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Using Computer Simulation to Study Hospital Admission and Discharge Processes

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USING COMPUTER SIMULATION TO STUDY HOSPITAL ADMISSION AND DISCHARGE PROCESSES

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ABSTRACT

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Hospitals around the country are struggling to provide timely access to inpatient beds. We use discrete event simulation to study the inpatient admission and discharge processes in US hospitals. Demand for inpatient beds comes from two sources: the Emergency Department (ED) and elective surgeries (NonED). Bed request and discharge rates vary from hour to hour; furthermore, weekday demand is different from weekend demand. We use empirically collected data from national and local (Massachusetts) sources on different-sized community and referral hospitals, demand rates for ED and NonED patients, patient length of stay (LOS), and bed turnover times to calibrate our discrete event simulation model. In our computational experiments, we find that expanding hours of discharge, increasing the number of days elective patients are admitted in a week, and decreasing length of stay all showed statistically significant results in decreasing the average waiting time for patients. We discuss the implications of these results in practice, and list the key limitations of the model.

TABLE OF CONTENTS

Page

ABSTRACT v

LIST OF TABLES ix

LIST OF FIGURES x

CHAPTER

1. INTRODUCTION 1

1.1 Motivation 1
1.2 Background 1
1.3 Discrete Event Simulation 2
1.4 Problem of Description 3

2. LITERATURE REVIEW 6

2.1 Admission Scheduling 6
2.2 Elective Admission 9
2.3 Emergency Department 11
2.4 Computer simulation in health care processes 13

3. METHODOLOGY 16

3.1 Baseline parameters 16
3.1.1 Replication Parameters 16
3.1.1.1 Number of Replications 17
3.1.1.2 Warm Up Period 17
3.1.1.3 Replication Length 19
3.1.1.4 Replication Start Date and Base Time Units 21
3.1.2 Uncontrollable Parameters 21
3.1.2.1 Type of Hospital 22
3.1.2.2 Hospital Patient Make Up 23

3.1.2.3 Length of Stay (LOS) ... 24
3.1.2.4 Weekly Arrival Rate ... 28
3.1.2.5 ED Patient Arrival Distribution ... 29
3.1.3 Controllable Parameters (CP) ... 35
3.1.3.1 Number of Beds ... 35
3.1.3.2 NonED Admission Rates ... 36
3.1.3.3 Patient Discharge Hours ... 38
3.1.3.4 Bed Turnover Time ... 38
3.1.3.5 Patient Priority ... 39
3.2 Modified Parameters ... 40
3.2.1 Patient Discharge Times ... 40
3.2.2 Allowable days of arrival for NonED patients ... 41
3.2.3 Patient length of stay ... 42
3.3 ARENA Model ... 42
3.3.1 Patient Arrival ... 43
3.3.2 Waiting for Bed Queue ... 44
3.3.3 Patient Receives Care in Bed ... 47
3.3.4 Patient Discharge ... 47

4. RESULTS ... 49

4.1 Baseline Parameters ... 49
4.2 Peaks and Valleys ... 52
4.3 Patient Discharge Times ... 52
4.3.1 75 bed community hospital ... 53
4.3.2 150 bed community hospital ... 54
4.3.3 150 bed referral hospital ... 56
4.3.4 300 bed referral hospital ... 57
4.4 Allowable day of arrival for NonED patients ... 58
4.4.1 75 bed community hospital ... 59
4.4.2 150 bed community hospital ... 61
4.4.3 150 bed referral hospital ... 62
4.4.4 300 bed referral hospital ... 64
4.5 Patient length of stay ... 65

4.5.1 75 bed community hospital 65
4.5.2 150 bed community hospital 67
4.5.3 150 bed referral hospital 68
4.5.4 300 bed referral hospital 70

5. DISCUSSION 72

5.1 Summary of Results 72
5.2 Transparency and Validation 74
5.2.1 Face Validity 74
5.2.2 Verification 75
5.2.3 Cross Validation 76
5.2.4 External Validation 77
5.3 Limitations 78
5.3.1 Input parameters 78
5.3.2 ARENA Limitations 80
5.3.3 System Limitations 81

6. CONCLUSION 83

APPENDIX: FULL ARENA MODEL 84

BIBLIOGRAPHY 85

LIST OF TABLES

Table Page

1. Mass hospital percentage of admission in 2010 23

2. Baseline percent admission for community and referral hospitals 24

3. Arrival rate chart based on hospital size 29

4. Two hours with percentages of events occurring with a Poisson distribution compared to actual events during a 1 year simulation run 34

