emergency department without considering the CCU and ICU separately, the DSS-generated staffing plan was then heuristically modified to obtain schedules for the CCU and ICU. In the current hospital policy, the nurses are split equally between the ICU and CCU, with the extra nurse being assigned to the CCU in case of an odd number of nurses. For instance, if there are a total of eleven nurses working on a day shift in the first week, six of them are assigned to CCU and five of them are assigned to ICU. The process of assigning nurses to the ICU and CCU becomes much more difficult, however, when the entire work schedule is considered. Since each nurse has different days off throughout the work, it is impossible to simply assign half of the day-shift workers in a given week to the ICU and half to the CCU, since this could result in no nurses working in a particular unit on some day. Therefore, it was necessary to examine the process of assigning nurses to the ICU and CCU more thoroughly. Toward this end, Matlab 5.1.3 was used to develop a program for assigning nurses to the ICU and CCU. This program guaranteed that no shifts were unstaffed in either the ICU or CCU throughout the 28-day planning period. Ten of these ICU and CCU nurse staffing schedules obtained by Matlab were then evaluated by Arena simulation models, with all other resources following at their current working schedules, in order to determine how the DSS-based nursing schedule impacted the average waiting time for patients. The best of these ten alternatives is reported below.

The results obtained from the DSS solution approach are presented below in Table 4.1, which indicates the total number of nurses working each shift throughout the four-week planning horizon. For the specific working schedules of all 39 nurses, see Table B.1 in Appendix B. The simulation results for the average waiting times of patients in the emergency department are presented in Table 4.2.

Table 4.1: Total Number of Nurses Working Each Shift using the DSS Solution Approach

Week	Day:	Day#	Day-Shift	Evening-Shift	Night-Shift	OFF
1	Monday:	1	9	9	14	7
	Tuesday:	2	11	12	16	0
	Wednesday:	3	8	8	14	9
	Thursday:	4	6	7	8	18
	Friday:	5	7	10	7	15
	Saturday:	6	7	8	10	14
	Sunday:	7	8	6	11	14
2	Monday:	8	7	12	6	14
	Tuesday:	9	5	13	10	11
	Wednesday:	10	5	14	10	10
	Thursday:	11	5	13	8	13
	Friday:	12	6	14	9	10
	Saturday:	13	6	14	9	10
	Sunday:	14	6	15	8	10
3	Monday:	15	5	9	14	11
	Tuesday:	16	9	11	19	0
	Wednesday:	17	8	10	16	5
	Thursday:	18	8	8	13	10
	Friday:	19	6	6	13	14
	Saturday:	20	5	5	11	18
	Sunday:	21	4	6	9	20
4	Monday:	22	9	15	6	9
	Tuesday:	23	6	17	4	12
	Wednesday:	24	7	13	5	14
	Thursday:	25	8	16	6	9
	Friday:	26	8	15	7	9
	Saturday:	27	10	13	5	11
	Sunday:	28	6	11	7	15
	Total		195	310	275	
	Average		6.964	11.1	9.821	
	Actual Ratio		0.250	0.397	0.353	
	Ideal Ratio		0.248	0.429	0.323	

Table 4.2: Waiting Time of Patients in the DSS-Generated and Current Staffing Plan

ESI Level	DSS-Generated Staffing Plan		Current Staffing Plan	
	Average Waiting Time (hrs)	Maximum Waiting Time (hrs)	Average Waiting Time (hrs)	Maximum Waiting Time (hrs)
ESI-1	0.41± 0.04	3.96	0.50± 0.03	4.78
ESI-2	0.44± 0.03	4.14	0.53± 0.02	4.61
ESI-3	0.48± 0.04	4.27	0.56± 0.03	4.92
ESI-4	0.52± 0.03	4.22	0.59± 0.03	4.18
ESI-5	0.51± 0.03	3.99	0.57± 0.04	4.11

For both the DSS-generated staffing plan and the current staffing plan, twenty replications were run on Arena, with each replication consisting of 35 days plus a seven-day warm-up period. Figure 4.7 shows the 95% confidence intervals for the average waiting time for two these scenarios. The study shows that the DSS-generated nurse staffing plan does statistically outperform the current staffing plan. The DSS-generated staffing plan improves the average waiting times by 18.66%, 16.58%, 14.02%, 12.37%, and 10.80% for ESI-1, ESI-2, ESI-3, ESI-4, and ESI-5 patients, respectively. The 95% confidence interval graphs show no overlap between the two nurse staffing plans, indicating that the DSS-generated staffing plan is statistically better than the current staffing plan.

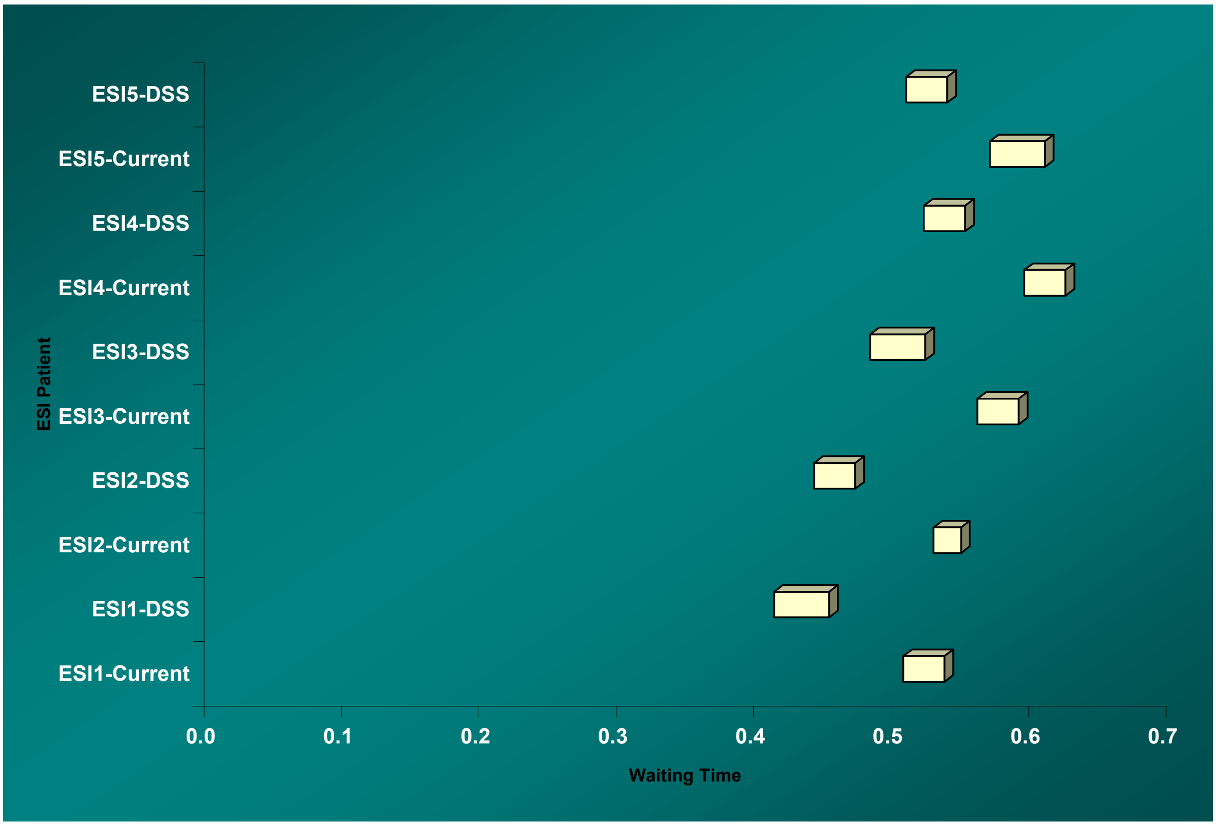


Figure 4.7: 95% Confidence Intervals for Waiting Times in the Current and DSS-Generated Staffing Plans

4.2 OptQuest for Arena

While the DSS approach can be useful in developing a nurse staffing plan, it also has some limitations. One major limitation is that the DSS software requires a user-specified ratio to represent the number of nurses who work each shift, and that ratio must remain constant throughout the week. In order to minimize patient waiting times, the hospital may prefer to allow this ratio to change throughout the week; for example, it might help to provide more nurses on weekends when patient arrivals are typically greater. For this reason, we use OptQuest for Arena to search for more flexible nurse staffing plans that may allow the emergency department at York Hospital to operate even more efficiently.

