The Pennsylvania State University
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Department of Industrial Engineering

USING DISCRETE-EVENT SIMULATION TO IMPROVE
PATIENT FLOW IN AN EMERGENCY DEPARTMENT

A Thesis in
Industrial Engineering and Operations Research

by

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ABSTRACT

U.S. hospital emergency departments are experiencing a crisis: overall capacity is decreasing while patient demands are increasing (IOM, 2007). Thus physician-directed queuing (PDQ) is an approach to improving process flow in the emergency department (ED). PDQ places a physician at triage. The physician listens to every triage nurse evaluation and makes some initial care recommendations. The physician will immediately treat and discharge patients who do not require the full resources of the ED. PDQ reduces waiting time for those patients who are not experiencing severe illness or injury, and reserves ED capacity for more serious cases.

In this thesis, simulation is used to model the PDQ process at the Hershey Medical Center (HMC) ED. The simulation is used to understand current state conditions, predict performance under varying patient demand, and evaluate resource requirements. Model results are similar to actual system performance over a three-month trial of the PDQ process at HMC.

Results show that a single physician at PDQ is insufficient to meet current demand levels using the proposed process flow. An additional two hours of physician time per day is required. Two alternatives for providing the additional capacity are compared.
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Chapter 1
INTRODUCTION

1.1 Motivation

The motivation for this research stems from a national effort in the healthcare community to address many of the issues affecting emergency care in the United States. The current literature published by the Institute of Medicine since 2003 indicate that the nation’s emergency medical system is in a state of crisis (IOM, 2007). The problems at our nations emergency departments (EDs) include crowding, patient boarding, ambulance diversion, and an increasing level of patients who leave without being seen (IOM, 2007). Patient boarding occurs when hospitals admit ED patients and there are no in-patient beds available. The admitted patients remain in the ED where they occupy a treatment room or are left in a hallway until an inpatient bed is available. Ambulance diversion is a status that hospitals enter when they cannot safely handle any additional patients. The hospital will divert incoming ambulances to other area hospitals.

The Pennsylvania State University’s Hershey Medical Center (HMC) is an example of a hospital whose ED is dealing with many of these problems, and this research looks at a new concept called “physician-directed queuing” and its application to the ED. The research is in direct response to the Institute of Medicine’s charge to hospital administrators to look for ways to improve patient flow (IOM, 2007).
1.2 Scope

The purpose of this thesis is to use simulation to gain an understanding of how both internal and external factors affect the process flow in physician-directed queuing at the Hershey Medical Center. The simulation will be used to identify bottlenecks in the system and to explore potential methods to mitigate these bottlenecks. The physician-directed queuing (PDQ) concept is being developed jointly by the Hershey Medical Center’s Emergency Department (ED) and the Penn State Industrial and Manufacturing Engineering Department as a way to modernize emergency department process flow and change the way the Hershey Medical Center conducts its emergency department operations.

PDQ is an innovative method that redefines patient flow through the emergency department. The physician listens as the nurse conducts a triage evaluation, selects patients who do not require complex diagnostics or therapeutics, and treats them in an adjacent treatment area. All other patients are processed through to the main ED. Through the use of a real-time automated patient database, the PDQ physician becomes aware of patient delays and resource utilization in the main ED. When all treatment rooms are at capacity, the PDQ physician will initiate complex diagnostics or therapeutics on patients who require a main ED treatment room. This physician intervention at triage saves valuable time in the patient care process.
1.3 Research Objectives

There are three research objectives for this thesis. The first is to identify bottlenecks in the PDQ process. The second is to analyze the effect of changes in patient demand on system performance. The third is to compare alternative methods to improve system performance.

1.4 Organization

The remainder of this thesis is organized into four chapters. Chapter Two contains a detailed literature review of the issues surrounding emergency department congestion and the need for process flow improvement. Additionally, there is a review of the current research in the field of process flow improvements, including prior simulation studies and analytical methods used to evaluate and improve ED process flow. Chapter Three contains a detailed description of the actual PDQ process as implemented by the staff at the Hershey Medical Center. Following the discussion of the PDQ is a detailed overview of the simulation model used to replicate PDQ. The performance measures, model assumptions, and model validation are also discussed. Chapter Four presents the results of the simulation model and a discussion of methods to improve process flow in a PDQ. The final Chapter Five contains the conclusions of the research and suggests areas of future work.
Chapter 2
LITERATURE REVIEW

2.1 Introduction

Emergency departments play a critical role in the safety and well-being of most people in the United States. Open 24 hours a day, the emergency department (ED) is where many Americans get life-saving medical care. It is also many people’s introduction to the hospital. Unfortunately, crowding in the nation’s EDs is a serious epidemic that compromises the quality of care (especially urgent and lifesaving care) that hospitals provide to the citizens they serve. In this chapter, I discuss several areas surrounding emergency department operations. The first area covers the causes and effects of ED congestion. The second area covers some innovative methods that hospitals have implemented to reduce crowding and improve patient flow. The third area covers some modeling approaches or methods used to understand the problem.

2.2 Emergency Department Patient Flow

2.2.1 ED Congestion

In 2002 the American College of Emergency Physicians (ACEP) Crowding Resources Task Force defined ED crowding as “a situation in which the identified need for emergency services outstrips available resources in the ED” (ACEP, 2002). Fatovich
(2002) concludes that crowding is the biggest problem facing EDs in the developed world. Crowding can reduce the quality of care administered in the emergency department, as medical providers are forced to handle more patients with fewer resources (Jenkins et al., 2006). Overworked medical providers are more likely to make errors and overlook serious conditions, which lead to an increase in patient pain and suffering. In the United States, ED crowding is a major problem that affects both rural and urban areas alike. The Institute of Medicine stated that in a recent national survey of hospital EDs, almost 40% of the hospitals that participated reported daily crowding conditions (IOM, 2007). Crowding is the result of many factors that have been on the rise in recent years. Among those factors is an increase in annual patient demand for ED services, along with a significant reduction in the number of EDs and hospital beds nationally (IOM, 2007).

### 2.2.1.1 Causes of ED crowding

Among the numerous causes of ED crowding are a sharp rise in the number of both urgent and non-urgent patient arrivals, a shortage of treatment rooms, a shortage of bed space in the main hospital for admitted patients, an increase in the number of ED visits nationally, delays in the radiology and laboratory departments, and a decrease in the number of EDs in the nation (IOM, 2007). In theory crowding in the ED is a supply versus demand problem. Patient arrivals (the demand) overcome the EDs resources, namely beds, doctors, and nurses. On a macro scale this supply versus demand theory is summarized in the 2007 IOM report, “Hospital-Based Emergency Care.” The IOM reported that between 1993 and 2003, the number of hospital admissions increased by 13
percent as compared to an increase in the US population of 12 percent. Also during that same period, ED visits rose by 26 percent or roughly 2 million a year. This sharp rise in patient arrivals was further exacerbated by a total US loss of 198,000 beds in 703 hospitals due to the closure of 425 emergency departments nationwide (IOM, 2007).

Uninsured, underinsured, and Medicaid patients are also contributing to the crowding due to the financial burden of primary care. Unlike private practice and community health centers, emergency care facilities are federally mandated to accept all patients regardless of ability to pay (IOM, 2007). Although legally bound to accept all patients, hospitals are often not compensated for uninsured or underinsured patients (IOM, 2007). EDs must then do their best to absorb those patients and the mounting costs that accompany them.

Several years ago it was estimated that there were over 45 million uninsured people in the United States who use the ED as their sole alternative to receiving medical care; that number was expected to exceed 50 million by 2006 (IOM, 2007). In addition to the uninsured population, the underinsured population is also on the rise and was estimated by some to be near 30 million (IOM, 2007). In terms of non-urgent or semi-urgent care, the underinsured are as likely to visit an ED as the uninsured. Medicaid patients are insured patients; however, the rate of reimbursement is so low that the number of providers who will accept to treat them is low (IOM, 2007). Therefore, Medicaid patients have limited access to non-ED care and often find themselves with no option but to go to the ED.

Widely accepted as the most significant or major contributor to crowding is patient boarding in the ED (Fatovich, 2002; Fatovich and Hirsch, 2003; Asplin, Brent R.
Patient boarding is the bottleneck that occurs when ED patients are admitted to the hospital but remain in the ED. Fatovich and Hirsch (2003) define this condition as exit block or access block. In a busy hospital, patients admitted to the hospital via the ED may board for 24 or even 48 hours (IOM, 2007). But since boarders must have a serious enough condition, they are likely to require the highest level of care even when they are boarding. This additional requirement of care for boarders will further stretch the ED staff as it continues to provide emergency care for newly arriving patients.

Unfortunately, many of the causes of ED crowding are outside the control of the ED and in some cases the hospitals themselves (Patel and Vinson, 2005; Cowan and Trzeciak, 2005; IOM, 2007). The ED is just one department in the hospital and it must rely on other departments such as radiology, the laboratory, and all the inpatient wards for support. Until many of the primary causes of hospital crowding are resolved and until hospitals address the problem of patient flow in the ED in terms of the hospitals at large and not just in terms of the ED, EDs are going to have to rely upon their own resources to help mitigate crowding, decrease average patient length of stay, and increase patient satisfaction.

2.2.1.2 Effects of Crowding

The effects of crowded EDs are as numerous as the causes. Symptoms of an overcrowded ED are usually higher ambulance diversions and higher numbers of patients who left without being seen (Fatovich and Hirsch, 2003). Ambulance diversion occurs
when a hospital has no resources available to receive new ambulance patients and would therefore divert incoming ambulance patients to neighboring EDs. Consequently, patient satisfaction decreases as the number of patients awaiting care increases along with the average wait time and since patient borders take up a growing number of ED beds, providers often have to treat patients in the hallway or in any space that would hold a mobile bed or a wheelchair (Asplin et al, 2003; Cowan and Trzeciak, 2005; Patel and Vinson, 2005).

Another side effect of ED crowding is the high potential for medical error. Cowan and Trzeciak (2005) state that an overcrowded ED can compromise patient safety especially in regards to critically ill patients. The lack of inpatient beds forces the ED to board critically ill patients; however, the ED is not organized to provide continual and intensive care to severely ill patients. Cowan and Trzeciak (2005) further explain that traditional ED nurse-to-patient ratios do not allow for the concentrated attention that a single critically ill patient requires. Therefore boarding critically ill patients would either take nursing resources from routine ED patients or force the nurses to service more patients. Either way, patient care will suffer.

2.2.2 Surge: Variable Patient Arrival Rates to the Emergency Department

The rate at which patients enter the ED has a major effect on crowding. Asplin et al. (2003) developed a conceptual model of ED crowding that analyses the ED in three parts: input, throughput, and output. In terms of input, a key factor that can lead to crowding is a rapid spike in arrivals. This rapid spike is often referred to as “surge.”
Kelen and McCarthy (2006) define surge as “a sizeable increase in demand for resources compared with a baseline demand.” In order to counter surge, hospitals try to have some surge capacity. Kelen and McCarthy (2006) define surge capacity as “the maximum potential delivery of required resources, either through augmentation or modification of resource management and allocation.”

Hospital emergency departments deal with two types of surge, large-scale and daily surge (Jenkins et al. 2006), where a large-scale surge is the result of a major disaster or disease outbreak, whereas a daily surge could be the result of an isolated multiple casualty event. Kelen and McCarty (2006) believe that daily surge is often predictable and that daily surge response only involves the resources readily available in the ED. They also argue that large-scale surge is more of a hospital issue than an ED problem. Regardless, when EDs are already operating at an overcrowded state, they have little to no reserve capacity to handle any type of surge.

Fatovich and Hirsch (2003) define the symptoms of surge as entry block or entry overload, which occurs over a short duration when patients arrive much faster than they can be processed into the ED. The overwhelming number of patients waiting effectively blocks access to the ED. They also point out that when entry block is big enough, it would overwhelm the ED regardless of how many beds are available.

The timing of a surge (whether expected or unexpected) is an important factor in the ability of the ED to deal with the influx of patients. Daily surge capacity is higher in the early morning when the average patient to staff ration is at its minimum (Jenkins et al., 2006). This is true as long as a hospital ED has not already reduced resource capacity to minimal manning.
2.3 Fast-Track and Similar Models for Non-Urgent Patients

As a result of crowded conditions, hospital EDs across the United States and in many developed nations have had to look for ways to improve patient flow and satisfaction without incurring excessive costs. One area where EDs have had some success is with non-urgent patients. Instead of turning non-urgent patients away or letting them wait, some EDs have established fast track units, see and treat units, or placed a provider at triage. Fast track and see-and-treat are very similar concepts that identify low-acuity ED patient arrivals early in the triage and divert them away from traditional ED operations into a separate treatment area where a mid-level provider would treat and discharge them. In either case, some EDs are testing new ways to mitigate the overall demand for treatment rooms by filtering patients by acuity. Fast track and see-and-treat (S&T) units in particular try to overcome the main ED bottleneck (lack of treatment rooms) by taking patients who do not require a bed and treating them in a separate location.

Low acuity patients would normally be classified as non-urgent or, in other words, those that would require attention within 24 hours (IOM, 2007). The percentage of total ED visits that are considered low acuity varies widely from hospital to hospital. According to a National Hospital Ambulatory Medical Care Survey conducted by the Center for Disease Control and Prevention, there were in 2001 nearly 114 million visits to the ED. Of those 114 million, the CDC estimates that 10% were for non-urgent care. Rodi et al. (2006) cites that the percentage of non-emergency visits comprise between 10% and 66% of all ED visits. The term non-emergency includes non-urgent, semi-
urgent, and unknown patients. Dr. Thom Mayer, a fellow of the American College of Emergency Physicians, stated that as many as 30% of patients who come to the ED can be seen and treated without ever requiring an ED room (American College of Emergency Physicians, 2006). To clarify, not requiring a room does not always equal non-urgent. Not requiring a room could be extended to some semi-urgent patients if they are evaluated within one hour (IOM, 2007). Regardless of the actual percentage, it is important to note that the number of non-urgent patients is increasing.