5. Baystate Medical Center bed cleaning time statistics 39

6. ED and NonED waiting times comparing hospital types using baseline values 51

7. ED and NonED wait times comparing discharge times for a 75 bed community hospital 54

8. ED and NonED wait times comparing discharge times for a 150 bed community hospital 55

9. ED and NonED patient wait time comparing discharge times for a 150 bed referral hospital 57

10. ED and NonED patient wait time comparing discharge times for a 300 bed referral hospital 58

11. ED and NonED wait time comparing NonED arrival schedule for a 75 bed community hospital 60

12. ED and NonED patient wait time comparing NonED arrival schedule for a 150 bed referral hospital 63

13. ED and NonED patient wait time comparing NonED arrival schedule for a 300 bed referral hospital 65

14. ED and NonED patient wait time comparing LOS for a 75 bed community hospital 66

15. ED and NonED patient wait time comparing LOS for a 150 bed community hospital 68

16. ED and NonED patient wait time comparing LOS for a 150 bed referral hospital 69

17. ED and NonED patient wait time comparing LOS for a 300 bed referral hospital 71

LIST OF FIGURES

Figure Page

1. Simplified admission discharge process 4

2. Simplified admission discharge process at full capacity..... 5

3. Run setup box in ARENA showing the replication parameters..... 16

4. Bed utilization of a 150 bed community hospital with 10 replications..... 18

5. Queue length of a 150 bed community hospital with 10 replications..... 19

6. Length of stay distribution of NonED patients not needing surgery..... 25

7. LOS lognormal distribution compared to ARENA LOS exported data 26

8. Equations of lognormal location and scale parameters..... 27

9. ARENA LOS exported values best fitted to a lognormal distribution..... 28

10. Average patient arrival for ED patients each day of the week at Baystate Medical Center ..30

11. ED admission comparing actual distribution to a Poisson distribution on Mondays at Baystate Medical Springfield Massachusetts..... 31

12. Average ED admission by percent of the daily arrival rate per hour..... 32

13. Comparison of the number of ED patients being admitted in a 1 year simulation run compared to the theoretical value 33

14. The arrival rate of NonED patients comparing the theoretical and simulation values 37

15. Basic flow of patients in the model..... 42

16. Arrival process of ED and NonED patients in ARENA 44

17. Waiting for bed process in ARENA model 45

18. Dummy variables created to search and remove patients with completed LOS..... 46

19. Patients receiving a bed in the ARENA model..... 47

20. Discharge process in ARENA simulation ... 48

21. ED patient wait time comparing hospital types with baseline values ... 50

22. NonED patient wait time comparing hospital types with baseline values ... 50

23. ED wait time by day and hour of bed request comparing hospital types using baseline values ... 51

24. NonED wait time by day and hour of bed request comparing hospital types using baseline values ... 51

25. 150 bed community hospital queue length for baseline values from time 0 to 10000 hours ... 52

26. ED patient wait times comparing discharge times for a 75 bed community hospital ... 53

27. NonED patient wait times comparing discharge times for a 75 bed community hospital ... 53

28. ED patient wait time comparing discharge times for a 150 bed community hospital ... 54

29. NonED patient wait time comparing discharge times for a 150 bed community hospital ... 55

30. ED patient wait time comparing discharge times for a 150 bed referral hospital ... 56

31. NonED patient wait time comparing discharge times for a 150 bed referral hospital ... 56

32. ED patient wait time comparing discharge times for a 300 bed referral hospital ... 57

33. NonED patient wait time comparing discharge times for a 300 bed referral hospital ... 58

34. ED wait time comparing NonED arrival schedule for a 75 bed community hospital ... 59

35. NonED wait time comparing NonED arrival schedule for a 75 bed community hospital ... 60

36. ED patient wait time comparing NonED arrival schedule for a 150 bed community hospital ... 61

37. NonED patient wait time comparing NonED arrival schedule for a 150 bed community hospital ... 61

38. ED and NonED patient wait time comparing NonED arrival schedule for a 150 bed community hospital ... 62

39. ED patient wait time comparing NonED arrival schedules for a 150 bed referral hospital 62

40. NonED patient wait time comparing NonED arrival schedule for a 150 bed referral hospital 63

41. ED patient wait time comparing NonED arrival schedule for a 300 bed referral hospital 64

42. NonED patient wait time comparing NonED arrival schedule for a 300 bed referral hospital 64

43. ED patient wait time comparing LOS for a 75 bed community hospital 65

44. NonED patient wait time comparing LOS for a 75 bed community hospital 66

45. ED patient wait time comparing LOS for a 150 bed community hospital 67

46. NonED patient wait time comparing LOS for a 150 bed community hospital 67

47. ED patient wait time comparing LOS for a 150 bed referral hospital 68

48. NonED patient wait time comparing LOS for a 150 bed referral hospital 69

49. ED patient wait time comparing LOS for a 300 bed referral hospital 70

50. NonED patient wait time comparing LOS for a 300 bed referral hospital 70

CHAPTER 1

INTRODUCTION

1.1 Motivation

This study was motivated by the knowledge of hospitals being overcrowded more than ever. A decrease in the total number of US hospital beds (hospital closures), nursing shortage, poor economic status of hospital businesses, and an aging US population has all contributed to the crowding occurring in hospitals today. Many hospitals have more patients than they can handle. A congested hospital experiences delays in elective and emergency admissions which gave the foundation to the problem in this study.