A preliminary plan for using Arena to completely generate the nursing staffing plan was determined to be unmanageable in size. The overall problem addressed in this research is to determine which one of the three shifts (day, evening, or night) that each of the 39 nurses should work on each of the 28 days in the scheduling period, resulting in a formulation with over 1000 discrete variables. The formulation also included a large number of constraints to force each nurse to work a particular shift throughout a given week. In preliminary efforts, it became clear that the scope of this formulation was too large for OptQuest to handle efficiently. In addition, modeling the restrictions that represent the nurses' working preferences (number of days on/off, working on weekends, etc.) was extremely difficult. As mentioned in Chapter 2, even when the effect of nurse scheduling on patient waiting time is not considered, the nurse scheduling problem is a very difficult problem to solve. With this added complication, it became clear that the problem could not be adequately addressed with current software capabilities.

In order to allow OptQuest to search for an improved nurse staffing plan, the scope of the problem was narrowed. Since the DSS approach was useful in identifying schedules that met the working requirements of the nurses, this feature was re-used. Using the same penalty costs as previously described in Section 4.1, the DSS model was used to generate a template of 50 possible schedules that each were below the maximum allowable penalty as specified by the nurses. Before turning to OptQuest, an Excel spreadsheet was created to verify that the template of schedules provided a sufficient number of alternative scenarios. This spreadsheet indicated that each shift throughout the 28-day planning horizon was covered by at least four different schedules in the scheduling template. OptQuest was then employed to determine the number of nurses that should work each of the schedules in the template.

Since the Arena model must re-seize the same nurse for follow-up treatment, it was not possible to simply define a variable for each of the 50 schedules to represent the number of nurses working that schedule. The problem with this approach is that if multiple copies of one resource are placed in a resource set, Arena does not provide a way to re-seize the specific resource; rather, Arena will try to seize any one of the multiple copies of the resource. Therefore, it became necessary to create a separate resource for each possible nurse working a given shift. Specifically, resources were defined as CCU-X-Y or ICU-X-Y (such as CCU1A or ICU2B), representing a CCU or ICU nurse who follows schedule X, where X ranged from 1 to 50. Since it is possible that the hospital might want to have more than one nurse in the same treatment area working exactly the same schedule, the Y index (with values of A, B, or C) was used to differentiate between up to three nurses working identical schedules. Each one of these resources was linked to a particular resource schedule with a unique 0-1 variable, named CXY or IXY to represent a CCU or ICU nurse, respectively, with schedule XY. A value of 1 indicates that a nurse was hired to work the associated schedule, and a value of 0 indicated that no nurse was hired for that schedule. This process resulted in 150 nurse resources in the ICU and 150 nurse resources in the CCU, each with specified schedules throughout the 28-day planning horizon. The goal of OptQuest was to assign values to the 0-1 scheduling variables (effectively determining which of these potential nurses were actually hired) in order to minimize the average time in the system across all patient types. The only constraint was that the total number of full-time nurses remains at or below its current level of 39. As was done in the DSS solution approach described in Section 4.1, the schedules of all part-time nurses were assumed to remain as they are currently used. Similarly, all other resources were fixed at their current levels. The OptQuest search used a replication length of 35 days, including 7-day warm-up period, with 10-11 replications in each run.

The results obtained from the OptQuest solution approach are presented below in Table 4.3, which indicates the total number of nurses working each shift throughout the four-week planning horizon. For the specific working schedules of all 37 nurses, see Table B.2 in Appendix B.

Table 4.3: Total Number of Nurses Working Each Shift Using the OptQuest Approach

Week	Day:	Day#	Day-Shift	Evening-Shift	Night-Shift	OFF
1	Monday:	1	8	9	17	3
	Tuesday:	2	8	11	18	0
	Wednesday:	3	6	8	18	5
	Thursday:	4	2	6	12	17
	Friday:	5	3	8	7	19
	Saturday:	6	6	7	7	17
	Sunday:	7	7	6	11	13
2	Monday:	8	9	12	4	12
	Tuesday:	9	8	13	8	8
	Wednesday:	10	6	11	10	10
	Thursday:	11	6	13	9	9
	Friday:	12	4	9	8	16
	Saturday:	13	8	14	7	8
	Sunday:	14	4	13	9	11
3	Monday:	15	6	16	9	6
	Tuesday:	16	9	17	11	0
	Wednesday:	17	8	14	5	10
	Thursday:	18	7	11	5	14
	Friday:	19	6	10	10	11
	Saturday:	20	5	7	8	17
	Sunday:	21	4	10	7	16
4	Monday:	22	7	8	7	15
	Tuesday:	23	8	12	9	8
	Wednesday:	24	9	11	9	8
	Thursday:	25	11	11	7	8
	Friday:	26	11	12	4	10
	Saturday:	27	10	12	5	10
	Sunday:	28	9	9	4	15

The average waiting times associated with the scheduled determined by OptQuest are presented below in Table 4.4.

Table 4.4: Waiting Time of Patients in the OptQuest-Generated and Current Staffing Plans

ESI Level	OptQuest-Generated Staffing Plan		Current Staffing Plan	
	Average Waiting Time (hrs)	Maximum Waiting Time (hrs)	Average Waiting Time (hrs)	Maximum Waiting Time (hrs)
ESI-1	0.42± 0.04	4.79	0.50± 0.03	4.78
ESI-2	0.43± 0.03	4.34	0.53± 0.02	4.61
ESI-3	0.33± 0.02	4.23	0.56± 0.03	4.92
ESI-4	0.26± 0.01	2.62	0.59± 0.03	4.18
ESI-5	0.26± 0.01	2.23	0.57± 0.04	4.11

This table shows that the nurse staffing plan determined by OptQuest improves the average waiting time in the system by 16.26%, 17.93%, 41.62%, 55.74%, and 53.97% for ESI-1, ESI-2, ESI-3, ESI-4, and ESI-5 patients, respectively. In addition, after running twenty replications of the simulation model, the Arena confidence intervals for the patient’s waiting time for each ESI level are shown in Figure 4.8. Since the 95% confidence interval graph shows no overlap between the two scenarios, the OptQuest-generated staffing plan is shown to be statistically better than the current staffing plan, in terms of average waiting across all patient types. In addition, it is important to note that the OptQuest-generated schedule uses a total of 37 nurses, which is *two fewer* than the number used in the DSS approach.