2.3.1 Fast Track

There have been numerous articles and studies published about fast track units and their effect on emergency department operations. Sanchez et al. (2006) tested the fast track concept in 2002 during a two-year study at a 700-bed urban tertiary care adult teaching hospital. In Sanchez et al.’s study, patients were triaged by a triage nurse who determined their severity. All patients who were non-urgent and within the treatment capability of a mid level provider were coded as fast track area (FTA) and moved to a separate seven bed treatment area. The FTA operated from 8:30 am until 11:00 pm. Sanchez et al. (2006) concluded that establishing a fast track unit can significantly reduce patient wait time, total length of stay, and the number of patients who left without being seen. They feel that the improvements did not sacrifice the quality of care that patients received and that patient satisfaction went up. They did not conduct a patient satisfaction survey, but attributed the significant gains in the three performance measures as reasonable indicators that patient satisfaction improved under the fast track system.
Rodi et al. (2006) also implemented and tested the performance of a fast track unit at the Dartmouth-Hitchcock Medical Center in Lebanon, NH. The performance measures of interest in this study were patient length of stay and patient and staff satisfaction. In Rodi et al. (2006), the fast track unit operated during the busiest arrival times from 9:00am until 7:00pm. Arrivals during this time were triaged by the ED triage nurse and if the patients were determined to be low acuity they were routed to a separate waiting area. Once in this area, they were treated in one of two treatment rooms by a physician’s assistant and an ED technician. Rodi et al. reduced personnel costs associated with the fast track unit by moving a PA from the traditional ED to the fast track unit and hiring a dedicated ED technician.

The results of the Rodi et al. study were that average length of stay per patient decreased from 127 to 53 minutes while patient satisfaction significantly increased. The results of the staff satisfaction survey indicated a positive trend as well. What this study does not tell is whether a fast track unit could be implemented in different types of ED’s with different acuity levels. Rodi et al. acknowledge that establishing this fast track unit in this hospital was relatively straightforward, since the waiting area and treatment rooms were available and the PA was already on staff. The main cost was hiring the ED technicians to cover the fast track shift.

One of the key concepts in reducing ED crowding is to process patients through the ED as fast as safely possible. Haugh (2003) discusses several examples of how fast track units have helped to reduce patient load in the ED. One example is from Northwestern Memorial hospital in Chicago where the ED staff has broken the ED into four levels of care. The last level is a fast track unit that operates much like a medical
clinic. It keeps non-urgent patients out of the main ED waiting areas and out of critical ED treatment rooms. This reduces the arrival rate to the traditional ED and helps to mitigate the bottleneck associated with the lack of treatment rooms. Haugh (2003) also cites the efforts of the staff at Miriam hospital in Providence RI. Miriam’s ED established a fast track unit that operated out of some adjacent treatment rooms; however, when the main ED was overloaded and needed the fast track rooms, the fast track operation shifted to the hospital’s auditorium. This flexibility further demonstrates that fast track can be an efficient method to treat low-acuity patients and keep them from congesting the system.

2.3.2 See-and-Treat

See-and-treat units are the United Kingdom’s equivalent to our fast track unit. The see-and-treat model is designed to reduce waiting times and improve patient satisfaction for these patients who come to an accident and emergency (A&E) department with minor complaints (NHS, 2004). See-and-treat replaces triage and attempts to reduce the number of queues that non-urgent patients wait in until they are seen. The see-and-treat concept works best when there is a competent and experienced clinical staff dedicated to the process. Non-urgent patients come to the A&E and are diagnosed and treated by the first clinician they see, whereas, semi-urgent or urgent patients are referred to other areas of the A&E.

The see-and-treat units, like their US counterparts, target the low acuity patient population which is often left to wait in long queues. Rogers et al. (2004) evaluated an
S&T pilot study at the Addenbrookes MHS Trust Hospital, UK. The S&T unit was operated from 8:00am until 6:00pm daily by a doctor or ENP (emergency nurse practitioner). Patients first came to an assessment nurse, who quickly decided if the patient was suitable for the S&T unit. If so, the patient would be seen by either the ENP or a doctor. Patients who had more serious conditions were directed to another area of the ED. Rogers et al. (2004) reported significant improvement in terms of average wait to see a doctor/ENP, percentage of patients seen within an hour, and average total time in the department. Additionally, the S&T unit also had a positive effect on other performance measures relating to higher-acuity patients. Just as in the fast track units, the S&T units can be beneficial in moving faster low-acuity patients through the ED. But see-and-treat has some drawbacks, such as the cost of hiring or diverting hospital staff to work in the S&T area, plus the space requirement for the ENP or doctor.

2.3.3 Rapid Medical Evaluation

An alternative to the fast track concept is a related technique called rapid medical evaluation. Dr. Thom Mayer coined the T3 approach [team, triage, and treatment] (ACEP, 2006). Mayer’s approach was to create at triage a team of medical staff that would consist of an emergency physician, nurse, scribe, registrar, and technician. His team would assemble at triage and quickly start to evaluate and treat patients. In theory, this would reduce the number of patients who leave without being seen and quickly treat low-acuity patients who do not need major tests and diagnostics. Mayer agrees that this technique might not be feasible for smaller hospitals to implement full-time, but that it
could be a short duration alternative. If small EDs could temporarily increase their capacity at triage then that would help to relieve bottlenecks.

Travers and Lee (2006) took a similar approach to Mayer’s. Travers and Lee evaluated the effect on patient waiting time by teaming up a senior emergency physician with an emergency nurse at triage. The triage team saw all walk-in patients from 10:00am until 4:00pm. The triage nurse’s tasks were essentially unchanged. The triage physician evaluated walk-in patients to determine if their condition could be treated at the door. If so, the physician would evaluate their condition, treat them, and write prescriptions as needed. Travers and Lee (2006) conducted their study in two 10-day segments. The first was the control and the second operated with the triage team in place. Travers and Lee claim that during the 10 days of operating with this new technique almost 35% of walk-in patients could be seen by the doctor only. Shifting a physician to triage freed one-third of the consulting rooms for stretcher or high acuity patients. Also, the mean total waiting time for walk-in patients dropped from 36 to 19 minutes. Additionally, they surveyed patient satisfaction and found that two-thirds of the patients preferred to see the triage team first and 89% were satisfied with the lower wait time.

There are numerous advantages and disadvantages to the rapid medical evaluation approach to treating low-acuity patients. The main advantage is that low acuity patients will have shorter wait times and shorter lengths of stay. These low-acuity patients would be treated outside of a traditional treatment room, thus freeing treatment rooms for those patients who really need them. The main drawback is that EDs may not be able to afford to put one of their providers forward in the triage area. Physicians are expensive, and,
therefore, smaller EDs that only have one or two on duty at any time cannot afford to take that resource away from the high acuity patients.

2.4 Emergency Department Process Modeling

In the following sections two groups of current ED research are discussed. The first group deals with comparative studies of ED operations. The second deals with simulation modeling and how ED staffs have used simulation models to understand process flow in the ED. These two areas provide some ground-breaking research that may lead to innovations in the healthcare delivery sector of the economy, a sector that now represents 16 percent of the gross domestic product and is outpacing inflation at a rate of two to one (IOM, 2007).

2.4.1 Comparative Studies

Several researchers have used comparative studies to include statistical analysis of historical data to analyze the causes of ED crowding. Rathlev et al. (2007) conducted a time series analysis of the variables associated with daily mean ED length of stay. The data used was from a 19-month period starting in April 2002. The three factors determined to affect mean length of stay were hospital occupancy, number of ED admissions, and elective surgery admissions (Rathlev et al. 2007). Each of the above factors increased the daily mean length of stay: 4.1 minutes for every 5% increase in
occupancy, 2.2 minutes for each additional ED admission, and 13 seconds for each elective surgery (Rathlev et al. 2007).

The consensus among scholars including the latest publication by the IOM, is that exit block is the biggest cause of ED crowding. The exit block is directly tied to the number of available rooms in the hospital. Therefore, as occupancy in the hospital increases, ED patients waiting for hospital space will have to compete for fewer rooms and thus be forced to board.

Miro et al. (2003) conducted a similar analysis of an ED in Spain in order to analyze the internal factors that effect ED patient flow and determine what changes in resource capacity could mitigate crowding. The first part of their study examined the current state of the ED over a three-week period. Some of the statistics collected were the number of patients in the waiting area, the initial assessment area, and treatment and observation area. In addition, the daily average number of staff workers was computed. After careful analysis of the data, the ED staff reorganized their operation by increasing the structural resources or treatment areas by 50 percent and increasing the human resources by 34 percent. Once these changes had been in effect for several months, a second round of data was collected and analyzed. Despite a 13 percent increase in the daily arrivals to the ED since the first part of the study, the post reorganization data showed a 15 percent decrease in the average number of patients in the ED at any given time. The biggest contributor of that reduction was the decrease in the average number of patients in the waiting and initial treatment area (Miro et al., 2003).

The results in the Miro et al. study demonstrate that, in at least their hospital setting, changes to the number of providers and the layout of the treatment area can
improve process flow. But although these improvements worked in that case, not every ED will be able to hire additional staff and reorganize physical space. Increasing the number of treatment rooms means one of two things: new construction or conversion of existing hospital space to ED rooms. Nonetheless, increasing capacity at process bottlenecks is an effective means to improve process flow.

Patel and Vinson (2005) conducted a comparative study that analyzed the average time of physician assessment before and after implementing a team assignment system. The team assignment concept was designed to speed the time it takes a provider to sign up to treat a patient. In their hospital, patients who are ready-to-be-seen wait until a provider signs up to see them. The team assignment concept organizes a team into a physician, two nurses, and one EDT. Once patients are triaged, they are assigned to a team. Each team has a dedicated section of treatment rooms to see their assigned patients. Patients are tracked electronically, so teams know when new patients have been assigned to them. This team concept forces providers to take ownership of assigned patients faster. The results of this study showed that the mean time to physician assessment (defined as the time from the end of triage to the start of the emergency medical evaluation) decreased by 9.5 minutes while patient satisfaction rose (Patel and Vinson, 2005).

A similar study was conducted by Chan et al. (2005) at the University of California, San Diego. Here, the objective was to redesign the process flow at the ED to reduce the number of patients who left without treatment. Instead of using a team concept, the intent of this study was to eliminate any processes that create queues and thus slow a patient’s access to care. By removing full registration at the door and by
automating the care process, the ED staff was able to get patients through triage and into beds faster. Also, when there were no beds available, their new process flow included starting some diagnostics at triage. After these process improvements, overall length of stay remained unchanged, but there was a 50% reduction in the number of patients who left without treatment (LWOT). The reduction in LWOTs indicates that small changes in the ED process flow can significantly impact patient care. Although not specifically stated in the article, it appears that in this hospital ED population, patients are more likely to stay for treatment if the care process starts faster.

Cowan and Trzeciak (2005) analyze the issue of ED crowding in terms of critically ill patients. They propose three models (ICU-centric, ED-centric, and a collaborative model) that EDs could implement to better handle critically ill patients who enter the ED but must board for some time until an intensive care bed is available. These models focus on the resources and protocols to deal with the critically ill in the ED.

In the ICU-centric model, a designated critical care consultant would oversee all care to critically ill patients regardless of their location. Due to their proximity to the patient, ED physicians would still have some oversight of boarders, but the responsibility of providing critical care would be removed from the ED staff. This would free up ED physicians to treat newly arriving patients.

In the ED-centric model, the ED staff would have full responsibility for all critical care until the patient is transferred and handed off in the ICU. This model assumes that timely critical care is essential and that the location of the patient determines who provides the care. In practice this model cannot function unless the ED is staffed with an appropriate number of critical care ED physicians. Since critically ill patients require
additional resources, there has to be sufficient staff to handle the boarders as well as other ED patients.

The third model proposed by Cowan and Trzeciak is the collaborative model. This model is a combination of the first two where the ED staff does the initial diagnosis and initiates standard protocols. The ICU is notified of the patient and would conduct a consultation. While the patient is boarding, the ED physician has oversight of the execution of the standard ICU protocols. This collaborative technique was adopted by the Cooper University Hospital in Camden, NY, where Cowan and Trzeciak work.

There are good and bad points to each model. The drawback to the collaborative model is that there is a gap between who is responsible and in charge of patients during their stay in the ED. This gray area could present problems during peaks in ED crowding, since ED physicians will be busy stabilizing new patients and may not be giving boarders the oversight and care they require.

Asplin et al. (2003) analyzed the ED in a conceptual model that contained three parts: input, throughput, and output. Their work focused on describing the three components and their interactions in an environment driven by unscheduled arrivals. But that research does not solve the problems with ED crowding; it rather identifies many of the ED shortfalls and provides the framework for future research. Taking a similar approach, Sinrich and Marmor (2005) analyzed the ED in terms of each process and its associated time. The goal was to analyze every step of the emergency care process to determine which processes took the largest part of a patient’s length of stay. Their study is focused around six hospitals of varying size in Israel. The results of their study not surprisingly showed that between 51-63% of the average patients length of stay is spent
waiting for care, as opposed to receiving care. Although their study does not offer any immediate solutions to the problems of timely patient care in the ED, it does examine where patients are spending their time and how much of that time is value-added. As in the Asplin et al. (2003) work, understanding where the problem areas are and how they relate is an important first step to improving patient flow in the ED.

Spaite et al. (2002) used a rapid process redesign approach to improve ED efficiency. After an extensive internal review, Spaite and his team decided on five process improvement areas: staffing/internal processes, triage-registration, diagnostic radiology, laboratory, and bed-availability. Improvements included increasing the number of medical staff to keep pace with rising ED arrivals, removing registration from the entrance, and increasing communication among ED staff, radiology, and the laboratory. The ED did not increase its physical space but it did incur about $1 million per year in additional costs. Spaite et al. (2002) reported that process improvements reduced patient-to-room time and throughput as well as patient dissatisfaction.

2.4.2 Simulation Studies

The number of simulation studies in hospital EDs has steadily increased over the past decade. The growing demand for emergency care in the United States and in many of the developed nations has forced hospitals to look for ways to increase efficiency, without necessarily increasing resources or physical space. Discrete event simulation is one method that is gaining popularity within the healthcare field because simulation software can capture the dynamics and uncertainty of patient arrivals to the ED.
Mahapatra et al. (2003) used discrete event simulation to model the ED at the York Hospital in Pennsylvania. In the York Hospital simulation, patient emergency severity index (ESI) was used to classify patients as they moved through the care process. The goal of the simulation was to determine if altering the hours of operation of the Alterna Care unit would result in an overall reduction in average patient length of stay. The Alterna care unit is similar to a fast track unit where patients with low acuity (ESI4 or ESI5) are treated. The results of the simulation study showed a significant reduction in waiting time across all ESI levels when the AC clinic was open from 9:00am to 9:00pm, as opposed to 11:00am to 11:00pm (Mahapatra et al., 2003). In this study, waiting time is defined as the total length of stay minus the sum of all the process times (value-added time where the patient is with a provider).