1.2 Background

There is not a single answer to the problems that the health care industry faces today. Although technology and medical advances are being made at incredible rates, the process of delivering care is still inefficient where wait delays and cancelations occur regularly. Hospitals have responded by adding resources such as more beds, larger facilities, and increased staff to mitigate the delays but have found this alone is not the answer. But rather, the answer is believed to lie within understanding patient flow as a system and improving ways patients are able to receive timely care (Haraden and Resar, 2004).

The health care industry takes 15% of the United States' gross domestic product as of 2006 while 45% of the cost is funded publically (Gupta and Denton 2008). Not only do delays have a financial burden on the provider as patients have waiting time thresholds, cause longer turnover time, and increase the number of ambulance diversions, wait times impose an even greater risk of jeopardizing the quality of patient care. Patient waiting causes unnecessary suffering, adverse medical outcomes, further complications of handling delayed patients, added costs and reduced efficiencies. Improving the health care process by finding bottlenecks and system failures will involve understanding the system as a whole as patients flow through the system. Understanding the interactions between patients, clinicians, support services, and resources will help show how different departments within the hospital interact (Hall *et al.* 2006). We believe that one method of improving and understanding the causes of waiting time is through building a discrete event simulation model that simulates the admission and discharge process of patient flow of both ED and elective admissions (NonED).

By studying the admission process, the overcrowding that exists in emergency departments all over the United States can also be better understood. Overcrowding is considered to be a serious public health problem in 91% of surveyed hospital directors and is forecasted to maintain or get worse due to increased closures of EDs, increased ED volumes, growing number of uninsured, and decreased reimbursement of uncompensated care (Olshaker and Rthlev 2006). Overcrowding in the ED creates delays, cause patients to leave without seeing a physician, decrease patient satisfaction, increase patient pain and suffering, and negatively affects the quality of care provided (Han *et al.* 2007). The inability to transfer emergency patients to inpatient beds is considered to be the most important factor causing overcrowding in the emergency department (Olshaker and Rathlev 2006). Studying the admission and discharge process of patients will also help benefit overcrowding issues within the emergency department.

1.3 Discrete Event Simulation

As the admission process is a multi-factorial problem involving many different input variables and processes such as ED and NonED admission rates, discharge hours, waiting for bed queue and LOS distributions, a discrete event simulation (DES) software was used. The use of discrete event simulation provides a flexible means to model, analyze, and understand dynamic systems. Computer simulations is considered to be a promising tool which provides a method to study and improve processes without affecting patient care or needing significant monetary investments (Khare *et al.* 2009).

Discrete event simulation software is also considered as a research technique able to ask what if questions and test different process scenarios while assessing the efficiency of the health care process (June *et al.* 1999). DES models also provides greater flexibility by being able to use custom parameters and variables compared to the more traditional queuing analytic theory approach. Also, due to the complex nature of the health care industry, DES models have gained popularity to be used to effectively improve the process of health care systems (Duguay and Chetouane 2007). The chosen discrete event simulation software is ARENA version 13.5 created by Rockwell Automation Inc.

1.4 Problem of Description

The hospital admission and discharge process system is complex involving many components and is simplified within this study to better understand the major variables affecting the process. The simplified model will have two types of patients, patients admitted into the hospital through the emergency department (ED) and elective (NonEd) patients. ED patients are those who are admitted to the hospital through the emergency department who are in need of additional emergent/urgent care within the hospital. ED patients are admitted at random and can be admitted any time of the day and has a stochastic element. NonED patients are those who are admitted mostly by appointment with a majority of patients admitted during the day on weekdays and are scheduled ahead of time.

Each patient will enter a bed request queue upon arrival and will wait for an open bed. If a clean bed is available, the first person in the queue will be given a bed, spend time through receiving care, and be discharged once the care is completed. As a patient is discharged, the bed will be cleaned and prepped for the next patient. This simplified process can be seen in Fig X. below.

