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USE OF SIMULATION MODELING TO INVESTIGATE THE URGICARE OPERATION DURING PHASE I TRANSITION

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ABSTRACT

Crowding is when an Emergency Department (ED) is operating in a state in which it does not have sufficient resources to accommodate another patient. Operating in this condition can ultimately compromise a patient's quality of care. Several best practices have been developed to lessen the occurrence of ED crowding. An example of one such practice is a fast track – a dedicated set of resources within an ED reserved for processing patients of the lowest severity.

The ED of the Williamsport Regional Medical Center (WRMC) utilizes a fast track (referred to as Urgicare). Currently, the hospital is undergoing a renovation and expansion. As construction is completed, the ED will transition to the remodeled areas in phases. It is the interest of WRMC to avoid the use of the existing Urgicare treatment area due to the distance between the Main ED and the Urgicare treatment area during the transition. Therefore, WRMC is interested in reserving beds of the Main ED for treating Urgicare patients.

In this thesis, simulation is used to model the bed allocation for ED patients at WRMC. The model is used to simulate a Baseline Scenario and three proposed operational scenarios for Urgicare. The results of the Baseline Scenario are used as a benchmark from which the success of each proposed scenario can be evaluated. The proposed scenarios vary in the number of beds reserved in the Main ED for providing treatment to Urgicare patients. The key performance measures used are Provider after Triage time and Departure after Triage time, because this ED did not experience large delays before triage.

All of the proposed scenarios maintained or improved on the performance level of the Baseline Scenario. Reserving three beds in the Main ED for Urgicare patients and a fourth bed for a Super-Urgi treatment area provided the greatest improvement. Main ED and Urgicare patients experienced a percent improvement in Provider after Triage time of 21.4% and 16.5%; likewise, the percent improvement in Departure after Triage time was 4.2% and 9.3%, respectively.

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Chapter 1

INTRODUCTION

1.1 Motivation

The motivation of this thesis comes from the desire to use simulation modeling as a tool to reduce the occurrence of Emergency Department (ED) crowding. Much of the existing literature about the operating conditions of EDs demonstrates that crowding is a growing concern in the United States. Nationwide, patient arrival rates to EDs continue to increase while the number of EDs has been steadily declining (Institute of Medicine, 2007).

The Williamsport Regional Medical Center (WRMC) is currently remodeling and expanding its ED to better serve its patients. This hospital utilizes a practice known as fast track (Urgicare) to improve its efficiency. Operations will transition to the new ED in multiple phases. Within a year, WRMC will implement Phase I of the transition. A concern surrounding Phase I stems from the location of the existing Urgicare unit. Currently the distance separating the Main ED and Urgicare is insignificant; therefore, a nurse can transport a patient from triage to Urgicare without being occupied for a significant amount of time. During Phase I, however, a significant distance exists between the location of the ED and Urgicare. As a result, nurses will be occupied for a greater amount of time as they transport patients from triage to Urgicare, thus constraining the resources of the ED. Also, the path from the future ED to Urigcare will force patients to travel through a construction area which is not ideal. For these reasons, WRMC seeks to determine the best way to avoid the negative consequences resulting from this situation prior to the Phase I transition.

1.2 Scope

An interest of WRMC is whether the Phase I operation can proceed without using the existing Urgicare. An option discussed has been reserving a number of rooms within the Phase I ED for patients who would typically be sent to Urgicare. However, the number of treatment rooms that should be reserved is unknown. Each room reserved for Urgicare reduces the capacity of the Phase I ED. This limits the ability of the ED to provide treatment for patients of greater severity. WRMC has also discussed developing a Super-Urgi within the main ED to provide treatment to patients who can be processed the quickest, which would further restrict the capacity of the ED. The simulation model presented in this research is designed to use the information that can be derived from the patient timestamp data currently collected by WRMC. Specifically, the model will make use of arrival times, ESI, Door-to-Doc, and Length of Stay data of each patient.

A total of four operational scenarios are simulated. A baseline scenario was simulated to provide a performance level from which the success or failure of the proposed scenarios will be determined. The three proposed operational scenarios of WRMC are as follows:

1. Urgicare patients are treated only in the existing Urgicare unit
2. Urgicare patients are either treated in the beds reserved in the Phase I ED (3) or in the beds of the existing Urgicare unit (4)
3. Scenario 2 with the addition of a fourth bed (Super-Urgi) for patients with relatively short treatment times

Average differences in performance measures of each scenario with respect to the baseline scenario were calculated. The resulting confidence intervals are used to provide an overall recommendation to WRMC for future operation.

1.3 Research Objectives

It is the goal of this research to use simulation modeling to provide insight into the feasibility of some of the scenarios described above. Simulation modeling is an appropriate tool, because of its ability to predict future performance of complex systems, such as the operation of an ED. Specifically, the goal of this research is to use simulation modeling to analyze the three scenarios presented to address the following objectives:

1. Analyze the feasibility of reserving rooms in the Phase I ED for Urgicare;
2. Assess whether a Super-Urgi is sensible.

1.4 Organization

The remainder of this document is divided into four chapters. Chapter Two provides a review of the existing literature relevant to the fundamental causes of ED crowding as well as frequently-used process improvement techniques that lessen the frequency of its occurrence. This chapter also provides a review of other research that uses simulation modeling to analyze ED performance. Chapter Three serves to provide a description of the developed simulation model. It provides an overview of the process flow logic for the simulation model, how the model was developed in Simio modeling software as well as the differences for each scenario, and how the model was validated and verified. An outline for the experimental design and primary methods for analyzing the simulation results is provided in Chapter Four. This section also provides a recommendation for the best operating scenario(s) for WRMC. The final chapter, Chapter 5, summarizes the conclusions of this research and provides suggestions for future avenues of exploration.

Chapter 2

LITERATURE REVIEW

2.1 Introduction

The emergency department (ED) of hospitals is an often-researched area of health care service. This is attributed to vast differences that exist in acuity and needs of patients who arrive to the ED. Due to the Emergency Medical Treatment and Labor Act, the ED provides medical services to the poor and uninsured. Further exacerbating the ability to efficiently manage ED resources and patient flow is the arrival of patients because it is unplanned. Put another way, much variability exists in the types of patients who arrive and the rate at which they arrive to an ED. Variability in these factors prohibit the efficient use of resources and compromise the flow of patients. This chapter provides three sections that summarize the existing condition of EDs in the United States. The first section identifies the reasons for ED crowding and the observed consequences. The second section covers methods that are being implemented in hospitals to lessen the occurrence of ED crowding. The final section covers simulation models used as tools to identify opportunities for improvement of patient flow.

2.2 Emergency Department Crowding

Unlike other areas of a hospital, the arrival of patients to the ED is unplanned. The patient who arrives to the department is either in need of immediate care or is uninsured with limited access to medical care. The former patient type is a result of illness or injury of varying severity. The Emergency Medical Treatment and Labor Act (EMTLA) brings the latter type of patient to the ED because it ensures that patients receive screening regardless of their ability to pay (ACEP, 2008). The convolution of these patient types creates a significant demand that occupies many resources of the ED, such as physicians, nurses, and beds.

The variability of patient arrivals often causes an imbalance between ED capacity and demand. This condition is known as crowding. One definition of crowding is when no resources remain to accommodate the needs of the next arriving patient (ACEP, 2008). The Center for Disease Control (CDC) has reported that nearly 50% of EDs experience crowding (Burt and McCaig, 2006). Moreover, according to Olshaker and Rathleve (2006), 90% of physicians reported in 2006 that crowding is a recurrent problem. These conditions are unsustainable because they exhaust the resources of the ED, thus compromising the quality of patient care. Crowding is an epidemic in the United States' health care system and continues to increase in severity.

2.2.1 Assignable Causes of ED Crowding

In its simplest form, ED crowding is a demand-capacity matching problem, where the demand is the arrival of patients to the ED and capacity is the resources of the ED used to provide patient care. An inequality between these factors exists for a multitude of reasons.

A significant contributor of ED crowding identified by the Institute of Medicine (IOM) (2007) is that the demand for EDs continues to rise while the number of EDs have decreased. One reason for an increase in demand is that, on average, the population is living longer. Even in the past 30 years, the life expectancy of a newborn child has increased by nearly 8.5 years (Keeler et. al, 2010). A declining relationship exists between age and one's health. More frequently, individuals become sick due to sicknesses of accumulation—such as cancer, diabetes, and cardio vascular disease—and transition to a sedentary lifestyle. These illnesses often result in instant complications requiring immediate attention. According to the CDC the number of annual ED visits rose by nearly 25% in the decade ending 2002 (McCaig and Burt, 2002). That is, the number of ED visits increased from 89.8 to 108 million during the ten-year period (Shafermyer and Asplin, 2003). Also, seasonal diseases and epidemics can cause significant, forecasted spikes in the arrival rate of patients to the ED. When this occurs, the staffing level is ill-equipped to meet the increase in demand.

The Lewin Group, a healthcare policy research and management consulting firm, conducted a survey that investigated hospital capacity (Lewin Group, 2002). The study found that 62% of all U.S. hospitals were fully utilizing or over-utilizing their ED operating capacity. This proportion was even higher for urban and Level I trauma centers (79% and 87%). As hinted in the Lewin Group study, patient demand is further amplified in poorer communities. This fact is validated by the United States Government Accountability Office (GAO) that determined that ED crowding was more prevalent in hospitals of larger uninsured populations. Urban areas are more densely populated with individuals of lower economic status (such as the unemployed), because of low-income housing. In the absence of health care coverage, these individuals have no other option other than the ED to receive medical treatment. The ED is viewed as a safety net for these patients and may result in “unnecessary” visits that constrain health care providers (IOM, 2007).

While the demand for EDs continues to rise, the number of EDs has declined. During the same time that the CDC reported an increase in annual ED visits of 25%, it was also found that the number of EDs was reduced by nearly 15% (McCaig and Burt, 2002). Similarly, Schafermeyer and Asplin (2003) concluded that the number of hospital emergency rooms decreased from approximately 6,000 to 4,000. The greatest contributor to the decline in number of EDs was closure. Logically, fewer available EDs means that patients in need have less options in times of crisis.

Another reason for inadequate capacity identified by the American College of Emergency Physicians (ACEP, 2008) is that although hospitals are a 24-hour per day operation, the hospitals are staffed as a standard 9:00 AM – 5:00 PM occupation. The hospital is staffed with a limited number of health care providers for the remainder of the day. Hospitals operate in this way to reduce operational expenses. If a physician is not available in the hospital, then a patient occupies a physician from the ED to receive appropriate treatment. Consequently, hospital patients often occupy the capacity of ED physicians. The consequence is that the patients who arrive to the ED experience extended waiting times until a physician becomes available again (ACEP, 2008). The reason for scheduling hospital physicians as a 9:00 AM – 5:00 PM occupation is a result of the tendency of demands in the 1960s being primarily based on elective surgeries. Even though there has been a dramatic shift in the influx of patients by type and rate, the hospital physician staffing model remains largely unmodified.

Additionally, physicians' capacity is reduced early in the week because of the tendency to schedule elective surgeries during these days. The reason for scheduling surgeries early in the week is because most surgeries require additional care during the immediate days. Therefore, to provide adequate care, surgeries are scheduled earlier in the week to improve patient care (McCaig and Burt, 2004). Scheduling elective surgeries in this manner reduces the capacity of physicians to treat emergency patients early in the week. Adding to this problem is that the ED arrival rate is typically higher during the beginning of the week (ACEP, 2008). These two factors compromise the treatment of patients, because these patients must either wait in the ED or be directed to another hospital.

There is currently a shortage of health-care providers. The health care service in general is a complex, exhaustive, and technical service requiring extensive training and education. The need for health care providers continues to grow; however, fewer individuals are pursuing this career because of the substantial investment of time and money involved. Also the service is physically and mentally demanding. For these reasons the supply of nurses and physicians continues to be compressed. To exemplify this condition, the turnover rate of nurses is 21% annually (Kosnik, 2006).

Hospital silos further contribute to the inadequate capacity of EDs. This term refers to healthcare units focused on meeting their own individual resources, technology, and patient needs. When healthcare units function as a silo they fail to consider the impact on over/under utilized departments in the hospital (Kosnik, 2006). This creates bottlenecks in patient flow. The problem of ED crowding is a hospital-wide problem, and silos prevent the commitment of resources from other areas to address the needs of the hospital.

Blood, x-rays, and other technical screening tests are often used to identify the cause of an emergency patient's condition. The ability of an ED to communicate with other departments of the hospital plays a significant role in the turnaround time of these ancillary tests. A breakdown in communication between departments occurs when silos exist. This creates a delay in the turnaround time of ancillary test results, thus lengthening the duration that a patient occupies the resources of an ED.

A practice used by hospitals that cause their ED to operate at full capacity is patient boarding. A patient is said to be boarded when an admitted patient spends more than two hours before departing from the ED. A patient may be boarded in the ED to make more inpatient beds available for elective surgeries, and it allows for higher utilization of hospital capacity (Pines et. al., 2006). In short, patient boarding constrains the resources of the ED.

Further contributing to ED crowding is the distribution of patient interarrival times. Most hospitals staff their ED's according to an average hourly rate of patient arrivals. The population size of arrivals during a one-hour period is comparatively small and much variability exists in interarrival times (Medeiros et al., 2008). The small population of arrivals discourages many EDs from providing sufficient staff to account for variability because to do so would mean that ED staffs additional physicians, nurses, and other health care providers. As a consequence, the ED may be adequately staffed for the average number of patients expected to arrive during a given hour, but will be ill-prepared to accommodate a surge in the expected number of patients. When this situation obtains, the ED does not have sufficient capacity.

2.2.2 Crowding Consequences

The inability of an ED to meet the demand of emergent patients causes a multitude of complications. Ultimately, the demand-capacity imbalance compromises the quality of treatment. Not having sufficient resources lengthens the duration that an emergency patient must wait before receiving treatment. An increase in the amount of time that patients are forced to wait hinders their ability to recover from their illness or injury. This decreases the quality of patient care and, in the most extreme case, can lead to death.

One situation that delays the time before a patient is admitted to a hospital is ambulance diversion—a condition in which a hospital is no longer formally accepting patients. When this condition exists, the destination of an emergent patient is dependent on capacity and not proximity. Logically, this extends the amount of time that passes before a patient is admitted. A recent study conducted a binomial regression analysis on acute myocardial infarction deaths (deaths resulting from heart attack) and the extent of ambulance diversion in New York City. The results of the study determined that a link between diversion and mortality exists (Yankovic et al., 2010). Ambulance diversion is implemented in approximately 50% of EDs (Burt et al., 2006).

The practice of ED boarding contributes to the length of stay (LOS) of a patient and the quality of care that a patient receives. Pines (2006) performed an analysis of trends in boarding of admitted patients to the ED between the years 2003 – 2005. Data from this study came from the National Hospital Ambulatory Medical Care Survey (NHAMCS) which is a sample survey of US

ED visits collected annually. The study found that during this time period the average LOS decreased from 5.4 to 4.6 hours. A linear regression model was developed to determine significant factors associated with LOS, one of which was the proportion of ED boarding. The regression analysis concluded with statistical significance that the decrease in LOS was related to the decrease in the proportion of ED boarding (11.3 - 17.3% in 2003 to 2.8 - 12.0% in 2005). For these reasons it can be concluded that ED boarding is linked to LOS and ED quality of care.

Another consequence of crowding is that patients waiting in the ED may leave the ED without receiving evaluation from a physician. ED boarding also contributes to this situation. The proportion of patients who leave without being seen is correlated with the time interval between patient arrivals and the time that a physician meets with the patient (often referred to as Door-to-Doc time). Anecdotal evidence has confirmed that the longer patients wait the greater the likelihood that they will leave without receiving treatment (ACEP, 2008). The patients who leave without being seen often return to the ED at a later time, because they did not receive the treatment that they originally needed. Returning patients can be considered a factor that contributes to increased ED demand. Another consequence of patients leaving without being seen is that their acuity level is often higher when they return to the ED, because they failed to receive appropriate treatment earlier (Weiss et al., 2005).

Crowding also increases the frequency of medical errors. Medical errors result from health care providers in the ED having to simultaneously provide service to inpatients and manage the new, emergency patients. This is a large cognitive load to handle resulting in many omissions, non-commissions, and misdiagnosis (ACEP, 2008). These consequences result because of this large cognitive burden coupled with the fact that many symptoms are not unique to a particular ailment.

Kuan and Mahadevan (2009) conducted a retrospective study that examined unscheduled returns to an ED during a six month period in 2005. The objective of this study was to identify the reasons behind patients returning to the ED within 72 hours of their initial visit. Of the 38,414 patients that entered the ED, 842 patients returned unscheduled to the ED, and nearly 50% of these patients returned for a third visit. A common symptom expressed by patients arriving to the ED was abdominal discomfort for which there is a myriad of possible diagnosis that corresponds to different treatments. Of the 211 patients that returned to the ED with the same symptoms, 36.4% received intravenous hydration, 16.1% were advised to reduce physical activity, and 12.2% were diagnosed with appendicitis. The disparity in diagnosis despite common symptoms is suggestive of the mental stress of health care providers. Moreover, it was also concluded that 19.1% of patients were re-admitted because of their inability to take care of themselves at home—that is, the health care providers did not provide adequate discharge instructions. Kuan and Mahadevan (2009) present the argument that the primary reasons for repeat visits by a patient can be linked to health care error and inadequacies, and not the ailment itself. Therefore it was the conclusion of this study that improved diagnostic tools should be used. Naturally, this may require the increase of ED resources.

The death rate of patients is significantly higher during times of ED crowding. This is the most extreme consequence of ED crowding. A 2007 study examined the impact of delay in transfer time of critically ill patients from the ED to the Intensive Care Unit (ICU). It was determined that a significant increase in average mortality existed when the ED was crowded—an increase in death rate from 8.4% to 10.7% (Chaflin et al., 2007). Similarly, it has been estimated that deaths would be reduced to a range between 75 and 83 for every 100 patients that would have died due to crowding (ACEP, 2008) if methods were implemented that reduced the frequency of its occurrence. In short, the correlation between mortality rate and crowding further requires the need to lessen ED crowding.

2.3 Methods Used to Allay Demand – Capacity Challenges

The fundamental reason that EDs in the United States are frequently crowded is a result of the inequality that exists between demand and capacity. Despite awareness of this inequality, many challenges have been encountered when trying to improve this condition. One challenge is fiscal. It has been estimated that approximately 35% of the money spent annually on health care is spent on costs associated with the challenges derived from the EDs inability to meet demand (IOM, 2007). A logical way to improve the ability of EDs to meet the demand of patients is to increase the resources, both human and technological. Unfortunately, increasing resources incurs a significant cost. Lack of financial support of the ED exists because unlike other departments of the hospital, such as the Operating Room (OR), the ED is not a significant revenue-generating source (Sacchetti et al., 2002). Unfortunately the savings associated with improving patient flow are often inferior to the costs of implementation. Therefore, many practices are being developed and implemented that attempt to improve the efficiency of ED resources. The ultimate goal is to satisfy the dual objective of maximizing quality of care and minimizing costs.

2.3.1 Physician at Triage

The triage is an area of an ED used to determine a patient's priority—typically based on acuity of ailment—when resources are constrained and the ED is unable to provide service immediately. Traditionally, this section of the ED is staffed by nurses and nurse practitioners. In 1963, the Yale-New Haven Hospital was one of the first EDs to staff an additional physician at triage with the intention of improving ED efficiency. Many hospitals realized the potential benefits that this initiative might have and incorporated it into their triages (Han et al., 2010). However, most EDs have reverted back to the old staffing model of the triage and the role that the physician served has been assumed by nurses and other health care providers who are less costly (IOM, 2007).