In contrast to the conventional discrete event simulation models used in some of the recent ED simulations, Hay et al. (2006) introduce a unique modification of discrete event simulation that places the emphasis on medical resources as opposed to the patient. Instead of a patient requesting a medical resource, the medical resource selects the next patient based on the patient’s clinical priority, how long the patient has been waiting, and the skill set of the resource. This technique helps eliminate unnecessary claims against senior medical staff by patients with low acuity. In an ED simulation using a conventional software package, Hays would argue that the low-acuity patient would get the next available doctor. The results of this simulation study showed that the average length of stay was significantly lower when using skill sets and operating priority than when they were not used. This technique could prove helpful in a large ED where there are multiple resources with varying degrees of capacity and skill level.
Lane et al. (2000) conducted a UK simulation study that was focused on whether or not reducing hospital bed capacity had any effects on the waiting time in an accident and emergency department (A&E). The results of their simulation showed that bed capacity had little effect on the waiting time in the A&E. Although this may seem counter-intuitive, the hospitals surveyed gave ED patients a higher priority for inpatient beds than elective care patients. Reducing the number of available beds just reduces the number of elective surgeries.

Six sigma is a measurement-based strategy that focuses on process improvement and variance reduction. Each process is defined, measured, analyzed, improved, and controlled to produce output within a specific tolerance (Raisinghani et al., 2005). Miller et al. (2003) used a six sigma approach to modeling a hospital ED. The approach started with an extensive analysis of the current processes in the ED and in the hospital. This phase was followed with a simulation model that replicated current ED operations. Based on their process analysis, they selected several areas that were in need of improvement. They used the simulation model to predict how various changes both internal to the ED and external (number of inpatient beds, lab test turnaround time, etc) would affect the average length of stay in the ED. The results of their study showed that many of the factors that will reduce ED length of stay were outside the control of the ED staff.

In much of the literature surrounding hospital ED crowding, it is widely accepted that many of the problems that cause ED crowding are outside the control of the ED. Many of the problems would require hospital changes or government action as noted earlier. Although the six sigma approach in this hospital ED identified many of the
external factors affecting length of stay, shifting the approach to study more internal ED areas may better help the ED staff identify and fix areas that they directly control.

Johnson et al. (2004) also took a six sigma approach to improving ED operations. The focus of their study was primarily on the internal processes that the ED had control over. Part of their research included building a simulation model to help understand current operations in the ED. The results of their work identified many processes that could be streamlined by simply rerouting patients in a more efficient manner or consolidating or relocating supplies to reduce patient waiting time and medical resources.

Ruohonen et al. (2006) used simulation modeling in a large hospital ED in Finland to introduce a new triage-team concept and measure the effect that that will have on patient waiting times and throughput times. All aspects of patient care in the ED were modeled. The team-triage method was added at the entrance of the ED. All patients arrive to the hospital and report to the triage-team consisting of receptionist, nurse, and doctor. The triage-team quickly evaluates each patient, orders any required diagnostics tests, and then sends the patient to a specialty area of the ED based on the patient’s acuity. One of the goals of this team concept was to start the diagnostic testing process as soon as the patient arrives. The simulation model was then analyzed under varying team-triage process times. In all cases but one the average throughput time decreased, indicating that the team triage method could help reduce average throughput times (average length of stay).

One advantage of using simulation modeling in hospital EDs is that simulation models can closely approximate the real system yet be flexible enough to analyze process flow and process interactions. The dynamic nature of hospital EDs can often make it
difficult to understand exactly why a bottleneck is occurring or how to improve the system. In Blasak et al. (2003), a simulation model was used to help the staff at Rush North Shore Medical Center in Skokie, Illinois, evaluate and improve operations between their ED and their telemetry unit. Samaha et al. (2003) modeled the current state of ED operations at the Cooper Health System in New Jersey. In these simulation studies, the hospital staffs were concerned with the amount of time patients were spending in the ED and were looking for ways to reduce average length of stay without arbitrarily increasing resource capacity. Although many of the details of the models are not publicly available, the results showed that, through the use of simulation, the hospitals could identify opportunities to reduce patient wait times and improve throughput. Additionally, the ED staff was provided with a simulation tool that could help predict how future resource or design changes would affect system output.

In conclusion, the steady rise in the ED census in the US is driving ED researchers to redefine patient care and patient flow. More and more hospital EDs are turning to simulation to improve their processes. Simulation studies allow ED staffs to implement and test new concepts without interrupting patient care. The quantity of current literature on simulation modeling in EDs is rapidly growing; however, much of the work is limited in its application and normally tailored to a specific hospital.

2.5 Chapter Summary

This chapter summarizes the literature regarding hospital crowding and the methods that other scholars have used to improve process flow in the emergency
department. The recent report from the Institute of Medicine summarizes much of the literature surrounding ED crowding, as well as provides direction to future researchers. This chapter highlights work done both by researchers in the United States and abroad and encompasses not only simulation but also comparative studies on ED process flow and many of the concepts used to treat low-acuity or less resource-intensive patients. The next chapter will discuss the physician-directed queuing (PDQ) process flow and a simulation used to model the PDQ.
Chapter 3
MODEL DESCRIPTION AND VALIDATION

3.1 Introduction

To achieve our objectives, a simulation model of the physician-directed queuing (PDQ) process was constructed and validated using available data from the Hershey Medical Center’s emergency department (HMC ED). The simulation model was constructed using Rockwell Automations Incorporated’s Arena 9.0 software. This chapter describes the PDQ process in more detail as well as describes the Arena model.

3.2 Physician-Directed Queuing

Physician-directed queuing occurs at the entry of the hospital emergency department. The PDQ is designed to shorten the total time from patient presentation at the ED until treatment. A PDQ physician upfront in the ED observes the triage and determines if the patient requires an ED room for treatment. If not, the patient is moved to a PDQ area adjacent to triage and is treated by the PDQ physician and supporting staff.

Figure 3-1 was developed by the staff at the HMC ED and was the first high level flow diagram of the PDQ. The flow diagram is an overview of how PDQ works and how it fits in with regular ED operations. The shading on the diagram was used to show the location and resources of a process.
Figure 3-1: The PDQ process visually represented in a flow diagram
The following discussion follows the flow diagram in Figure 3-1. Patient arrivals at the ED are not shown in the figure. Patients arrive at the ED from two sources: ambulance and walk-in. Patients who require immediate resuscitation are classified as ESI 1 and are sent to a traditional ED team. All other patients complete a mini-registration process (not shown) where they provide their names, addresses, and complaints. These patients are then triaged by a nurse with the PDQ physician observing the process. As part of the triage, the triage nurse assigns each patient a triage category. The Hershey Medical Center’s emergency department uses a five-level emergency severity index (ESI) to categorize arrivals during triage.

If the patient needs complex diagnostics and therapeutics and if clinical space is available, then the patient is moved to the main ED. When clinical space is not available, the PDQ physician starts the treatment by ordering appropriate tests such as labs, x-rays, and EKGs to reduce idle time. The results of all the tests will follow the patient to their ED treatment room. The triage nurses will initiate the lab draw and monitor the patients waiting for an ED room. If a patient requires an EKG, the PDQ physician will read the EKG results as soon as they are completed and take action as needed. The current automated patient tracking system in the hospital allows the PDQ physician to check bed availability in the main ED, as well as electronically place orders for patients who need diagnostic tests.

The PDQ physician evaluates all patients who do not require complex diagnostics. During the emergency medical evaluation, the PDQ physician may order some limited diagnostic tests. Once all tests are complete, the PDQ physician will determine if a procedure is needed. Patients requiring simple treatments are retained in the PDQ
process and are treated and discharged. Patients who require more advanced treatment as a result of the limited diagnostic tests are sent to the main ED area.

There are several resources that comprise the PDQ staff. Table 3-1 lists the PDQ resources and the processes that they perform. The physician is ultimately responsible for directing patients to their next process and for expediting the treatment for patients who do not require complex diagnostics. The triage nurses work together to triage newly arriving patients and to support the PDQ physician in treating and managing all patients. Either a triage nurse or the physician can complete the discharge paperwork and counsel patients on their discharge paperwork. The EDT assists the nurses and physician in conducting EKGs and minor medical procedures on PDQ patients. The last two resources are the administrative assistants. The entry clerk works the mini-registration desk, whereas the exit clerk is responsible for conducting the final checkout procedures for patients who are discharged from the PDQ.
3.3 Model

The physician-directed queuing emergency department model is a representative simulation model of the actual process/patient flow at the Hershey Medical Center’s emergency department. This simulation model focuses specifically on the physician-directed queuing part of the ED and does not attempt to model all emergency departments.

3.3.1 Performance Measures

The purpose of the physician-directed queuing simulation model is to estimate the performance of the actual PDQ. The goal of the simulation is to accurately predict how
changes to the real system will affect the desired performance measures. There are several common performance measures found in the literature that hospital emergency departments use when evaluating patient flow. For this model, average patient length of stay, average patient census, and average PDQ resource utilization are the primary performance measures:

1. Average length of stay. This is the average time that a PDQ patient stays in the ED, a statistic that captures the time from the presentation to the ED until the patient has paid for services and is leaving the ED. This does not take into account patients who were assigned traditional treatment rooms because they required either complex diagnostics or a procedure. This statistic is collected both hourly and daily. The length of stay per hour is computed based on hour of the day that the patient arrived to the ED. For example, a patient arriving at 9 am and leaving at noon would be included in the 9 am LOS data. There is an associated average length of stay for every hour of PDQ from 9am to 10pm.

2. Average PDQ patient census and average complex diagnostic (CD) census. These two statistics calculate the time-averaged number of patients in the PDQ process and in complex diagnostics. Both are computed hourly and daily. Patients are in the PDQ process from the time they start mini-registration until the time they complete checkout or leave the PDQ for either complex diagnostics or the main ED. Patients are in complex diagnostics from the time it is determined that there are no ED beds available until completion of their final test results.
3. Average resource utilization. This performance measure is calculated for the physician, triage nurses, and EDT. It indicates the percentage of time that a resource is busy in a given hour or over the PDQ day.

3.3.2 Model Assumptions

1. Patients arrive at the ED individually according to a non-homogeneous Poisson process. Patient arrival rates change hourly but are consistent from day to day at any given hour. The average number of arrivals per hour is known and reported by the electronic records system. The distribution of the time between arrivals is exponential.

2. The PDQ system starts empty each morning at 0900 hours and runs until 2300 hours. At the end of each PDQ day, remaining patients will be moved under the care of the ED staff.

3. Shift changes in nurses, medical doctors, emergency department technicians (EDT), and clerks would occur as scheduled. The time for a shift change is assumed to be negligible. No patient history or pertinent treatment information is lost in the transfer during a shift change because of the electronic medical record system.

4. Time for staff to move from one patient to another is small and is not included in the model. The physician-directed queuing footprint in the hospital ED is small, and, therefore, the PDQ staff can move quickly from patient to patient.

5. The rate at which medical staff (nurses, doctors, technicians, administrative clerks) perform their tasks does not change during the day and is independent of census.
6. No patients leave before being completely processed through the ED (none left without treatment).

7. All equipment and hardware in the ED remain fully operational with no unscheduled downtime.

8. Physician decisions on which patients to be treated in the PDQ can be approximated from patient emergency severity index (ESI). In particular, the PDQ physician will treat all ESI 4 and 5 patients, whereas ESI 2 and 3 patients will enter complex diagnostics or get an ED bed immediately after triage. Table 3-2 provides a brief summary of the five ESI categories.

<table>
<thead>
<tr>
<th>ESI Category</th>
<th>Patient condition</th>
</tr>
</thead>
<tbody>
<tr>
<td>ESI 1</td>
<td>Requires immediate live saving intervention</td>
</tr>
<tr>
<td>ESI 2</td>
<td>High risk (confused, lethargic, disoriented, suffer from severe pain or distress) or Similar to ESI 3 with one or more vital signs at critical level</td>
</tr>
<tr>
<td>ESI 3</td>
<td>Not high risk; require two or more external resources</td>
</tr>
<tr>
<td>ESI 4</td>
<td>Not high risk; require one external resources</td>
</tr>
<tr>
<td>ESI 5</td>
<td>Not high risk; require no external resources</td>
</tr>
</tbody>
</table>

Note: External resources can include but not limited to labs, x-rays, and consultation.
Source: Eitel et al., 2003.

3.3.3 Model Logic

Figure 3-2 shows the patient flow through the PDQ process. Figure 3-2 was developed from the original HMC flow diagram in Figure 3-1. The following paragraphs
briefly describe the flow diagram in terms of how patients flow through the various processes in the PDQ model.

As shown in block 1, patients enter the PDQ once they arrive at the hospital ED. Since the physician’s decision on which patients to treat in the PDQ is approximated by the ESI, arriving patients are assigned an ESI classification. Arriving patients are also assigned an attribute that identifies their time of arrival. Once the patient arrives he or she enters a decision block that separates out ESI 1 patients. All ESI 1 patients bypass the PDQ process and enter the main ED. All non-ESI 1 patients proceed to mini-registration where they wait in a queue to be registered by the entry administrative clerk. After completing mini-registration, patients wait in another queue for a triage evaluation. A patient receives a triage evaluation once the physician and a triage nurse are simultaneously available. The PDQ physician is allocated to patients based on a preempt system whereas nurses are allocated on a first-come-first-serve (FCFS) priority system. The following paragraph explains the logic for the different methods.

Since physicians are shared among multiple processes and make decisions to treat patients based on acuity, a preempt function controls which process has priority and whether a physician can be preempted. Processes that require a physician are prioritized from one to three with one being the highest priority. Table 3-3 lists the processes that require the physician and their associated priority level. The only way for the PDQ physician to be interrupted from working on one patient is when another patient is at a higher priority.
Figure 3-2: PDQ simulation model logic translated to a standard flow diagram.
Triage nurses are also responsible for more than one process; however, their primary responsibility is to triage incoming patients. Triage nurses operate under a priority system rather than a preempt system, and they can not be interrupted during a task. Once they are done with a process they will select their next patient based on priority; selection within a priority category is FCFS. There are two high priority processes for a triage nurse: triage and assisting with trauma patients. All other processes are considered routine. Setting up the priorities in this manner is an attempt to approximate the teamwork that occurs in the PDQ process. PDQ team members work together to prioritize and treat patients in an efficient manner.

<table>
<thead>
<tr>
<th>Priority</th>
<th>Process</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-Triage</td>
</tr>
<tr>
<td></td>
<td>-Electrocardiogram evaluation</td>
</tr>
<tr>
<td></td>
<td>-Assisting with matters outside PDQ</td>
</tr>
<tr>
<td>2</td>
<td>-Emergency medical evaluation</td>
</tr>
<tr>
<td>3</td>
<td>-Write prescriptions</td>
</tr>
<tr>
<td></td>
<td>-Assess labs and x-rays</td>
</tr>
</tbody>
</table>

In block one, Figure 3-2, patients leave triage and are sent to complex diagnostics or to MD evaluation. ESI 2 and ESI 3 patients are sent to complex diagnostics and eventually to a treatment bed in the main ED. Each ESI 2 and 3 patient who enters complex diagnostics decrements the variable that is counting the number of patients in the PDQ process.