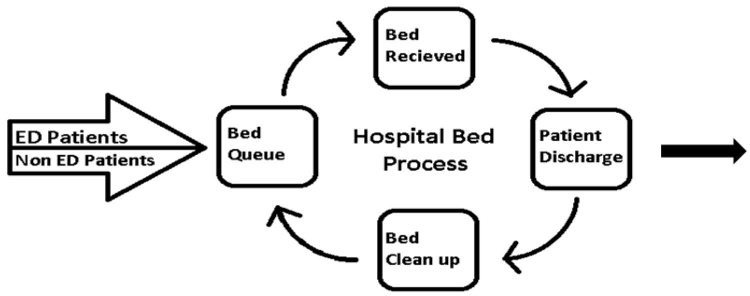


Figure 1 Simplified admission discharge process

In reality, the admission and discharge process is more complex with different types of beds, many types of patients (intensive care, intermediate care, monitored or unmonitored, surgery) being moved around, with beds even set aside for only specific types of patients (i.e. male, female, children, adult). Even this scenario is a simplified version of reality. However, we are creating a model with the belief that a simplified version will help better understand the real system and provide invaluable information about the process.

Once beds are all occupied, the hospital is at full capacity which create delays in bed availability, and cancelations accrue to create a system that causes hospitals to inefficiently serve their patients. Patients waiting to be admitted through the ED are known as boarding, where patients wait in the ED to be admitted into the hospital. Boarding also increases the chance of overcrowding in the ED as the bed that is used by the patient waiting to be admitted is not able to be used for patients needing emergency care. Elective patients who are scheduled for an appointment or surgery who need to be admitted to the hospital can also be delayed due to full capacity which can also cause cancelations. The figure below displays the simplified admission discharge process at full capacity.

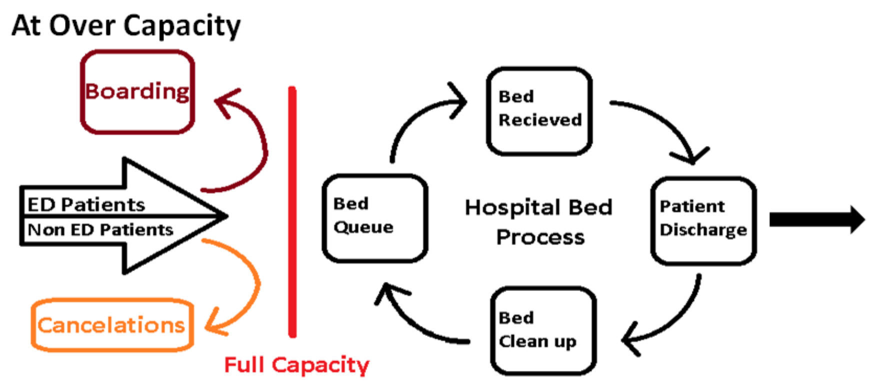


Figure 2 Simplified admission discharge process at full capacity

CHAPTER 2

LITERATURE REVIEW

A literature review was conducted on the hospital admission system and the use of simulation as a means to understand and decrease waiting time. There is a need to understand the literature within this field as an introduction to the topic but also provide a foundation to this study. A number of databases: PubMED Central (PMC), Pub Med, Web of Science, Academic Search Premier, Engineering Village were searched through the Umass Amherst Library website. Articles focusing on those that predated the past 20 years were not included due to the major changes in the medical practice with the turn of the 21st century. The review was broken into a number of categories; admission scheduling, elective admission, emergency department, and computer simulation in health care processes.

2.1 Admission Scheduling

Helm *et al.* (2011) simulated a partner hospital through a custom designed c++ program. The group studied the effects of zone based admission control using one year of historical data of arrival rates, length of stay distributions, and transfer probabilities. In the study, expedited patients were identified within the ED as a third class of patients. Patients who are being admitted through the ED that are able to delay their admission 1-3 days but unable to wait and be admitted as an elective patient due to excessive waiting times are the types of patients which fit the expedited patient category. This study provides a call-in mechanism to serve this third class of patients which allow the reduction of excess load that is placed on the ED during peak congestion periods. Helm *et al.* (2011) also suggest in their study a Markov decision process model which focuses on using the expedited patient category and elective admission cancelations to create a balance between bed utilization and hospital congestion to provide an optimal admission policy.

Helm *et al.* (2009) also studied patient flow and admission control and found that hospitals are able to improve hospital occupancy and alleviate congestion by reducing variability through a more flexible system. It was found that many hospitals make decisions independently without considering the downstream effects on workload strain and costs of hospital resources. High variability of elective surgeries due to independent scheduling of each surgeon creates blockages for ED inpatients beds, increases ED waiting times and lowers the quality of health care. Using a patient flow simulation framework of a 160 bed hospital with three main units; surgery, medicine, and ICU beds, they showed that level loaded scheduling with call-in and cancellation thresholds compared to a hospital with the typical front loaded scheduling without daily control thresholds provided a dramatic reduction in the number of cancelations and reduction in variability by 27%. Such improvements could provide healthcare facilities with a means to efficiently staff hospitals to match workload and patient demand with overall improvement in quality of care and cost savings from reduction of understaffing and overstaffing.