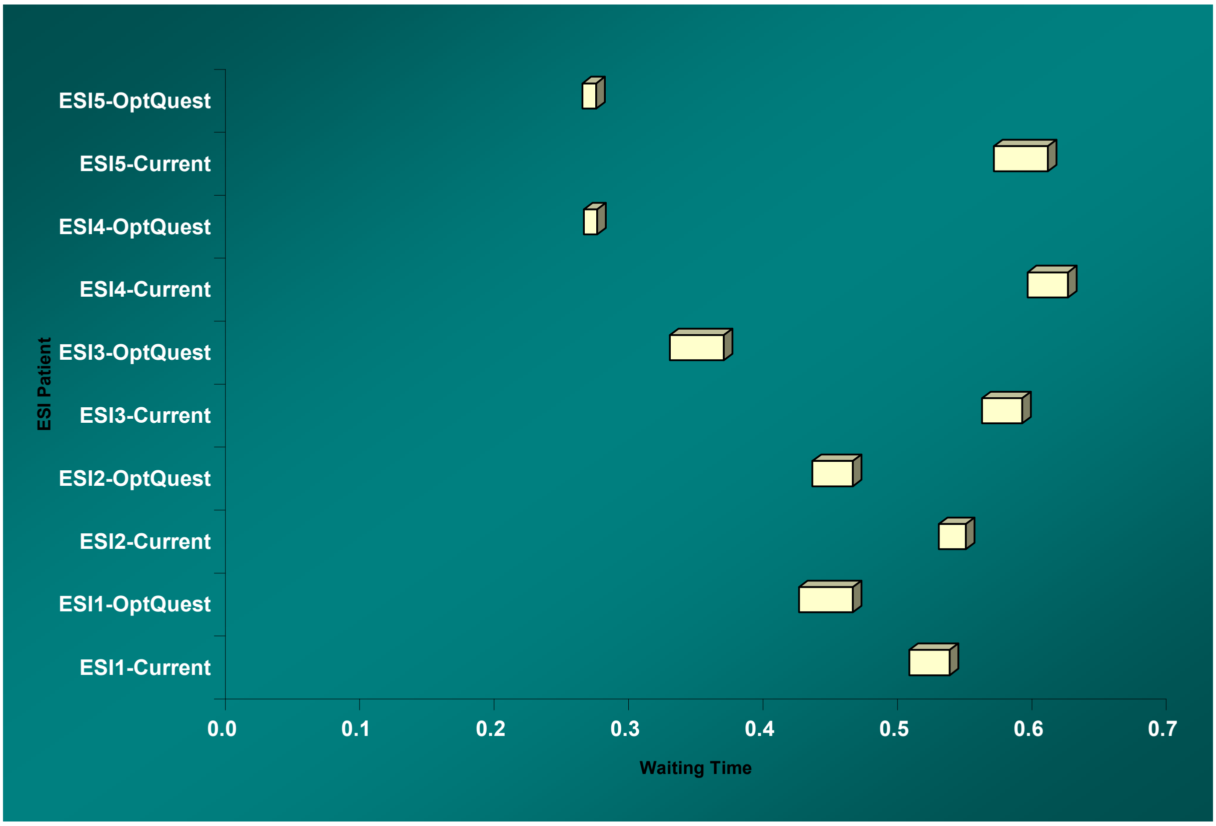


Figure 4.8: 95% Confidence Intervals for Waiting Times in the Current and OptQuest-Generated Staffing Plans

Figure 4.9 shows a comparison of the 95% confidence intervals for the average waiting time for the DSS-generated schedule and the OptQuest generated schedule. The results indicate that the OptQuest-generated schedule reduces the average waiting times by 32.10%, 49.49%, and 48.39% for ESI-3, ESI-4, and ESI-5 patients, respectively. As Figure 4.9 shows, the confidence intervals obtained by two scenarios do not overlap for any of these three patient types, indicating that the OptQuest-generated schedule is statistically better than the DSS-generated schedule in terms of the average waiting time for ESI-3, ESI-4, and ESI-5 patients. For ESI-1 and ESI-2 patients, however, the confidence intervals on average waiting time do overlap. This indicates no statistical difference between the OptQuest-generated and DSS-generated staffing plans in term of the average waiting time for ESI-1 and ESI-2 patients. This conclusion was also validated by using Arena's Output Analyzer to run a paired-t test on the data gathered from the OptQuest and DSS staffing plans. This paired-t test indicated no significant difference between the two scenarios at the 95% confidence level.

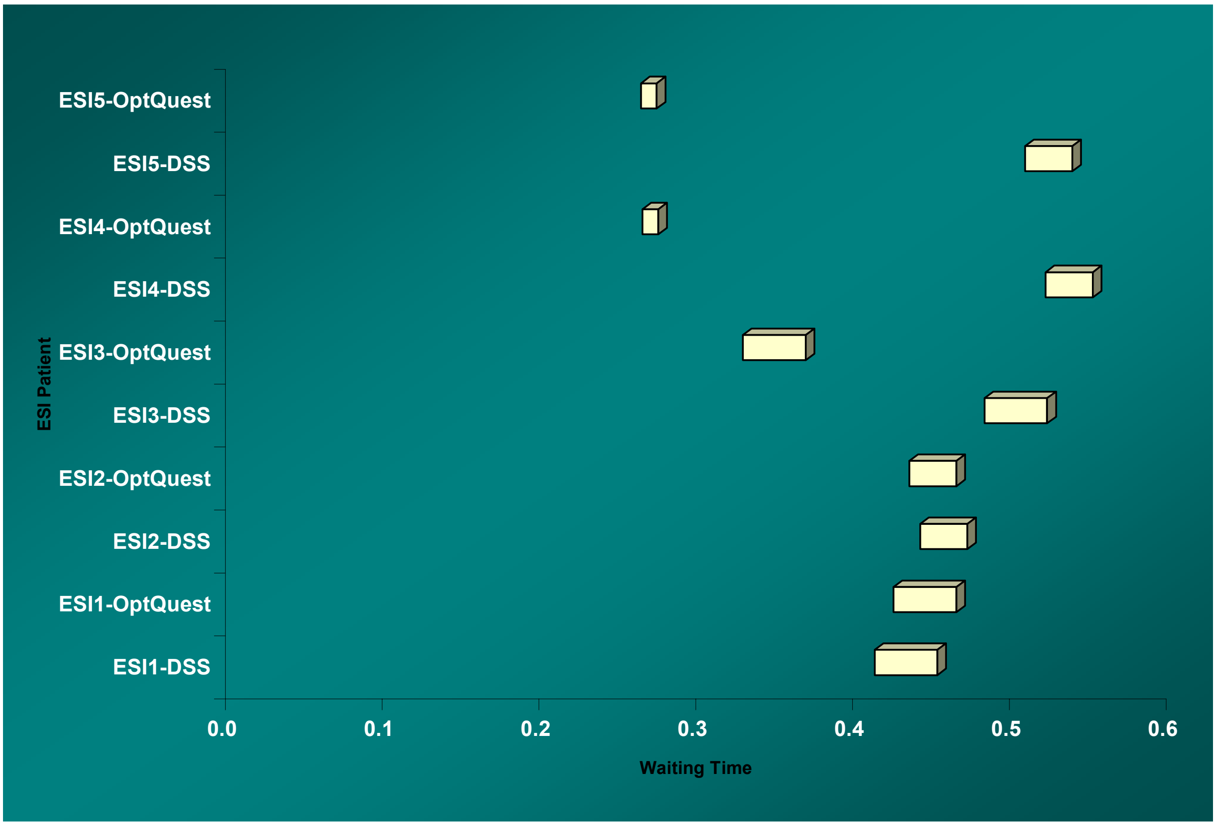


Figure 4.9: 95% Confidence Intervals for Waiting Times in the DSS-Generated and OptQuest-Generated Staffing Plans

4.3 Recommended Scheduling Strategy

Although the nurse staffing plan determined by OptQuest is statistically better than the current staffing plan, it does not show statistically significant improvement in the average waiting time for ESI-1 and ESI-2 patients when compared to the DSS-generated plan. However, the OptQuest-generated staffing plan utilized only 37 nurses, which is two fewer than the current system (as well as the DSS-generated staffing plan). We next chose to analyze the system to see whether this excess nurse capacity could be used elsewhere in the system to eliminate other bottlenecks. By analyzing the output results from the current system, it became apparent that the triage nurse queue became excessively large during the evening shift. Therefore, the suggested nurse staffing plan was obtained by assigning CCU and ICU nurses according to the OptQuest-generated staffing plan and adding one extra triage nurse in the evening shift. The simulation results for this modified schedule were obtained by running twenty replications of the Arena model. Table 4.5 presents a summary of the results obtained from the recommended, DSS-generated, and current staffing plans. This comparison is displayed graphically in Figure 4.10. Figure 4.11 and 4.12 compare the 95% confidence intervals from the recommended staffing plan to those from the current system and DSS-generated plan, respectively.