ESI 4 and ESI 5 patients who require little to no external ED resources are sent to MD evaluation, shown in block 2. These patients are seen by the PDQ physician in a
separate multi-capacity treatment area. After their evaluation, ESI 4 patients are routed to Limited Diagnostics which is shown in block 3.

The simulation divides ESI 4 patients into two groups once they enter Limited Diagnostics. A small percentage gets x-rays, whereas the remainder gets lab work. Since x-rays are taken at radiology, an external ED resource, the x-ray technician is not modeled as part of PDQ process. Therefore, the process time for an x-ray is modeled as a time delay, the total time from movement to radiology to completion of test. In limited diagnostics, lab draw POC refers to lab draw point of care. The triage nurse draws the lab sample in the ED. The sample is processed in the ED, and processing is modeled as a time delay. Once the Limited Diagnostic tests are complete and the results have been evaluated by the PDQ physician, ESI 4 patients enter block 4. ESI 5 patients bypass limited diagnostics and enter block four directly from block two.

As shown in block four, a percentage of patients will need a procedure that would require a main ED treatment room. These patients would leave the PDQ process and decrement the variable that is counting the number of patients in the PDQ. The remainder of ESI 4 and 5 patients who do not require a procedure enter a decision block that asks if an EDT action is required. Depending on their condition, patients may receive a minor procedure such as a splint, bandage, or crutches from an EDT. Following any EDT procedure, patients are given prescriptions as needed and counseled on their diagnosis. Counseling can be done by the PDQ physician or one of the triage nurses. Patients are counseled by the first available resource. Patients are then sent to checkout where they complete any required paperwork before exiting the hospital. This process is
completed by the exit administrative clerk. Once patients have completed checkout they leave the hospital and decrement the variable counting the number of patients.

In block 1, ESI 2 and 3 patients are routed to complex diagnostics. Block five shows the flow path that ESI 2 and 3 patients take after triage. Since patients who require complex diagnostics need treatment beds, the first decision block in complex diagnostics asks if there is space available in the main ED. Since this PDQ model does not encompass the entire ED the status of available main ED rooms at any given time is unknown. The PDQ model approximates bed availability by assigning a bed availability probability to each hour of the day. When a patient enters block five, a check is made to determine if a bed is available. The simulation assigns the patient a random number between 0 and 1. If the random number is less than or equal to the current bed availability probability, the patient is moved into the main ED. All other patients are retained in the PDQ until they have completed their complex diagnostic tests. Patients who do not get a room increment a variable that counts the number of patients waiting in complex diagnostics.

As shown in block five, if a room is not available, the physician initiates complex diagnostics. These patients are assigned a group of tests based on a probability. Each group of tests or path is associated with a probability and the sum of the four probabilities equals one. The Complex Diagnostic process flow is similar to the limited diagnostic process flow. The paths that include lab work require one of the triage nurses to draw the lab sample. In Complex Diagnostics, the lab sample is processed in the hospital laboratory, as opposed to POC samples which are done in the ED. The lab processing time is modeled as a longer time delay than in limited diagnostics. The EDT completes
all EKG tests and the EKG process time is modeled as a time delay. The PDQ physician assesses all EKG results. Radiology tests are modeled as a time delay. At the conclusion of complex diagnostics, it is assumed that the patients no longer need the direct support of the PDQ staff. For each patient, the variable that counts the number of patients in complex diagnostics is decremented by one.

In block six, two parallel actions operate in addition to the main PDQ process. The first action is the temporary removal of a triage nurse from PDQ. This process uses an exponential arrival generator to randomly generate a trauma patient arrival at a time when there is trauma nurse shortage. The mean time between arrivals was approximated from ED staff estimates. When a trauma patient arrives, a triage nurse is requested with high priority from the PDQ process. The time that the nurse is unavailable to the PDQ is modeled as a time delay.

The PDQ physician’s parallel action is also shown in block six. In addition to his duties in the PDQ process, the physician is responsible for mentoring his residents and maintaining some oversight over a small portion of traditional emergency department patients. To capture these randomly timed instances throughout the day, the PDQ model generates priority one procedures for the physician that are independent of patient arrivals and based on an exponential inter-arrival time. These short duration procedures preempt the PDQ physician throughout the day.
3.3.4  Model Data

The data for the model comes from two sources: the HMC electronic medical record and estimates from senior emergency medical staff. For this model, the mean hourly arrival rate is based on calendar year 2007’s arrival data obtained from the emergency medical record system (Figure 3-3). These arrival rates by hour represent arrivals to the ED. That average arrival data from 0900-2300 hours were extracted from Figure 3-3 and entered into the simulation non-homogeneous Poisson process arrival generator. Figure 3-4 shows the resulting simulated average number of arrivals by hour. The averages are based on 30 replications and shown with 95% confidence intervals. Since the PDQ primarily treats ESI 4/5 patients, approximately 38% of the total arrivals will enter the PDQ process.
Figure 3-3: CY2007 average number of total patient arrivals to the HMC ED by hour.

Figure 3-4: Average number of arrivals to the ED during PDQ hours.
In block five of Figure 3-2, the first decision block asked if main ED space was available. The probability that there will be an available bed in the main ED when needed is shown in Figure 3-5. These data were obtained via expert opinion from the HMC staff. Patients who complete triage between 0900 hours until 0959 hours and are determined to need a bed will have an 88 percent probability of getting one. Patients who enter after 1600 hours will have a one percent probability of getting a bed after triage.

![Bed Availability in ED](image)

Figure 3-5: The probability that a bed is available given the time of day that it is requested. The probabilities are represented as percentages.

For each process shown in the flow diagram in Figure 3-2, there is an associated uniformly distributed process time. All process times are estimated based on expert opinion from the HMC ED staff. Table 3-4 contains a list of each process that requires an estimated time. All time estimates are drawn from uniform distributions. Minimum and maximum values are given in the table.
Additionally, there are several patient care paths in the model. There are five separate areas in the PDQ process where the patients care path is determined by more than their ESI classification that was assigned at triage. The five areas are the following: limited diagnostic procedure, complex diagnostic procedure, procedure required, EDT action required, and prescription required. The care path that a patient takes in each of these areas is determined by a predefined probability that is based on expert opinion. Table 3-5 lists the predefined probabilities.

Table 3-4: Processes with time estimates

<table>
<thead>
<tr>
<th>Process and Time Estimates (in minutes)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mini registration</td>
</tr>
<tr>
<td>Triage evaluation</td>
</tr>
<tr>
<td>E/M evaluation</td>
</tr>
<tr>
<td>EDT procedure</td>
</tr>
<tr>
<td>Discharge instructions</td>
</tr>
<tr>
<td>Write prescription</td>
</tr>
<tr>
<td>Counsel patients</td>
</tr>
<tr>
<td>Complete checkout</td>
</tr>
<tr>
<td>Lab draw</td>
</tr>
<tr>
<td>Lab results (complex diagnostics)</td>
</tr>
<tr>
<td>Lab results (limited diagnostics)</td>
</tr>
<tr>
<td>Assess lab results</td>
</tr>
<tr>
<td>Administer X-ray</td>
</tr>
<tr>
<td>Assess X-ray</td>
</tr>
<tr>
<td>Administer EKG</td>
</tr>
<tr>
<td>Develop EKG</td>
</tr>
<tr>
<td>Assess EKG</td>
</tr>
</tbody>
</table>
Table 3-5: Processes requiring a probability and ESI percentages.

<table>
<thead>
<tr>
<th>Processes requiring a probability</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Limited diagnostics</td>
<td></td>
</tr>
<tr>
<td>-% who require lab work</td>
<td>20%</td>
</tr>
<tr>
<td>-% who require x-rays</td>
<td>80%</td>
</tr>
<tr>
<td>Complex diagnostics</td>
<td></td>
</tr>
<tr>
<td>-% who require lab work</td>
<td>20%</td>
</tr>
<tr>
<td>-% who require x-rays</td>
<td>5%</td>
</tr>
<tr>
<td>-% who require both labs and x-rays</td>
<td>55%</td>
</tr>
<tr>
<td>-% who require EKG, labs, and x-rays</td>
<td>20%</td>
</tr>
<tr>
<td>% who require a procedure</td>
<td>15%</td>
</tr>
<tr>
<td>% who require an EDT action</td>
<td>40%</td>
</tr>
<tr>
<td>% who require a prescription</td>
<td>80%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>ESI percentages by category</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>ESI 1</td>
<td>0.81%</td>
</tr>
<tr>
<td>ESI 2</td>
<td>15.60%</td>
</tr>
<tr>
<td>ESI 3</td>
<td>45.60%</td>
</tr>
<tr>
<td>ESI 4</td>
<td>20%</td>
</tr>
<tr>
<td>ESI 5</td>
<td>18%</td>
</tr>
</tbody>
</table>

Table 3-5 also includes the ESI percentages used in the simulation model. The model uses ESI to determine which patients can be discharged by the PDQ physician and the category of diagnostics required (none, limited, complex). In the actual system, the PDQ physician uses judgment and experience to make these decisions. The percentages of arrivals by ESI category at HMC are shown in Table 3-6. Through expert opinion of the HMC staff, we also obtained percentages of patients requiring each category of diagnostics. We found that ESI classification was not a good predictor of diagnostics used at HMC. However, ESI is a widely used method in ED’s and is intended to reflect resource requirements. Therefore, we chose to use ESI categories in the model and to adjust the ESI percentages obtained from HMC to reflect estimated percentages of patients needing each category of diagnostics. The modeled ESI’s are also shown in Figure 3-6. Since this simulation only captures three main external resources (labs, x-
rays, and EKGs), there are likely other resources to be considered when the triage nurse assigns patients their ESI classification. These additional resources are not captured in the PDQ model and are beyond the scope of the model.

To test the calculated ESI percentages, we built a model without ESI levels that was based on the estimated need for diagnostics. Results from 30 runs of the two models are shown in Table 3-7. Differences between the two models are small and not significant at the 95% confidence level for 30 runs.

Table 3-6: Percentage of total arrivals by ESI category.

<table>
<thead>
<tr>
<th>ESI category</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Actual %</td>
<td>0.81%</td>
<td>15.64%</td>
<td>53.80%</td>
<td>28.50%</td>
<td>1.22%</td>
</tr>
<tr>
<td>Modeled % (modified)</td>
<td>0.81%</td>
<td>15.64%</td>
<td>45.55%</td>
<td>20.00%</td>
<td>18.00%</td>
</tr>
</tbody>
</table>

Table 3-7: Comparison of original model to ESI model.

<table>
<thead>
<tr>
<th>ESI model</th>
<th>Avg LOS</th>
<th>Avg PDQ census</th>
<th>Avg # discharged from PDQ</th>
</tr>
</thead>
<tbody>
<tr>
<td>ESI model</td>
<td>111.22</td>
<td>145.32</td>
<td>4.37</td>
</tr>
<tr>
<td>Percentage based model</td>
<td>112.29</td>
<td>149.47</td>
<td>5.16</td>
</tr>
</tbody>
</table>
3.4 Verification and Validation

3.4.1 Model Logic

Verification and validation of model logic was accomplished in several steps. Initially, the concept of PDQ was discussed at length with several key leaders at the Hershey Medical Center’s emergency department. A high-level flow diagram for PDQ was drafted by the ED staff. The flow diagram was expanded into a detailed low-level diagram and then imported into Arena. The model quickly expanded to encompass many of the details that were not originally included in the original flow diagram. After numerous meetings with the ED staff, I was able to construct an ED simulation model that captured the general flow of patients from arrival to departure through the PDQ checkout or to their main ED treatment room. Once the base model was complete, several walkthroughs of model logic were conducted with the ED staff to verify that the logic replicated the process flow in the ED. Finally, several personal observations of the PDQ process were conducted both individually and with senior members of the ED staff. Given the limited amount of real data available to validate the model at each step, much of the validation occurred via expert opinion and consensus in comparing the simulation model output to observed performance by the ED staff.

3.4.2 Verification of Arena’s Non-homogeneous Poisson Process Arrival Generator

Patient arrivals were modeled in the PDQ simulation using a non-homogeneous Poisson process. The arrival generator in Arena was tested over a variety of different
mean rates to determine if the long-term simulated averages were comparable to the input means. The simulated averages are based on 100 runs. The results of the experiment are shown in Figure 3-6. The conclusion from Figure 3-6 is that Arena’s non-homogeneous Poisson process arrival generator can accurately reproduce a set of given input means. The differences in the test means and the long term averages from the simulation are small and consistent with the use of an exponential arrival generator.

Figure 3-6: The verification test results for Arena’s arrival process generator. The error bars shown for the simulated data represent 95% confidence intervals around the averages.
3.4.3 Comparison of Simulation Output to Actual Output

To validate that the PDQ model described above can accurately represent the current state in a hospital emergency department, the PDQ model was populated with input data and run. The model was run using the input parameters and assumptions listed above. The simulation was run for 30 replications of a single PDQ workday (a day is 14 hours). The model started each morning at 9:00am in an empty, idle state. The output was compared to actual data exacted from the Hershey Medical Center’s patient database.

The main performance measure used to validate the model output is average patient length of stay. Since the PDQ simulation model is designed to treat and discharge ESI 4/5 patients the two performance measures that were evaluated were average length of stay for ESI 4 patients and average length of stay for ESI 5 patients.

Table 3-8 displays the results from the simulation model experiment and the actual data from HMC. The HMC length of stay (LOS) data represent the average LOS for all ESI 4 and 5 patients who reported to the ED from July 18 to August 22, 2007. During this period, HMC was operating the PDQ on a regular basis. Therefore, the averages from HMC include ESI 4/5 patients who were discharged through the ED when the PDQ was not running (2300 - 0900 hours). The average LOS for ESI 4 patients at HMC falls within the confidence interval for the simulation data. The confidence intervals for the simulation data are large due to high variability in the PDQ process, and the LOS for ESI 5 patients is slightly overestimated by the simulation model. There are three explanations for this. The first is that average daily LOS from the model is based on a small number of data points. For both ESI 4 and 5 patients, the LOS is based on
approximately 13 patients per day (Table 3-8 lists the 95% confidence intervals). Since the PDQ system uses an exponential inter-arrival rate to model patient arrivals and uniform distributions to model process times, there is a large amount of built-in variability. The high variability coupled with the low number of data points leads to high variability in the LOS statistics. A second explanation for the model overestimating the ESI 5 LOS is that the LOS from the simulation only considers patient arrivals during the PDQ day when the ED arrival rates are very high. The LOS data from HMC includes ESI 4/5 patients who are seen during the PDQ and afterhours in the traditional ED. The third explanation is that the model uses the modified ESI percentages whereas the HMC data present the LOS based on the actual ESI percentages. The HMC LOS statistic for ESI 5 patients only includes 1.22% of the arriving patients, whereas the model output includes 18% of the arriving patients.