Haraden and Resar (2004) discusses the importance of patient flow in hospitals as a major area to study for understanding and improving patient wait and cancelations. Hospitals have responded by adding more resources through more beds, larger facilities, and increased staff numbers but have seen that just increasing resources does not solve the common occurrences of waiting. Interventions that smooth the flow of elective surgery, reducing waits for inpatient admission through the ED is critical in that understanding variation is the first step in providing timely flow of patients.

Lowery (1996) explains that when creating a hospital admission scheduling system through simulation, the simulation model should be able to be easily applied to multiple hospitals, be valid, representing an actual system, and be able to show improvements in variability. Some of the input variables that are highlighted include number of beds, average standard deviation of LOS, arrival rates of emergency patients by day of week, and distribution of elective admits. Using a graphical approach is the most common method of validating a model and explained how understanding the admission process would prove to be invaluable to explaining how the system behaves.

White *et al.* (2011) conducted a study on the interactions between patient appointment policies and capacity allocation policies and their effects on performance measures in an outpatient healthcare clinic. They found that scheduling lower-variance, shorter appointments earlier would maintain physician utilization and clinic duration but lower overall patient waiting. From the study they also saw that the number of exam rooms displayed a bottleneck behavior where there would be no effect on physician utilization beyond a certain point and cause critical problems when too low.

Boston Medical Center in 2004 showed that elective surgery scheduling had a big impact on hospital systems and was a larger source of bottlenecks on patient throughput than emergencies. By also incorporating non-block scheduling of a pavilion at Boston Medical Center, dramatic results were seen with 334 elective surgeries that were canceled or delayed before the change dropped down to 3 delays/cancelations. Actively addressing patient flow problems through studying the issues and developing methods to modify the process is seen as a critical step in creating a more efficient health care delivery system.

The Chartis Group (2007) introduced the potential benefits of optimizing patient throughput not only on improved operating performance but also on the return on assets and use of capital. The group noted that some hospitals have had 5-12% increase in available capacity by just improving admission throughput which also improves the number of discharges per available bed, increasing overall net revenue. In order for a hospital to optimize patient throughput, there has to be an organizational commitment where each part of the process must be aligned as a coherent system.

Kloehn (2004) in an executive summary tries to address how problems with patient throughput causes a wide array of unsolved issues in overcapacity, diversions, excessive wait times, bed placement control, and discharge process. A facility over 85% occupied is considered to have a high chance of throughput issues and delays in the ED. Throughput is also to have an impact in how patients are admitted and cause unnecessary delays and excessive wait times.

2.2 Elective Admission

Bowers and Mould (2002) conducted a study on reducing waiting time through "deferrable elective patients" to maximize utilization and still ensuring quality of care for orthopaedic patients in the UK. "Deferrable elective patients" are elective patients given the opportunity to receive earlier care with the possibility of postponement based on the event that the demand of care needed for that day is high. Using this policy would allow for patients to be seen earlier having an impact on waiting time but with the cost of 19% probability of treatment being deferred.

Gupta and Denton (2008) summarized key issues in the health care field using different kinds of models to help represent a scheduling system. There was concern that existing manufacturing, transportation and logistics models are not able to easily fit into the health care field due to the nature of the health care industry. There are many issues that must be addressed such as patient and provider preferences, stochastic and dynamic nature of multi-priority demand, technology changes, and soft capacities to name just a few. The paper also describes the challenges and future opportunities to implement novel industrial engineering and operation research techniques to hospital appointment scheduling systems.

May *et al.* (2011) reviews the problem of surgical scheduling by surveying past work and suggesting potential future research on capacity planning, process reengineering, surgical services portfolio, procedure duration estimation, schedule construction, and schedule execution, monitoring and control. Surgical scheduling was considered to deviate significantly from even a detailed plan through the course of a surgical day due to the stochastic elements of arrivals, cancelations, and duration of the surgical procedures. However, the study concluded with the idea that a better guide will allow operational management to use their resources more effectively and efficiently with the economic and project management aspect of surgical scheduling having the greatest potential for relevant research.

Min and Yih (2009) studied patient priority within the elective surgery scheduling problem. Using a stochastic dynamic programming model, patients with the highest priorities were selected to be scheduled for surgery when capacity became available. The study showed that using patient priority had significant impacts on surgery schedules.