Table 4.5: Simulation Results from Recommended, DSS-Generated, and Current Staffing Plans

ESI Level	Recommended Staffing Plan		DSS-Generated Staffing Plan		Current Staffing Plan	
	Average Waiting Time (hrs)	Maximum Waiting Time (hrs)	Average Waiting Time (hrs)	Maximum Waiting Time (hrs)	Average Waiting Time (hrs)	Maximum Waiting Time (hrs)
ESI-1	0.33± 0.02	3.79	0.41± 0.04	3.96	0.50± 0.03	4.78
ESI-2	0.35± 0.02	3.81	0.44± 0.03	4.14	0.53± 0.02	4.61
ESI-3	0.29± 0.01	4.22	0.48± 0.04	4.27	0.56± 0.03	4.92
ESI-4	0.27± 0.01	2.45	0.52± 0.03	4.22	0.59± 0.03	4.18
ESI-5	0.27± 0.02	2.76	0.51± 0.03	3.99	0.57± 0.04	4.11

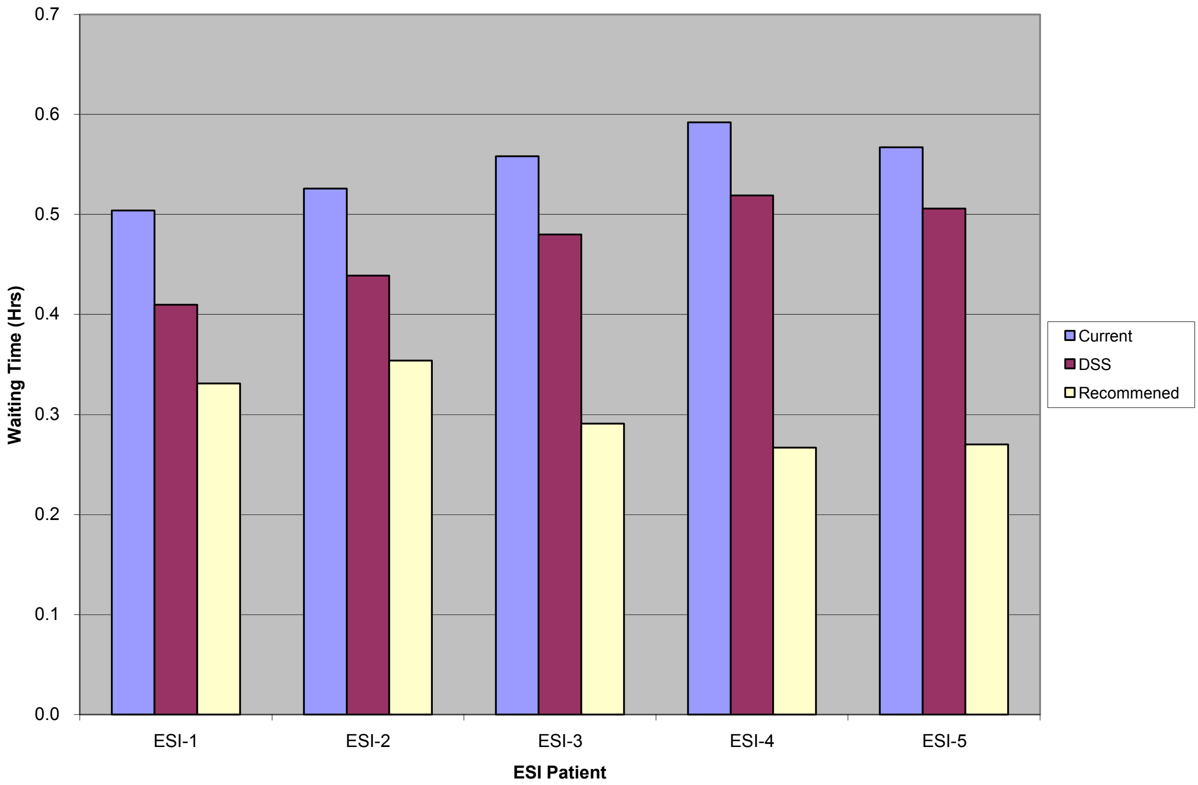


Figure 4.10: Average Waiting Time for the Current, DSS-Generated, and Recommended Staffing Plans

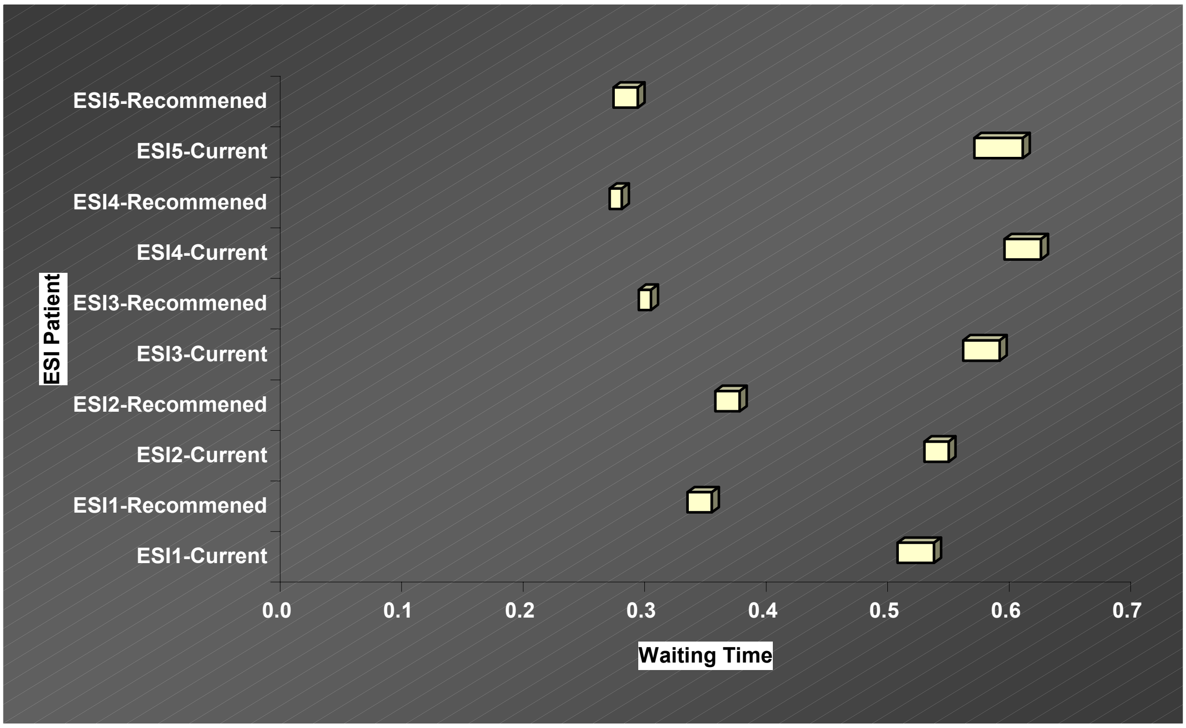


Figure 4.11: 95% Confidence Intervals for Waiting Times in the Current and Recommended Nurse Staffing Plans

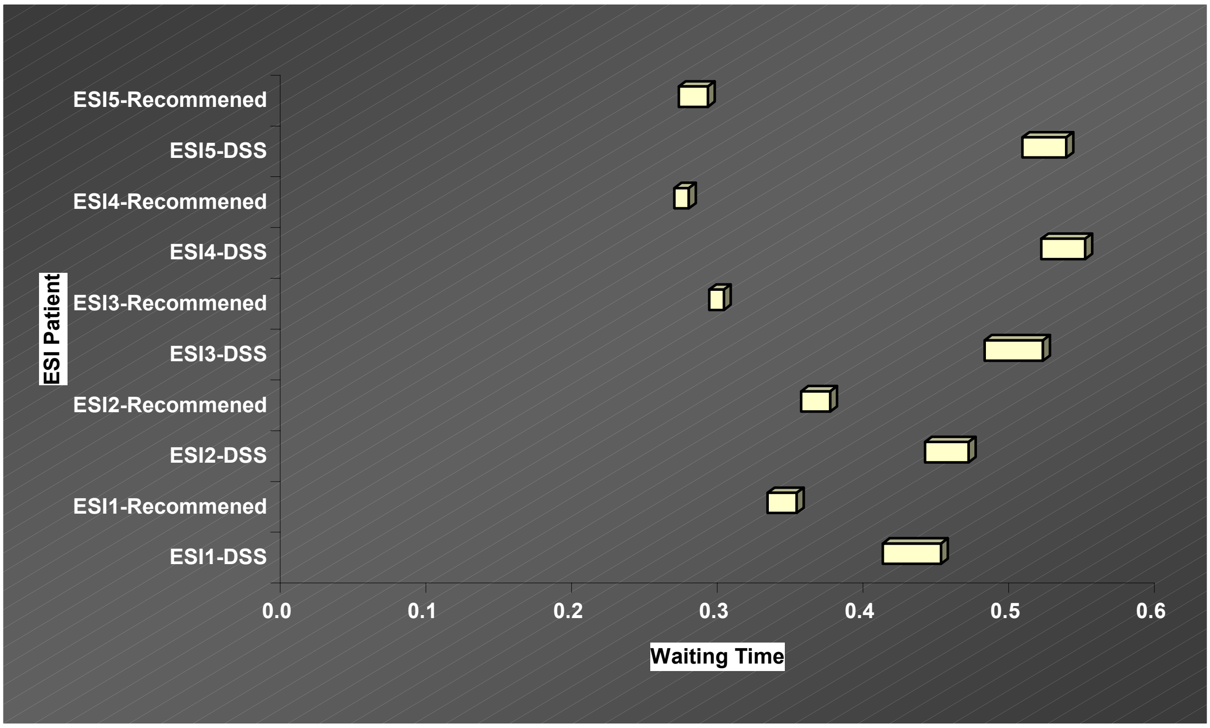


Figure 4.12: 95% Confidence Intervals for Waiting Times in the DSS-Generated and Recommended Nurse Staffing Plans