Despite the differences in the ESI percentages, the simulation output provides a good approximation for average LOS for ESI 4 and 5 patients. The ESI-based simulation model accounts for approximately the same percentage of total patients at each process and in each patient care path as the percentage-based model. The ESI model provides similar results in terms of LOS for ESI 4/5 patients when compared to actual LOS data from the HMC emergency medical database.

Table 3-8: A verification table of output for emergency severity index (ESI) 4 and 5 patient length of stay (LOS) data. LOS reported in minutes.

<table>
<thead>
<tr>
<th></th>
<th>LOS from HMC</th>
<th>LOS from model (95% confidence interval around mean)</th>
<th># patients included in model data (95% confidence interval around mean)</th>
</tr>
</thead>
<tbody>
<tr>
<td>ESI 4</td>
<td>189 (28.5% of arrivals)</td>
<td>128.8 207.4</td>
<td>11.08 15.18</td>
</tr>
<tr>
<td>ESI 5</td>
<td>83 (1.45% of arrivals)</td>
<td>86.4 123.8</td>
<td>11.76 14.5</td>
</tr>
</tbody>
</table>
3.5 Chapter Summary

This chapter defines the concept and execution of physician-directed queuing by the Hershey Medical Center’s emergency department. A simulation model was built to analyze how changes to the PDQ system would affect system performance. The simulation model was explained using a flow diagram, where the active entities are patients in the PDQ process. Under normal base line operating conditions and when run for 30 replications of a PDQ day, the simulation model closely approximated the HMC average LOS for ESI 4 patients. The simulation model slightly overestimated the average length of stay for ESI 5 patients. The PDQ simulation model discharges ESI 4 and 5 patients who are the least resource intensive of the five emergency severity index categories. ESI 4 patients require one external ED resource, whereas ESI 5 patients do not require any external ED resources. Although the PDQ simulation model has a limited scope and cannot fully predict ED processes outside of the PDQ, it is robust enough to approximate actual system performance and can produce reasonable length of stay measures that are comparable to the actual measures at HMC.
Chapter 4

ANALYSIS OF RESULTS

4.1 Introduction

We have three research objectives for this thesis. The first is to identify bottlenecks in the PDQ process and predict the length of stay of PDQ patients. The second is to analyze the effect of changes in patient demand on system performance. The third is to compare two methods for setting staffing levels in a PDQ.

Chapter 4 starts with a detailed analysis of the baseline model. The first step is to review the baseline model conditions. Then the baseline model is analyzed by performance measure starting with resource utilization and followed by average length of stay and average census. The baseline analysis is then summarized to highlight any modifications to the model. The modified model is evaluated under both increased and decreased patient demand to the ED. The final stage of chapter 4 is to analyze methods to improve system performance. Several resource-based improvements are presented and discussed in detail, and the advantages and disadvantage of each are presented. The chapter concludes with a brief summary of model analysis.
4.2 Analysis of Baseline Model

4.2.1 Review of Baseline Model Conditions

The simulation model is run under the baseline model conditions that were presented in chapter 3. All assumptions from section 3.3.2 apply. The arrival data used in the simulation is based on the actual average arrival rates per hour from Figure 3-3. The arrival rates in Figure 3-3 are total arrivals to the ED. The PDQ processes treats and discharges ESI 4/5 patients; therefore, only approximately 38% of the total arrivals per hour will enter the PDQ process. Tables 3-4 and 3-5 show the times for each process in the PDQ, as well as the percentages of patients who enter each process not defined by a patient’s ESI classification. Each day the PDQ process starts in an empty and idle state at 0900 hours. The PDQ process ends each day at 2300 hours. Patients remaining in the PDQ after 2300 hours are assumed to be transferred to the main ED area, which is outside the scope of the PDQ. Patients who remain in the ED after 2300 hours are not included in the PDQ statistics.

4.2.2 Resource Utilization

Figures 4-1 and 4-2 show the average hourly resource utilization for each of the four PDQ resources: the EDT, physician (MD), triage 1 nurse (T1), and the triage 2 nurse (T2). All averages are based on 30 replications and shown with 95% confidence intervals. Appendix A lists the results in table form.
Figure 4-1: EDT and physician utilization by hour for the baseline model.

Figure 4-2: T1 and T2 utilization by hour for the baseline model.
Clearly the PDQ physician is the most utilized resource in the PDQ. The physician is the bottleneck resource. The daily physician utilization is high with an average that lies between 83% and 89%, with 95% confidence (over 30 replications). What is more alarming is the very high average hourly physician utilization toward the end of the day. This steady rise to a near 100% utilization suggests that the arrival rate exceeds resource capacity and that the system would not be stable if the arrival process continued. The physician is involved in many of the processes in PDQ and is the only resource that can accomplish several of the tasks, such as MD evaluation, writing prescriptions, and evaluating diagnostic tests. By system design, the physician is the critical resource.

The remainder of the resource utilizations are at a moderate to low level. The next highest average utilization is for the T1 nurse, who is the primary triage nurse conducting initial patient triage on newly arriving patients. The T2 nurse is the supporting triage nurse. Since both triage nurses can complete the same set of tasks, they can more efficiently process a high volume of waiting patients. In essence, the triage nurses function as one resource with a capacity of two. As the day progresses, the triage nurse utilizations increase. This increase corresponds to the increasing patient demand to the ED. The maximum utilization for the T1 nurse occurs between 1900 and 2000 hours (7-8 pm) with an average hourly utilization between 54% and 58%, with 95% confidence. The EDT has a relatively steady average daily utilization between 31% and 33%, with 95% confidence (over 30 replications). This low utilization rate is partly due to the lack of EDT actions that are captured in this model. Many of the tasks that EDTs accomplish in PDQ are in support of either the nurses or physician and are hard to record in practice.
and equally as hard to model in the simulation. Therefore, EDT utilization is not an accurate predictor of system performance.

4.2.3 Average LOS

Figure 4-3: Average hourly length of stay.

Figure 4-3 displays the average length of stay in minutes by hour of day. All averages are based on 30 replications and shown with a 95% confidence interval. The average length of stay is reported based on the patient arrival hour; therefore, patients arriving during the first hour are included in the first hour LOS data, even though they may have left the ED in the second or third hour of the day.
The average LOS increases through most of the day. Around 1600 hours when the LOS starts to decrease, patient arrivals continue to increase. Figure 3-4 shows that the average hourly arrival rate at the ED peaks at 1900 hours and then gradually declines. Since demand is increasing, it would seem reasonable that LOS would increase, yet the opposite trend is observed. This is because the LOS statistic only includes patients who leave before 2300 hours. The model assumes that patients who remain in the PDQ after 2300 hours are transferred to the main ED. This assumption underestimates the LOS statistic and also explains the reduction in variability around the mean LOS after 1600 hours. The variability in LOS is reduced when patients with long lengths of stay are not included in the LOS statistic for the latter hours of the PDQ day.

To explore the termination condition bias, the model was modified such that the PDQ arrivals end at 2300 hours, but the PDQ process continues to operate until all patients are discharged. Figure 4-4 shows a comparison of the average LOS before and after the termination condition modification.
Figure 4-4 shows that both the original and modified models are identical through 1100 hours. After 1100 hours, the average hourly LOS in the modified model is slightly higher than in the original model, but the difference is not statistically significant until 1900 hours. Modifying the termination condition increases the number of patients included in the hourly LOS averages, which keeps the confidence interval more stable toward the end of the day. Allowing all patients who enter PDQ to exit the system helps correct some of the termination condition bias, but it also highlights another problem with using average hourly LOS as a performance measure.

The modified termination condition plot in Figure 4-4 still shows a reduction in average LOS in the later hours as well as a reduction in the variance. Even though all PDQ patients are allowed through the system, there are no new arrivals to PDQ after
Therefore patients are treated and released faster. This reduces the average patient LOS and the variance in the LOS.

In the modified model, the 95% confidence intervals for the average hourly LOS prior to 1900 hours are wide and suggest high variability in the system. This could be caused by a combination of the following: exponential inter-arrival times, the small number of arrivals to PDQ per hour, or the method used to model physician decisions. Since arrivals at the ED are human-based, there is not much that can be done to mitigate variability in the first factor. With a small number of arrivals and departures each hour at the PDQ, even small increases in individual patient LOS times can have a big impact on the hourly average LOS statistic. The modeling assumption used to replicate physician decision making could be an area that is artificially inflating the variance.

To explore whether the method used to model physician decision making is inflating the variance, the current preempt method is compared to an alternative priority-based method. Recall that the physician moves from patient to patient, based on the highest priority patient. Patient priorities are determined by the process that the patient is waiting at. The physician can be preempted or interrupted if there is a patient waiting at a higher priority process. Table 3 lists each physician process by preempt priority level. Allowing physicians to be preempted from lower priority to higher priority patients will result in some patients having extremely long lengths of stay. A physician can be preempted at any time and as many times as needed during a patient’s treatment, without regard for remaining processing time. For example, a patient at a low priority process could keep getting preempted each time a new patient enters the ED, since triage is a
preempt priority one process (the highest). Each interruption further extends the patient’s LOS, which in turn increases the variability in the average hourly LOS.

An alternative method to modeling physician decision making is to prioritize processes but not allow the physician to be interrupted from a current patient. In this priority method, the physician will select the patient with the highest priority and who has been waiting the longest. This method should reduce some of the variability in average hourly LOS, since it will reduce the number of patients with extremely long waiting times. The priorities are the same as shown in Table 3-3.

Figure 4-5 shows average hourly LOS for both preempt and priority physician decision modeling methods.
For the majority of the PDQ day, the priority-based method has a lower average hourly LOS and narrower 95% confidence interval when compared to the preempt method. This indicates that using a priority-based decision method helps minimize the maximum patient LOSs. In the latter hours of the PDQ (1800 to 2300 hours), the trend reverses and the priority method has a slightly higher average and slightly wider confidence interval. In the priority method, the confidence intervals become narrower in the latter hours of PDQ, but not as fast as with the preempt method. This indicates that the variance is decreasing but at a slower rate than for the preempt model.

The variance in average hourly LOS is large in both methods, as noted from the confidence intervals around the majority of the hourly statistics. The confidence intervals for the average hourly LOS are smaller using a priority-based method to represent physician decisions.

### 4.2.4 Average Census

In this section, the average hourly PDQ and complex diagnostic (CD) census for the baseline model will be compared to the priority-based model. Thus far, we have looked at three different models. The first was the baseline model, the second was the modified termination condition model, and third was the priority-based model. Since the average hourly census statistics are calculated for each hour and the statistics are only reported up to 2300 hours, the modified termination condition will have no effect on the average hourly census statistics. Figure 4-6 shows the average hourly PDQ census for each model.
In both models, the average hourly PDQ census data increase for the majority of the day and peak around 2000 hours. This peak is approximately one hour after the previous peak in the arrival rate plot (Figure 3-4) indicating that the system has a lag of one hour between changes in arrival rate and changes in the number of patients in the PDQ. In both models, the confidence intervals start small, steadily increase through the morning hours, and then remain relatively constant for the later hours of the day. The average PDQ census starts small and quickly builds as a result of the empty and idle starting condition. Just as in the average LOS plot (Figure 4-5), the priority-based method used for physician decision making reduces the mean and 95% confidence interval around the hourly PDQ census. Although the differences in the average hourly
PDQ census data are not statistically significant given the number of replications, the priority-based method reduces the average number of patients in the PDQ process. This follows from the LOS argument in which the priority-based method reduced the extremely long patient LOSs. Processing patients without interruption at low-priority processes keeps patients moving through the PDQ process, hence, reducing the average number of patients in the process each hour. The end-of-day behavior seen in the average hourly LOS plot does not occur in the census plot. The decrease in average hourly census at the end of the day is directly tied to the arrival rate.

Average hourly PDQ census is a better measure of system performance than average hourly LOS. Average hourly PDQ census is a stable statistic that does not vary wildly from hour to hour. It follows both the arrival rate and the physician utilization trends. As the arrival rate builds through most of the day the bottleneck resource’s utilization increases toward fully utilized. As patients compete for a highly utilized physician, they back up at various processes within the PDQ, which in turn increases the average PDQ census. As patient arrivals to the ED decrease, the number of new patients that require the physician at triage decreases, which allows the physician to treat and discharge patients waiting at lower priority processes within the PDQ. The variance in the average hourly PDQ census does slightly increase through midday, which is attributed to the empty and idle startup conditions and the extremely high variability in the patient arrival rates.

Care must be used when using the average hourly LOS statistic to describe system performance. The average hourly LOS has large variability due to the small number of patients who arrive each hour and the exponential inter-arrival rates. Additionally, the
end of day behavior involving the lack of new patient arrivals to the PDQ at 2300 hours affects the average hourly LOS for patients who arrive in the later hours of the PDQ day. Average hourly LOS does not intuitively follow the trends in the arrival rate, PDQ census, and physician utilization.

Figure 4-7 shows the average hourly Complex Diagnostic census data.

The average hourly CD census statistic steadily increases in both preempt and priority-based physician decision methods. This indicates an explosive system where arrivals to complex diagnostics quickly outpace departures to the main ED. The explosive trend in the Complex Diagnostic area is a function of model design. The bed availability probability shown in Figure 3-5 controls the percentage of newly arriving ESI 2/3 patients who immediately get a bed and bypass complex diagnostics. Since the bed availability probability quickly drops to one percent in the first few hours of the day,
roughly 60 percent of all patients who arrive after 1500 hours will enter Complex Diagnostics. As the arrival rate increases throughout the day so does the number entering complex diagnostics. Patients arrive to complex diagnostics faster than they can leave.

The only task in Complex Diagnostics that the bottleneck resource (physician) completes is to review the EKG. The remainder of the Complex Diagnostics processes is completed by either a triage nurse, EDT, or an external resource such as radiology or the laboratory. Since the percentage of arriving patients who require an EKG is small, reviewing EKGs accounts for a very small amount of physician time. Also, since the maximum hourly average utilization of each triage nurse and the EDT is less than 70 percent, the rise in Complex Diagnostics census is not due to PDQ resource capacity.

The average hourly CD census in the priority model is slightly lower at each hour than in the preempt method. The 95% confidence intervals steadily wider in both models for the first few hours of the day and then stabilize by the later hours of the day. The slight reduction in average hourly CD census using the priority-based system follows from the earlier discussion. The priority-based decision method minimizes the maximum time patients spend in a process that requires a physician.

### 4.2.5 Summary of Baseline Model Analysis

The results of the baseline model show that the physician is the bottleneck resource. The physician has a capacity of one, yet is solely responsible for multiple tasks. When the physician is utilized for most of the day with an average utilization near 90%, the PDQ process or any system for that matter loses its ability to effectively handle
system variability. Any variability under extremely high resource utilization normally results in system bottlenecks, as seen in this model. The utilization rates for the triage nurses and EDT are not extremely high and, therefore, are not a likely bottleneck.