Bekker and Koeleman (2011) assessed a study on scheduling elective admissions that minimized the target and offered load of patients in order to maintain more consistent bed occupancy levels. Target load levels were determined based on the capacity in relation to the variability in offered load as well as incorporating weekly patterns of bed availability. Smoother admission best stabilizes bed occupancy levels. The more even distribution of elective admissions throughout the week provided the most stable time performances by decreasing variability in bed demand and the probability of refusals. The article also found that patients with longer LOS scheduled on Fridays provided a more optimal schedule while higher admissions on Mondays with shorter LOS also were found to be advantageous. The model in this study however does not capture the discharge process.

Gallivan *et al.* (2002) conducted a study looking at inpatient admissions of a cardiac surgery department and hospital capacity using a mathematical model. The LOS although averaged less than 48 hours, had considerable overall variability with a lengthy tail which was found to have considerable impact on capacity requirements. A reserve capacity was required in order to avoid high rates of cancellations. Caution was advised when considering booked admission systems when there is a high degree of variability in length of stay due to the result of possible frequent operational difficulties for hospitals with limited reserve capacity.

2.3 Emergency Department

Forster *et al.* (2003) studied the effects of hospital occupancy on emergency department length of stays and patient disposition. They conducted an observational study of a 500 bed acute care teaching hospital which showed that increased hospital occupancy seemed to be a major indicator of increased ED LOS for admitted patients. A threshold of 90% bed occupancy appeared to indicate extensive increase in ED length of stay which is believed to be a an important determinant of ED overcrowding. Also, although there is little data verifying the claim, they suggested increasing hospital bed availability might contribute to less ED overcrowding especially when at the 90% bed occupancy threshold.

Han *et al.* (2007) assessed a study on the effects of expanding the emergency department and its effects on overcrowding. An increase in ED bed capacity had little effects on ambulance diversion, and increased the length of stay for admitted patients due to other bottlenecks within the hospital network.

Olshaker and Rathlev (2006) explored how emergency department overcrowding and ambulance diversion impacts boarding times of patients waiting to be admitted into the hospital. The inability to admit ED patients have been highlighted by the Joint Commission on Accreditation of Healthcare Organizations (JCAHO), the General Accounting Office, and others as the leading factor contributing to ED overcrowding. Olshaker and Rathlev (2006) also covers the causes of overcrowding through the development and changes within the health care industry as there is an increase in ED visits due to a number of ED closures, a greater percentage of patients not having health insurance, and a number of laws and programs effecting increased volumes.

Asplin *et al.* (2003), provide a conceptual model of the emergency department, described as an acute care system, a delivery system providing unscheduled care. We are most interested in the output component and the discussion of boarding, the inability to move admitted ED patients to an inpatient bed which is the most frequent reason for ED crowding and a reason for the ED's inability to take on new patients. Some factors found to cause inpatient boarding in the ED is the lack of "physical inpatient beds, inadequate or inflexible staffing, isolation precautions, delays in cleaning room after patient discharge, over reliance on ICU or telemetry beds, inefficient diagnostic and ancillary services on inpatient units, and delays in discharge of hospitalized patients to post-acute care facilities."

Derlet *et al.* (2000) published a paper on the complexity of emergency departments and its interwoven issues as reasons for overcrowding and its effects on "patient risk, prolonged pain and suffering of patients, long patient waits, patient dissatisfaction, ambulance diversions, decreased physician productivity, increased frustration among medical staff, and violence." One reason for overcrowding in the study was due to the lack of beds for patients being admitted to the hospital, where patients in the ED must wait, known as boarding until a bed is freed which seem to be common in all ED's. The paper goes on to discuss other issues as well as a more detailed explanation of the effects of overcrowding and overall decrease in quality of healthcare.

Khare *et al.* (2008) studied the influence of emergency department crowding by comparing the effects of adding more ED beds to reducing admitted patient boarding times. The study showed that by improving the rate at which admitted patients left the ED decreased the overall ED length of stay, while increasing the number of beds did not. Admitted patient departure from the ED proves to be a major factor and a possible bottleneck in ED crowding and is of important value to study.

Liu *et al.* (2012) conducted a study through survey on the effects of reducing crowding in the emergency department through crowding initiatives like vertical patient flow, a method of evaluating and managing patients without using an ED room. Further study was suggested in examining the effects of such crowding initiatives in patient outcomes (safety, LOS, satisfaction) as there is yet a widespread support system in place to create enough momentum to see improvements in ED crowding.