Recently, some EDs have returned to the practice of placing a physician at triage. Incorporating an additional physician at the triage of an ED allows for initial diagnostic workups and the ability to treat patients in the waiting room. The purpose of this is to decrease Door-to-Doc time, delays in ancillary/diagnostic tests, and discharge patients who do not require immediate care. The overall goal is to improve ED efficiency via reduction of patient LOS. Also, because patients interact with a physician sooner, their perceived quality of treatment is improved (Partovi et al., 2001).

The effect of using a triage physician on throughput has been studied (Han et al., 2010) by observing differences in ED LOS, left without being seen rates (LWBS), and time that a hospital spends on ambulance diversion. This study compared these performance measures during two separate nine-week periods when a physician was present and not present at triage. The studied hospital was a Trauma 1 center located in an urban area, and therefore, the test subjects consisted of a mix of ill, injured, and the uninsured. The role of a physician at triage was to screen the patient, order necessary diagnostic testing, and discharge the patient if possible. Using an analysis of covariance, the results of this study found that having a physician at triage is significantly correlated with ED LOS; however, the effect on LOS is marginal. The interpretation of this finding is that whether physician evaluation is used during the triage process affects the LOS of a patient such that physician evaluation decreases LOS. It was also observed when a physician is used during triage that LWBS decreased from 4.5% to 2.5% (*p-value* < 0.001) and occurrences of ambulance diversion decreased from 36 to 29 ($p = 0.025$).

Another result of Han et al.’s study (2010) was that incorporating a physician during the triage process increases the throughput of the ED. Although throughput does increase, the effect on LOS is limited by the prolonged boarding times experienced during periods of crowding. For this reason it is hypothesized that addressing bottlenecks may be a more beneficial method for improving ED efficiency (and LOS) during periods of crowding.

Another study with the aim of determining the impact of placing a physician at triage on ED LOS and LWBS rates was conducted in 2001 by Partovi et al. This study measured patient LOS and LWBS rates on 16 consecutive Mondays—eight of which with a physician present at triage. The researchers developed a multiple linear regression model to predict average LOS. The observation data determined that the presence of a physician at triage was a significant predictor of average patient's LOS. It also found that the number of patients admitted, time of day, and whether X-Rays/ancillary services are needed were significantly related to the average LOS. These may suggest additional avenues of investigation for improving patient flow. Additionally, the study concluded with statistical significance that average LOS and LWBS rates were reduced by 18% and 46%, respectively. More specifically, average LOS decreased from 445 to 363 minutes and LWBS rates decreased from 14.7% to 7.9%. The pattern of these results is consistent with the results of the previously cited study and further justifies incorporating a physician in triage.

From these studies it can be concluded that that a main contributor to the decreases in LOS, LWBS rates, and time spent on diversion is a result of a physician's ability to discharge patients and administer initial evaluation. Logically, the LOS experienced by a patient is shorter when a non-urgent patient is screened and discharged by a physician at triage rather than having to wait for a bed before being seen by a physician and then discharged. Similarly, patients that require diagnostic workup, but are not of a severity level that requires a bed immediately, will experience a decrease in LOS because the physician can order necessary ancillary tests prior to the patient being allocated a bed.

A variation of placing a physician at triage was analyzed by Medeiros who examined an approach to patient flow known as Physician Directed Queuing (PDQ) (Medeiros et al., 2008).

This approach involves implementing a PDQ team at triage consisting of a physician, physician assistant, a triage nurse, a charge nurse, and an emergency department technician. The role of the physician is to listen to both the complaints of patients and the nurse's assessment of the patient. Then a decision is made on where to direct the patient based first on acuity of ailment and second on the real-time capacity of the ED. For example, if incoming patients are considered to be of high acuity, then they will be directed immediately to a room. If it is determined that an incoming patient is non-urgent, then the destination of the patient is dependent on the availability of rooms in the ED and the availability of resources needed to treat that patient.

The Hershey Medical Center ED conducted a pilot study of the PDQ for approximately a month. Performance measures were collected on LWBS rates, LOS, Door-to-Room time (interval between patient arrival to the ED and room allocation), and Door-to-Doc time to evaluate the efficacy of PDQ. All of the studied performance measures experienced an improvement. Although the statistical significance of the improvements was not specified, the magnitude of the observed changes was substantial. The pilot study observed a decrease in LWBS rate from 5.6% to 2.7%, LOS decreased from 8 hours, 6 minutes to 6 hours, 16 minutes, and Door-to-Room and Door-to-Doc times were reduced by approximately 35%. Moreover, the results of the pilot study demonstrated substantial improvements for all types of patients and not just low acuity patients that are treated by the PDQ physician. These results encouraged the use of PDQ as a method for improving ED efficiency.

The benefits of placing a physician at triage are realized at a cost. Incorporating a physician at triage requires that a hospital schedules a physician in addition to their existing ED staffing model. Patrovi et al. (2001) provided an estimate of the additional cost per patient incurred by the hospital to provide this performance improvement during the study days. This was calculated by dividing the product of the number of hours in triage and hourly wage by the total number of patients. The cost was estimated to be an additional $11.98/patient arrival.

Extrapolating this figure to a full-time status over a year translates into a cost of more than a million dollars for the study hospital. It is true that the improvements in patient flow and ED efficiency are statistically significant; however, financial considerations often serve as a barrier preventing justification. The additional cost, in conjunction with the limited benefits, is often a factor prohibiting implementation in many hospitals.

2.3.2 Fast Track

A Fast Track unit (FT) is an area separate from the ED (or separate set of resources) that is dedicated to patients who have been determined to be of non-urgent care (low acuity). This track of the ED has resources such as health care providers dedicated to it. The ability for an ED to provide quick service to non-urgent patients and prevent these patients from occupying resources of the main ED (ACEP, 2008) is improved.

EDs primarily use patient acuity to determine service priority. Consequently, the ED often services longer processing times first, thereby forcing non-urgent patients to wait longer before receiving initial evaluation. This approach for sequencing patient service is juxtaposed to the most efficient method determined by operations research for servicing a group of entities. As determined by operations research, for a given batch size, processing entities with the shortest processing times first improves the efficiency. The implementation of FTs provides a solution that overcomes the EDs tendency to use sub-optimal processing sequences. When utilized, a FT has the ability to decrease patient Door-to-Doc time and time until discharge without occupying the resources of the ED (Yoon et al., 2003). FTs improve the flow of non-urgent patients through the ED without hindering the flow of high acuity patients. This advantage is similar to the advantage provided by placement of a physician at triage.

Skow-Pucel (2006) presents a summary of the benefits of implementing an FT in her M.S. thesis. She cites, that based on a survey received from 49 EDs, 58% indicated that they utilize an FT and another 25% indicated that they intend on opening an FT. The most common reason for interest in an FT option was related to operational improvements. These improvements include reduction of LOS, reduction of ED congestion, reduction of LWBS rates, and attraction of new clients.

Considine et al. (2008) have studied the effect of providing the FT option has on patient LOS. The results of their study concluded that an FT unit can significantly reduce the LOS of patients who express non-urgent complaints without compromising the care of other ED patients. They conducted their study in a metropolitan teaching hospital with an ED that provided care to over 70,000 patients annually. The census of patients arriving to the ED was primarily composed of the two highest levels of acuity. The study performed statistical analysis that compared the LOS for patients that were fast tracked and patients who were serviced prior to the implementation of the FT unit. The analysis was conducted as a paired difference—that is, FT and non FT patients were matched according to ailment or procedures received. In total, 822 FT patients were matched with non-FT patients during the evaluation period.

One of the results of Considine et al. (2008) was a significant reduction in non-admitted patient LOS for FT patients. The median value decreased from 132 to 116 minutes ($p < 0.01$). It was also concluded that significantly more FT patients were discharged within 2 hours (53% vs. 44%, $p < 0.01$) and 4 hours (92% vs. 84%, $p < 0.01$). However, no significant improvement was seen for admitted patients. Additionally, ED LOS was analyzed for all patients during the time in which an FT option was available. No significant difference in LOS was observed. This meant that FT patients did not affect the treatment of other patients in the ED.

Another benefit of using an FT is that it provides a cost advantage. It has been reported that an ED loses, on average, $84 per patient visit (Pate and Pete, 2004). However, Yoon (2003) concluded that this average cost can be lessened by directing non-urgent patients through an FT process. Non-urgent patients treated via FT cost the hospital, on average, $27 per visit, compared to $57 per visit, because fewer resources (time, staff, and technology) are required to provide the treatment. Furthermore, the argument can be made that a correlation exists between improved patient flow and patient satisfaction. Therefore, operating an ED with an FT unit has the ability to attract more patients, thus increasing revenue.

Having an FT option in an ED is not always sufficient. Poor management of an FT can prohibit the ED from achieving their potential efficiency. A case study of the Grady Health System in Atlanta, Georgia, provides evidence of this caveat (Wilson et al., 2005). The Grady Health System is a set of public hospitals that experiences more than 100,000 annual ED visits. As a result of patient dissatisfaction, the Grady Health System was interested in operational improvements to reduce the inefficiencies of its EDs. Patient dissatisfaction was primarily a result of ED crowding. FT Patient LOS was in excess of seven hours and the hospital was on ambulance diversion over 20% of the time.

Several corrective initiatives were taken by Grady Health System's hospital management to improve the FT option. It was determined that the primary cause of the excessive wait times experienced by patients is an artifact of the providers being unaware of how long patients wait or the volume of patients in the waiting room. Therefore, improvements were made to increase the transparency of these conditions. Additionally, staff members were counseled to proactively assess patients triaged to the FT for ancillary services. Also, LOS goals were determined and presented to the staff. In summary, the ED improved its ability to track statistics that evaluate the current condition of the ED and provide the staff with goals to strive for. This method for improving traceability and analyzing the results allowed for the average LOS of FT patients to decrease from 5 hours, 40 minutes to 3 hours, 31 minutes. The trend of other performance measures related to patient satisfaction (e.g. Door-to-Bed, productivity, etc.) experienced a similar behavior. This study demonstrated that the use of an FT is not sufficient and that effective management was needed. This often corresponded to the enlisting of additional hospital resources.

Another challenge created by the presence of an FT is that it has its own set of dedicated rooms, beds, and technology—thus, creating another sector in the ED. The resources of the FT unit are not always shared by other areas of the ED. This limits the ability of the ED to increase its capacity during surges of patient arrivals. The condition creates silos in the ED that have previously been identified as a contributor to ED crowding. By functioning as separate entities, the FT unit prevents the ED from achieving its full potential.

2.3.3 Proactive EMS Destination Selection

Rather than approaching the inequality between ED demand and capacity as a challenge, practices have been explored to improve the demand of patients arriving to EDs. Naturally, demand cannot be changed because it is a result of emergency situations (e.g., outbreaks of illness, automotive accidents, etc.); however, the method for managing demand could be improved. An opportunity for improvement exists in routing patients that arrive to an ED via ambulance.

As previously stated ambulance diversion is a negative consequence of crowded EDs; it compromises the quality of care because it increases the amount of time before an emergency patient receives evaluation and treatment. Intuitively, if the duration or frequency that a hospital spends on diversion can be decreased, then the hospital can operate with improved patient flow. Reduction of ambulance diversion can potentially be achieved by improving the selection of emergent patients’ hospital destination.

A way to improve destination selection is by monitoring variables that classify the current state of hospitals in a specific region. Insight into these performance indicators provides the EMS staff with improved decision making capabilities to coordinate routing of patients to hospitals that are most ready to receive them. An example of this has been implemented in the Urban Calgary medical region (McLeod et al., 2010). This medical region is composed of three adult care facilities and one pediatric center.

Existing in the Calgary region is the Regional ED Information System (REDIS). This system is a database that monitors information to describe the current load and functionality of each ED in the region. Examples of data that it provides are an ED-specific triage code, bed availability, and volume of admission requests. REDIS is used as the data source for Calgary's Regional Emergency Patient Access and Coordination (REPAC) system. The REPAC system is an information technology (IT) implement that specifies at two-minute intervals the current state of EDs in the area as well as a reception ranking for each. Additionally, the REPAC system takes into account ambulances in transit to the various ED departments. The REPAC system analyzes the performance indicators to classify an ED with either a green/yellow (favorable) status or orange/red (unfavorable) status. The REPAC system ranks the EDs based on a formula that determines the best available alternative. Furthermore, if the ED is operating at a level that is suggestive of capacity challenges, it is put on avoidance (diversion) status for an amount of time. EMS coordinated with the city's public safety communications department, which tracks the REPAC system to determine the destination of an emergent patient.

McLeod et al. (2010) analyzed the efficacy of this approach to patient routing in reducing ambulance diversion and crowding conditions. The primary evaluation criteria used to assess the success of routing patients according to the REPAC system was by measuring the differences that existed in the amount of time that a hospital was placed on diversion. Additionally, the proportion of time that hospitals were identified as having favorable or unfavorable status was as also monitored.

Three different time periods were measured and compared: pre-implementation of the dispatch system (ED visits = 103,745), the first six months following implementation (ED visits = 101,727), and the second six months following implementation (ED visits = 107,239). The study used three-way comparisons of the specified performance measures through Kruskal-Wallis testing for nonparametric variables.

The results of this study found that using the REPAC system reduced periods of ambulance diversion from 4.4% to 1.8% to 0.6% ($p < 0.001$) for pre-implementation, first six months of implementation, and second six months of implementation, respectively. Additionally, the proportion of time that the hospitals receiving patients were identified as having favorable status increased from 57.5% to 64.1% to 78.7% ($p < 0.001$), respectively, for the three time periods. Because of these results, it was concluded that the use of the REPAC system significantly improved the proportion of time that an ED spent on diversion and in favorable receiving status. The results suggested that the REPAC system was able to create a balance between supply and capacity of EDs. McLeod et al. (2010) also noted that other researchers have observed similar successes. It was also identified that limiting the time that a hospital spends on diversion to 1 – 3 hour increments or implementing a regional diversion system (such as REPAC) could reduce hospital diversion rates from 68% to 78%.

In addition to time spent on diversion and the receiving state of the hospitals, McLeod et al. (2010) statistically compared the LOS for patients during the same time periods. In their analysis it was found that no significant advantage existed with the use of the REPAC system. That is, improvements to the internal processes of the EDs were needed to improve patient flow.

Despite the discouraging result that patient LOS was not affected, the REPAC system still provides a distinct advantage in preventing ED crowding and ambulance diversion. The importance of preventing ED crowding and ambulance diversion is validated by the use of similar destination selection systems that have been implemented in Edmonton, Canada, and Perth, Australia. The Edmonton system coordinates the routing of ambulances with an Emergency Status Screen primarily for its mid-level to low acuity patients (Larson, 2009). The goal of this dispatch system is to maximize available ED resources. The Perth system used an online workload schematic that operated similar to the REPAC system, but however, did not take into account the volume of patients in transit to a specific hospital (Sprivulis and Gerrad, 2005). It was observed that use of these systems had results similar to the results of the REPAC system. That is, ED crowding was prevented and utilization of ED resources was maximized. Validation for the importance of these dispatch systems can be found in the fact that they are still actively being used and improved. In short, the proactive EMS destination selection methods provide a beneficial effect on flow management, thereby creating an opportunity for improvement in overall quality of emergent patient care.

2.3.4 Bedside Registration

Patients that enter the ED must go through a registration process. The purpose of registering patients is to gather patient information, cull previous medical history, and create a record of their current visit. Typically, registration is performed in the waiting room or triage area.

Bedside registration (BR) is a practice that has been experimented with in various hospitals to decrease a patient's LOS and improve ED efficiency. BR is different from traditional registration, because rather than registering patients while they are in the waiting room or triage area (thus prolonging the amount of time before a patient receives initial screening), BR registers patients while they are in the treatment area. Feasibility of this practice is a result of the inevitability of patients incurring periods of idle time after being assigned to a bed (e.g., waiting for test results). This idle time is non-value added. Therefore, BR takes advantage of this idle time by converting it to a value-added process. The registration process, is appealing because by avoiding the registration process, Door-to-Doc time would decrease and would allow a patient to receive initial evaluation and care sooner. As a result LOS will decrease, and patient care and ED efficiency will improve.

The effect of BR on Door-to-Doc time and time from room to disposition (RTD) has been studied (Takakuwa et al., 2003). That study was administered at an urban academic center in Philadelphia. It compared Door-to-Doc and RTD for ED patients during six different time periods – one month prior to implementation and five one-month intervals after implementation. Observed times were categorized by patient acuity (critical, acute, urgent, and non-urgent). The tested hypothesis was whether BR would decrease Door-to-Doc time and have no effect on RTD time. Confirmation of this hypothesis suggests reduction of ED patient LOS.

Statistical analysis was conducted using more than 18,000 ED patients' duration. It should be noted that the studied hospital also had an FT unit and that these patients were excluded from the dataset. The statistical analysis was conducted via two-way ANOVA with type II sum of squares (to account for differences in monthly census). It was concluded that Door-to-Doc time decreased for all triage classifications ($p < 0.0001$). In order of subsequent months, the average Door-to-Doc time decreased from 59 to 42, 44, 50, 53, 48 minutes. It could not be concluded that a decrease in average RTD time resulted. Despite the fact that RTD time did not decrease, patient total LOS decreased, because it is the sum of Door-to-Doc and RTD time. It was also found that the average reduction in Door-to-Doc time began to experience diminishing returns 2-3 months following the initiation of BR. Therefore, sustainability of the advantage provided by BR is limited (Takakuwa et al., 2003).

A similar conclusion were made by Gorelick et al. (2005), who conducted a study at an academic pediatric ED. Gorelick, Yen, and Yun (2005) analyzed the effect of in room registration on average LOS. At that hospital, the registration process occurred following triage, room placement, and initial physician evaluation. The study analyzed average LOS over a 209 week period that included pre and post-BR implementation. It was concluded that the presence of BR led to an average decrease in LOS of 15 minutes, or 9.3%. Despite the significance and practicality of that result, the researchers also concluded that the improvement lessened as time progressed, thus confirming a limitation of BR.

2.3.5 Scheduling of ED Health Care Providers

Another approach that EDs employ to address the Demand – Capacity inequality is to adjust the volume and distribution of healthcare providers (nurses, technicians, physicians). Different methods have been used to ensure that an adequate number of health care providers are scheduled to serve the arrival of patients to the ED. Each method has a varying range of success.

Forecasting patient demand creates a scheduling challenge for most EDs. Ideally, an ED would staff its department using an analytically-based workload—that is, determining the volume of health care providers staffed throughout the day according to predicted patient arrivals. Methods for predicting demand (arrivals) has not been a well-researched area. A few trends in patient arrivals have been identified though. Mondays generally have the highest number of arrivals, with fewer arrivals occuring during the night and early morning hours, and a surge of arrivals starting at 7:00AM that continues until about noon (McCaig and Burt, 2004). These patterns are traditionally used as a guideline for staffing.

McCarthy et al. (2008) developed a Poisson model to forecast through regression analysis patient arrivals at a particular hospital. Patient arrivals were modeled as a Poisson process because the next patient arrival was independent of previous patient arrivals and the arrival rate fluctuated over time. Of all the possible factors investigated, their model concluded that hour of day and day of week had the greatest influence on arrival rate. Additional factors included patient severity, season, holiday status, and climatic conditions. The forecasting model was validated by ensuring that the underlying assumptions of a Poisson process were met and that a close fit of data existed.