As originally suspected, the waiting time is significantly decreased by using the recommended nurse staffing plan, with one extra triage nurse on the evening shift, and CCU and ICU nurses assigned by the OptQuest-generated staffing plan. When the results of the recommended staffing plan were compared to those of the current staffing plan, they showed that the suggested staffing plan decreases the average waiting times by 34.33%, 32.73%, 47.87%, 54.92%, and 52.41% for ESI-1, ESI-2, ESI-3, ESI-4, and ESI-5 patients, respectively. The results also show that the proposed nurse staffing plan yields an improvement of more than 33% in the average waiting time for CCU patients and 53% in the average waiting time for ICU patients. Therefore, it is certainly a competitive alternative to the current configuration. Moreover, the average waiting time comparison for all ESI level patients between the suggested and the DSS-generated staffing plan shows that the suggested alternative significantly reduces the waiting time by 19.27%, 19.36%, 39.37%, 48.55%, and 46.64% for ESI-1, ESI-2, ESI-3, ESI-4, and ESI-5 patients, respectively. A paired-t test was also performed to determine whether the recommended plan significantly differed from the DSS plan, and those tests indicated a significant difference at the 95% confidence level across all patient types. The graphical illustration of the confidence intervals in Figure 4.11 and 4.12 also demonstrates statistically significant decreases in average waiting time when the recommended staffing plan is compared to both the current system and the DSS-generated staffing plan. The reduction in patient waiting times when using OptQuest apparently results from the increased flexibility of OptQuest to vary the shift ratios throughout the week in order to better meet patient demands. Additionally, the suggested configuration not only improves the average waiting times in the system for all ESI-level patients, but it also has tighter intervals for all five ESI-level patients, which implies more accurate predictions of the waiting times in the system.

Chapter 5 Conclusions

This thesis has demonstrated how staff scheduling decisions in the Emergency Department at York Hospital can be improved through the use of simulation and optimization. In order to evaluate the impact of nurse scheduling policies on patient waiting times, an Arena simulation model of York Hospital's Emergency Department was developed, validated, and verified based on the information provided by the hospital. In addition, a Decision Support System (DSS) program was implemented using Pascal to provide heuristic solutions for the nurse-scheduling problem. Originally, three specific nurse staffing scenarios were tested with the simulation model, including the current nurse staffing plan, a DSS-generated nurse staffing plan, and an OptQuest-generated staffing plan. For each of these staffing scenarios, the simulation model was run for twenty replications of 35 days, including a seven-day warm-up period, in order to evaluate the effect on the average waiting time for patients in each of the five ESI levels. The output results obtained from this analysis showed that both the DSS-generated and OptQuest-generated nurse staffing plans yielded statistically significant improvements in the patients' waiting time as compared to the current staffing plan. Specifically, the DSS-generated nurse staffing plan decreased the average waiting time from the current system by 18.66%, 16.58%, 14.02%, 12.37%, and 10.80% for ESI-1, ESI-2, ESI-3, ESI-4, and ESI-5 patients, respectively. When the results of the nurse staffing plan provided by OptQuest were compared to those obtained using the DSS approach, the average waiting time was significantly reduced for ESI-3, ESI-4, and ESI-5 patients; however, the OptQuest-generated plan did not show statistically significant improvement (at the 95% confidence level) for ESI-1 and ESI-2 patients.

Since the OptQuest-generated schedule utilized only 37 nurses (a decrease of two nurses from both the current system and the DSS-generated solution), further analysis was conducted to determine whether this excess capacity could be used elsewhere to improve the overall system. After analyzing the output results from the current staffing plan, a bottleneck in the system was observed to occur during the evening shift at the nurse triage station. Therefore, an additional scenario (using the OptQuest-generated schedule and an additional triage nurse for the evening shift) was evaluated. This scenario led to significant improvements in the average waiting times for each of the five ESI levels when compared to both the current system and the DSS-generated schedule. The average waiting times for ESI-1, ESI-2, ESI-3, ESI-4, and ESI-5 patients in this recommended staffing plan were reduced by 34.33%, 32.73%, 47.87%, 54.92%, and 52.41%, respectively, from the current staffing plan. In addition, the recommended staffing plan reduced the average waiting time from the DSS-generated schedule by 19.27%, 19.36%, 39.37%, 48.55%, and 46.64% for ESI-1, ESI-2, ESI-3, ESI-4, and ESI-5 patients, respectively. The average waiting times for each of the four scenarios and each of the five patient levels are summarized below in Figure 5.1. These reductions were found to be statistically significant at the 95% confidence level after conducting paired-t tests of the results. In addition, the confidence intervals obtained from the recommended schedule were tighter than those obtained from the DSS-generated schedule, indicating less variability in the average waiting times associated with the recommended plan.

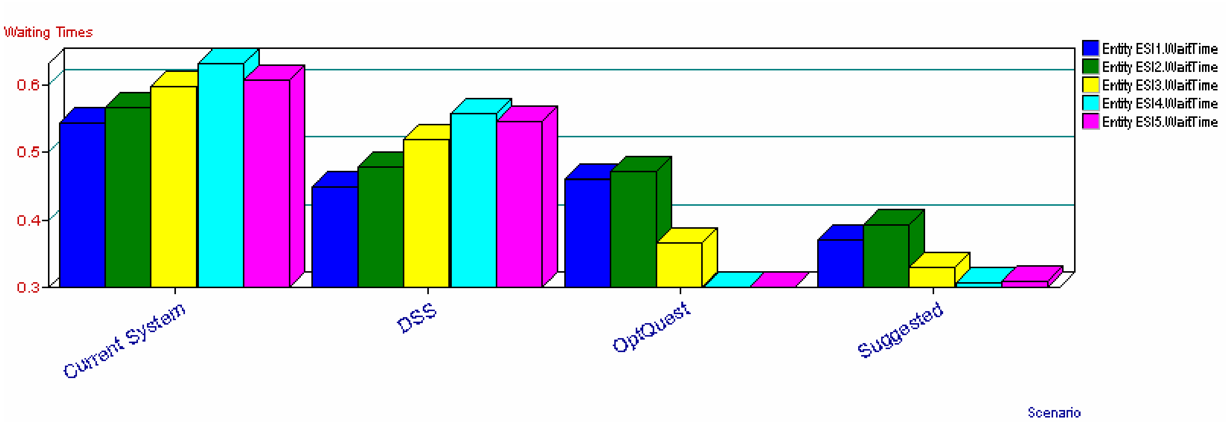


Figure 5.1: Average Waiting Time for Each Scenario and Each Patient Type

In summary, using simulation as an analysis tool in this study allowed the research team to determine an improved nurse staffing plan. Simulation was used to test and evaluate four alternative nurse staffing plans before they were implemented, which prevented the disruption of the department and assisted in identifying effective nurse scheduling policies. The recommended plan uses one less nurse than the current system, providing the hospital with a reduction in employee salaries. At the same time, this staffing plan substantially reduces the average waiting times for all patient types and can therefore lead to significant improvements in the overall operation of the Emergency Department at York Hospital.