2.4 Computer simulation in health care processes

The use of simulation is growing and is seen as a powerful tool within the health care industry being able to model a wide range of topic areas and answer a variety of research questions as explained in the systematic review regarding computer simulation in health care done by Fone *et al.* (2003). The review also discusses how computer modeling should provide valuable evidence in how to deal with stochastic elements within the industry. However, it is still yet to be seen the effects and true value of modeling such processes due to the lack of model implementation on real systems.

Duguay and Chetouane (2007) modeled the emergency department using discrete event simulation and found DES to be an effective tool due to the complexity of healthcare systems. They suggested the combination of total quality management and continuous quality improvement techniques to specially be useful in combination with DES. The group studied a regional hospital to improve the current process through data collection and the use of control variables (physicians, nurses, and examination rooms). Analysis of waiting times and best staffing scenarios was conducted by adding and reducing staff and exam rooms within budget limitations.

Kumar and Mo (2010) provide three different methods of bed prediction models, one of which was simulated through ARENA 10.0 to model bed occupancy levels for 3 different wards for three different types of patients. Data was collected from a hospital for values on the daily number of admissions, average length of stay over one year, and average number of beds for each patient type. The simulation showed to be a useful tool in predicting bed occupancy levels for coming weeks and actual values fell within the 95% confidence interval of the model.

Jacobson *et al.* (2006) reviewed journal articles using discrete event simulation on health care systems and showed the benefits of using optimization and simulation tools to give decision makers optimal system configurations. Using discrete-event simulation to analyze health care systems have become more accepted by healthcare decision makers. A benefit of using discrete-event simulation is the ability to incorporate multiple performance measures associated with health care systems to help understand the relationships that exist between various inputs.

Jun *et al.* (1999) also reviewed the literature involving discrete event simulation and found that distributing patient demand improved patient flow by decreasing waiting times in outpatient clinics. The survey also shows that there has been many studies on patient flow that use discrete event simulation but found a void in integrated multi-facility systems.

Sargent (2011) discusses verifying and validating simulation models through different approaches, graphical paradigms, and various techniques. The author mentions that there is yet to be a set of specific tests that easily applies to the validity of a model giving every new simulation project unique challenges.

Eddy *et al.* (2012) conclude the importance of creating a model that is transparent, showing how the model is built and valid in reproducing reality to become successful within the health care industry. Face, internal, cross, external, and predictive validity are all a means to validate a model with the latter two being the strongest forms. Validation of a model is also suggested with 4 criteria in mind: rigor of the process, quantity and quality of sources used, model's ability to simulate sources with detail, and how closely results match observed outcomes.

There are also many studies of simulation that have been applied to the emergency department such as studies done by Miller *et al.* (2003), Samaha *et al*. (2003), and Blasak *et al.* (2003).

CHAPTER 3

METHODOLOGY

3.1 Baseline parameters

The baseline parameters can be defined as the input parameters of the simulation model known to be standard within this study. The set of baseline parameters also acts as a guideline for future studies and researchers by providing the standard needed for reproducing the model. Many instances within the study compare a single parameter change to the baseline values.

3.1.1 Replication Parameters

Replication parameters are the values that provide information on the replication within the simulation software, found under Run Setup. Replication values include the number of replications, replication length, warm up period, replication start day, as well as time units. The replication parameters remained the same for every simulation in this study, and were not altered.

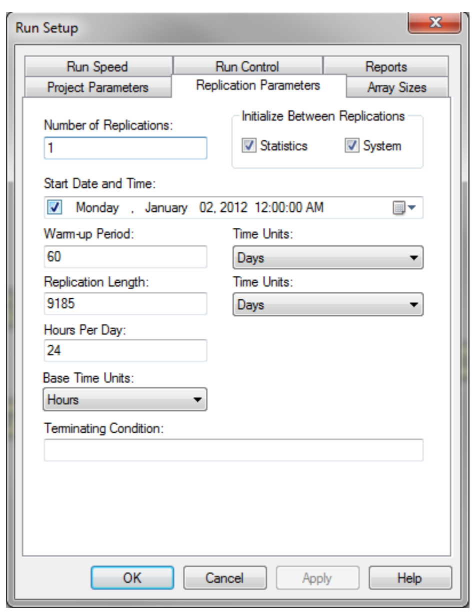


Figure 3 Run setup box in ARENA showing the replication parameters

3.1.1.1 Number of Replications

The simulation model within this study initially exists in an empty and idle state, where there are no patients and no beds utilized in the hospital. As the simulation begins to run, patients enter the hospital and start filling beds without waiting in a queue due to the capacity of beds being underutilized. In a real life setting, a hospital is never empty, and therefore, a steady state simulation was necessary for this study. Understanding the capacities at any given time should not be affected by the initial idle state of the model. A steady state simulation model will help to understand the hospital's long-run performance measures and give insight into the waiting times of patients.