The baseline conditions as summarized in section 4.2.1 do not adequately represent the performance of the PDQ process. The termination conditions imposed on the model at 2300 hours underestimate the average hourly LOS in the latter hours of day. Modifying the termination conditions, such that all PDQ patients who arrive before 2300 are discharged, increases the number of patients used to calculate the LOS statistics. These newly counted patients have larger LOSs, therefore, increasing the average hourly LOS statistics in the latter part of the day. Modifying the termination conditions but stopping arrivals to PDQ at 2300 allows remaining patients to be discharged faster.

Furthermore, the preempt method used to model physician decision making increases the average and variance of the hourly LOS, hourly PDQ census, and hourly CD census. The preempt method creates some artificially long patient LOSs. It allows the physician to be preempted from a current patient regardless of how much or little treatment time is left. Since the PDQ process is designed to treat and release ESI 4/5 patients who are not critically ill, replacing preemptive decision making with a priority method that does not allow interruptions should not effect the timeliness of care to high-priority patients. It would reduce waiting times for the lower priority process. The actual physician decision method is probably somewhere between these two extremes. Given that the priority based method has lower variability and lower average means in the census and LOS performance measures, it will be used for the remainder of the experiments.
4.3 Changes in Demand

This section investigates the effects of varying patient demand. Over the past several years the trend in annual ED patient census in the US has increased (IOM, 2007). Under the current demand at HMC, the average hourly PDQ census steadily increases until 2000 hours when it peaks and then starts to decrease (Figure 4-6). It would appear based on current system performance that an increase in patient demand at the ED (and subsequently at the PDQ) would cause the average PDQ census to increase through the end of PDQ indicating that the system is explosive.

To test this hypothesis, we will assume that the arrival rate to the ED follows the same pattern, but that each hourly rate is increased by 10%. Additionally, each hourly arrival rate will be decreased by 10% from the base case. Although a decrease in arrivals is unlikely, for completeness the ranges of tests will include a slight decrease and a slight increase.

Figures 4-8 and 4-9 are bar charts showing the average hourly physician utilization and average hourly PDQ census, respectively, for each variation in demand.
Figure 4-8: Average hourly physician utilization by arrival rate.

Figure 4-9: Average hourly PDQ census by arrival rate.
The average hourly physician utilization and average hourly PDQ census increase with increases in patient demand. Physician utilization was already high in the baseline model, and therefore increases in demand increases the average hourly utilizations slightly but in most hours the increase is not statistically significant. Despite the increase in demand in the first three hours of the day, the average utilization does not significantly increase. This is probably a result of the starting conditions (empty and idle). Also, there is no statistically significant difference in the average hourly PDQ census between the baseline model and the increased arrival rate model until the hour 1900. The means and confidence intervals in the plus 10% model for PDQ census increase each hour through the end of the PDQ. On average, the PDQ process cannot discharge patients faster than they arrive.

When the arrival rate is reduced by 10%, physician utilization follows a similar trend by hour as in the baseline case. The averages are lower, but the confidence intervals remain relatively constant. Even when the arrival rate is decreased by 10%, the physician is still utilized for the majority of the day at an 80% or higher average hourly utilization. At a 10% decrease in arrivals, the average hourly PDQ census follows a similar pattern as in the baseline model yet the averages are lower. At a 95% confidence level, the differences are not significant.

In conclusion, the PDQ system may be sustainable at lower arrival rates, though physician utilization is still high late in the day. The PDQ system becomes unworkable with increases in the patient demand. Increased patient demand forces the utilization to near 100%, which is not sustainable. Also, at increased demand, the PDQ process is taking in patients faster than it discharges them. This will have a negative effect on the
performance of the PDQ. The increased arrival rate will put a large strain on the PDQ as patients find themselves waiting in long queues. These awaiting patients will take up floor space in the ED and cause additional congestion and slowdowns as they block the normal flow of patients from process to process.

4.4 System Improvement

Up to this point of the experimentation, the PDQ simulation model has been run and analyzed under baseline and modified termination conditions. Additionally, the preemptive physician decision making assumption was altered to a priority-based method to alleviate some artificial variability created by the preemption assumption. The PDQ simulation model was also run under both increased and decreased arrival rate to project system performance.

In this section, the priority-based PDQ simulation model is used to evaluate three methods of increasing bottleneck resource capacity. The first is to add an additional physician to the PDQ process. The second is to increase physician capacity at peaks in patient demand. The third uses current system performance to determine when additional capacity is required. The goal is to improve system performance while minimizing additional resource costs.
4.4.1 Two-Physician Model

Figures 4-10 to 4-13 show the effects of adding a second physician on the average hourly physician utilization, average hourly LOS, average hourly PDQ census, and average hourly CD census.

Figure 4-10: Average hourly physician utilization with changes in physician capacity.
Figure 4-11: Average hourly LOS with changes in physician capacity.

Figure 4-12: Average hourly PDQ census with changes in physician capacity.
When the physician capacity is doubled for the entire day, the PDQ process is over capacitated. For most of the day the average hourly physician utilization is below 60%, and only during the peak in arrival rates around 1900 hours does the upper end of the 95% confidence interval exceed 60%. The 95% confidence interval around the average hourly physician utilization is constant, which indicates constant variance and a stable system. For every hour, the difference in the two systems is statistically significant.

A similar trend occurs in both the average hourly LOS and PDQ census. In the average hourly LOS plot the additional capacity drastically reduces the average patient LOS. Patients are quickly and efficiently being processed through PDQ with little delay. At every hour except for the first, the average LOS using two physicians is significantly lower than with one physician. With the exception of the utilization plot, the high
variability observed with only one physician is drastically mitigated when two physicians are added. The average in the hourly physician utilization is reduced by adding more capacity, but the variability remains constant. This is due to high variability in patient arrivals to the ED.

Although the average hourly PDQ census is reduced when additional capacity is added, there is no significant difference in the average hourly CD census. This further shows that the complex diagnostic census data are related to factors outside the PDQ, and, therefore, changes in bottleneck resource capacity will not significantly impact it.

4.4.2 Schedule-Based

The schedule-based method will increase physician capacity around periods of increased demand. The periods are selected based off historical averages and do not take into account specific daily peaks in demand that result from using exponential inter-arrival times. The performance measures will be used to evaluate whether a schedule-based method can significantly reduce average daily PDQ census and average daily LOS while conserving resources. This is an economy-of-force model, where the ED staff wants to judiciously distribute critical physician resources to get the biggest improvement in system performance for the least investment in resource cost. Resource cost is approximated by average additional physician minutes.

The schedule-based method increases PDQ resource capacity by placing a one-hour physician shift at each of the peaks in the arrival rate. Referring back to Figures 3-4 and 3-5, the average hourly arrival rate peaks twice at 1200 and 1900. The two peaks in
the arrival rate are small and not statistically significant at a 95% confidence level over 30 replications. Since it is common practice in EDs to add staff at peak hours, we chose to follow that approach. Increasing the capacity during peak demand should help mitigate the bottleneck caused by an increase in patient demand. Each additional shift is designed to be one hour long; however, if the additional resource is busy at the end of the shift, then the shift will end when the physician completes his or her current process.

4.4.3 Trigger-Based

The trigger-based method to improve system performance differs from the schedule-based system in how it increases physician capacity. The best way to reduce the bottleneck in the PDQ is to increase the capacity of the bottleneck. Intuitively, the best times to have an additional physician at PDQ would be just as the demand increases beyond physician capacity. In this method, the number of patients in the PDQ is monitored, and when a trigger value is reached, another physician would be added to the PDQ. Determining the initial trigger requires an analysis of the arrival rate plot from Figure 3-4 and average hourly physician utilization from Figure 4-1. The arrival rate reaches its first peak at 1200 hours and its second peak at 1900 hours. Likewise, physician utilization quickly rises to approximately 90 percent by 1200 hours and then holds relatively steady until it spikes again at 1900. The average hourly PDQ census increases throughout most of the day at a steady rate (Figure 4-6). At 1200, hours the 95% confidence interval around the average hourly census is 4.59±0.89 patients (3.70, 5.48). Since physician utilization is high and relatively steady after 1200 hours, it would
indicate that around 1200 hours the physician is operating close to capacity. If the trigger is set low enough to capture the surge in arrivals at 1200 hours, it should offset the physician utilization and decrease the bottleneck. The initial trigger was set to five patients which lies in the upper portion of the confidence interval around the average PDQ census at 1200 hours. Since the trigger is based on an actual number of patients, only counting numbers will be used for the trigger value. Additional trigger values around five are also evaluated.

This method assumes that the ED staff can borrow an additional physician from somewhere else in the hospital or ED to step into the PDQ as needed. Borrowed physicians will work in the PDQ in one-hour shifts. If at the end of each hour-long shift, the number of patients in the PDQ is still above a pre-specified trigger level, then the physician will work an additional shift. If that number is less than the trigger, then the physician will leave the PDQ. The number of times that the additional physician can augment the PDQ is only limited by the number of hours in the PDQ day. Figures 4-14 to 4-16 show the average additional physician time per day, the average daily LOS, and the average daily PDQ census at several trigger levels.
Figure 4-14: Average additional physician time required at each trigger level.

Figure 4-15: Average daily LOS by trigger level.
At the initial trigger level of five patients, the average PDQ census is between 1.95 - 2.43 patients (with 95% confidence). This represents a significant reduction from the baseline model when there is only one physician at any one time. The average daily PDQ census under baseline conditions is between 3.7 - 5.44 patients with 95% confidence. Since the initial trigger level of five patients in the PDQ is an estimate based on current system conditions, several more triggers ranging from four to ten are selected.

At a trigger level of four, the average PDQ census is between 1.85 - 2.17 patients (with 95% confidence), approaching the average daily PDQ census when there are two physicians at the PDQ for the duration of the day. The average daily PDQ census with two physicians is between 1.04 - 1.26 patients with 95% confidence.

Figure 4-16: Average daily PDQ census by trigger level.
The opposite trend in the census occurs when the trigger level is increased from five. At a trigger level of ten, the average census approaches that of the base case when there is only one physician at the PDQ for the entire day. Ideally, the trigger level should be determined based on the cost-benefit of adding the additional resource. As in the schedule-based model, the cost is based on the average additional physician minutes required at each trigger; the benefit is the reduction in average daily LOS and average daily PDQ census.

There is no statistically significant difference in the average PDQ census between small increments of the trigger level. When the trigger is at 8-10 the confidence intervals around the means are wide, signifying a higher variance in the PDQ system. At trigger levels less than eight, the variance is relatively constant with tighter confidence intervals. There is a statistically significant difference in the PDQ census and average daily LOS between a trigger of 6-8. When comparing the average number of additional physician minutes required at a trigger level of 6-8 there is no statistically significant difference. There is a steady upward trend in average physician minutes required when the trigger level decreases toward four. There is a statistically significant difference in average additional physician hours between a trigger level of 5-7.

The costs associated with adding physician capacity is more tangible than the costs associated with reducing patient census. There is no simple method to calculate the costs associated with longer waiting time in system, higher patient census, or the costs of increased risk of spreading infectious diseases from patients who spend a longer time in the ED. These costs exist but are not quantifiable. Furthermore, the PDQ patients are
ESI 4 or 5 and normally have low acuity; therefore, minor increases in the average census do not carry life threatening consequences.

For the purposes of this research, the average additional physician time is weighted higher than the PDQ census, since ED physicians are a critical resource, their time is valuable, and their costs are tangible. The difference in additional physician time between trigger levels five and seven is statistically significant. As the trigger moves from five to four the difference in average additional physician time drastically increases, which would significantly increase resource costs. At trigger levels seven and eight there is no statistically significant difference in physician time. Therefore, for the purposes of this research, the ideal trigger level is seven.

In summary, setting a trigger level of seven ESI 4/5 patients in the PDQ process reduces the PDQ bottleneck, which in turn reduces the average daily PDQ patient census and LOS. At a trigger level of seven, the upper end of the 95% confidence interval for the average additional physician time required each day is 125.64 minutes. Additionally, the average PDQ census at that trigger level is between 2.3 - 2.72 patients (95% CI) and the average daily LOS is between 75.9 - 83.68 minutes (95% CI). These results assume that the PDQ process can take an additional physician as needed and that the physician is available and ready to start work as soon as the trigger is reached.

4.4.4 Comparison of Different Methods

The ideal number of physicians at the PDQ is somewhere between one and two. From the results of section 4.4.2, having two dedicated physicians at the PDQ over-
capacitates the system, resulting in a significant reduction in average hourly physician utilization, average hourly PDQ census, and average hourly LOS. The additional capacity also reduces the variance in the performance measures, signifying a more stable system. Although the benefit of having two dedicated physicians at the PDQ greatly improves the system, it comes at the cost of two additional seven-hour physician shifts.

Figures 4-17 and 4-18 show the comparison of the schedule-based method to the selected trigger-based method (trigger of 7) in terms of average additional physician time, average daily LOS, and average daily PDQ census. All averages are based on 30 replications and shown with 95% confidence intervals.

Figure 4-17: Average additional physician time and LOS by method.
The trigger-based system has a lower average daily PDQ census and lower average daily LOS than the schedule-based method, but at a 95% confidence level the statistics are not significantly different for 30 replications. The schedule-based method uses a full two hours of physician time, whereas the upper end of the 95% confidence interval in the trigger-based system is just over two hours (125.64 minutes).

The average additional minutes required is slightly lower in the trigger-based method but has a much higher variance. The average LOS and average PDQ census are slightly lower in the trigger-based method and have smaller variances. It is possible to reduce the confidence intervals in each measure by increasing the number of replications. However, there is no practical significance to such small changes. Due to the high variability in the system, the day-to-day additional minutes required using the trigger-based method will not always be less than the schedule-based method.

Figure 4-18: Average daily PDQ census by method.
Table 4-1 compares the performance measures for scheduling method, the trigger method, and the priority-based method with only one physician. Both the trigger and schedule-based methods significantly reduce the average daily PDQ census and average hourly LOS.

<table>
<thead>
<tr>
<th>Model</th>
<th>AVG PDQ Census (patients)</th>
<th>AVG LOS (minutes)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Schedule</td>
<td>2.56 (3.64)</td>
<td>76.28 (97.4)</td>
</tr>
<tr>
<td>Trigger 7</td>
<td>2.3 (2.72)</td>
<td>75.9 (83.68)</td>
</tr>
<tr>
<td>One MD</td>
<td>3.7 (5.44)</td>
<td>100.67 (129.31)</td>
</tr>
</tbody>
</table>

The average PDQ census data presented in Table 4-1 represents the daily averages over 30 replications. Due to the high variability in the PDQ process, the hourly PDQ census and LOS were also analyzed. Recall from section 4.2.3 that there is a large amount of variability in the average hourly LOS statistics when there is only one physician. Also, the average daily PDQ census does decrease in the last two hours of the PDQ day when only one physician is at the PDQ. It seems likely that adding additional resource capacity would either maintain that trend or improve it slightly. Figures 4-19 and 4-20 show the average hourly PDQ census and average hourly LOS for each method.
Figure 4-19: Average hourly PDQ census by method.