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Appendix A

The Working Schedules of All Resources in the Emergency Department at York Hospital

Table A.1: Working Schedules for Upper-Level Residents

ULR No.	Sunday	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday
ULR 1	7AM-5PM	7AM-5PM	Off	7AM-5PM	7AM-5PM	7AM-5PM	7AM-5PM
ULR 2	8AM-6PM	8AM-6PM	12AM-7AM	8AM-6PM	8AM-6PM	8AM-6PM	8AM-6PM
ULR 3	1PM-11PM	1PM-11PM	1PM-11PM	1PM-11PM	1PM-11PM	1PM-11PM	1PM-11PM
ULR 4	4PM-2AM	4PM-2AM	4PM-2AM	4PM-2AM	4PM-2AM	4PM-2AM	4PM-2AM
ULR 5	9PM-7AM	9PM-7AM	9PM-7AM	9PM-7AM	9PM-7AM	9PM-7AM	9PM-7AM

Table A.2: Working Schedules for Lower-Level Residents

LLR No.	Sunday	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday
LLR 1	9PM-7AM	9PM-7AM	9PM-7AM	9PM-7AM	9PM-7AM	9PM-7AM	9PM-7AM
LLR 2	5PM-1AM	5PM-1AM	5PM-1AM	5PM-1AM	5PM-1AM	5PM-1AM	5PM-1AM
LLR 3	1AM-7AM	1AM-7AM	1AM-7AM	1AM-7AM	1AM-7AM	1AM-7AM	1AM-7AM
LLR 4	9AM-5PM	9AM-5PM	9AM-5PM	9AM-5PM	9AM-5PM	9AM-5PM	9AM-5PM

Table A.3: Working Schedules for CCU/ICU Doctors

Dr No.	Sunday	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday
DR 1	12AM-4PM	7AM-4PM	7AM-1PM	11PM-7AM	11PM-7AM	11PM-7AM	11PM-7AM
DR 2	9AM-5PM	9AM-5PM	7AM-4PM	7AM-4PM	7AM-4PM	7AM-4PM	7AM-4PM
DR 3	1PM-10PM	1PM-10PM	9AM-5PM	9AM-5PM	9AM-5PM	9AM-5PM	9AM-5PM
DR 4	4PM-1AM	4PM-1AM	1PM-10PM	1PM-10PM	1PM-10PM	1PM-10PM	1PM-10PM
DR 5	5PM-1AM	5PM-2AM	4PM-2AM	4PM-1AM	4PM-1AM	4PM-1AM	4PM-1AM
DR 6	11PM-2AM	11PM-7AM	5PM-7AM	5PM-2AM	5PM-2AM	5PM-2AM	5PM-2AM

Table A.4: Working Schedule for Physician Extender (PE)

PE No.	Sunday	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday
PE 1	Off	Off	Off	Off	11AM-11PM	11AM-11PM	Off

Table A.5: Working Schedule for AC Doctor

AC DR No.	Sunday	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday
AC DR 1	Off	11AM-11PM	11AM-11PM	11AM-11PM	Off	Off	Off

Table A.6: Working Schedule for AC Technician

AC Tech No.	Sunday	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday
AC Tech 1	Off	11AM-11PM	11AM-11PM	11AM-11PM	11AM-11PM	Off	Off

Table A.7: Working Schedules for AC Nurse

Nurse No.	Sunday	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday
Nurse 1	Off	11AM-11PM	11AM-11PM	11AM-11PM	11AM-11PM	11AM-11PM	Off

Table A.8: Number of Full-Time Nurses Working Each Shift in Triage, ICU, and CCU **

Shift	Number of Triage Nurses	Number of CCU Nurses	Number of ICU Nurses
7:00AM-3:00PM	1	4	3
3:00PM-11:00PM	1	6	6
11:00PM-7:00AM	1	5	4

Table A.9: Number of Part-Time Nurses Working Each Shift in ICU and CCU **

Shift	Number of CCU Nurses	Number of ICU Nurses
11:00AM-3:00PM	2	2
11:00PM-3:00AM	1	1

** Note that this staffing pattern is constant throughout the week.

Appendix B

The Recommended Nurse Staffing Plan of the DSS and the OptQuest Approaches

Table B.1: The DSS-Generated Nurse Staffing Plan

Nurse No.	Day																											
	M	T	W	T	F	S	S	M	T	W	T	F	S	S	M	T	W	T	F	S	S	M	T	W	T	F	S	S
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28
1	D-I	D-I	D-I	D-I	D-I	O	O	D-C	D-C	D-C	D-C	D-C	O	O	O	D-I	D-I	D-I	D-I	D-I	O	O	D-C	D-C	O	D-C	D-C	D-C
2	D-I	D-I	D-I	O	O	D-I	D-I	D-C	D-C	O	O	D-C	D-C	D-C	E-I	E-I	E-I	E-I	O	O	E-I	D-C	D-C	D-C	O	D-C	D-C	O
3	N-I	N-I	N-I	N-I	O	O	N-I	E-C	O	E-C	E-C	O	E-C	E-C	O	D-I	D-I	D-I	D-I	D-I	O	O	E-I	E-I	E-I	E-I	O	E-I
4	E-I	E-I	E-I	E-I	E-I	O	O	D-I	O	D-I	D-I	D-I	D-I	O	O	D-C	D-C	D-C	D-C	D-C	O	D-I	D-I	D-I	D-I	O	O	D-I
5	E-I	E-I	O	O	E-I	E-I	E-I	O	N-I	N-I	N-I	O	N-I	N-I	O	N-I	N-I	N-I	N-I	N-I	O	E-I	E-I	O	E-I	E-I	E-I	O
6	N-I	N-I	N-I	O	O	N-I	N-I	O	E-I	E-I	O	E-I	E-I	E-I	D-I	D-I	D-I	D-I	O	O	D-I	E-I	E-I	E-I	O	E-I	E-I	O
7	N-C	N-C	N-C	N-C	N-C	O	O	O	E-I	E-I	E-I	O	E-I	E-I	N-I	N-I	O	O	N-I	N-I	N-I	O	E-C	E-C	E-C	O	E-C	E-C
8	N-C	C-C	C-C	O	O	N-C	N-C	E-I	E-I	E-I	E-I	O	O	E-I	E-I	E-I	E-I	O	O	E-I	E-I	N-C	O	N-C	N-C	N-C	O	N-C
9	O	D-I	D-I	D-I	D-I	D-I	O	D-C	D-C	D-C	D-C	O	O	D-C	O	N-C	N-C	N-C	N-C	N-C	O	D-C	D-C	O	D-C	D-C	D-C	O
10	N-I	N-I	N-I	N-I	O	O	N-I	E-I	O	O	E-I	E-I	E-I	E-I	N-I	N-I	N-I	O	O	N-I	N-I	E-I	O	E-I	E-I	O	E-I	E-I
11	D-C	D-C	O	O	D-C	D-C	D-C	E-I	O	O	E-I	E-I	E-I	E-I	N-C	N-C	N-C	N-C	O	O	N-C	N-C	O	N-C	N-C	N-C	O	N-C
12	N-I	N-I	O	O	N-I	N-I	N-I	O	E-I	E-I	E-I	E-I	O	E-I	E-C	E-C	E-C	E-C	E-C	O	O	O	N-C	O	N-C	N-C	N-C	N-C
13	N-I	N-I	N-I	N-I	O	O	N-I	O	O	E-I	E-I	E-I	E-I	E-I	D-I	D-I	D-I	D-I	O	O	D-I	D-C	O	D-C	D-C	O	D-C	D-C
14	N-I	N-I	N-I	N-I	O	O	N-I	N-I	N-I	O	N-I	N-I	O	N-I	E-I	E-I	E-I	E-I	O	O	E-I	E-I	E-I	E-I	E-I	O	O	E-I
15	O	D-C	D-C	D-C	D-C	D-C	O	N-I	N-I	N-I	O	N-I	O	N-I	N-C	N-C	N-C	N-C	O	O	N-C	D-I	O	O	D-I	D-I	D-I	D-I
16	D-C	D-C	O	O	D-C	D-C	D-C	E-C	O	E-C	E-C	E-C	E-C	O	E-C	E-C	E-C	O	O	E-C	E-C	O	D-I	D-I	D-I	D-I	D-I	O
17	E-I	E-I	O	O	E-I	E-I	E-I	O	N-I	N-I	N-I	N-I	N-I	O	N-I	N-I	N-I	N-I	N-I	O	O	E-C	E-C	E-C	E-C	E-C	O	O
18	N-C	N-C	N-C	O	O	N-C	N-C	E-I	E-I	O	O	E-I	E-I	E-I	O	N-C	N-C	N-C	N-C	N-C	O	E-C	O	O	E-C	E-C	E-C	E-C