The McCarthy et al. (2008) study provides a procedure for a hospital to predict the average volume and distribution of patient demand. However, the actual arrivals to an ED will vary about the average, like a Poisson variate. This makes allocating the appropriate number of resources over the short run challenging for smaller EDs that do not experience as many arrivals because a Poisson mean is equal to the variance. Depending on the time of the day, the average hourly arrival rate for many EDs can be as low as two or three. Matching a demand level as low as two or three patients with health care providers for one hour is impractical. Therefore, it may be of greater value to make predictions over several hours.

An ED can use a forecasting model like the one developed by McCarthy et al. to account for variability. This can be achieved by staffing in a manner that ensures there is adequate coverage for a given probability (e.g., arrivals 80% greater than expected). Staffing the ED in this way makes the assumption that the ED has sufficient capital to meet higher than expected arrivals. If an ED cannot afford this additional expense, then it will likely experience periods of crowding. Therefore, an ED must compare the cost of the risks associated with operating in the crowded condition against the additional cost of increasing resources. Fortunately, because of the stochastic nature of arrivals, it is likely that an ED will not experience successive hours of higher than expected arrivals, therefore reducing the risk of operating in a crowded state.

A similar staffing approach for EDs that frequently operate in the crowded state or spend a significant amount of time on ambulance diversion is to increase the total number of resources (overstaff). The theory behind this is to incorporate a safety factor when scheduling (IOM, 2007). By over-scheduling, an ED can operate knowing that it can compensate for any surge of patients. If the is no surge, then the ED can dismiss underutilized health care providers. However, the success of this approach is limited by the number of physical resources, such as rooms and technological equipment that patients may need. Additionally, this is an inefficient use of resources, because health care providers will experience greater durations of idle time. For these reasons, this practice is often implemented for only a brief period of time.

Another approach to scheduling is to use resource zoning (usually applied to the scheduling of nurses). This scheduling method for ED resources is similar in principle to the engineering concept of collocation—that is, assigning associated resources to a specific area to accomplish a process. EDs that implement zone scheduling do not increase the total number of health care providers on duty; instead they modify the assignment of the health care providers. The advantage of zone nursing is that it ensures that all patients for a given health care provider are located in the same area. This decreases the amount of travel time incurred by a health care provider when servicing multiple patients. Support for zone nursing is evidenced by the frequency of its use in hospitals nationwide. EDs operating with this scheduling practice have reported increased nurse efficiency and decreased ED crowding rates (IOM, 2007).

The potential advantage of zone nursing is exemplified by the Boston Medical Center (BMC). BMC initiated zone nursing and other best practices because the performance of the ED was inadequate—high LWBS rates, high crowding rates, and a significant proportion of time spent on ambulance diversion. Exacerbating the problem was the limited supply of nurses, thus making zone nursing appealing. In addition to decreases in LWBS rates, crowding status, and time spent on ambulance diversion, BMC experienced a reduction in nursing hours per patient per day from 8.66 to 8.16 hours (Wilson et al., 2005). Also, average LOS for patients was reduced by 70 minutes per case (Wilson et al., 2005).

The ultimate goal of the different approaches to scheduling health care providers is to reduce the difference between hospital demand and capacity. If an ED can achieve this goal, the effects of crowding would be reduced and the quality of patient care could be improved.

2.4 Applications of Simulation Modeling for Improved ED Patient Flow

Many of the identified methods used to decrease the difference between demand and capacity require a significant capital investment. Moreover, the efficacy of these best practices has varying success that is dependent on the environment unique to each ED (e.g., the ability of an ED to adequately account for the variability in patient arrivals). The convolution of these factors often acts as a barrier that prevents justification.

Computer simulation can be used as a tool to predict the performance of a system that does not yet exist. Simulation is often applied when there is interest in determining whether a proposed system or a change in methodology will meet a desired performance measure—such as throughput during a given period. Another reason simulation modeling is used is because some environments are too complex, and analytical methods cannot be used to solve for system performance.

Analysis of performance measures from a simulation model also provides identification of potential opportunities for improvement of a system. Identification of these opportunities prior to actual system implementation may result in significant capital savings. Because simulation modeling is a heuristic tool, the results of a simulation model are not always definitive and often are assumption-based. Despite this fact, the results may provide sufficient insight for improved decision making.

Because of the advantages presented by simulation modeling, EDs have recently been recruiting industrial engineers or engineering consultants to evaluate the impact that process improvement initiatives may have on patient flow and ED efficiency. The remaining sections of this chapter are then dedicated to providing examples from the literature of the simulation modeling used to evaluate ED operations. These examples provide insight into the capabilities of simulation modeling that make this tool applicable to a wide range of situations.

2.4.1 PDQ at Hershey Medical Center

Medeiros et al. (2008) built a simulation model to predict the performance of Physician Directed Queueing (PDQ) at the Hershey Medical Center (HMC). As previously specified, PDQ is a variation of placing a physician in triage. Specifically PDQ places an emergency care physician in triage and he works with a team of other health care providers to determine the best way to allocate resources to a patient. The decision is based on patient acuity and current availability of resources. The medical center was interested in a simulation model because it would provide insight into how to lay out their ED following an upcoming facility expansion. The performance measures of interest were resource requirements, patient census, and patient waiting times.

The computer language used to model the impact of PDQ was Arena. The model was developed by interpreting the decision logic associated with PDQ as a flow diagram. Simulation challenges were encountered when trying to model human activity (e.g., teamwork, decision-making) and processes external to the ED.

The Emergency Service Index (ESI) was used to model physician decision-making. ESI is a classification system used to categorize patients according to severity and likely resource needs. Decision logic for determining patient routing was based on patient's specific ESI. ESIs (or a range of ESIs) were correlated with a specific path through the ED.

Teamwork was modeled by assigning a list of the major tasks involved in PDQ to individual team members or sets of team members (who may be interchangeable for a specific task). Also incorporated in the model was the range of priorities and whether the task required additional help.

Examples of external processes that impact patient flow are laboratory testing and X-rays that cannot be performed in the ED. External processes were a necessary part of the model, because they can create time delays that lengthen a patient's LOS and decreases the availability of ED resources. Whether a patient needs additional diagnostic testing and type of testing is determined by sampling from a uniform distribution. The test type determined by the uniform random variate assigns a time delay to the patient in the model, thus lengthening the amount of time resources are occupied. Also, it is a practice of HMC to board patients in the ED. This was incorporated in the model by limiting the number of available resources throughout the day based on HMC's hourly distribution of boarding rates.

Model validation, or comparison of the results of the model to true system performance, was made possible by a pilot study conducted at HMC. The pilot study consisted of implementing PDQ in the ED for one month and monitoring LWBS rates, LOS, Door-to-Doc, and Door-to-Room times. These values were compared to the same month of the previous year to evaluate improvement. The simulation model was run for 30 replications and 95% Confidence Intervals (CI) were calculated on mean LOS for ESI 4 and 5 patients. The CI of the simulation for ESI 4 patients fell within the range of actual system performance; however, the average LOS for ESI 5 was greater. The difference in average LOS was attributed to the width of the CIs resulting from variability in patient arrivals and that the simulation statistics were generated from simulating the ED only when PDQ was in effect (true system performance was measured over a 24hr period).

Overall, the PDQ simulation model closely reflected the true system performance of the pilot study. HMC has since incorporated the simulation model in process for their facility expansion project. Specifically, the simulation model is being used to model patient flow in the areas of the hospital that the PDQ is to be implemented. The model provides insight into the best way to design these areas to achieve the greatest benefit of PDQ. The ultimate goal is to improve ED efficiency in the most cost-effective manner.

2.4.2 Integration of Balance Scorecard and Simulation for Decision Making

A common tool used to assess operating performance of a system is the Balance Scorecard (BSC). BSC refers to a methodology that compares pre and post-performance measures of interest to determine the value added (or lack there of) through implementation of a process change. Therefore, this is a post-implementation assessment tool. The benefits of BSC are that it provides insight into strategies and initiatives implemented by decision makers and establish a set of metrics that make the results of an operation measurable.

Because of its success in a wide range of applications, a version of BSC has been formulated for assessment of health care organizations. Evidence of successful use of BSC is demonstrated by its implementation in a hospital in Taiwan. Nine performance measures were monitored and all experienced improvement (Huang et al., 2004). However, the ability of this tool to ensure planned performance in an ED is limited because of budget constraints, the large number of variables, and high levels of uncertainties (Ismail et al., 2010). The capabilities of simulation provide the ability to overcome the challenge inherent to EDs.

Because of the ability of simulation modeling to predict complex system performance and the effects of process improvements initiatives (e.g., different resource allocation schemes), Ismail et al. (2010) conducted a case study that integrated BSC and simulation modeling. The goal of their study was to demonstrate that these two tools could be used together to improve ED performance.

The university hospital studied is located in Dublin, Ireland, and experiences 45,000 – 50,000 patient arrivals to the ED annually. Similar to ESI, the Dublin hospital has a classification scheme for patients based on acuity and type of resources needed for treatment. A patient's classification determines the processes that they will undergo while in the ED. The researchers worked with the ED staff to get a clear understanding of all the possible processes that arriving patients may be subjected to as well as the decision logic for determining the specific process path of a patient. Data input was provided by the university hospital from historical records that measured different attributes of a patient's stay at the hospital—such as classification type, LOS, and whether the patient departed before receiving treatment.

After all of the necessary information was understood, the researchers modeled the internal processes of the ED using Integration Definition for Functional Modeling (IDEF0). The reason for using IDEF0 was because of its ability to model decisions, actions, and processes in a hierarchal form. This improves the detail and adaptability of functions in the model. For example, if a patient is classified as having chest pain, then he is directed with a high priority to a specific sector of the ED and would require a set number of resources. Processing times are also determined by a patient's classification. Model verification and validation were accomplished through statistical comparison of simulation generated results to the performance measures of historical data. Modifications to the model were made until the university hospital agreed that no significant difference existed.

The BSC has been adapted to evaluate an ED by considering three primary categories: patient, ED processes, and training and development (Ismail et al., 2010). For example, an objective of the patient category is to maximize satisfaction. An objective of ED processes is to maximize ED efficiency and an objective of training and development is to maximize staff skills for improved utilization. Whether a proposed improvement achieves an objective provides indication of the success of that proposal.

Experimentation was conducted by running a baseline model to determine the “as-is” performance of the ED. The results of the baseline model identified three opportunities for improvement. Specifically these opportunities were unacceptable waiting times at the triage area, a significant volume of patients leaving without being seen, and an undesirable utilization of various treatment areas. Three different process improvements were proposed by the university hospital decision makers to remedy the existing challenges of the ED. The first proposal (Scenario 1) added a nurse to the triage area. Because it was determined that 14% of all ED patients left without receiving treatment and that this percentage was directly related to the capacity of the waiting room, the second proposal (Scenario 2) increased the capacity of the waiting room by 10 seats (Ismail et al., 2010). The third proposal (Scenario 3) implemented training and dynamic staff allocation (e.g., train respiratory nurses so that they can act as a triage nurse during peak times).

The simulation model determined that each of the proposals improved the performance of the ED. With respect to the patient category, Scenario 1 allowed for a significant reduction in patient waiting times. Scenario 2 significantly reduced average patient wait time compared to Scenario 1. Scenario 3, however, resulted in the greatest improvement in average patient wait compared to the baseline and the wait time is evenly distributed across all areas of ED. The results of Scenario 3 mean that the improvement in average wait time is independent of patient classification. As an added advantage, Scenario 3 established balanced utilization of the medical staff.

Without the integration of simulation modeling, the university health department would have had to conduct pilot studies for each of these three scenarios, observe the impact of the scenarios on the objectives of the BSC, and determine which scenario was most desirable. This was a risk that an ED could not always take due to the uncertainty of the results and the possibility of having an adverse effect on patient care.

The results of this case study demonstrate that integrating simulation modeling with the BSC has many advantages. It provides increased transparency into different views of performance measurement, eliminates the need to commit resources (such as time and capital) and the risk associated with uncertain outcomes of pilot studies, and improves the decision making process for selecting the best process improvement.

Support for these conclusions is confirmed by the case study of the university hospital in Dublin, Ireland. The analysis of the baseline model identified high waiting times in specific sectors of the ED, poor utilization of various resources, and an unacceptable volume of patients that left without receiving treatment (Ismail et al., 2010). Simulation modeling of the three process improvement scenarios identified the most effective corrective course without the unnecessary commitment of resources.

2.4.3 Simulating the Effect of Physician Triage

In response to the Norwegian Board of Health Supervision’s mandate that hospitals make efforts to reduce the wait time of a patient prior to interacting with a doctor (Door-to-Doc time), the Akershus University Hospital (AUH) incorporated the use of a physician for triage during the busiest hours of operation (weekdays, 10:00AM – 7:00 PM). As with most EDs, the ability to predict the effect of this structural change is challenging. Because AUH was interested in seeing the impact that this initiative had on patient flow, simulation modeling was a natural choice because of its statistical measurement and animation capabilities (Holm and Dahl, 2009).

The ED of AUH is relatively new (opened in 2008) and employs modern technology to automate many processes of the ED. Existent in the ED are two wards that house patients based on their expected time until discharge. In addition to complying with the Norwegian Board of Health Supervision mandate, AUH set goals of reducing the maximum Door-to-Doc time to 10 minutes and the maximum waiting time for a physician examination to 30 minutes.

Comparison of the effect of placing a physician at triage for initial patient evaluation was facilitated by creating two discrete event simulation models. These two models are referred in the literature as the nurse triage model and the physician triage model. Both of the models were built using Flexsim Healthcare (Flexsim, 2009)—a simulation platform specific to the healthcare environment.

The main difference that existed between the nurse triage and physician triage models was at the organizational level. In the nurse triage model patients received triage in the ER hall directly upon arrival. By contrast, the physician triage model triages patients in a treatment room. As a result, patients must wait for a room to become available prior to initial physician evaluation. Following triage and room placement, the two processes were similar, given a particular patient type.

Data were collected from AUH's patient database during a three-week period when nurse triage was used and a three-week period when physician triage was used. The data collected from these time periods were used during the verification and validation process. The researchers did not use data from the first three weeks following implementation of the two different triage processes. This was done because the initial period following a structural change is often a trial period when the system may not be operating at its full potential. Therefore, the trial period may not be descriptive of the true performance of the system.

Patient arrival rates were analyzed and it was determined that they could be explained by a time-variable Poisson process. The arrival behavior of patients to the ED could not be easily modeled via the functions of Flexsim. As a result, a method for simulating a time-variable Poisson process had to be developed and implemented for the simulation language. To accurately simulate the arrival of patients, the mean arrival rates for each hour of each day of the week were first determined. With knowledge of these values, a method known as censoring was used to ensure that patients arrived in the simulation models with constant arrival intensity for each hour. Censoring is a random variate generation method that involves creating an arrival of an entity and determining whether if falls within the current hour. If the arrival exists within the current hour, it is accepted; otherwise, the amount of time that it extends into the next hour is rejected and replaced with a sample drawn from the exponential distribution with the average rate of the subsequent hour. Similarly, the criterion was met that the sample falls within the subsequent hour. This was done to ensure that all entities arriving during the same hour arrived at the same average rate. Censoring is a variation of the acceptance-rejection method commonly, used to model non-stationary Poison arrivals in other simulation languages. Use of the censoring method was verified by ensuring that no significant difference existed between the total number of arrivals over a sufficiently long simulation period and the expected number of arrivals summed over each simulation hour. For comparison, it was found that when censoring was not used, the simulation model underestimated patient arrivals by 3% (Holm and Dahl, 2009), further verifying the necessity of censoring.

Processing times in the model, such as nurse triage, nurse examination, and physician examination, were determined from an ED quality survey conducted in the past. Information that was not available was estimated by experts who were familiar with a specific process. Other uncertainties existed in the processing times. However, it was felt that because these uncertainties were consistent in both the nurse and physician triage models, the ability to compare the two systems was not compromised.

The simulation models were ran as one replication over a period of 800 days. The nurse triage model resulted in an average Door-to-Doc time of 117 minutes. Comparatively, the physician triage model resulted in an average Door-to-Doc time of 26 minutes (a patient's first interaction with a physician). The average time before a patient received physician examination in the physician triage model was 110 minutes. For the nurse triage model, the Door-to-Doc time was the same as the average amount of time before a patient received an examination from a physician. Therefore, the physician triage reduced by seven minutes the amount of time until a patient received an examination. Additionally, confidence intervals were calculated for average LOS. The nurse triage model resulted in an average LOS of 287.50 – 306.50 minutes and the physician triage model resulted in an average LOS of 278.76 – 297.24 minutes. Because these two intervals overlapped, no significant difference exists.

The waiting times incurred by patients at various steps of the ED process in the two models were compared to historical data for validation. The analyses did not identify any significant difference in waiting times between simulation and actual data. The differences that did occur were attributed to not having a standardized method for reporting routines and the two time periods used for analysis were not of sufficient length to make definitive conclusions. Also, the researchers commented that the Hawthorne effect may have been a factor as well. This effect refers to the tendency of operators improving their performance (thus decreasing processing times) because they are aware of being monitored.

The results of simulation modeling concluded that having a physician perform triage in the treatment room reduced the amount of time that a patient must wait prior to interacting with a physician. This should have a positive effect on patient satisfaction. Additionally, this triage method reduced by seven minutes the amount of time before a patient received a full examination from a physician. The performance improvement demonstrated that AUH was near their goal of achieving a maximum Door-to-Doc time of 10 minutes, but improvements were still necessary to achieve their goal of patients waiting no longer than 30 minutes upon arrival before receiving a physician examination.

In summary, because of similarities that existed between the performance measures of the actual hospital and the simulation model it could be confirmed that the models accurately reflected the true performance of the ED. Because the models had been validated, AUH now had a tool to predict the impact that other structural changes on patient flow. This could serve as a decision making aid for upper management to determine whether implementation of certain practices was of value.

2.4.4 Additional ED Simulation Modeling Examples

Countless examples for uses of simulation modeling of an ED exist in addition to the ones we have previously described. These examples are so abundant that every year the *Winter Simulation Conference* has a section devoted to presentations related to the health care service industry. Simulation modeling is attractive because of its ability to predict performance of complex systems, such as that of an ED. The range of investigation topics researched via simulation modeling is expansive.

Simulation modeling has been used to estimate the impact of patient surges on boarding time in the regional hospitals of Los Angeles (Miller et al., 2009). A patient surge is defined as a sudden or prolonged increase in patient arrivals. This could be a result of an epidemic, extreme accident, or local catastrophe. Patient surges overwhelm the capacity of an ED and can lead to patient crowding. Therefore, the Miller et al. study developed a simulation model that used performance indicators (such as the amount of time spent on diversion, LWBS rates, and LOS) to analyze the impact that 5%, 10%, 15%, and 20% surges had. Additionally, the impact of the surges was investigated when the hospitals were operating at 80%, 85%, 90%, and 95% staffing.

Successful modeling determined that the performance indicators for all three hospitals were compromised as the surge increased. This was dependent on the ability of the hospital to handle surge volumes. When a hospital reached its capacity limit, the impact of the surge would be felt by surrounding hospitals where patients are diverted. Also, the simulation model determined occupancy thresholds for staffing more inpatient beds to accommodate surges. Overall, the simulation model provided insight into the flow of patients during a surge and identified probable bottleneck areas. The value of predicting system performance during periods of unexpected surges provides management with the foresight to determine a method for proactively resolving the issues rather than retroactively (Miller et al., 2009).