Figure 4-20: Average hourly LOS by method
There is no statistically significant difference in the average hourly PDQ census at any hour up to 2100; however, there are some distinguishable trends in the data. The average hourly PDQ census starts out equal in both methods through 1100 hours. At 1200 hours, the average hourly PDQ census in the schedule-based method drops below the average hour PDQ census in the trigger-based method. This drop occurs due to the additional resource that starts at 1200 hours. The average hourly PDQ census is reduced for a few hours after the first shift ends, but soon increases and surpasses the average PDQ census in the trigger-based method. In the schedule based method the average hourly PDQ census continues to rise until the second one-hour physician shift starts. The average hourly PDQ census in the trigger-based method stays below that of the schedule-based method for most of the day. This is because the trigger-based method is adding capacity based on current system behavior. It will increase capacity when the current number in the PDQ reaches seven. This happens when the arrival rate exceeds the discharge rate. The schedule-based method adjusts capacity purely based on time and not current state. This can lead to inefficient resource management, since the system may not always need additional capacity at 1200 and 1900 hours. The trigger-based method is better suited for the high variability in the model.

The same trend that was observed in the average hourly PDQ census is also present in average hourly LOS. The average hourly LOS is larger in the trigger-based method through 1200 hours. After 1200 hours the trigger-based method has a lower average hourly LOS than in the schedule-based method, with the exception being for the patients who arrive at 1800 hours. Those patients benefit from the additional physician who starts his second shift at 1900 hours. The trigger-based method is more responsive
to system conditions and smoothes out the peaks in average hourly LOS. Also, reducing the peaks reduces the variance. The 95% confidence interval around the average hourly LOS is smaller for the trigger method (Table 4-1).

Of the two methods, the better one depends on the hospital ED and its flexibility in scheduling or allocating physician resources. EDs with stringent rules for setting staffing schedules may opt for slightly worse system performance in exchange for a predictable physician schedule. Others may be more flexible in how they schedule physicians, and, therefore, may be able to augment a physician for an hour here or there as PDQ conditions dictate. There are trade-offs in both methods.

The schedule-based method is predictable, since both the physician and PDQ staff know when they will work together. Also, the hospital can schedule the additional capacity well in advance. The disadvantage of the schedule-based system is that it carries a slightly higher average cost and can be inefficient given the variability of the PDQ system. The advantages of the trigger-based system are that it is responsive to the current state in the PDQ area. It is efficient in that it will not add an additional physician unless conditions warrant one. The trigger-based system has a slightly lower average cost than the alternative method and it smoothes out much of the variance in the average hourly patient LOS. The drawbacks to the trigger-based system are that it expects the additional physician to start work as soon as the trigger is reached, which means that the additional physician must be on call and able to shift from his current work to assist in the PDQ. Also, the additional physician does not know when, for how long, or how many times a day, he will be committed to PDQ. If multiple physicians are used on-call, then there may be integration issues with the remainder of the PDQ staff.
4.5 Chapter Summary

Our research goal is to improve the process flow in the PDQ system in order to reduce patient delays and improve patient care. The objectives that supported this goal were first to understand how the PDQ system operates under baseline conditions and to identify the system bottleneck(s); second, to understand how the system performs under increasing patient demand; and finally to test methods to reduce the bottleneck in the most efficient and sensible way.

The resulting analysis identified the physician as the bottleneck in the PDQ. Under baseline conditions, physician utilization was extremely high. High resource utilization coupled with highly variable patient demand led to system bottlenecks at processes that required the physician. Second, our analysis showed that termination conditions affect the average hourly LOS in the latter hours of the PDQ. Modified termination conditions were substituted into the model to allow all PDQ patients who arrived before 2300 to complete the PDQ process. This measure helped but also highlighted further problems when using average hourly LOS. As a variance reduction method, priority-based decision making replaced preemptive decision making.

After the priority-based model was adopted, the PDQ process was tested under varying arrival rates, but the system is sensitive to small increases in patient demand. Increases of up to 10% in patient demand resulted in extremely high physician utilization. Additionally, under increased demand the average hourly PDQ census continued to grow at an explosive rate. Finally, three methods to reduce the bottleneck are introduced.
The first calls for increasing physician capacity to two for the entire day, which over-capacitated the system. The last two are the trigger and schedule-based methods. These methods involve increasing physician capacity to help mitigate the bottleneck. Each has advantages and disadvantages. The ideal method is ED-dependant. The trigger-based method is tied to current system performance, which means that it can quickly react to spikes in the variable arrival rate at the PDQ; however, the drawback is that the on-call physician has to be ready to step in at any time. The schedule-based method can be staffed in advance so that the additional physician can prepare for his shift. The drawback is that the schedule is fixed and not tied to current system performance. This can lead to underutilization given variable patient demand.
Chapter 5

CONCLUSIONS AND FUTURE RESEARCH

5.1 Summary of the Thesis

One of the biggest challenges that hospital emergency departments (EDs) face today is how to handle the steady rise in patient demand with a steady decline in total number of hospitals and hospital beds. The Hershey Medical Center’s emergency department was designed to handle half of its current annual patient visits, and the number of visits continues to increase each year. In this thesis, an innovative process called physician-directed queuing (PDQ) is introduced and evaluated via simulation. The simulation model can help the ED staff understand how the PDQ process works under varying conditions, such as arrival rates and resource staffing. The results of the simulation show that increasing PDQ physician capacity for two hours a day can mitigate the bottleneck and significantly reduce ED census and length of stay (LOS) for ESI 4 and 5 patients. The model could be used by other hospitals considering PDQ for their EDs, by changing arrival rate data, and possibly ESI percentages and process times.

5.2 Future Work

There are numerous areas for future research in healthcare engineering. In recent years, there have been many healthcare simulation studies that have tried to improve process flow and reduce patient waiting times in the ED. This thesis looked at one part of
the ED, namely the PDQ process. Even modeling this small element required making assumptions about patient arrival rates, processes outside the ED, and how to represent human decision making. Relaxing any or all of the above assumptions would be worthwhile avenues for future work.

In this thesis, we assumed that patient arrival rates varied by hour of the day but were constant from day to day. What if the patient arrival rates were not constant from day to day or week to week? The PDQ model could be expanded to include daily, weekly, or seasonal fluctuations in demand that could result from environmental or social conditions. Examples include seasonal demand variations due to the start of the allergy season, the start of the flu season, or the spike in arrivals during a large sporting event or any other temporary surge in population. Another factor that was not considered but could impact daily arrivals rates is the human factor. EDs may experience larger daily patient volumes on Monday mornings, as opposed to Fridays, since patients may be more likely to “wait it out” over the weekend and then rush in on Monday. Modeling any of the above-mentioned areas would take considerable data analysis to identify the arrival trends as well as to determine the source of the trend.

Another area of future research would be in the expansion of the PDQ model to encompass the entire ED and eventually the entire hospital. Since the scope of our model is small, we made many assumptions about processes that affected the PDQ but were outside its scope. Modeling these processes would lead to a better understanding of the system dynamics between adjoining departments within the hospital. Expanding the PDQ model to include the main ED, the radiology department, the laboratory, and the in-
patient wards would provide better insight into hospital-based process/patient flow. This would better address the causes of patient bottlenecks along the entire patient care path.

A third area of future research deals with the modeling methods used to capture human decision making. In our present model, physician decision making was initially modeled using preemption where a physician could be moved from one patient to work on a higher priority. The preemptive model was later replaced by a priority-based system that prevented physician preemption. The question is how to model the middle ground between these two extremes. The PDQ physician multitasks based on many conditions, such as the number and priority of patients in the PDQ area, the number waiting at triage, and the order in which diagnostic results are received. Furthermore, not all physicians will make the same decision given the same set of conditions. Experience plays a big part in decision making. Using human-in-the-loop simulation may be a suitable method to better understand how physicians make decisions, given specific real-time factors.

A final area of future research is to build an analytic model of the PDQ and compare the results to the simulation model. Queuing theory, and, in particular, a network of queues is a mathematical approach that has been successfully applied in other areas such as manufacturing, computer networking, and telecommunications and broadcasting (Van Dijk, 1993). In a queuing network, each PDQ resource would be represented with a separate queue, and the resource would select patients based on priority. Patients would be routed to different queues or out of the network based on state dependent routing.

Modeling the PDQ would require a more complex network than a basic open Jackson network with the following assumptions: stationary homogeneous Poisson
arrival process, exponentially distributed service times, steady state conditions, Markovian or state independent routing, and a single class of customers. Examples of models with multi-class non-stationary arrivals and state dependent routing exist; however, these examples still hold the basic assumption of steady state performance.

Variable arrival rates can be modeled using a stationary independent period-by-period approach (Green et al., 2006) if it can be assumed that the system quickly reaches steady state in each period. The ability to estimate transient performance measures would be helpful for systems with low arrival rates and periods of high resource utilization. Queuing models are generally more efficient to build and run than are simulation models.

In conclusion, there are many areas of future research in the field of healthcare engineering. The above-mentioned areas are direct extensions to this thesis. Healthcare research, especially in the area of process flow, is more important now than ever before, given the steady rise in annual patient census, the steady decline in the number of hospitals and patient beds, and the rising cost of healthcare.
References


Appendix A

Tables of Results

Table A-1: Results of all base case experiments. All averages are given with the half width for the 95% confidence interval.

<table>
<thead>
<tr>
<th>Base case fourteen hour day with no extended hours</th>
<th>Table: Average hourly LOS</th>
</tr>
</thead>
<tbody>
<tr>
<td>9 10 11 12 13 14 15 16 17 18 19 20 21 22</td>
<td>AVG 58.7 98.8 136.2 123.3 139.9 149.2 146.0 166.2 157.2 125.8 106.6 85.4 73.2 32.4</td>
</tr>
<tr>
<td>95% CI 13.2 41.7 47.0 35.7 38.0 39.0 38.5 35.8 30.9 24.5 15.6 11.1 7.2 7.4</td>
<td></td>
</tr>
<tr>
<td>Average hourly resource utilization</td>
<td>AVG 41.7 98.8 10</td>
</tr>
<tr>
<td>9 10 11 12 13 14 15 16 17 18 19 20 21 22</td>
<td>MD 0.51 0.75 0.73 0.86 0.88 0.89 0.89 0.88 0.88 0.92 0.96 0.96 0.94 0.96</td>
</tr>
<tr>
<td>95% CI 0.08 0.06 0.09 0.06 0.05 0.06 0.06 0.07 0.06 0.05 0.04 0.04 0.05 0.04</td>
<td></td>
</tr>
<tr>
<td>T1 0.35 0.44 0.45 0.57 0.57 0.57 0.57 0.59 0.62 0.59 0.68 0.64 0.66 0.59</td>
<td></td>
</tr>
<tr>
<td>95% CI 0.06 0.05 0.06 0.05 0.06 0.06 0.06 0.06 0.07 0.06 0.05 0.06 0.05</td>
<td></td>
</tr>
<tr>
<td>T2 0.14 0.24 0.26 0.23 0.33 0.38 0.43 0.49 0.47 0.54 0.54 0.57 0.57 0.55</td>
<td></td>
</tr>
<tr>
<td>95% CI 0.04 0.05 0.05 0.05 0.05 0.05 0.07 0.07 0.05 0.04 0.07 0.08 0.07 0.05</td>
<td></td>
</tr>
<tr>
<td>Average hourly CD and PDQ census</td>
<td>AVG 38.0 157.2 16</td>
</tr>
<tr>
<td>9 10 11 12 13 14 15 16 17 18 19 20 21 22</td>
<td>CD 0.22 0.43 0.63 1.04 1.67 2.79 4.74 6.70 9.25 11.63 14.68 17.35 19.52 21.81</td>
</tr>
<tr>
<td>95% CI 0.15 0.23 0.30 0.35 0.45 0.54 0.81 0.94 1.08 1.28 1.40 1.47 1.75 1.67</td>
<td></td>
</tr>
<tr>
<td>PDQ 1.51 2.61 3.34 5.06 6.10 7.01 7.57 7.47 8.19 9.29 10.05 10.64 10.39 9.20</td>
<td></td>
</tr>
<tr>
<td>95% CI 0.29 0.48 0.84 1.12 1.54 1.91 1.96 1.98 2.06 2.29 2.34 2.22 2.24 2.02</td>
<td></td>
</tr>
<tr>
<td>Base case modified termination condition</td>
<td>AVG 22.8 147.2 21</td>
</tr>
<tr>
<td>9 10 11 12 13 14 15 16 17 18 19 20 21 22</td>
<td>AVG 58.7 98.8 136.2 129.6 152.8 165.8 168.3 176.6 177.5 149.4 147.2 133.2 120.8 74.5</td>
</tr>
<tr>
<td>95% CI 13.2 41.7 47.0 38.0 43.6 48.7 48.3 40.6 38.1 32.2 22.8 19.8 14.1 11.6</td>
<td></td>
</tr>
</tbody>
</table>
Table A-2: Results from priority based physician decision making with one MD and with 2 MDs. All averages are given with the half width for the 95% confidence interval.

<table>
<thead>
<tr>
<th>Priority based decision making</th>
<th>Average hourly LOS with one MD</th>
<th>Average hourly CD and PDQ census with one MD</th>
<th>Average hourly LOS with 2 MDs</th>
<th>Average hourly MD utilization with 2 MDs</th>
<th>Average hourly PDQ census with 2 MDs</th>
</tr>
</thead>
<tbody>
<tr>
<td>AVG</td>
<td>48.2</td>
<td>69.1</td>
<td>99.2</td>
<td>101.6</td>
<td>147.7</td>
</tr>
<tr>
<td>95% CI</td>
<td>0.10</td>
<td>0.16</td>
<td>0.26</td>
<td>0.30</td>
<td>0.37</td>
</tr>
<tr>
<td>CD</td>
<td>0.16</td>
<td>0.33</td>
<td>0.56</td>
<td>0.96</td>
<td>1.41</td>
</tr>
<tr>
<td>95% CI</td>
<td>0.04</td>
<td>0.06</td>
<td>0.06</td>
<td>0.07</td>
<td>0.06</td>
</tr>
<tr>
<td>AVG</td>
<td>40.8</td>
<td>41.4</td>
<td>39.6</td>
<td>41.0</td>
<td>41.8</td>
</tr>
<tr>
<td>CD</td>
<td>0.26</td>
<td>0.42</td>
<td>0.43</td>
<td>0.47</td>
<td>0.49</td>
</tr>
<tr>
<td>95% CI</td>
<td>0.04</td>
<td>0.06</td>
<td>0.06</td>
<td>0.07</td>
<td>0.06</td>
</tr>
</tbody>
</table>
Table A-3: Average hourly MD utilization and PDQ census by arrival rate factor. All averages are given with the half width for the 95% confidence interval.