Nurse No.	Day																											
	M	**T**	**W**	**T**	**F**	**S**	**S**	**M**	**T**	**W**	**T**	**F**	**S**	**S**	**M**	**T**	**W**	**T**	**F**	**S**	**S**	**M**	**T**	**W**	**T**	**F**	**S**	**S**
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**	**27**	**28**
19	N-C	N-C	N-C	O	O	N-C	N-C	O	O	N-I	N-I	N-I	N-I	N-I	E-I	E-I	E-I	E-I	E-I	O	O	D-I	O	O	D-I	D-I	D-I	D-I
20	D-C	D-C	D-C	O	O	D-C	D-C	D-I	D-I	D-I	O	O	D-I	D-I	D-C	D-C	D-C	D-C	D-C	O	O	D-C	O	O	D-C	D-C	D-C	D-C
21	E-C	E-C	E-C	E-C	O	O	E-C	N-C	N-C	N-C	O	N-C	N-C	O	O	D-C	D-C	D-C	D-C	D-C	O	N-I	O	O	N-I	N-I	N-I	N-I
22	O	N-I	N-I	N-I	N-I	N-I	O	D-I	O	O	D-I	D-I	D-I	D-I	N-I	N-I	N-I	N-I	O	O	N-I	E-I	E-I	E-I	E-I	E-I	E-I	O
23	E-C	E-C	O	O	E-C	E-C	E-C	E-I	E-I	O	O	E-I	E-I	E-I	N-I	N-I	N-I	N-I	N-I	O	O	D-I	D-I	D-I	O	D-I	D-I	O
24	E-C	E-C	E-C	O	O	E-C	E-C	O	E-C	E-C	E-C	E-C	O	E-C	N-I	N-I	N-I	N-I	N-I	O	O	N-I	N-I	N-I	O	N-I	N-I	O
25	D-I	D-I	D-I	D-I	O	O	D-I	E-C	E-C	E-C	O	E-C	E-C	O	N-C	N-C	N-C	O	O	N-C	N-C	E-I	E-I	E-I	O	O	E-I	E-I
26	O	E-I	E-I	E-I	E-I	E-I	O	O	O	D-C	D-C	D-C	D-C	D-C	N-C	N-C	N-C	N-C	N-C	O	O	O	E-C	E-C	E-C	E-C	E-C	O
27	O	E-C	E-C	E-C	E-C	E-C	O	N-C	N-C	N-C	N-C	N-C	O	O	N-C	N-C	N-C	N-C	N-C	O	O	E-C	E-C	O	E-C	E-C	O	E-C
28	E-C	E-C	E-C	E-C	E-C	O	O	N-C	N-C	N-C	N-C	O	O	N-C	N-C	N-C	O	O	N-C	N-C	N-C	O	E-C	E-C	E-C	E-C	E-C	O
29	O	N-C	N-C	N-C	N-C	N-C	O	E-C	E-C	O	E-C	E-C	E-C	E-C	E-C	E-C	E-C	E-C	O	O	E-C	N-C	N-C	N-C	O	O	N-C	N-C
30	D-C	D-C	D-C	D-C	D-C	O	O	O	N-C	N-C	O	N-C	N-C	N-C	O	N-C	N-C	N-C	N-C	N-C	O	O	E-C	E-C	E-C	E-C	E-C	O
31	N-C	N-C	N-C	N-C	N-C	O	O	D-I	D-I	O	O	D-I	D-I	D-I	D-C	D-C	D-C	D-C	O	O	D-C	E-C	E-C	O	E-C	E-C	O	E-C
32	N-C	N-C	O	O	N-C	N-C	N-C	O	E-C	E-C	E-C	O	E-C	E-C	O	E-I	E-I	E-I	E-I	E-I	O	O	O	N-I	N-I	N-I	N-I	N-I
33	E-C	E-C	O	O	E-C	E-C	E-C	O	N-C	N-C	N-C	O	N-C	N-C	O	N-C	N-C	N-C	N-C	N-C	O	E-C	E-C	O	O	E-C	E-C	E-C
34	D-C	D-C	D-C	D-C	O	O	D-C	O	E-C	E-C	E-C	E-C	O	E-C	O	E-C	E-C	E-C	E-C	E-C	O	D-C	D-C	D-C	O	O	D-C	D-C
35	E-I	E-I	E-I	E-I	E-I	O	O	E-C	E-C	E-C	O	E-C	E-C	O	E-C	E-C	E-C	E-C	E-C	O	O	E-I	E-I	E-I	E-I	E-I	O	O
36	D-I	D-I	O	O	D-I	D-I	D-I	O	O	N-C	N-C	N-C	N-C	N-C	N-C	N-C	N-C	O	O	N-C	N-C	E-C	E-C	E-C	O	O	E-C	E-C
37	O	E-I	E-I	E-I	E-I	E-I	O	N-I	N-I	O	O	N-I	N-I	N-I	E-C	E-C	O	O	E-C	E-C	E-C	N-C	N-C	O	N-C	N-C	O	N-C
38	N-C	N-C	N-C	O	O	N-C	N-C	E-C	E-C	O	E-C	E-C	O	E-C	D-C	D-C	O	O	D-C	D-C	D-C	E-I	E-I	O	E-I	E-I	O	E-I
39	N-I	N-I	N-I	O	O	N-I	N-I	E-I	E-I	E-I	O	O	E-I	E-I	N-I	N-I	O	O	N-I	N-I	N-I	E-I	E-I	O	E-I	E-I	O	E-I

Table B.2: The Nurse Staffing Plan Determined by OptQuest

Nurse No.	Day																											
	M	**T**	**W**	**T**	**F**	**S**	**S**	**M**	**T**	**W**	**T**	**F**	**S**	**S**	**M**	**T**	**W**	**T**	**F**	**S**	**S**	**M**	**T**	**W**	**T**	**F**	**S**	**S**
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**	**27**	**28**
1	D-C	D-C	O	O	D-C	D-C	D-C	E-C	O	E-C	E-C	E-C	E-C	O	E-C	E-C	E-C	O	O	E-C	E-C	O	D-C	D-C	D-C	D-C	D-C	O
2	N-C	N-C	N-C	O	O	N-C	N-C	E-C	E-C	O	E-C	E-C	O	E-C	D-C	D-C	O	O	D-C	D-C	D-C	E-C	E-C	O	E-C	E-C	O	E-C
3	E-C	E-C	O	O	E-C	E-C	E-C	O	N-C	N-C	N-C	N-C	N-C	O	N-C	N-C	N-C	N-C	N-C	O	O	E-C	E-C	E-C	E-C	O	E-C	O
4	N-C	N-C	N-C	N-C	D-C	O	N-C	O	O	E-C	E-C	E-C	E-C	E-C	D-C	D-C	D-C	D-C	O	O	D-C	D-C	O	D-C	D-C	O	D-C	D-C
5	E-C	E-C	O	O	E-C	E-C	E-C	O	N-C	N-C	N-C	N-C	N-C	O	N-C	N-C	N-C	N-C	N-C	O	O	E-C	E-C	E-C	E-C	O	E-C	O
6	N-C	N-C	N-C	O	O	N-C	N-C	E-C	E-C	O	O	E-C	E-C	E-C	O	N-C	N-C	N-C	N-C	N-C	O	E-C	O	O	E-C	E-C	E-C	E-C
7	D-C	D-C	D-C	O	O	D-C	D-C	D-C	D-C	D-C	O	O	D-C	D-C	D-C	D-C	D-C	D-C	D-C	O	O	D-C	O	O	D-C	D-C	D-C	D-C
8	D-C	D-C	D-C	O	O	D-C	D-C	D-C	D-C	D-C	O	O	D-C	D-C	D-C	D-C	D-C	D-C	D-C	O	O	D-C	O	O	D-C	D-C	D-C	D-C
9	E-C	E-C	E-C	E-C	E-C	O	O	N-C	N-C	N-C	N-C	O	O	N-C	N-C	N-C	O	O	N-C	N-C	N-C	O	E-C	E-C	E-C	E-C	E-C	O
10	E-C	E-C	E-C	E-C	E-C	O	O	N-C	N-C	N-C	N-C	O	O	N-C	N-C	N-C	O	O	N-C	N-C	N-C	O	E-C	E-C	E-C	E-C	E-C	O
11	E-C	E-C	O	O	E-C	E-C	E-C	O	N-C	N-C	N-C	N-C	N-C	O	N-C	N-C	N-C	N-C	N-C	O	O	E-C	E-C	E-C	E-C	O	E-C	O
12	O	N-C	N-C	N-C	N-C	N-C	O	E-C	O	O	E-C	E-C	E-C	E-C	E-C	E-C	E-C	E-C	O	O	E-C	N-C	N-C	N-C	O	O	N-C	N-C
13	N-C	N-C	N-C	O	O	N-C	N-C	O	E-C	E-C	E-C	O	E-C	E-C	E-C	E-C	E-C	E-C	E-C	O	O	N-C	N-C	N-C	N-C	O	O	N-C
14	D-I	D-I	D-I	O	O	D-I	D-I	O	O	N-I	N-I	N-I	N-I	N-I	E-I	E-I	E-I	O	O	E-I	E-I	O	E-I	E-I	O	E-I	E-I	E-I
15	N-I	N-I	N-I	N-I	N-I	O	O	D-I	D-I	O	D-I	D-I	O	D-I	E-I	E-I	O	O	E-I	E-I	E-I	O	D-I	D-I	O	D-I	D-I	D-I
16	N-I	N-I	N-I	N-I	N-I	O	O	D-I	D-I	O	D-I	D-I	O	D-I	E-I	E-I	O	O	E-I	E-I	E-I	O	D-I	D-I	O	D-I	D-I	D-I
17	O	E-I	E-I	E-I	E-I	E-I	O	D-I	D-I	O	D-I	D-I	D-I	O	E-I	E-I	E-I	E-I	O	O	E-I	N-I	N-I	N-I	N-I	N-I	O	O
18	N-I	N-I	N-I	N-I	N-I	O	O	E-I	E-I	E-I	O	E-I	O	E-I	O	D-I	D-I	D-I	D-I	D-I	O	E-I	O	O	E-I	E-I	E-I	E-I
19	E-I	E-I	E-I	O	O	E-I	E-I	D-I	D-I	D-I	D-I	O	O	D-I	D-I	D-I	D-I	O	O	D-I	D-I	D-I	O	O	D-I	D-I	D-I	D-I
20	D-I	D-I	D-I	D-I	O	O	D-I	N-I	N-I	O	N-I	N-I	O	N-I	O	E-I	E-I	E-I	E-I	E-I	O	O	D-I	D-I	D-I	D-I	D-I	O