Simulation modeling can also be used to monitor the current state of an ED. Marmor et al. (2009) used simulation modeling to facilitate a command-and-control solution to the current operating state of an ED. A command-and-control solution is a two-step process used by ED managers. The first step involves understanding the current state of the operating conditions of the ED (e.g., waiting times, Door-to-Doc) times. The second step involves determining the best staffing method. This is similar to the BSC process discussed in section 2.4.2, except that this solution process is geared toward real time control.

Marmor et al. (2009) explain at a high level the methodology for integrating simulation with command-and-control used to accurately staff the ED. First, the current state of the ED is determined by using the arrivals rates of the day. Second, stochastic arrivals are generated for future hours of the day. This is based on moving averages of historical data for each hour over the past 50 days (e.g., Monday 10:00 – 11:00). Next, key performance indicators are collected for the next eight hours based on simulation with an infinite amount of resources. Staffing recommendations are calculated by applying these results to “offered-load” equations (a set of capacity planning equations that distributes workload over time). The simulation is run from the current ED state with the staffing recommendations. Performance measures are then collected and analyzed by management for acceptability, and revisions to staffing are made accordingly. By using simulation to determine staffing levels an ED manager is better able to achieve the multi-criteria objective of staffing—minimizing cost, maximizing utilization, and maximizing quality of patient care.

Holding patients who are waiting in Inpatient Unit (IU) admission is a contributor to ED crowding. The use of buffers (a separate holding area for patients) is a practice that may lessen the occurrence of ED crowding. Consequently, Kolb et al. (2008) developed a simulation model that experimented with and compared the use of five different buffers zones in an ED. All of the buffers zones consisted of eight beds, monitoring equipment, and two nurses.

The “Holding Area” buffer places a buffer zone in the patient flow between arrival to the ED and physical admission to the IU. The goal of this buffer is to reduce the occurrence of patients blocking ER beds and resources by warding them in a separate area. The “ED-Discharge Lounge” is a buffer zone that removes from the ER patients who are waiting approval for discharge. An “Observation Unit” is used for patients whose expected time in the ED is less than 24 hours. Patients with this classification are sent to the “Observation Unit” instead of the IU. The fourth alternative investigated was a combination of the “Holding Area” and “ED-Discharge Lounge”, while the fifth alternative was a combination of all buffer concepts.

Kolb et al. (2008) concluded that each of the buffer concepts improved ED performance with respect to LWBS rates, LOS, and time spent on ambulance diversion. Logically, the combination buffers improved the performance of the ED more significantly than the individual concepts. In conclusion, implementation of a buffer zone will lessen the occurrence and effects of ED crowding. Because the implementation of the various buffer zones requires the commitment of additional resources, the appropriateness of a buffer zone must be evaluated. This is determined on a per hospital basis according to an expected patient census.

In summary, the complexity of the ED environment prohibits the use of analytical methods to effectively model it. As a consequence, simulation modeling is often used because of its ability to capture and predict the performance for systems with high variability and complexity. Each of the presented studies demonstrates this fact. Our intention of is to validate the broad range of applicability for simulation modeling in the ED environment. Examples are abundant and can be found in various sources, such as the proceedings of the *Winter Simulation Conference*.

2.5 Chapter Summary

Section 1 of this chapter serves to summarize literature that identifies the causes of ED crowding as a fundamental imbalance between capacity and demand. It also provides a synopsis of the effects that ED crowding has from both a patient and operational perspective. The literature summarized in Section 2 highlights best practices that are often employed in EDs to reduce the negative consequences of ED crowding. The final section provides examples from the literature of the use of simulation modeling to predict the performance of the ED department with the implementation of various best practices. Overall, this chapter concludes that the capabilities of simulation modeling make it ideal for predicting the effect of process improvements on ED crowding. As a result, simulation modeling provides management with improved information to determine whether implementation will bring the operation of the ED closer to its goals. This can be accomplished without unnecessarily risking patient safety, committing additional resources, or changing the structure of the physical system.

Chapter 3

MODEL DESCRIPTION AND VALIDATION

3.1 Introduction

The objectives of this study were addressed through simulation modeling of the ED at the Williamsport Regional Medical Center (WRMC). The simulation model was created using the academic version of Simio Simulation Software version 3.4.2. Historical patient data were provided by WRMC to address model verification and validation needs. This chapter will describe in greater detail the current decision logic associated with determining allocation of patients to beds in WRMC's ED, differences in the proposed decision logic associated with determining allocation of patients to beds in WRMC's Phase I ED, the development process of the Simio model, and verification and validation of the Simio model.

3.2 Current Bed Allocation Process

3.2.1 Patient Arrival to Triage

The following discussion follows the process flow depicted in Figure **3-1**. This figure demonstrates the decision logic involved when a new patient arrives at the ED. The flow diagram was developed after visiting the ED and shadowing nurses throughout the day. The flow diagram was also validated by the Registered Nurse in charge of task delegation at WRMC.

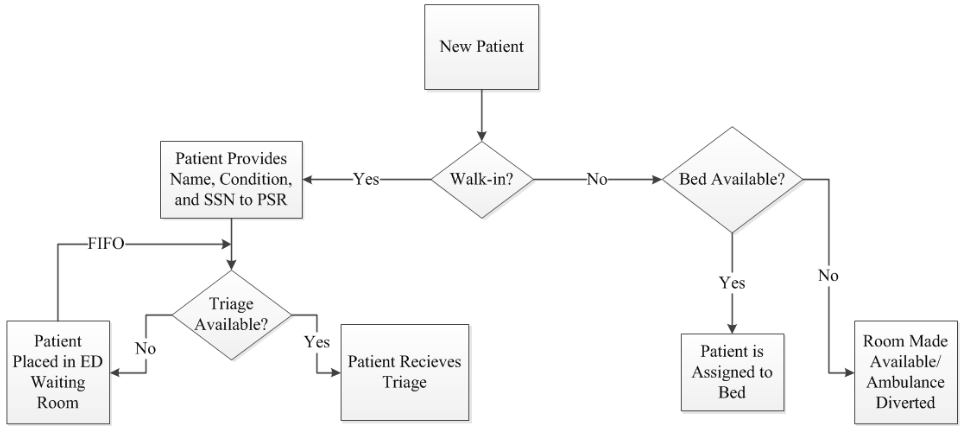


Figure **3-1**: Emergency Patient Arrival Process.

Emergency patients arrive via one of two methods. They either arrive by ambulance or are classified as “walk-ins”. Ambulance patients are assigned to a bed immediately upon arrival. There are two conditions where an ambulance patient will not be immediately assigned to a bed. One is that the triage process performed in the ambulance finds that the patient’s acuity is not high. The second is that there are no beds remaining, nor can auxiliary resources be recruited to increase the capacity of the ED, thus resulting in ambulance diversion.

“Walk-in” patients, those who arrive to the ED by means other than an ambulance, check in first with the Point of Service Representative (PSR). This is to provide the hospital with initial identification and reason for visiting the ED. After check-in, the patient either is triaged or waits in the general ED waiting room. Patients waiting for triage are seen in a traditional first-in-first-out (FIFO) order.

3.2.2 Triage to Bed Assignment

Figure **3-2** summarizes the process flow of patients after receiving triage. The process logic summarized in this figure commences following Figure **3-1**. As previously addressed in Chapter 2, the purpose of triage is to determine a patient’s acuity. WRMC uses the Emergency

Service Index (ESI) to quantify a patient's severity level. Patients who have an ESI of 1 are considered to be of the greatest severity (thereby the highest priority) and patients with an ESI of 5 are of the lowest severity. WRMC uses a patient's ESI to determine the order of patient assignment to beds in the ED. Moreover, if patients are classified with an ESI of 4 or 5, they can be directed to the hospital's Urgicare unit. Occasionally an ESI 3 patient may be sent to Urgicare by the decision of the triage nurse. Following triage, a patient goes through a registration process to provide the information needed by the hospital for any ancillary tests that may need to be administered as well as billing information. Patients are then either assigned to a bed if there is availability or they return to the waiting area of the main ED. Patients in the waiting room are processed according to their ESI. Currently, the main ED operates with 12 or 17 beds depending on the time of day. In extreme patient surges, the capacity of the ED can be increased by utilizing spare rooms.

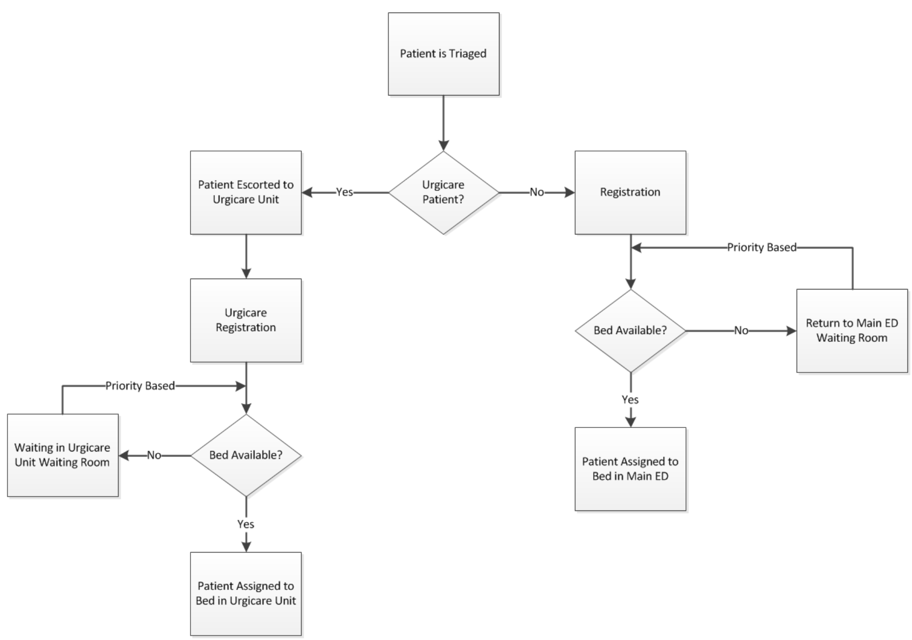


Figure **3-2**: Post Triage Patient Flow.

Urgicare operates as a fast track for ED patients of the lowest severity (ESI 4 or 5) or whose treatment will not take a significant amount of time. Assuming that the patient arrived during Urgicare's operating hours, and if it is determined that a patient should be treated in the Urgicare unit, a nurse is required to escort the patient because Urgicare is in a separate area of the hospital. Also the registration process for these patients takes place upon their arrival to the waiting room of Urgicare. As with the main ED, patients wait in the waiting room of the Urgicare unit until a bed is available. They are then processed based on ESI. The current capacity of Urgicare is 8 beds.

Patients are discharged by a physician following treatment in either the main ED or Urgicare. After discharge, a patient pays for the treatment and leaves the hospital. This terminates the stay at the ED. Some patients are admitted to the hospital; they then leave the ED.

3.3 Operational Changes to Bed Allocation During Phase I Transition

3.3.1 Phase I Patient Arrival to Triage

The patient arrival at triage will proceed during the Phase I transition primarily in the same manner as it currently operates. One difference during Phase I is that patients will initially arrive to a main ED waiting room. This is the area that has been reserved for patients waiting triage following arrival. After patients are called from the main ED waiting room they receive triage within the main ED in a reserved triage room. In the event that no rooms are immediately available for patients to receive treatment, they are directed to a Triage Results Waiting Room instead of returning to the main ED. This change in process flow seeks to improve patient satisfaction because the patient perceives that he is making progress toward receiving treatment. The change, however, does not have an impact on the LOS of the patient.

3.3.2 Phase I Triage to Bed Assignment

Another operational change that will exist during the Phase I transition of the ED is the use of Bedside Registration (BR). It is anticipated that the future use of BR, however, will not have a significant impact on the treatment time of a patient, because it will take place during periods of time that a patient is idle in a treatment room.

From triage, or the Triage Results Waiting Room, a more complex logic is involved with determining whether a patient is sent to a room in the main Phase I ED or the existing Urgicare. The logic flow captured by Figure **3-3** is a result of WRMC's desire to avoid the use of the existing Urgicare during Phase I.

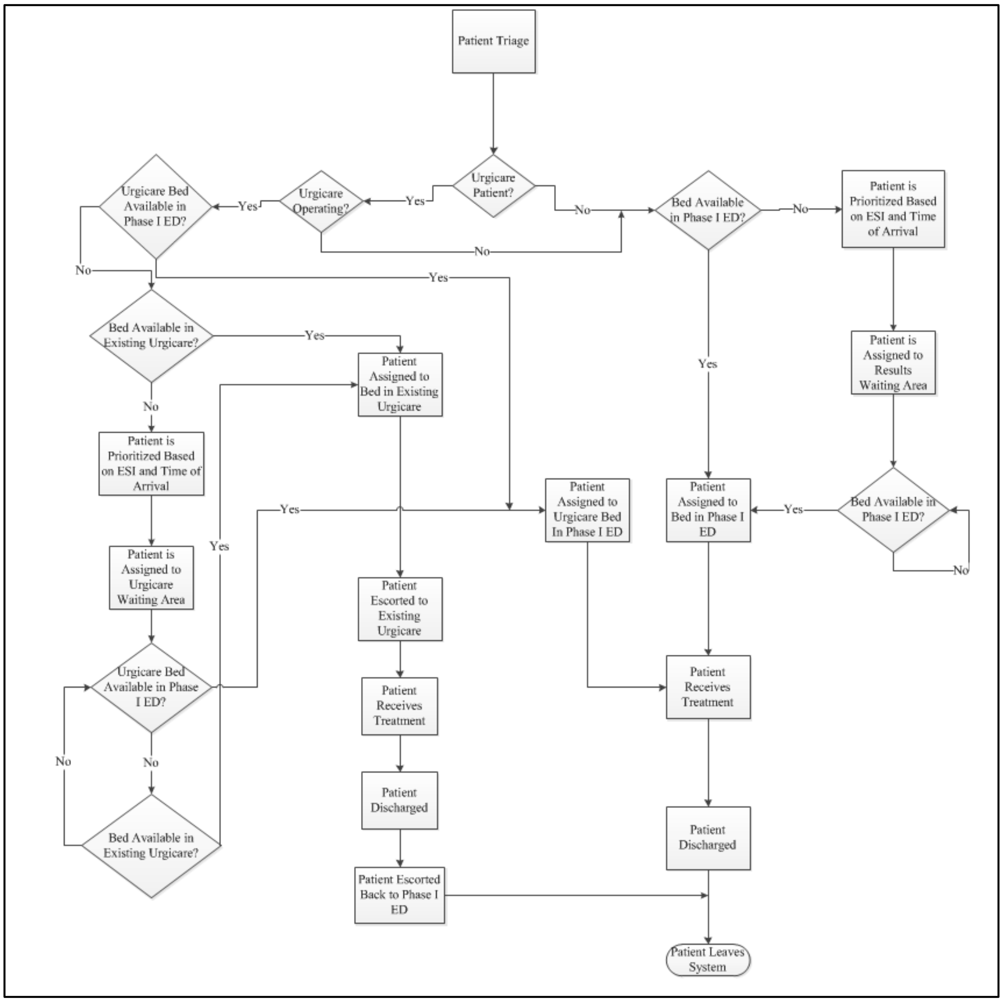


Figure **3-3**: Conceptual Model of Bed Allocation Process.

A patient's destination will continue to be dictated according to his ESI classification. The process flow for patients who require the resources of the Phase I ED will remain largely unchanged. Patients who qualify as Urgicare patients will either be assigned a bed in the Phase I ED or assigned a bed in the existing Urgicare. If an Urgicare patient arrives during the operating hours of Urgicare, the health care providers will assess whether there is available capacity in the beds reserved for Urgicare within the existing ED. It has been discussed that up to three beds may be reserved within the existing ED to operate as an Urgicare unit. In the case that none of these rooms is available, the patient may be directed to the existing Urgicare unit that is disconnected from the Phase I ED. In the event that neither of these Urgicare units has available capacity, the patient will be directed to an Urgicare Waiting Area. From this area patients will wait for a bed in the Phase I ED reserved for Urgicare or the existing Urgicare.

Patients who are assigned a bed reserved in the main ED for Urgicare patients will receive treatment and be discharged in a manner similar to the current treatment and discharge procedure. Patients who are assigned to the existing Urgicare will be escorted to Urgicare by a health care provider. A significant distance separates the existing Urgicare and the Phase I ED, and thus this travel time will have an impact on the time before a patient receives initial evaluation from a physician. After receiving treatment and being discharged, the patient will also have to be escorted back to the Phase I ED for payment.

3.3.3 Model Scope

Understanding how the bed allocation process currently operates and will operate during the Phase I transition is a critical step toward determining the processes that need to be included in the Simio simulation model to meet the research objectives. A second factor that determined the model scope was the data collected and provided by WRMC. The patient flow process in Figure **3-3** is the basis for the simulation model. As depicted, the simulation model begins after a patient enters triage and terminates with his departure from the main area of the Phase I ED.

3.4 Simio Model Description

Simio simulation software was used to translate the logic of the conceptual model. This section will describe how the tools provided by Simio were used to develop this model.

3.4.1 Input Data

WRMC uses an electronic monitoring system to record timestamp data for Main ED and Urgicare patients. The timestamps keep track of the starting time for significant events during their visit to WRMC and can be used to calculate performance measures of interest. Timestamps are recorded for patients when they arrive, enter triage, are first visited by a health care provider, and exit the ED. The electronic monitoring system segregates patient data according to whether patients received treatment in the Main ED or Urgicare treatment areas. This record also provides details regarding each patient's reason for coming to the ED, the physician who provided treatment, and the ESI level. WRMC was willing to provide a month's worth of main ED and Urgicare patient data. The provided historical file contained patient data from February 2010. It is important to note that in no way can the data of this file be traced back to the patients themselves.

3.4.2 General Model Layout and Overview

Figure **3-4** presents the floor plan of the Phase I ED, and Figure **3-5** presents the relative locations of the Phase I ED and the existing Urgicare unit. The floor plans contained in these figures were provided by WRMC and were the actual floor plans being used during the facility expansion project. The areas in Figures **3-4** and **3-5** highlighted in green represent treatment areas used for patients in the Main ED, whereas the areas highlighted in red represent Urgicare treatment areas. As can be concluded from Figure **3-5,** a significant distance exists between these two areas.

Figure **3-4**: Floor Plan of Phase I ED.

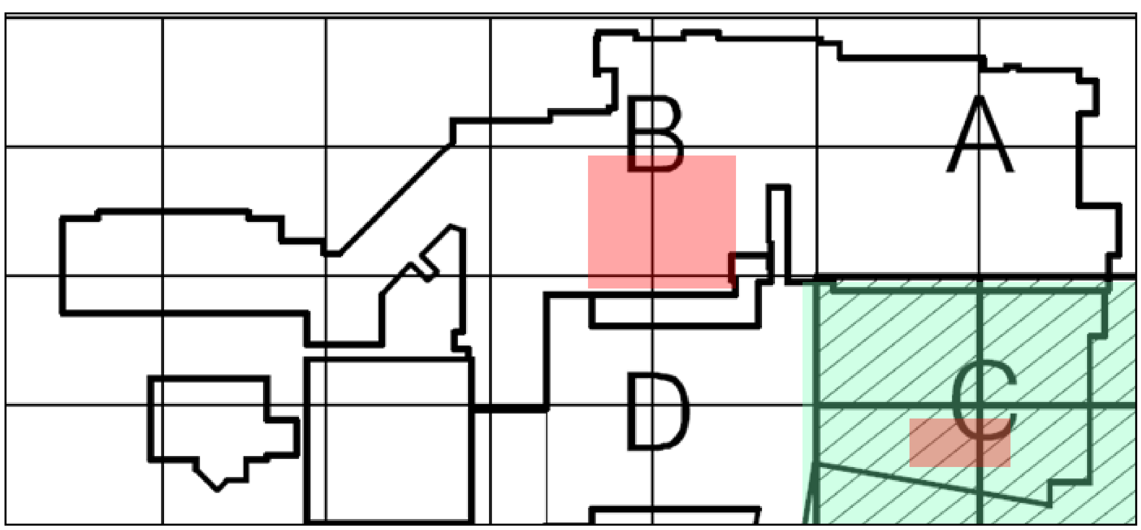


Figure **3-5**: Relative Location of Phase I ED and Existing Urgicare Unit.