<table>
<thead>
<tr>
<th>Average hourly MD utilization with 10% decrease</th>
<th>9</th>
<th>10</th>
<th>11</th>
<th>12</th>
<th>13</th>
<th>14</th>
<th>15</th>
<th>16</th>
<th>17</th>
<th>18</th>
<th>19</th>
<th>20</th>
<th>21</th>
<th>22</th>
</tr>
</thead>
<tbody>
<tr>
<td>AVG</td>
<td>0.443</td>
<td>0.636</td>
<td>0.708</td>
<td>0.798</td>
<td>0.813</td>
<td>0.83</td>
<td>0.896</td>
<td>0.847</td>
<td>0.797</td>
<td>0.911</td>
<td>0.914</td>
<td>0.934</td>
<td>0.907</td>
<td>0.844</td>
</tr>
<tr>
<td>95% CI</td>
<td>0.071</td>
<td>0.091</td>
<td>0.071</td>
<td>0.064</td>
<td>0.075</td>
<td>0.067</td>
<td>0.057</td>
<td>0.062</td>
<td>0.085</td>
<td>0.043</td>
<td>0.044</td>
<td>0.054</td>
<td>0.053</td>
<td>0.07</td>
</tr>
</tbody>
</table>

Average hourly MD utilization at baseline arrivals

| AVG                                          | 0.51 | 0.75 | 0.73 | 0.86 | 0.88 | 0.89 | 0.89 | 0.88 | 0.88 | 0.92 | 0.96 | 0.96 | 0.94 | 0.96 |
| 95% CI                                       | 0.08  | 0.06 | 0.09 | 0.06 | 0.05 | 0.06 | 0.06 | 0.07 | 0.06 | 0.05  | 0.04 | 0.04 | 0.05 | 0.04 |

Average hourly MD utilization with 10% increase

| AVG                                          | 0.517 | 0.744 | 0.789 | 0.885 | 0.932 | 0.954 | 0.978 | 0.949 | 0.979 | 0.965 | 0.984 | 0.96 | 0.981 | 0.969 |
| 95% CI                                       | 0.076 | 0.081 | 0.068 | 0.055 | 0.034 | 0.036 | 0.02  | 0.038 | 0.034 | 0.058 | 0.042 | 0.037 | 0.029 | 0.032 |

Average hourly MD utilization with 20% increase

| AVG                                          | 0.544 | 0.795 | 0.852 | 0.91  | 0.931 | 0.95  | 0.955 | 0.975 | 0.997 | 0.992 | 0.978 | 0.963 | 0.998 | 0.971 |
| 95% CI                                       | 0.07  | 0.074 | 0.058 | 0.049 | 0.051 | 0.046 | 0.043 | 0.039 | 0.01  | 0.011 | 0.026 | 0.035 | 0.019 | 0.031 |

Average hourly MD utilization with 30% increase

| AVG                                          | 0.606 | 0.877 | 0.909 | 0.949 | 0.986 | 0.99  | 1.01  | 0.987 | 0.982 | 0.992 | 0.999 | 0.998 | 0.998 | 0.993 |
| 95% CI                                       | 0.071 | 0.06  | 0.055 | 0.046 | 0.014 | 0.018 | 0.01  | 0.018 | 0.024 | 0.013 | 0.013 | 0.012 | 0.016 | 0.013 |

Average hourly PDQ census with 10% decrease

| 95% CI                                       | 0.274 | 0.421 | 0.58  | 0.771 | 1.089 | 1.132 | 1.067 | 1.424 | 1.536 | 1.447 | 1.505 | 1.511 | 1.66  | 1.782 |

Average hourly PDQ census at baseline arrival rate

| AVG                                          | 1.51  | 2.61  | 3.34  | 5.06  | 6.10  | 7.01  | 7.57  | 7.47  | 8.19  | 9.29  | 10.05 | 10.64 | 10.39 | 9.20  |
| 95% CI                                       | 0.29  | 0.48  | 0.84  | 1.12  | 1.54  | 1.91  | 1.96  | 1.98  | 2.06  | 2.29  | 2.34  | 2.22  | 2.24  | 2.02  |

Average hourly PDQ census with 10% increase

| AVG                                          | 1.593 | 2.632 | 3.773 | 5.296 | 6.8   | 7.951 | 9.145 | 10.25 | 11.75 | 13.44 | 15.76 | 17.26 | 18.4  | 19.49 |
| 95% CI                                       | 0.306 | 0.589 | 0.801 | 0.942 | 1.318 | 1.639 | 1.827 | 2.126 | 2.334 | 2.779 | 3.42  | 3.928 | 3.957 | 4.203 |

Average hourly PDQ census with 20% increase

| 95% CI                                       | 0.339 | 0.556 | 0.878 | 1.058 | 1.744 | 2.293 | 2.731 | 2.86  | 3.032 | 3.115 | 3.83  | 4.383 | 4.573 | 5.008 |

Average hourly PDQ census with 30% increase

| AVG                                          | 1.86  | 4.309 | 6.523 | 8.709 | 11.32 | 13.78 | 16.08 | 18.25 | 20.11 | 23.24 | 27.89 | 31.4  | 34.4  | 36.68 |
| 95% CI                                       | 0.331 | 0.769 | 1.359 | 1.635 | 1.756 | 2.101 | 2.237 | 2.883 | 3.412 | 3.613 | 3.693 | 3.988 | 4.511 | 4.795 |
Table A-4: Average PDQ census for trigger based method. All averages are given with the half width for the 95% confidence interval.

<table>
<thead>
<tr>
<th>Trigger</th>
<th>AVG PDQ Census</th>
<th>95% CI</th>
</tr>
</thead>
<tbody>
<tr>
<td>4</td>
<td>1.96</td>
<td>1.81</td>
</tr>
<tr>
<td>5</td>
<td>2.19</td>
<td>1.95</td>
</tr>
<tr>
<td>6</td>
<td>2.25</td>
<td>2.03</td>
</tr>
<tr>
<td>7</td>
<td>2.51</td>
<td>2.3</td>
</tr>
<tr>
<td>8</td>
<td>2.9</td>
<td>2.61</td>
</tr>
<tr>
<td>10</td>
<td>2.97</td>
<td>2.69</td>
</tr>
<tr>
<td>One MD</td>
<td>5.3</td>
<td>4.11</td>
</tr>
<tr>
<td>Two MD</td>
<td>1.15</td>
<td>1.04</td>
</tr>
</tbody>
</table>

Table A-5: Average additional physician time and LOS for trigger based method. All averages are given with the half width for the 95% confidence interval.

<table>
<thead>
<tr>
<th>Trigger</th>
<th>AVG min/day</th>
<th>95% CI</th>
<th>AVG LOS</th>
<th>95% CI</th>
</tr>
</thead>
<tbody>
<tr>
<td>4</td>
<td>274</td>
<td>236.61</td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>192</td>
<td>163.54</td>
<td></td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>132</td>
<td>101.21</td>
<td></td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>102</td>
<td>78.36</td>
<td></td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>94</td>
<td>68.57</td>
<td></td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>50</td>
<td>34.34</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table A-6: Average additional physician time, average PDQ census, and average LOS for schedule based method. All averages are given with the half width for the 95% confidence interval.

<table>
<thead>
<tr>
<th>Schedule</th>
<th>AVG min/day</th>
<th>AVG PDQ Census</th>
<th>AVG LOS</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>120.84</td>
<td>121.82</td>
<td>76.28</td>
</tr>
<tr>
<td></td>
<td>121.82</td>
<td>3.64</td>
<td>97.4</td>
</tr>
</tbody>
</table>
Table A-7: Average hourly PDQ census data by method. All averages are given with the half width for the 95% confidence interval.

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<th>11</th>
<th>12</th>
<th>13</th>
<th>14</th>
<th>15</th>
<th>16</th>
<th>17</th>
<th>18</th>
<th>19</th>
<th>20</th>
<th>21</th>
<th>22</th>
</tr>
</thead>
<tbody>
<tr>
<td>AVG</td>
<td>1.49</td>
<td>2.34</td>
<td>3.29</td>
<td>4.55</td>
<td>4.59</td>
<td>4.79</td>
<td>4.97</td>
<td>4.69</td>
<td>4.66</td>
<td>5.40</td>
<td>5.62</td>
<td>5.77</td>
<td>5.09</td>
<td>4.06</td>
</tr>
<tr>
<td>95% CI</td>
<td>0.31</td>
<td>0.50</td>
<td>0.63</td>
<td>0.88</td>
<td>0.77</td>
<td>0.90</td>
<td>0.86</td>
<td>0.75</td>
<td>0.86</td>
<td>1.06</td>
<td>0.97</td>
<td>0.96</td>
<td>0.88</td>
<td>0.78</td>
</tr>
</tbody>
</table>

Average hourly PDQ census for Schedule A

<table>
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<th>10</th>
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<th>12</th>
<th>13</th>
<th>14</th>
<th>15</th>
<th>16</th>
<th>17</th>
<th>18</th>
<th>19</th>
<th>20</th>
<th>21</th>
<th>22</th>
</tr>
</thead>
<tbody>
<tr>
<td>AVG</td>
<td>1.49</td>
<td>2.34</td>
<td>3.29</td>
<td>3.71</td>
<td>3.59</td>
<td>4.36</td>
<td>5.42</td>
<td>5.45</td>
<td>6.25</td>
<td>6.71</td>
<td>6.68</td>
<td>6.15</td>
<td>6.55</td>
<td>6.34</td>
</tr>
<tr>
<td>95% CI</td>
<td>0.31</td>
<td>0.50</td>
<td>0.63</td>
<td>0.83</td>
<td>0.85</td>
<td>0.94</td>
<td>1.01</td>
<td>1.41</td>
<td>1.12</td>
<td>1.49</td>
<td>1.10</td>
<td>1.23</td>
<td>1.51</td>
<td>1.51</td>
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</tbody>
</table>

Table A-8: Average hourly LOS by method. All averages are given with the half width for the 95% confidence interval.

<table>
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<tr>
<th></th>
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<th>10</th>
<th>11</th>
<th>12</th>
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<th>15</th>
<th>16</th>
<th>17</th>
<th>18</th>
<th>19</th>
<th>20</th>
<th>21</th>
<th>22</th>
</tr>
</thead>
<tbody>
<tr>
<td>AVG</td>
<td>48.3</td>
<td>62.1</td>
<td>79.1</td>
<td>76.5</td>
<td>85.8</td>
<td>71.9</td>
<td>76.2</td>
<td>81.4</td>
<td>101.1</td>
<td>88.8</td>
<td>86.0</td>
<td>79.6</td>
<td>70.7</td>
<td>51.2</td>
</tr>
<tr>
<td>95% CI</td>
<td>6.77</td>
<td>9.87</td>
<td>10.6</td>
<td>8.23</td>
<td>12.5</td>
<td>10.16</td>
<td>7.64</td>
<td>9.88</td>
<td>17.10</td>
<td>13.92</td>
<td>13.05</td>
<td>11.44</td>
<td>10.55</td>
<td>4.70</td>
</tr>
</tbody>
</table>

Average hourly LOS census for Schedule A

<table>
<thead>
<tr>
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<th>10</th>
<th>11</th>
<th>12</th>
<th>13</th>
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<th>15</th>
<th>16</th>
<th>17</th>
<th>18</th>
<th>19</th>
<th>20</th>
<th>21</th>
<th>22</th>
</tr>
</thead>
<tbody>
<tr>
<td>AVG</td>
<td>48.3</td>
<td>61.5</td>
<td>54.3</td>
<td>62.8</td>
<td>90.7</td>
<td>110.8</td>
<td>115.4</td>
<td>107.2</td>
<td>110.0</td>
<td>78.8</td>
<td>95.4</td>
<td>113.7</td>
<td>92.2</td>
<td>71.6</td>
</tr>
<tr>
<td>95% CI</td>
<td>6.77</td>
<td>8.84</td>
<td>6.19</td>
<td>17.26</td>
<td>22.36</td>
<td>23.94</td>
<td>24.83</td>
<td>26.56</td>
<td>20.41</td>
<td>15.75</td>
<td>20.46</td>
<td>17.98</td>
<td>15.21</td>
<td>9.77</td>
</tr>
</tbody>
</table>
## Appendix B

### List of Acronyms

<table>
<thead>
<tr>
<th>Acronym</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>A&amp;E</td>
<td>Accident and Emergency</td>
</tr>
<tr>
<td>ACEP</td>
<td>American College of Emergency Physicians</td>
</tr>
<tr>
<td>CD</td>
<td>Complex Diagnostic</td>
</tr>
<tr>
<td>CI</td>
<td>Confidence Interval</td>
</tr>
<tr>
<td>CY</td>
<td>Calendar Year</td>
</tr>
<tr>
<td>ED</td>
<td>Emergency Department</td>
</tr>
<tr>
<td>EDT</td>
<td>Emergency Department Technician</td>
</tr>
<tr>
<td>EKG</td>
<td>Electrocardiogram</td>
</tr>
<tr>
<td>ENP</td>
<td>Emergency Nurse Practitioner</td>
</tr>
<tr>
<td>ESI</td>
<td>Emergency Severity Index</td>
</tr>
<tr>
<td>FCFS</td>
<td>First-Come-First-Serve</td>
</tr>
<tr>
<td>FTA</td>
<td>Fast Track Area</td>
</tr>
<tr>
<td>HMC</td>
<td>Hershey Medical Center</td>
</tr>
<tr>
<td>ICU</td>
<td>Intensive Care Unit</td>
</tr>
<tr>
<td>IOM</td>
<td>Institute of Medicine</td>
</tr>
<tr>
<td>LOS</td>
<td>Length of Stay</td>
</tr>
<tr>
<td>LWOT</td>
<td>Left Without Treatment</td>
</tr>
<tr>
<td>MD</td>
<td>Medical Doctor</td>
</tr>
<tr>
<td>PDQ</td>
<td>Physician-Directed Queue</td>
</tr>
<tr>
<td>S&amp;T</td>
<td>See-and-Treat</td>
</tr>
<tr>
<td>T1</td>
<td>Triage Nurse 1</td>
</tr>
<tr>
<td>T2</td>
<td>Triage Nurse 2</td>
</tr>
<tr>
<td>UK</td>
<td>United Kingdom</td>
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</table>