Nurse No.	Day																											
	M	T	W	T	F	S	S	M	T	W	T	F	S	S	M	T	W	T	F	S	S	M	T	W	T	F	S	S
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28
21	O	E-I	E-I	E-I	E-I	E-I	O	O	O	N-I	N-I	N-I	N-I	N-I	E-I	E-I	O	O	E-I	E-I	E-I	O	N-I	N-I	N-I	N-I	N-I	O
22	D-I	D-I	D-I	O	O	D-I	D-I	E-I	E-I	O	E-I	E-I	O	E-I	E-I	E-I	E-I	E-I	E-I	O	O	D-I	D-I	O	D-I	D-I	O	D-I
23	N-I	N-I	N-I	N-I	O	O	N-I	E-I	O	E-I	E-I	O	E-I	E-I	O	D-I	D-I	D-I	D-I	D-I	O	O	E-I	E-I	E-I	E-I	O	E-I
24	N-I	N-I	N-I	O	O	N-I	N-I	O	E-I	E-I	E-I	O	E-I	E-I	E-I	E-I	E-I	E-I	E-I	O	O	N-I	N-I	N-I	N-I	O	O	N-I
25	N-I	N-I	N-I	O	O	N-I	N-I	O	E-I	E-I	E-I	O	E-I	E-I	E-I	E-I	E-I	E-I	E-I	O	O	N-I	N-I	N-I	N-I	O	O	N-I
26	N-I	N-I	N-I	N-I	O	O	N-I	E-I	E-I	E-I	O	E-I	E-I	O	E-I	E-I	E-I	E-I	E-I	O	O	N-I	N-I	N-I	N-I	O	N-I	O
27	N-I	N-I	N-I	N-I	O	O	N-I	D-I	D-I	D-I	O	O	D-I	D-I	E-I	E-I	E-I	E-I	E-I	O	O	D-I	O	D-I	D-I	D-I	O	D-I
28	N-I	N-I	N-I	N-I	O	O	N-I	N-I	N-I	N-I	O	N-I	O	N-I	E-I	E-I	E-I	E-I	O	O	E-I	O	D-I	D-I	D-I	D-I	D-I	O
29	E-I	E-I	E-I	E-I	O	O	E-I	D-I	D-I	D-I	D-I	O	D-I	O	N-I	N-I	N-I	N-I	O	O	N-I	E-I	O	E-I	E-I	E-I	O	E-I
30	N-I	N-I	N-I	N-I	N-I	O	O	E-I	E-I	O	E-I	O	E-I	E-I	N-I	N-I	O	O	N-I	N-I	N-I	O	E-I	E-I	O	E-I	E-I	E-I
31	N-I	N-I	N-I	N-I	N-I	O	O	E-I	E-I	O	E-I	O	E-I	E-I	N-I	N-I	O	O	N-I	N-I	N-I	O	E-I	E-I	O	E-I	E-I	E-I
32	E-I	E-I	E-I	O	O	E-I	E-I	O	N-I	N-I	O	N-I	N-I	N-I	E-I	E-I	E-I	E-I	O	O	E-I	N-I	N-I	N-I	O	N-I	N-I	O
33	E-I	E-I	E-I	E-I	E-I	O	O	D-I	O	D-I	D-I	D-I	D-I	O	O	D-I	D-I	D-I	D-I	D-I	O	D-I	D-I	D-I	D-I	O	O	D-I
34	E-I	E-I	O	O	E-I	E-I	E-I	O	N-I	N-I	N-I	O	N-I	N-I	O	N-I	N-I	N-I	N-I	N-I	O	E-I	E-I	O	E-I	E-I	E-I	O
35	N-I	N-I	N-I	O	O	N-I	N-I	O	E-I	E-I	O	E-I	E-I	E-I	D-I	D-I	D-I	D-I	O	O	D-I	E-I	E-I	E-I	E-I	O	O	E-I
36	N-I	N-I	N-I	N-I	N-I	O	O	O	E-I	E-I	E-I	O	E-I	E-I	N-I	N-I	O	O	N-I	N-I	N-I	O	E-I	E-I	E-I	O	E-I	E-I
37	D-I	D-I	D-I	D-I	D-I	O	O	E-I	E-I	E-I	E-I	O	E-I	O	N-I	N-I	O	O	N-I	N-I	N-I	O	N-I	N-I	N-I	N-I	N-I	O

** D, E, and N represent the Day, Evening, and Night shift, respectively.
** I and C represent the ICU and CCU, respectively.
** O represents a day off.

Vita

Lisa Patvivatsiri was born in Bangkok, Thailand, on September 26, 1978. She earned a Bachelor of Engineering degree in Industrial Engineering from Chulalongkorn University, Bangkok, Thailand, in 2000. As a requirement in the third year of college, she had a distinguished opportunity to integrate classroom learning with real world experience in Hiraiseimitsu (Thailand) Co., LTD., plastic injection industry, as a production engineering intern. In my senior year, she also worked part-time as project assistance for her advisor in Industrial Engineering department. Her main responsibility was as a quality assurance auditor who studied the manufacturing processes and completely audited the production processes to meet the requirements of ISO 9002:1994 standard. After completing her bachelor of Engineering, she worked as an Industrial Engineering Consultant at NOVO Quality Services (Thailand) Co., Ltd. Here, most clients were progressive organizations across a wide spectrum of many industries, from which she gradually gathered the knowledge and experience of manufacturing systems.

In the Fall of 2001 Lisa enrolled at Virginia Polytechnic Institute and State University (Virginia Tech) in pursuit of a Master of Science degree, specializing in Operations Research in the Department of Industrial and Systems Engineering. She completed her studies under the guidance of Dr. Fraticelli and Dr. Koelling and obtained her M.S. in the summer of 2003. Upon graduation from Virginia Tech, she has been admitted into the Department of Industrial Engineering at Texas Tech University in pursuit of a Doctor of Philosophy degree.