The model was animated to reflect the actual layout of WRMC's Phase I ED. There were two reasons for animating the model in this way. The first is that animation aids in the understanding of simulation modeling for those who are unfamiliar, and the second is that it provides improved insight into future patient flow. A facility view of the animated model in Simio is presented in Figure **3-6**.

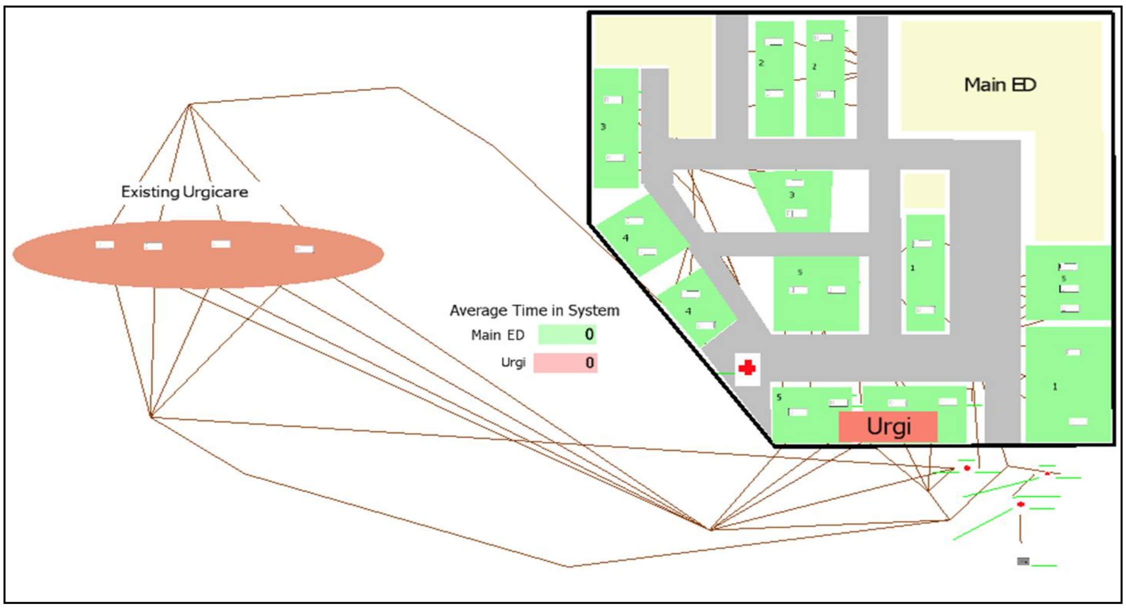


Figure **3-6**: Model Animation of Phase I ED Layout.

The objects of the model used in this animation, such as Simio Sources, Servers, and Links, have been replaced with graphical images and are arranged to reflect the true layout of the Phase I ED. Although the animations are beneficial for addressing issues related to patient flow, they do not have a significant impact on the performance of the model. Therefore, in the interest of ease of explanation, a structural overview of the model is presented by Figure **3-7**. The following discussion references Figure **3-7** as an aid of how the model operates. This figure uses the default images for all Simio objects, and Entities travel in a left to right manner. The purpose of the figure is to demonstrate the simulation model.

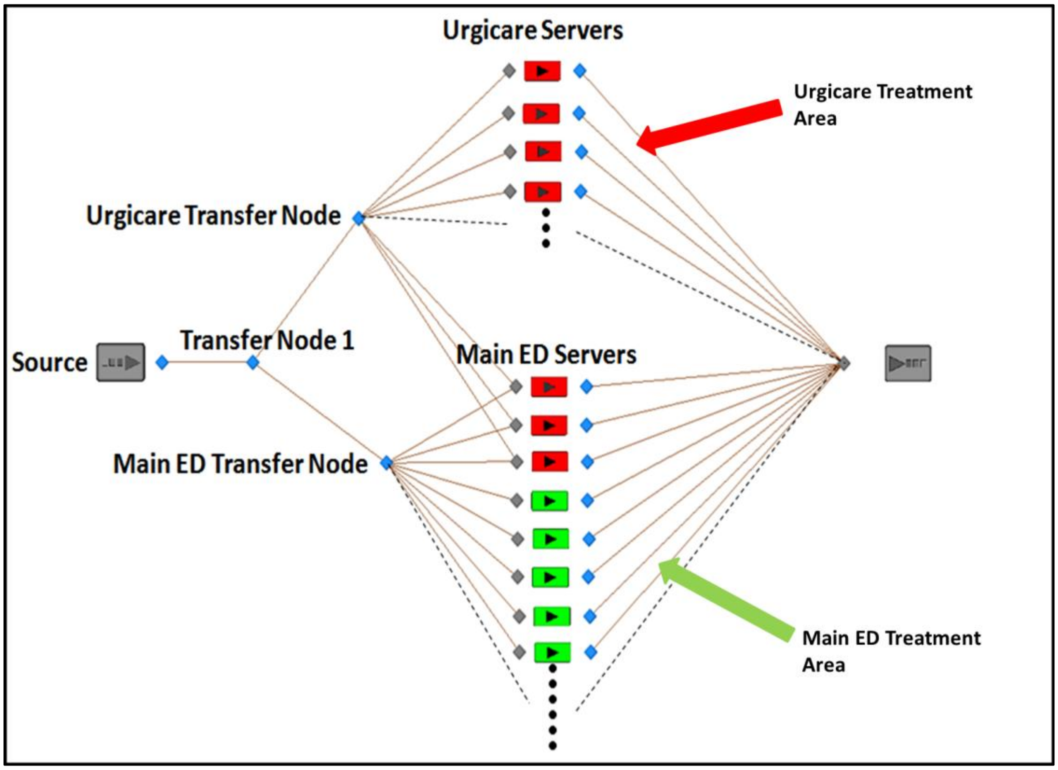


Figure **3-7**: Structure of the Simulation Model.

A Simio Source was used to model the arrival of patients to the ED. The Source uses an imported file containing information that could be derived from the historical timestamp data for significant events (i.e., arrival time, first physician visit time) during a patient's stay. The columns correspond to Arrival Date, Arrival Time, ESI, Treatment Time, and whether that patient was treated in Urgicare. The data file is for a month's (February 2010) worth of Main ED and Urgicare patients. Using the Set Table Assignment, the Simio model creates Entities according to the historical arrival dates and times of each patient. The Set Table Assignment also links the row to an Entity. This provides the capability to reference Entity attributes elsewhere in the model in order to utilize their ESI, Treatment Time, and whether they were processed in Urgicare. The Simio Source introduces patients into the model at their respective arrival times.

The Entities of the model are the patients who arrive at the ED. In all, there are 5 different patient types that can arrive to WRMC's ED – one associated with each ESI level. For this reason the model consists of 5 different Entity types. Naturally, the Simio Source creates Entities named 'ESI1', 'ESI2', 'ESI3', 'ESI4', and 'ESI5'. A Priority is also assigned to each Entity type. The specific priority is set equal to the ESI level of the Entity. Figure **3-8** presents the animation used in the Simio model to represent each Entity type. The animation varies in the color and labels of each patient. The values displayed in the labels represent the ESI of the Entity when the simulation is running.

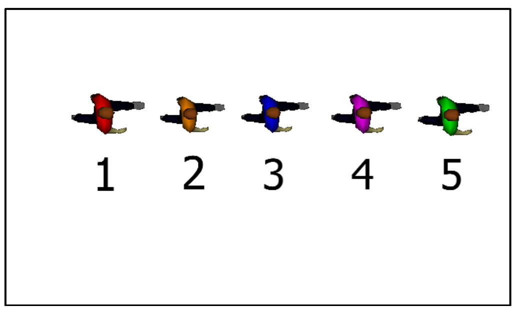


Figure **3-8**: Animation of ESI1, ESI2, ESI3, ESI4, and ESI 5 Entities.

After an Entity is created it travels a Simio Path to "Transfer Node 1" of Figure **3-7**. A Path is a specific type of link that connects two nodes together and provides Entities the ability to move throughout the model. Transfer Node 1 uses a Simio Add-On Process to decide treatment area destination - Urgicare or Main ED. This decision evaluates the ESI of a patient. In general, Entities with an ESI of 4 or greater that arrive to Transfer Node 1 during the operating hours of the Urigcare unit are routed to the Urgicare Transfer Node; otherwise, they are routed to the "Main ED Transfer Node" of Figure **3-7**.

Beds, both Urgicare and Main ED, are modeled using Simio Servers. The processing time of each server is set to reference the treatment time of the activating Entity. By modeling beds in this way, the treatment times are deterministic and are reflective of the actual treatment times that patients incurred during their visit to the ED in February 2010. Each Server has a capacity of either zero or one. Servers that have a capacity of zero are not available for an Entity. Naturally, Servers that have a capacity of one are available for an Entity. The number of Servers available in each treatment area varies according to the simulation scenario being run and the simulation time. Server assignment is made by referencing a Simio List. Multiple Lists that contained the possible Servers according to each simulation scenario were created. If multiple Entities were waiting for a Server to become available, then the next available Server was assigned to the Entity that arrived first with the lowest Priority/ESI. This logic was consistent for Entities waiting at either the Urgicare Transfer Node or the Main ED Transfer Node.

Once a Server became available, the Entity traveled a Simio Path to the Server. As mentioned previously the Server processed the Entity according to its respective treatment time. While processing, Add-On Processes were used to gather and write to a file the duration of time that the Entity had spent in the model since its creation. This was done to provide the ability to calculate the Average Provider after Triage times (the timespan between the arrival time of the patient and time a health care provider visited the patient). The model recorded these values in separate files according to whether the Entity was processed by an Urgicare or Main ED Server.

After the Entity was processed it traveled a Path to a Simio Sink. A Sink Object is used to destroy Entities during a simulation run. This is representative of a patient completing his stay at the ED. All Entities in the model are routed to the same Simio Sink. An Add-On Process is used to gather statistics for each Entity upon entrance into the Simio Sink. The Add-On Process determines whether the activating Entity was processed by an Urgicare or Main ED Server. Based on this result the total duration that the Entity spent in the system was tallied and written to a file to be used for statistical analysis.

3.4.3 Model Differences According to the Simulation Scenario

Four different operational scenarios were simulated for this research. The first scenario was a Baseline scenario which is used to model the actual performance of the patients that visited WRMC's ED during February 2010. Scenario 1 represents sending Urgicare patients to the existing Urgicare unit. Scenario 2 investigates reserving multiple beds in the main ED for Urgicare patients as well as the existing Urgicare unit. Scenario 3 is Scenario 2 with the addition of reserving an additional bed (Super-Urgi) for patients with relatively short treatment times who arrive during the operating hours of Urgicare. Scenarios 1 -3 represent the different operational scenarios proposed for the Phase I transition. Figure **3-9** presents a summary of the simulation scenarios. Again, the areas highlighted in red and green represent treatment areas dedicated to Urgicare and Main ED patients. The values contained in these images represent the maximum capacity of beds available for each scenario.

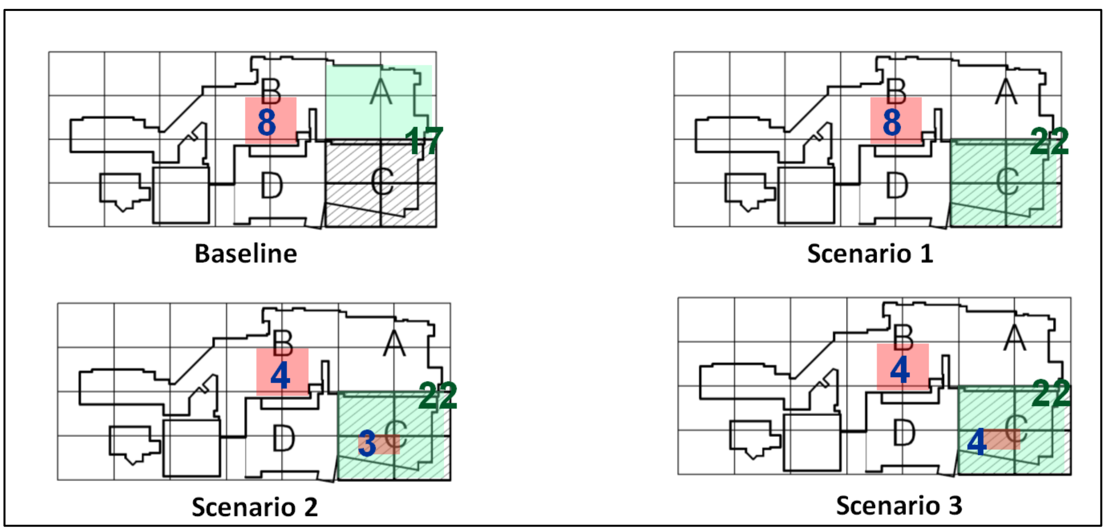


Figure **3-9**: Capacities of Simulation Scenarios.

The Baseline Scenario does not make use of beds in the Main ED for Urgicare patients. Therefore, this scenario would be represented in Figure **3-7** as 8 red (Urgicare) servers and 17 green (Main ED) servers. The Urgicare Transfer Node is only capable of routing patients to red servers; likewise, the Main ED Transfer Node is only capable of routing patients to green servers. Scenario 1 functions similarly to the Baseline Scenario with two exceptions. The first is that the number of red and green servers is 8 and 22. The second is that the red servers have an Add-On Process that adds a time delay to Entities as they enter and exit the server. This was done to model patients being escorted to and from the existing Urgicare treatment area during the Phase I Transition.

Scenario 2 would be represented in Figure **3-7** as 4 red servers in the existing Urgicare area, 3 red servers in the Main ED area, and 19 green servers in the Main ED area. The Urgicare Transfer Node has paths that are capable of routing Entities to red servers in either the Urgicare or Main ED areas. Priority is given to Urgicare servers in the Main ED area. As with Scenario 1, the red servers of the Urgicare area add a time delay to Entities that are processed there.

Scenario 3 would be represented in Figure **3-7** as 4 red servers in the existing Urgicare area, 4 red servers in the Main ED area, and 18 green servers in the Main ED area. Consistent with Scenario 2, the Urgicare Transfer Node has the capability of the accessing red servers in both the Urgicare and Main ED areas. The fourth red server bed in the Main ED, however, is also accessible via the Main ED Transfer Node. This fourth bed represents the Super-Urgi concept. Entities with processing times less than a specific value are routed to this red server if the capacity exists.

Two server objects are used to model each of the beds that can be reserved in the Main ED for Urgicare patients. When the capacity of a server representing an Urgicare bed is set to one, the capacity of the Main ED server is zero. Therefore, the total number of Main ED servers during Urgicare operating hours can be calculated as the total number of servers possible less the number of Servers reserved for Urgicare and Super-Urgi. This is done to reflect the constraint that is placed on the Main ED when multiple beds are reserved. The capacity of servers is updated throughout the simulation by using a Timer Event to trigger an Add-On Process. This Timer Event sets the capacity of the servers to zero or one during the simulation run according to the operating hours for the two different treatment areas. These values were provided by WRMC.

3.4.4 Specifying Simulation Scenario

Another function provided by the Simio Simulation Software is the ability to conduct experiments. Experiments can be set up and run using the Experiment application of the Simulation Software. This function allows a modeler to manipulate control variables and evaluate the impact that different scenarios have on performance measures of interest. The Experiment feature also has the ability to calculate confidence intervals of performance measures and produce various plots that aid in the analysis.

Control parameters that can be manipulated correspond to the Reference Properties specified in a simulation model. A Reference Property is an attribute that can be used to assign a value to various attributes in a simulation model. In the simulation model, Reference Properties were created to specify the maximum capacity of the Urgicare and Main ED treatment areas. By creating these Reference Properties, the Experiment function of Simio allows for the ability to determine how changing these parameters affect the performance of the model.

3.5 Verification and Validation

Before carrying out the experiments it is imperative to verify and validate the Simio model. Failure to do so would preclude sound engineering analysis. Even more so, any conclusion made from the results of the Simio model pertaining to Urgicare operating conditions could not be justifiable.

3.5.1 Model Verification

A continual process imperative to the success of a simulation model's ability to accurately reflect a real world system is verification. Verification is ensuring that the model is performing as intended. It is a qualitative analysis that typically makes use of simulation animation, deterministic input values, and high level analysis of system outputs.
The first step in verification of the Simio model was to become familiar with the environment being modeled. Prior to constructing the model, I visited WRMC several times. The goal of these visits was to identify patient arrival, triage, and waiting processes, as well as the bed allocation process of the ED. This goal was achieved by shadowing the Registered Nurse responsible for task delegation during the ED's peak operating hours on multiple days. While observing, I constructed flow diagrams of the processes and verified with the Registered Nurse that my interpretation of how the system operates was correct. The results of these meetings were the flow diagrams that have been presented earlier in this chapter.

Another visit was made to walk through the construction zone of the Phase I ED. It was beneficial to walk through the future ED with the floor plans because it provided a better sense of the layout, patient flow, and operational considerations that were relevant to the objectives of the model. Walking through the construction zone also provided an improved understanding of the challenge that is presented by the proximity of the Phase I ED and the existing Urgicare unit.

The Simio model was constructed piecewise. Constructing the model this way allowed for efficient detection of errors in the model logic. Once it was confirmed that the logic of a part of a model was performing appropriately, the model was expanded. Animation was integral to ensuring that various process logics were being modeled correctly. This was especially useful when ensuring that patients were allocated to beds in the model with the appropriate priority as well as whether the model was successfully determining their destination (Main ED or Urgicare Bed resources). Another advantage of verification using animation was the identification of unanticipated errors.

A specific example of the benefit of using animation occurred during the early stages of modeling. Animation exposed that an unexpectedly large queue of patients existed for those who arrived to Urgicare prior to closing hours but have not received treatment yet. These patients were essentially “trapped,” because they had no available destination during the non-operating hours of Urgicare and would not receive treatment until Urgicare reopened. In the real world these trapped patients would be transferred back to the Main ED waiting room. Failure to identify this oversight would have resulted in the model significantly overestimating the performance measures of interest.

Once the model was completed another meeting was scheduled with multiple healthcare providers of WRMC to demonstrate the model. The purpose of this meeting was to verify that the model logic was true to the operation of their ED, resolve any operational questions that I had as a modeler, and determine if there were any additional areas of investigation. In all, the process of frequently meeting with WRMC, becoming familiar with the ED operations from a first-hand experience, piecewise modeling, and analyzing animations resulted in a simulation model that accurately reflected the real world system.

3.5.2 Model Validation

Validation is the comparison of the performance of the model with statistics that have been gathered from the actual system for the month of February 2010. Calculating these statistics was necessary to validate the model. Knowledge of these statistics provided a metric for comparing the performance of the simulation model. To validate the model, the simulation was run for the same month's worth of data and with the same number of resources. Specifically, the model was set to run for one month with 17 beds in the Main ED and 8 beds in the Urgicare treatment area. The operating hours of Urgicare were set to open at 8:00 AM and close at 12:00 AM. Statistics were calculated from the results of this simulation. Table **3-1** presents a comparison of the initial simulation run with the actual values. The values contained in the Actual row are the performance measures that have been calculated from the historical data. The values contained in the Model row represent a 95% confidence interval of the same performance measures that the model generated.

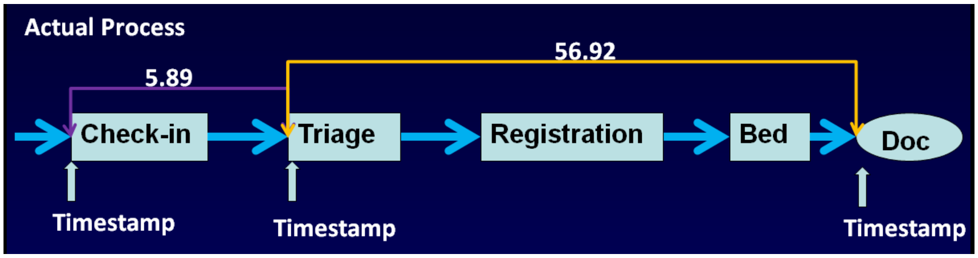
Table **3-1**: Actual Performance Versus Simulation for February 2010.

		Provider After Triage		**Departure After Triage**		
Patients:		**Main ED**	**Urgi**	**All**	**Main ED**	**Urgi**
Baseline: 17 Main Beds 8 Urgi Beds	**Actual**	59.92	49.37	148.85	203.48	91.25
	Model	(0.38, 0.40)	(0.63, 1.36)	(96.14, 96.35)	(146.83, 146.84)	(43.28, 43.69)

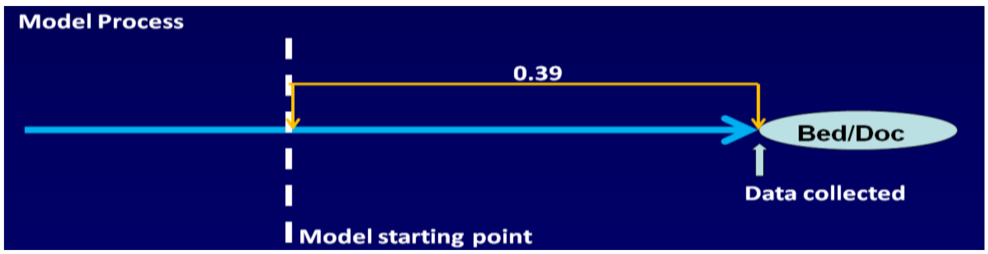
As demonstrated by Table **3-1**, the simulation model consistently underestimated the true system performance by approximately 50 minutes. This fact is true regardless of where in the ED a patient received treatment, thus suggesting that the model failed to account for a process that all patients must go through during their visit to the ED.

An additional reason for underestimating the true performance of the system can be attributed to the simulation being run with 17 beds available in the Main ED regardless of the time of day. This means that the model was running with a greater capacity for 12 hours each day, thus decreasing the duration of a patient's stay in the ED. Another assignable cause for underestimation stems from the way that the data were collected. To monitor the time it takes for a patient to be visited by a health care provider, the model records the difference between the time the activating Patient Entity was created and the current simulation time each time a Patient Entity had a bed allocated to it. Monitoring the Provider after Triage time in this way assumes that patient is visited by a provider immediately upon arrival. Although possible, this situation is not always the case.

The primary cause of the differences observed between the statistics of the true system and the model is due to the granularity of the patient data provided by WRMC. The historical data is time-stamped information for each patient who visited the ED and Urgicare areas of the hospital during the month of February 2010. Time stamps are recorded when a patient arrives to the ED, enters triage, is visited by a health care provider, and departs the ED. Although these are significant processes during a patient's visit to the ED, they do not encompass all processes that a patient goes through. Figure **3-10 (a)** summarizes the points of a patient's stay that times are recorded as well as the processes not recorded. From the figure it is readily identified that the data do not record the time that a patient starts registration and when a patient arrives to a bed.



(a)



(b)

Figure **3-10**: Inconsistencies Between True System and Model Logic.

Figure **3-10 (b)** presents a comparison of the scope of the system environment captured by the simulation model. As presented, a patient arrives to the system and is immediately assigned a bed, if a bed is available. As soon as the Patient Entity is assigned a bed, the patient's Provider after Triage Time is recorded. By modeling this way, the simulation does not contain processes for Triage, Registration, and Bed Assignment. With the absence of these processes a Patient Entity does not incur any delays prior to being placed in a bed. Thus, the average time it takes for a Patient Entity to be visited by a Provider is roughly 0.39 minutes, which is significantly shorter than the time this process takes in the real system (approximately 56.92 minutes). It is therefore concluded that the reason the model consistently underestimates true system performance is a result of not including these processes.

A reason for not including the Triage process in the model is because the provided data do not contain enough information to derive or estimate how long this process takes. Another reason for not including this process is because from firsthand experience it is known that Triage is not a bottleneck process. That is, the majority of time that patients spend in the ED prior to having a bed allocated to them is a result of waiting for a bed – not waiting on Triage. Furthermore, all patients go through this process prior to being assigned to a bed. The convolution of these facts means that the inclusion of the Triage process will have a nominal impact on values. Such an impact would be consistent for all scenarios investigated, thus not impacting any conclusions drawn from the analysis. Similar arguments can be made for the Registration process. As with Triage, specific times or estimates of process times for Registration and Assignment to a Bed could not be determined from the available data. Likewise, it was not possible to model these processes. Another reason for not including the Registration process in the model is because WRMC intends on using Bedside Registration during the Phase I transition.

A final assignable cause for the model underestimating actual performance is because the initial simulation was run starting in an empty and idle state. EDs in general can be classified as non-terminating system because they operate 24 hours per day and 7 days per week. Because they continuously operate, the initial Patient Entities of the simulation model that arrive in the model enter an ED that is empty. These patients are immediately treated, thus decreasing their overall time in the ED. Failure to consider the ED as a non-terminating system biased the performance measures.

These inconsistencies were presented to WRMC. Following this meeting many of the model inadequacies were resolved. Specifically, the bed schedule of the main ED, approximation of the Triage process, and approximation of the Registration process were clarified. The ED operated with 12 beds from 11:00 PM to 11:00 AM and 17 beds from 11:00 AM to 11:00 PM. An average time as well as a range of times were provided for the Triage and Registration processes. The values were determined from a previous study that investigated value-added time during a patient's visit to WRMC's ED. Estimates were provided for the Triage (average: 5 minutes, range: 1 – 17 minutes), Registration (average: 6 minutes, range: 2 – 15 minutes), and time between being in a bed and visited by a provider (average: 2.58 minutes, range: 0 – 3.33 minutes).

The bed schedule and Triage and Registration processes were incorporated into the model to ensure that the observed inconsistencies in the statistics calculated for the performance measures were truly a consequence of these causes. As addressed previously, incorporation of Triage and Registration is immaterial to the final conclusions that are to be determined from the model and Registration will not be in place when analyzing the system during Phase I operation. Triage and Registration were modeled using Simio Server Objects, with processing times sampled from a triangular distribution according to the averages and ranges approximated by WRMC. In the absence of observational data, the model assumes that the processing times of the respective server can be approximated by sampling from a triangular distribution with the provided ranges as the minimum and maximum values and the mode as the average. An Add-On Process was used to revise how observations of Provider after Triage Time are recorded as well. Making the same assumption as were made for the Triage and Registration processes, the Add-On Process uses a Delay Instance Step that samples times from a triangular distribution according to the estimated values. After the delay is incurred, the observed statistic is recorded. This process is triggered when a Patient Entity enters a Server Bed. Also, to compensate for the model starting in an empty and idle state, a warm-up period of three days was used. A warm-up period allows a model to run without gathering statistics for a specified duration of time. This prevents the performance measures from being biased. A period of three days was used because it is good simulation practice to use a warm-up period that is approximately one-tenth of the total simulation length.

Table **3-2** presents a comparison of the performance measures with the revisions of the simulation model. The units for each performance measure are minutes. Even though not all of the intervals of the simulation results contain the actual performance measures (thus the performance measures are significantly different at the 95% confidence level), the differences do not make a practical difference in the analysis of the results from an operations perspective. For this reason it is determined that the model adequately reflects the true world and will not compromise the intended analysis. Because differences do exist between the true system and the model, however, the results of the simulation will be used as the Baseline Scenario for which the success of the alternative scenarios will be compared.

Table **3-2**: Revised Simulation Validation.

		Provider After Triage		**Departure After Triage**		
Patients:		**Main ED**	**Urgi**	**All**	**Main ED**	**Urgi**
Baseline: 17 Main Beds 8 Urgi Beds	**Actual**	56.92	49.37	148.85	203.48	91.25
	Model	(36.36, 38.70)	(43.83, 46.96)	(145.84, 149.25)	(204.17, 207.77)	(86.07, 89.44)

3.6 Chapter Summary

Section 1 of Chapter 3 served to identify the arrival and bed allocation process for patients to WRMC's ED. Section 2 described differences in processes as well as the decision logic that will be used to determine ED patient destination during the Phase I transition. The purpose of that section was to provide the foundation for the environment studied. Section 3 presented the scope and the conceptual model, that is, the processes that a patient goes through that are relevant for analysis. The Section 4 demonstrated how the conceptual model was converted into a simulation model. The section presented an animated and structural version of the model developed using the features of Simio. Also contained in that section are the differences that exist in the model to reflect the Baseline and proposed operational scenarios. The chapter concludes with Section 5, which demonstrates the verification and validation process that ensures the model is an adequate tool for analysis. It also provides the values of the performance measures for the Baseline Scenario that will be used for comparison.

Chapter 4

RESULTS AND ANALYSIS

4.1 Introduction

This chapter contains tables and graphs used to analyze the results of the different simulation scenarios. The chapter first provides a definition for the experimental design as well the method for analysis. The results of the experiments are presented next. The analysis of these results primarily focuses on the evaluation of the performance measures specified by WRMC (Provider after Triage and Departure after Triage times). The performance measures results are analyzed with respect to Urgicare and Main ED treatment areas. The ultimate goal of this chapter is to address the objectives specified in Section **1.3**.

4.2 Experimental Design

4.2.1 Scenario Definitions

Table **4-1** provides a summary of the input parameters for each scenario. Review of this table demonstrates how scenarios differ with respect to ED capacity. The bed schedule for the Main ED capacity is specified for each scenario. The non-peak hours are defined as 11:00 PM - 11:00 AM and peak hours as 11:00 AM - 11:00 PM. These operating hours are consistent regardless of scenario. The operating hours of Urgicare, is also consistent regardless of scenario, are 8:00 AM - 12:00 AM. The timespans of the bed schedules are consistent with the true hours of WRMC. The Registration column of Table **4-1** specifies the point during the patients stay that they are registered. Post Triage Registration involves Patient Entities going through a process prior to having a bed assigned to them. That is, these patients experience a delay before bed placement. By contrast, Bedside Registration occurs during the time a patient is already in a bed. The assumption was made that Bedside Registration will not have an impact on overall time in the system. Therefore, this difference in registration method is modeled by omitting the registration process step from the models for Scenarios 1, 2, and 3.

Table **4-1**: Scenario Definitions.

Scenario	Main ED Beds [Non-Peak]	Main ED Beds [Peak]	Total Urgicare Beds	Urgicare Beds Reserved in Main ED	Registration?
Baseline	12	17	8	0	Post Triage
1	12	22	0	0	Bedside
2	12	19	3	3	Bedside
3	12	18	4	4	Bedside

A parameter of the Scenarios not captured by Table **4-1** is that patients who receive treatment in the existing Urgicare during the Phase I Transition must incur a time delay for being transported to and from Urgicare. WRMC was uncertain how long it would take to escort a patient between the Main ED and the existing Urgicare because the exact path had not yet been established and it was dependent on the patient as well as resource availability. WRMC approximated that it would most likely take 5 minutes, but this could range from 2 to 7 minutes. Therefore, the escorting process is incorporated into the models for Scenarios 1, 2, and 3 by using an Add-On process for the servers that represent the Existing Urgicare treatment area. The delay for escorting patients to the Existing Urgicare treatment area was sampled from a Triangular distribution with a minimum, mode, and maximum value of 2, 5, and 7 minutes. This delay is incurred twice because patients must be escorted to the Existing Urgicare from the Main ED and from the Existing Urgicare back to the Main ED. The escorting process did not exist in the

Baseline Scenario because the distance from the current ED to the Existing Urgicare treatment area was not significant.

As can be concluded from Table **4-1**, the Baseline Scenario is distinctly different from Scenarios 1-3. This reflects the differences that exist between current and proposed operating conditions. During the Phase I transition, there is a maximum of 22 beds available in the Main ED. It should be noted that increasing the capacity of Urgicare within the Main ED decreases in a linear fashion the capacity of the Main ED during the peak hours of operation. Also there is a timespan from 8:00 AM - 11:00 AM when Urgicare is open during the non-peak hours of the Main ED. The assumption was made that during this time the spare rooms of the Main ED can be utilized for Urgicare service without the need to decrease the capacity of the Main ED. For example, in Scenario 2, from 8:00 AM - 11:00 AM the Main ED and Urgicare capacity is 12 and 3 beds, respectively; however, from 11:00AM – 11:00 PM, the capacity of the Main ED and Urgicare are 19 and 3 beds, respectively.

All the scenarios use the same data table of values derived from the historical data provided by WRMC. Therefore, the arrival time, the treatment time, and acuity of each patient is deterministic and consistent for each simulation run of each scenario. This eliminates a source of variability when comparing the performance of each scenario and ensures that differences observed in performance measures are a consequence of bed capacity. Each Scenario is run for 10 replications, with a 3 day warm-up period, and for the entire month’s data.

4.2.2 Method of Analysis

The primary metrics used for evaluation of the success of each Scenario are average Provider after Triage and Departure after Triage time of patients. Provider after Triage time is defined as the difference in time from when a patient enters triage and is visited by a health care provider. Likewise, Departure after Triage time is the duration between arriving to triage and departure from the ED. These two performance measures have been used as a basis for making decisions because they are associated with quality of patient care. Larger values of Provider after Triage and Departure after Triage times often correspond to poorer patient care.

In addition to the primary performance measures, bed utilization and average number of beds in use are presented for each scenario. Analysis of these performance measures provide justification for the results observed. Additionally, use of this metric provides the capability to investigate potential opportunities for revising bed schedules.

In general, the results of Scenarios 1, 2, and 3 are evaluated by estimating the average difference in the performance measures from the Baseline scenario. The difference in average is calculated for each simulation run by subtracting the average of each Baseline replication from the average of each alternative scenario average. Ten replications were determined to be a sufficient sample size for calculating average differences, because each scenario has low variability. The low variability is a benefit of using deterministic arrivals, processing times, and priority values. Sources of variability are from processes, such as travel delays and registration, where deterministic values could not be derived. Table **4-2** provides a summary of the standard deviations for each of the simulation scenarios for the Provider after Triage performance measure. The units of the standard deviations are in minutes. As can be concluded from Table **4-2** the maximum average deviation for 10 replications is approximately 36 seconds. This amount of deviation would not have a practical effect on the conclusions, thus increasing the number of replications to greater than 10 would have been of marginal benefit.

Table **4-2**: Standard Deviations of Scenarios.

Performance Measure	**Main ED Provider after Triage**		
Number of Replications	**5**	**7**	**10**
Baseline	1.006	0.723	0.593
1	1.006	0.708	0.390
2	0.322	0.196	0.167
3	0.746	0.581	0.535

Because of a sample size of 10 replications with an unknown variance, the Student t-distribution was used to approximate the average difference in performance measures from the Baseline Scenario. The t-test used for comparing the differences in averages assumes that the data are normally distributed. The assumption of normality is valid for this application because the sample (performance measure resulting from one simulation run) is an average over all patients seen during a month, and thus the central limit theorem applies. The value of the t-statistic for a 95% confidence interval with 9 degrees of freedom is 2.262. The interpretation of entirely positive confidence limits is that the scenario does not meet the current performance level of the ED. By contrast, the interpretation of entirely negative confidence limits is that the scenario improves the current service level of the ED. No conclusions can be derived from confidence intervals that contain zero.

4.3 Results

4.3.1 Provider after Triage

Figure **4-1** presents the trend in the estimated average Provider after Triage difference experienced in the Main ED for each scenario. This figure contains three plots – one corresponding to each simulation scenario. The total span indicated by the beginning and terminal points of the plots in Figure **4-1** are the minimum and maximum average differences calculated. The central point of each plot is the estimate of the average difference between the result of the specified simulation scenario and the Baseline Scenario. The bounds of the box surrounding the average differences indicate the upper and lower bounds of the confidence interval on the estimated average difference. The specific values summarized by Figure **4-1** have been placed in Table **A-1** of Appendix **A**. The piecewise trendline connecting each figure is used to provide an analysis of the trend in performance measures. The unit of measure of the plots is in minutes.

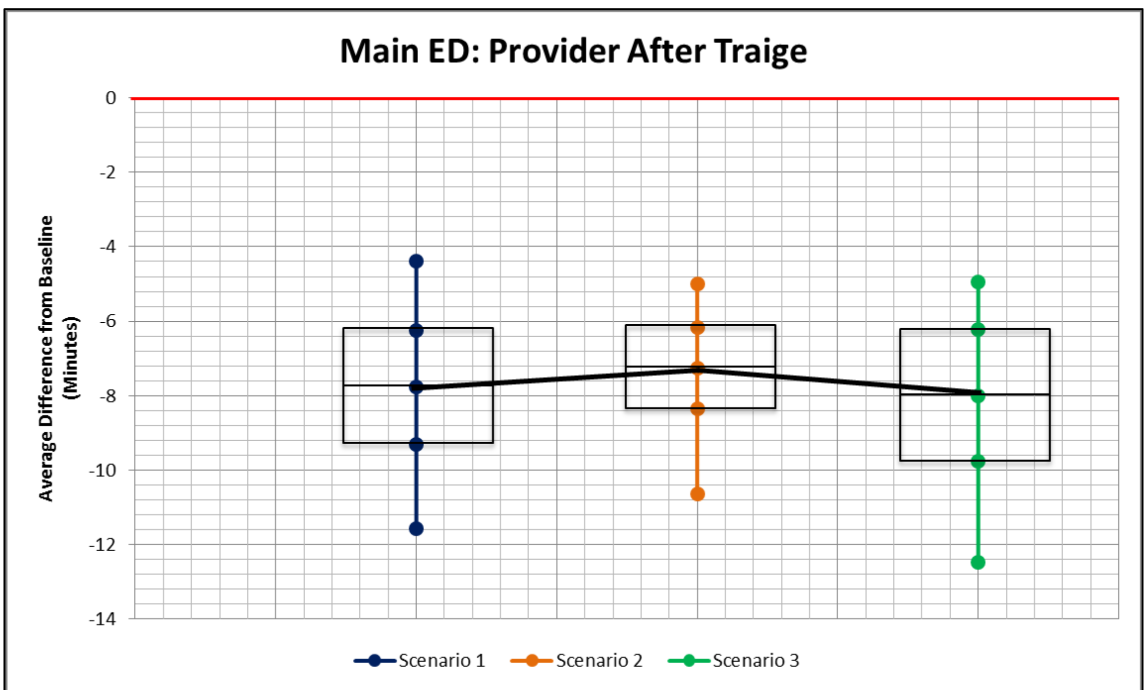


Figure **4-1**: Main ED Provider after Triage Results.

The interpretation of the plots contained in Figure **4-1** is that Scenarios 1, 2, and 3 decreases the timespan between when a patient first enters triage and when he is visited by a health care provider. This conclusion can be made because the average difference confidence intervals are all negative, thus implying that the expanded capacity of the Main ED during the transition will result in an improvement in service for patients visiting the Main ED area. Evaluating the trend of the improvement, it is observed that each scenario generates approximately the same benefit. Moreover, a comparison of the confidence intervals across all the scenarios further validates that no scenario provides a greater advantage than another. This conjecture can be made because of the overlapping bounds of the confidence intervals for each scenario. The consistency of the results across the scenarios is suggestive that the decrease in Provider after Triage time is most likely a result of the Phase I operation proceeding with the use of Bedside Registration. The elimination of this process means that patients will have a bed assigned to them more quickly, therefore allowing them to be visited by a health care provider sooner. These results can also be explained by analyzing the average number of beds in use during the simulation run. Table **4-3** presents a summary of the average number of beds in use. The value of each scenario is equivalent and is less than the minimum capacity of the ED during any period of its operating hours. Therefore, beds are immediately assigned to patients for all patients when they arrive to the Main ED.

Table **4-3**: Average Number of Beds Used in Main ED.

Performance Measure	**Main ED Average Number of Beds**	
Scenario	**Average**	**Half-Width**
1	5.26	0.02
2	5.28	0.02
3	5.25	0.02

Scenario 3 provides the greatest improvement in Provider after Triage time. This result is intuitive because this Scenario represents utilizing a Super-Urgi bed. As defined previously, Super-Urgi is reserved solely for any patient who has a relatively short processing time. The model used the 25th percentile of all patient treatment times as the cutoff value to decide whether a patient can access this resource. As suggested by its average utilization (29.4%), the bed is usually available to provide treatment for patients, thus reducing the amount of time until bed placement for a patient.

Figure **4-2** presents the estimation of the average difference in Provider after Triage times for Urgicare patients. The scope of the data presented by the three plots of Figure **4-2** is consistent with Figure **4-1**. Similarly, the specific values for the information summarized by these plots can be referenced in Table **A-2** of Appendix **A**.

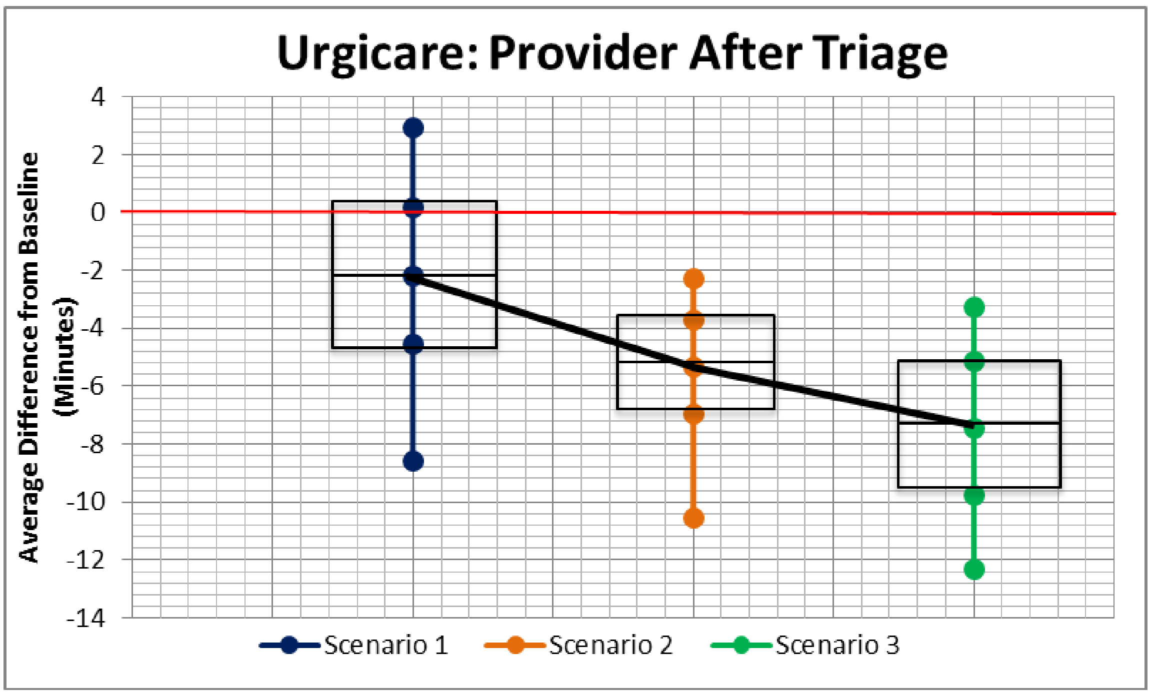


Figure **4-2**: Urgicare Provider after Triage Results.

Because the confidence interval of Scenario 1 contains zero, a statistically significant conclusion cannot be made about the performance during the Phase I transition. This is attributed to the fact that, although BR is being used in Scenario1, its benefit is offset by the travel time involved in escorting a patient from the waiting area of the Main ED to the existing Urgicare unit, that is, the amount of time incurred by a patient due to either being escorted or registered is nearly equivalent. Moreover, the simulation model for Scenario 1 made the assumption that a resource was always available to escort the patient to the existing Urgicare unit from the Main ED area. It is likely, however, that the availability of the escort resource could be dependent on the time of day or demand. The impact of this realization is that a greater delay may exist before a patient is placed in a bed and visited by a health care provider. Therefore, the results of Scenario 1 underestimate the value of the Provider after Triage time for Urgicare patients. It is plausible that the Baseline may be superior to Scenario 1.

Scenario 2 and Scenario 3 result in a significant improvement. An explanation for this is that these scenarios reserve capacity for Urgicare patients within the Main ED. Urgicare patients who are treated in the Main ED do not incur an additional travel time nor do they require an additional resource for escorting purposes. The benefit of these two factors is that the time before a bed is assigned to a patient and the time before being visited by a healthcare provider is decreased.

As evidenced by the negative slope of the piecewise trendline, the improvement in Urgicare Provider after Triage time increases with an increase in Urgicare rooms reserved in the Main ED for Urgicare patients. This trend is also explained by the avoidance of utilizing the existing Urgicare unit. Greater insight can be gained by comparing the average utilization of each Urgicare treatment area – Existing Urgicare, Main ED Urgicare, and Super-Urgi. The utilization values are summarized in Table **4-4**. The decrease in utilization of the Existing Urgicare from Scenario 1 to Scenario 2 to Scenario 3 means that fewer Urgicare patients are being routed to this area for treatment. Accordingly, fewer patients incur the time delay associated with being escorted. Furthermore, the decrease in Main ED Urgicare utilization from Scenario 2 to Scenario 3 results in fewer patients waiting before being placed in a bed. This is made possible because of the operating conditions of Super-Urgi. Table **4-4** implies that for Scenarios 2 and 3 the benefits of Bedside Registration are taken advantage of because escorting patients is avoided the majority of the time.

Table **4-4**: Urgicare Utilization by Treatment Area.

Performance Measure	**Urgicare Utilization**		
Scenario	**Existing**	**Main ED**	**Super-Urgi**
1	35.5%	-	-
2	23.0%	64.2%	-
3	19.4%	59.8%	29.4%

Scenario 3 provides the greatest improvement overall. As before, this result is expected because Scenario 3 has the greatest overall capacity for Urgicare patients. More importantly the use of a Super-Urgi improves the service of patients to a greater extent than a regular Urgicare bed. The Super-Urgi operates like a more specific Urgicare treatment area. That is, it adheres to a shortest processing time scheduling method. However, the range of processing times is limited. The net impact is an improvement in efficiency of Super-Urgi compared to the other treatment areas of the ED.

4.3.2 Departure after Triage

Departure after Triage is another primary performance measure of interest for WRMC. Generally, it is logical to expect that the Departure after Triage results and the Provider after Triage results to be comparable. Figure **4-3** presents the Departure after Triage results for patients who received treatment in the Main ED. The specific values for the plots of this figure can be referenced in Appendix **B**, Table **B-1**.

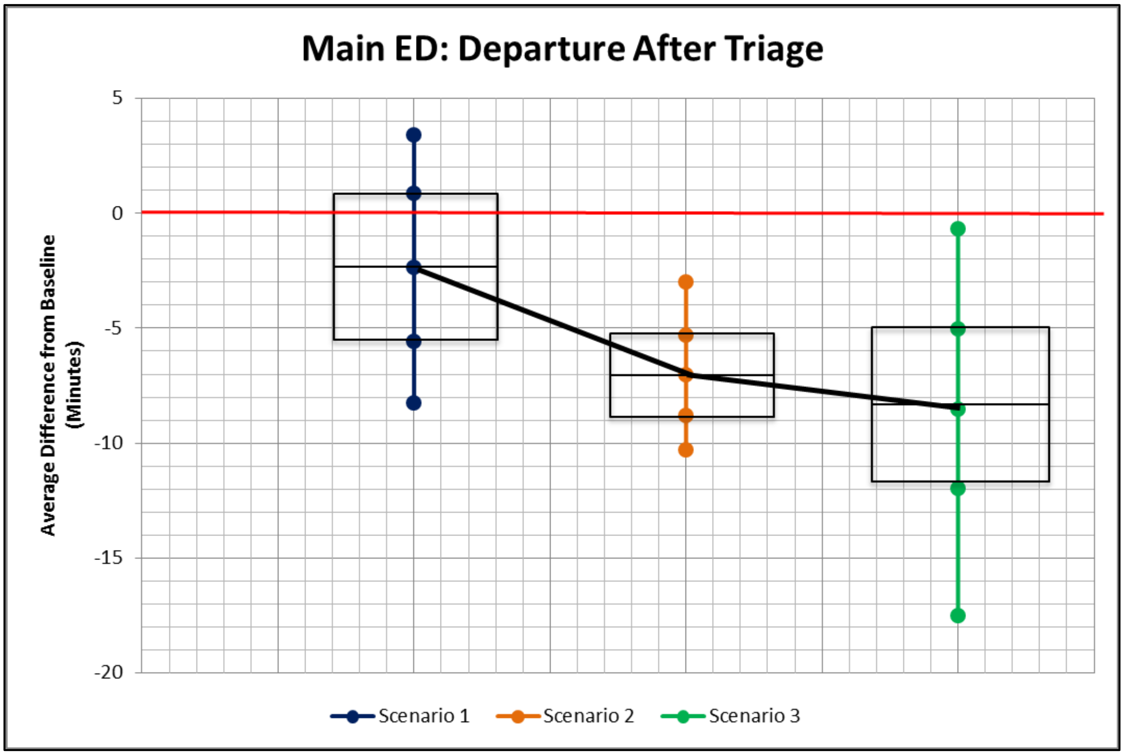


Figure **4-3**: Main ED Departure after Triage Results.

A statistical conclusion cannot be made with respect to improvement in the performance level of Scenario 1 because the calculated interval contains the value zero. Scenarios 2 and 3, however, provide a statistically significant improvement over the Baseline performance values. This is indicated by the entirely negative confidence intervals. Additionally, a decrease in the Departure after Triage time is observed across all of the scenarios. This result is not intuitive, because Scenario 1 has the greatest Main ED capacity followed by Scenario 2 and Scenario 3.

A plausible explanation for decrease in Departure after Triage time for Scenario 3 is that the model assumed that Super-Urgi is available to all patients, regardless of their ESI. Whether this is how the Super-Urgi will actually operate is uncertain. To verify if this hypothesis is valid, Scenario 3 was re-run with the restriction that Super-Urgi can only be accessed by patients with an ESI of 4 or 5 and who have a sufficiently short treatment time. Figure **4-4** presents the results of Scenarios 1, 2, and the modified version of Scenario 3. The marginal increase in the estimated average value for Departure after Triage time from Scenario 2 to Scenario 3 provides some justification for the tested hypothesis. It is also worthy to note that the variability of Scenario 3 decreased as well when the simulation was re-run with the modification. The reduction in the half-width length was from 3.49 to 2.37 minutes.

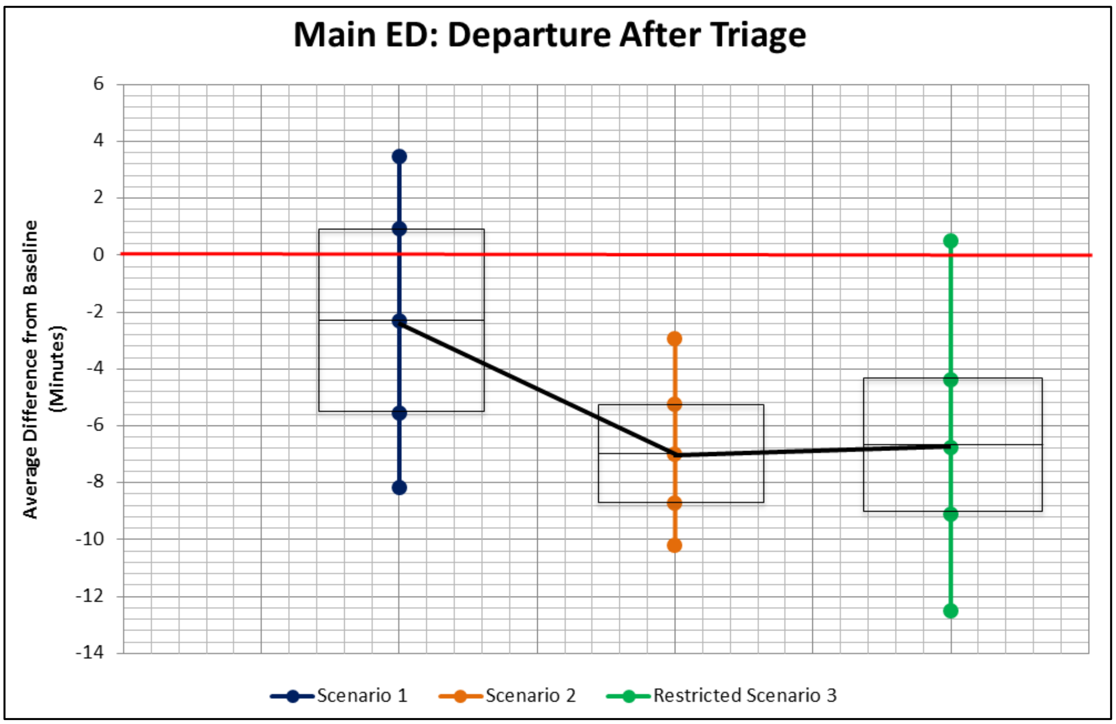


Figure **4-4**: Sensitivity Analysis of Scenario 3.

According to the initial results of the simulation model (Figure **4-3**) none of the scenarios provides a significant advantage over the other. The explanation is that the expanded capacity of the Main ED during the Phase I transition allows for an improved ability to provide treatment to patients. The average number of beds in use for each scenario provides justification for this explanation. As presented previously, Table **4-3** provided a summary of the estimates for the average number of Main ED beds in use during the simulation. The maximum capacity of the Main ED in Scenario 1, Scenario 2, and Scenario 3 is 22, 19, and 18 beds, respectively. The minimum capacity of the Main ED for all of these scenarios is 12 beds. As discussed, Table **4-3** demonstrates that the average number of beds in use is much less than the minimum number of beds. The averages are consistent for all of the operational scenarios. According to the results of the model it can be concluded that the expanded facility has enough capacity to provide treatment to patients, thereby justifying the similarity of the results observed for Departure after Triage times in Figure **4-3**.

Figure **4-5** presents the results for the estimated difference in the average Departure after Triage time for Urgicare patients. The specific values for the plots of this figure can be viewed in Table **B-2** of Appendix **B**. As expected, the general trend of this plot is consistent with the trends observed in Provider after Triage times.

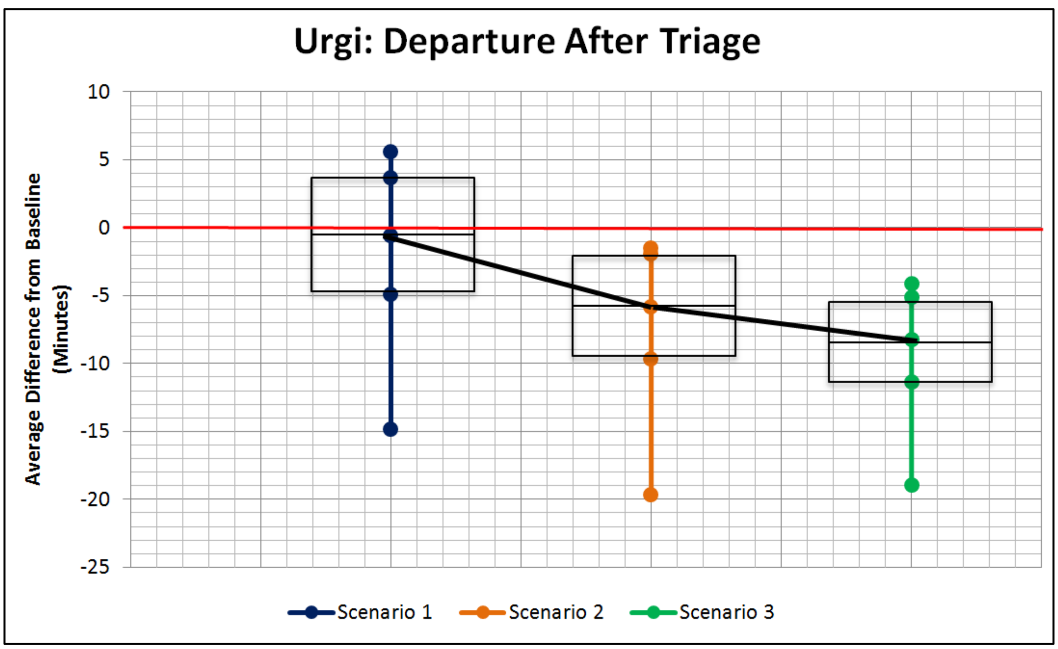


Figure **4-5**: Urgicare Departure after Triage Results.

The piecewise trend line of Figure **4-5** demonstrates that a decrease in the Departure after Triage time for Urgicare patients occurs when Scenario 1 is compared to Scenario 2 to Scenario 3. The convolution of the capacity of Urgicare and the location of the Urgicare beds provide an explanation for this observation. Although Scenario 1 is one of the scenarios with the greatest overall Urgicare capacity (8 beds), it has a travel delay associated with arriving to and departing from all of its beds. This condition is true for only 4 of the beds in Scenarios 2 and 3. Scenarios 2 and 3 have 3 and 4 beds reserved in the Main ED for Urgicare patients. The location and number of beds in each location are contributing factors to why a significant improvement cannot be concluded for Scenario 1, but can be for Scenarios 2 and 3.

As expected, Scenario 3 results in the most significant improvement in Departure after Triage time. This scenario also has the lowest amount of variability (half-width of 2.31 minutes). One factor contributing to this result is that Scenario 3 has the greatest overall capacity for Urgicare patients as well as the greatest capacity for Urgicare patients in the Main ED. It is plausible that this improvement would be greater if the capacity of Urgicare is increased. A practical way to increase the capacity of the Urgicare without reserving any additional rooms in the Main ED or scheduling additional health care providers is by restricting the Super-Urgi to just Urgicare patients. As addressed before, this may be a possible operating condition for the Super-Urgi room. Also, WRMC has explained that, because the patients sent to the Super-Urgi room are typically of the lowest severity, it may be feasible for one nurse to provide treatment to two patients in the same room. This virtually increases the capacity of Super-Urgi to two. The simulation model was modified to test this hypothesis and a confidence interval for the average difference in Departure after Triage time was calculated with respect to Scenario 3. The bounds of a 95% confidence interval for this statistic are -1.21 and 2.37 minutes. No statistical conclusion can be made about whether a benefit is achieved by modifying the operation of Urgicare in this way.

4.4 Discussion

4.4.1 Number of Urgicare Beds in Use

As hinted by the insignificant difference in Departure after Triage times when the modification to Super Urgi was run, the model is suggesting that there is more than enough capacity to treat Urgicare patients. This suggestion is supported by Table **4-5,** which presents a summary of the average number of Urgicare beds in use during the entire simulation run. The table segregates the average number of Urgicare beds used according to treatment area. The values of Table **4-5** confirms that there is more than enough beds available to provide treatment to Urgicare patients because the averages are consistently less than the capacity of Urgicare. This provides justification for the similarity in results for Departure after Triage times observed previously in Figure **4-5**.

Table **4-5**: Average Number of Beds Used in Urgicare.

Performance Measure	**Average Number of Urgicare Beds**					
Scenario	**Existing**		**Main ED**		**Super-Urgi**	
	Average	**Half-Width**	**Average**	**Half-Width**	**Average**	**Half-Width**
Baseline	1.76	0.03	-	-	-	-
1	1.71	0.02	-	-	-	-
2	0.56	0.01	1.70	0.01	-	-
3	0.47	0.02	1.64	0.01	0.18	0.00

Further analysis was conducted on Scenario 3 because this scenario resulted in the greatest improvement in Provider after Triage and Departure after Triage time. The additional analysis monitored the minimum, average, and maximum number of beds in use at the end of each hour for one simulation run (one month). The distribution of these values was plotted over time of day for the beds of the Main ED Urgicare, Super-Urgi, and Existing Urgicare treatment areas. Figures **4-6**, **4-7**, and **4-8** present the analysis for each of the respective treatment areas.

The interpretation of these figures is comparable to Urgicare demand throughout the day because the Urgicare unit has more than sufficient capacity. The central values plotted at each of the hours are the average number of beds in use during each simulation run. The green error bars that extend from each of these points span the minimum and maximum values of the number of beds in use.

Figure **4-6** represents the demand for beds in the Main ED for Urgicare. From this figure it is observed that the average number of beds in use is consistently less than the maximum capacity of the beds (3). According to this figure, the demand for Urgicare beds does not start until 9:00 A.M. The current operating hours of Urgicare are from 8:00 A.M. until 12:00 A.M. Consequently the potential exists to revise the operating hours of Urgicare by delaying the time it opens or revise the number of beds reserved in the Main ED for Urgicare patients. It should be noted that this may also be a consequence of how the data were collected for this preliminary analysis. The model calculates the number of beds that are being used at one instant (the end of every hour), thus it is plausible that patients arrive to the Urgicare area as early as 8:00 AM and complete treatment prior to data being collected. The trend of demand over time is that it reaches its maximum around 5:00 PM, at which point the demand begins to decline.

Scheduling bed capacity around average values is not advisable, however, because that would result in the Urgicare treatment area having sufficient capacity approximately 50% of the time. For this reason, the maximum number of beds in use at each hour has also been included in Figure **4-6**. It is observed that after 9:00 AM there are instances when the Urgicare treatment area is being fully utilized. Similarly, there are instances when none of the beds are in use. The occurrence of the former and latter conditions may provide improved insight into the variability of Urgicare demand and consequently the feasibility of revising bed scheduling. The frequency of 3 beds being in use simultaneously does not provide justification for reducing the total number of beds reserved in the Main ED for Urgicare patients.

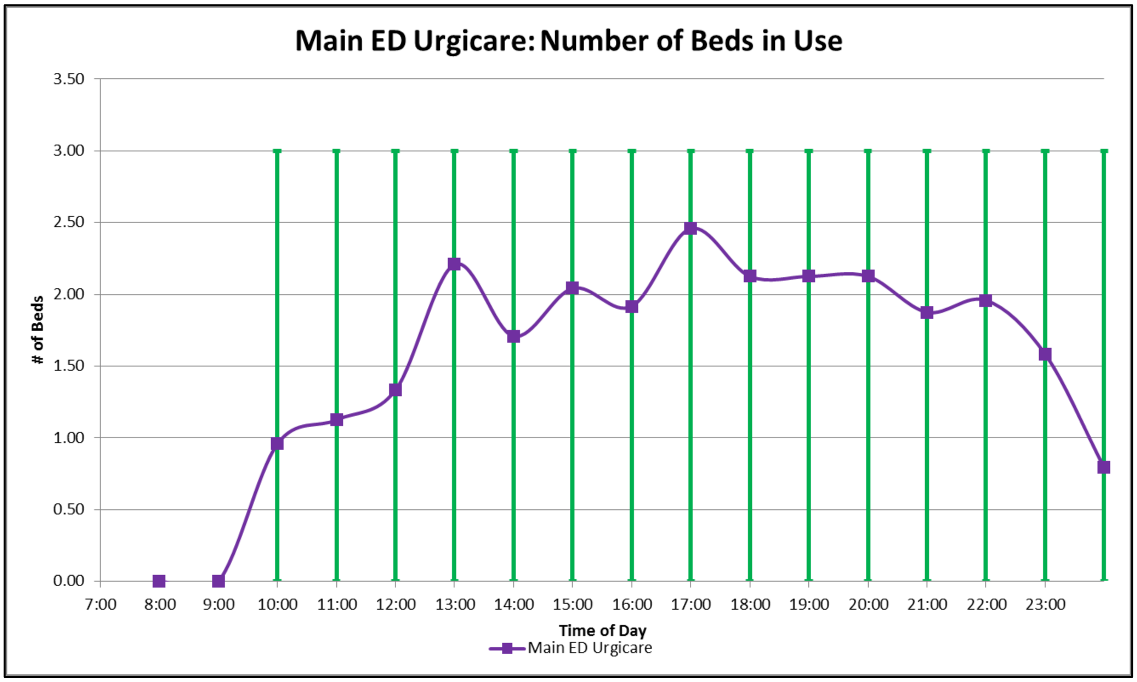


Figure **4-6**: Number of Beds Being Used in Main ED Urgicare.

Figure **4-7** provides the demand of beds in use for the Super-Urgi area. The interpretation of this figure is comparable to the interpretation of Figure **4-6**. The average number of beds in use throughout the day is consistently less than the maximum capacity of Super-Urgi (1 bed). A contributing factor is patients treated in Super-Urgi have treatment times less than or equal to the 25th percentile of all patient treatment times (.45 hours). Modifying this condition may shift the average number of beds in use accordingly. This also explains the consistency observed in the average number of beds during the day. As observed in Figure **4-6**, the number of beds in use does not begin until after 9:00 AM. Naturally, there are events during the month when the number of beds in use is the maximum and minimum. Using the same logic that was used for interpreting Figure **4-6**, the results of Figure **4-7** do not suggest that an opportunity exists for reducing capacity of Super-Urgi during its hours of operation.

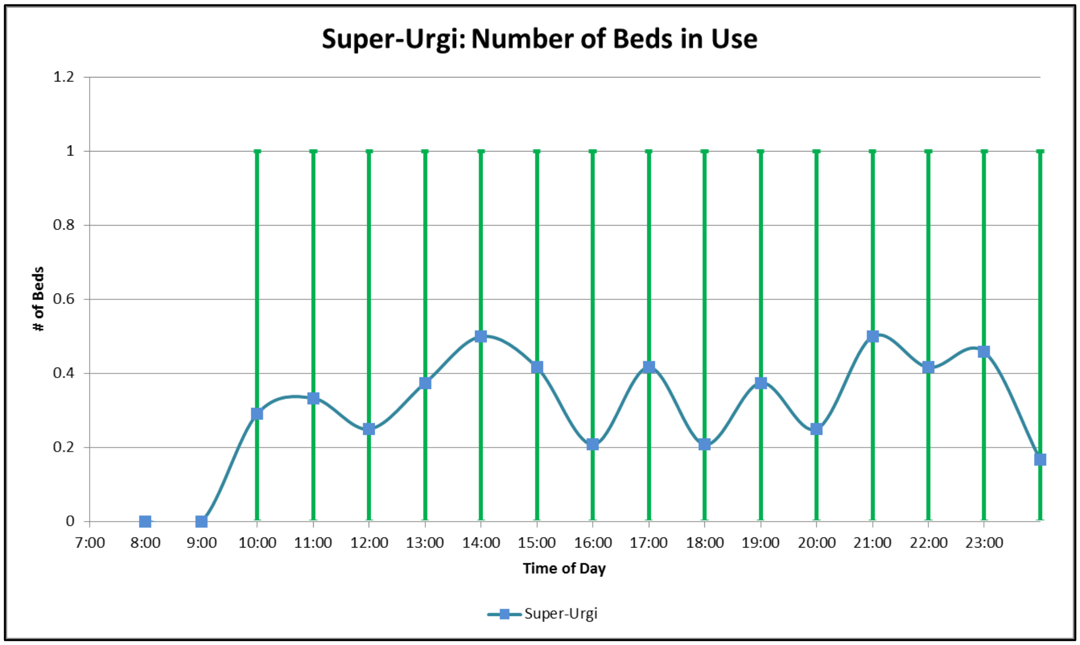


Figure **4-7**: Number of Beds Being Used in Super-Urgi.

Figure **4-8** presents the average, minimum, and maximum values for the average number of beds being used in the Existing Urgicare unit. The maximum capacity of this scenario is 4 beds. The average utilization of the number of beds in the Existing Urgicare unit is consistently less than its maximum capacity, and the demand on the resources of these beds does not begin until after 9:00 AM. The average demand also reaches local maximums around 4:00 PM and 8:00 PM. Unlike the other Urgicare treatment areas, there are instances when the maximum number of beds available is not in use. Such behavior is observed during the timespans of 10:00 AM – 2:00 PM and 5:00 – 7:00 PM. These occurrences provide the potential for reducing the number of active beds in the Existing Urgicare unit. The advantage of this from a managerial perspective is that the resources used for the Existing Urgicare could be reallocated elsewhere or a savings can be realized.

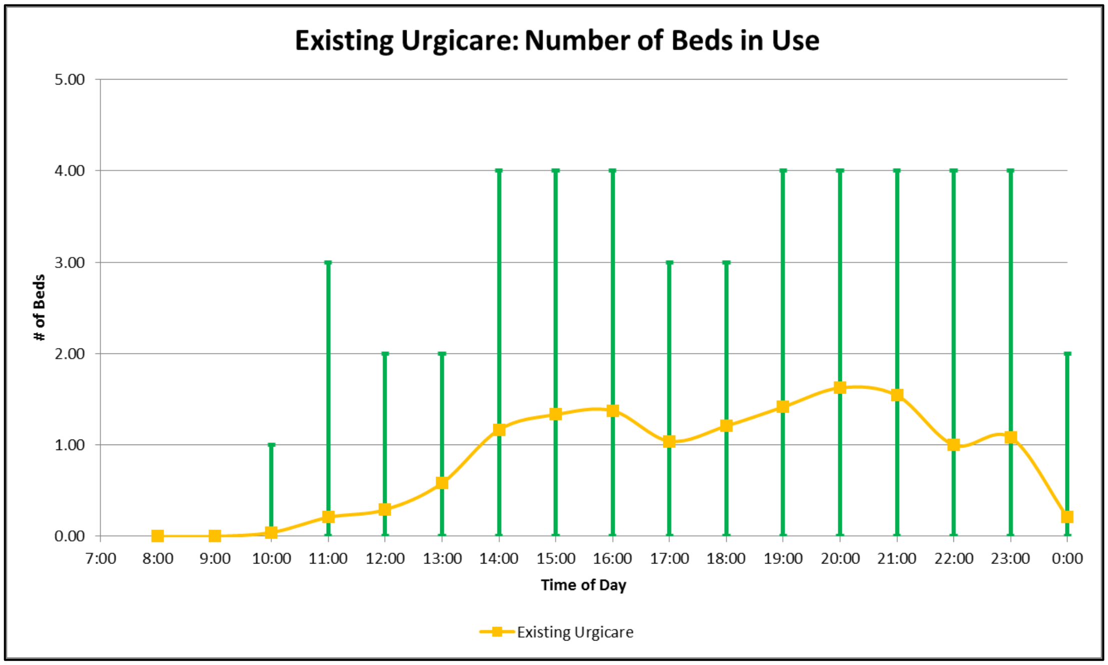


Figure **4-8**: Number of Beds Being Used in the Existing Urgicare.

4.4.2 Implications of the Data

Further explanations for the results presented in Sections **4.3.1** and **4.3.2** can be aided by analyzing the input data of the simulation model used for simulating and comparing the multiple operational scenarios. Factors that may have influenced the results are the method for determining patient treatment time and the use of historical data.

The simulation model made the assumption that the treatment time of each patient can be approximated solely by the difference between the timestamp of when a patient is first seen by a health care provider and the timestamp of when that patient departed the ED. The treatment time of each patient was calculated in this way because of the granularity of the data available. When this research was conducted, the data provided by WRMC did not record patient timestamps in between these two events. It is likely that a margin of error, both positive and negative, is involved with approximating treatment times in this way.

The total length of stay for a patient is partially reflective of workload. The assumption is made that the method used for patient treatment times would account for any correlation that may exist between length of treatment and ED workload. Justification for this assumption is provided by the fact that the model uses historical data; therefore, the recorded values should reflect any such correlation. However, patients in the model are arriving to a bed earlier than they were actually processed, thus shifting the demand earlier in the day because no waiting is incurred between entity creation and bed assignment. In actuality, the treatment time of a patient is affected by the availability of resources (such as physicians, nurses, equipment) that may be shared amongst all patients receiving treatment as well as workload in other areas of the hospital used for ancillary testing. It is probable that during times of high demand patients would incur a greater length of stay. Additional delays may be incurred during periods of peak demand due to ED congestion. This may exacerbate the ability of a patient to depart from the ED. If such a correlation is exists between workload and length of stay, then the patient treatment times should be adjusted accordingly.

Because the model uses historical data, the processing times are reflective of procedures used in February 2010. These times, therefore, may not be reflective of how the hospital currently operates or will operate in the future. The treatment times of patients in the future may be affected because of changes to operating conditions and procedures. Changes in the layout and increases in total area of the Phase I ED may adversely affect the efficiency at which the hospital provides treatment. It is equally likely, however, that since this data were collected, process improvements have been made due to the implementation of best practices. Incorporation of these considerations into the simulation model would provide an improved estimate of the key performance measures.

4.5 Chapter Summary

Section 2 of this chapter provided definitions for the scenarios investigated, the experimental design, and the method for analysis. After the definitions were provided, Section 3 presented the Provider after Triage and Departure after Triage results for each of the simulated scenarios. Evaluation for the success of each scenario was carried out by estimating the average difference between each scenario and the Baseline Scenario. Explanations for the results of the simulations were aided by investigating bed utilization and average number of beds in use. Section 4 of this chapter provided additional analysis of the use of Urgicare to further confirm the results of the simulation model. Also contained in this section is a discussion of the input data and its influence on the results.

Chapter 5

CONCLUSIONS AND FUTURE RESEARCH

5.1 Conclusions

According to the results of the simulation model, the best operating scenario occurred when Scenario 3 was simulated. Scenario 3 modeled the Main ED operation with a capacity of 12 beds from 11:00 PM until 11:00 AM. From 11:00 AM until 11:00 PM the capacity of this scenario is increased to 18 beds. This scenario also reserved three beds in the Main ED for Urgicare patients and a fourth Super-Urgi bed. Allocating resources according to the definition of this scenario resulted in the most significant improvements for Provider after Triage and Departure after Triage times for patients regardless of whether they received treatment in the Main ED or Urgicare treatment areas. Although the improvements over the Baseline Scenario for these performance measures are statistically significant, they are in the magnitude of minutes. The improvement in average Provider after Triage time for Main ED patients and Urgicare patients was 8.00 and 7.54 minutes, respectively. This is a 21.4% and 16.5% improvement. The improvement in average Departure after Triage time for Main ED and Urgicare patients was 8.50 and 8.26 minutes, respectively. The percent improvement of this performance measure was 4.2% and 9.3%.

The objective of this research was to provide an assessment for the feasibility of reserving rooms in the Main ED for Urgicare patients and determine if it is sensible to make use of a Super-Urgi treatment area. Because Scenario 3 provided the greatest improvement for all of the performance measures, the model confirms and recommends for resources to be reserved in the Main ED for these two functions. The estimated differences in the performance measures could be even greater if WRMC would implement process improvements during the Phase I transition.

Analysis of the average number of Urgicare beds used during the simulation indicated that the bed schedule of the Existing Urgicare unit can be modified because there are multiple timespans when the Existing Urgicare is operating at less than full capacity. Additionally, the distribution of demand also suggests that a potential exists for modifying the operating hours of Urgicare.

5.2 Future Research

Section **4.4.1** contained a high-level evaluation of the distribution of Urgicare bed demand for Scenario 3. This was done to investigate the possibility for modifying the bed schedule of the Urgicare treatment areas. The preliminary analysis provided some evidence that opportunities exist to reduce the capacity of Urgicare. Therefore, it may be of value to conduct a more complete analysis of the demand for Urgicare beds and simulate scenarios with different bed capacities. A similar analysis could be conducted for the beds of the Main ED as well.

As touched on in Section **4.4.2**, it may also be worthwhile to conduct a statistical analysis on whether a correlation exists between patient treatment times and the total number of patients being treated in the ED. If such a correlation between workload and treatment times is found, then the model should be modified to provide the ability to adjust the treatment time according to the number of patients in the ED.

Another potential for future research involves the routing of Urgicare patients. In some situations, when the beds reserved in the Main ED for Urgicare are completely utilized, an advantage may be gained by queueing patients for one of these beds instead of always escorting patients to the existing Urgicare treatment area. Various decision logics used for making this decision could be experimented with through simulation and comparison of performance measures.

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Appendix A

Provider After Triage Results

Table **A-1**: Main ED Provider after Triage Values.

Performance Measure	Main ED Provider after Triage				
	Minimum	**Lower Bound**	**Average**	**Upper Bound**	**Maximum**
Scenario 1	-11.565	-9.302	-7.770	-6.237	-4.398
Scenario 2	-10.644	-8.358	-7.258	-6.158	-4.998
Scenario 3	-12.487	-9.767	-8.002	-6.236	-4.951

Table **A-2**: Urgicare Provider after Triage Values.

Performance Measure	Main ED Provider after Triage				
	Minimum	**Lower Bound**	**Average**	**Upper Bound**	**Maximum**
Scenario 1	-8.575	-4.556	-2.188	0.180	2.907
Scenario 2	-10.552	-6.942	-5.338	-3.735	-2.289
Scenario 3	-12.304	-9.762	-7.454	-5.147	-3.267

Appendix B

Departure After Triage Results

Table **B-1**: Main ED Departure after Triage Values.

Performance Measure	Main ED Departure After Triage				
	Minimum	**Lower Bound**	**Average**	**Upper Bound**	**Maximum**
Scenario 1	-8.235	-5.589	-2.356	0.878	3.419
Scenario 2	-10.269	-8.780	-7.032	-5.284	-3.002
Scenario 3	-17.512	-11.992	-8.499	-5.007	-0.660

Table **B-2**: Urgicare Departure after Triage Values.

Performance Measure	Urgicare Departure After Triage				
	Minimum	**Lower Bound**	**Average**	**Upper Bound**	**Maximum**
Scenario 1	-14.817	-4.890	-0.603	3.684	5.609
Scenario 2	-19.672	-9.670	-5.821	-1.973	-1.495
Scenario 3	-18.940	-11.382	-8.264	-5.146	-4.169

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