In a steady state simulation, you can estimate a long run performance measure with a specified confidence interval by increasing the number of replications, or by increasing the run length of the simulation (Banks et al. 2005). The simpler method would be to make independent and identically distributed replications with a warm up period allowing to gather and analyze data of a process in a steady state. However, because a part of the analysis involved in this study required manual manipulation of exported data, having multiple replications made it difficult to capture the data from each replication. Due to this reason, the second method of creating a steady state simulation using a single replication with a long run length was found to be more advantageous. In every simulation run in this study, there is always 1 replication.

3.1.1.2 Warm Up Period

One method to help a simulation reach a steady state is with the use of a warm up period until the initial conditions bias on the data have subsided. After the point the warm up period is set for, the data would be reset and statistical information would be gathered from that point on. In our model, this would represent the point where we believed that the hospital could reflect the utilization on any given day. Kelton et al. 2007 explained in their simulation textbook that determining how long a warm up period is difficult and advised to make key output plots and eyeball where they stabilized.

The two different output plots used in order to determine the warm up period are bed utilization and the waiting for a bed queue. For these sets of plots, the same model was used with a shortened simulation length in order to plot multiple replications. Only the initial period of the simulation is important until there is a period in which the simulation enters into a state of steady state. The following two graphs show plots from 10 different simulation replications displayed by the ARENA output analyzer over a period of 2000 hours or 83.33 days.

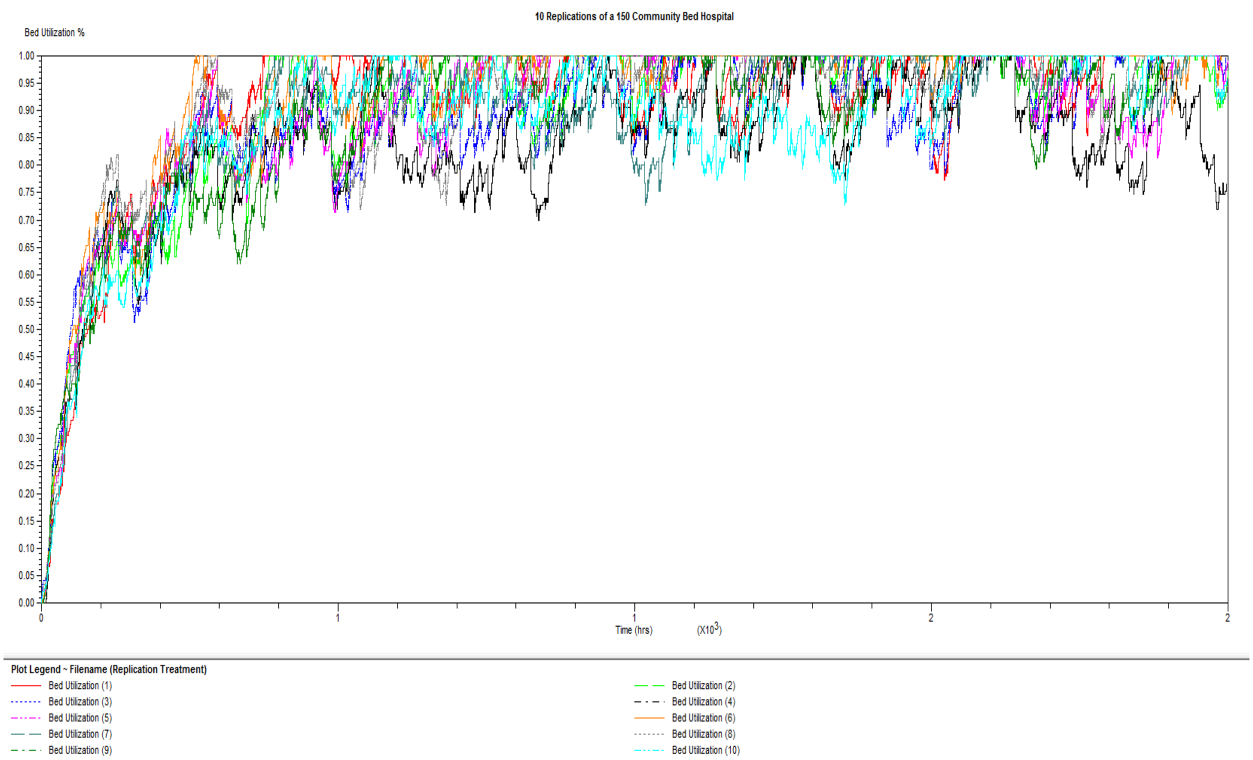


Figure 4 Bed utilization of a 150 bed community hospital with 10 replications

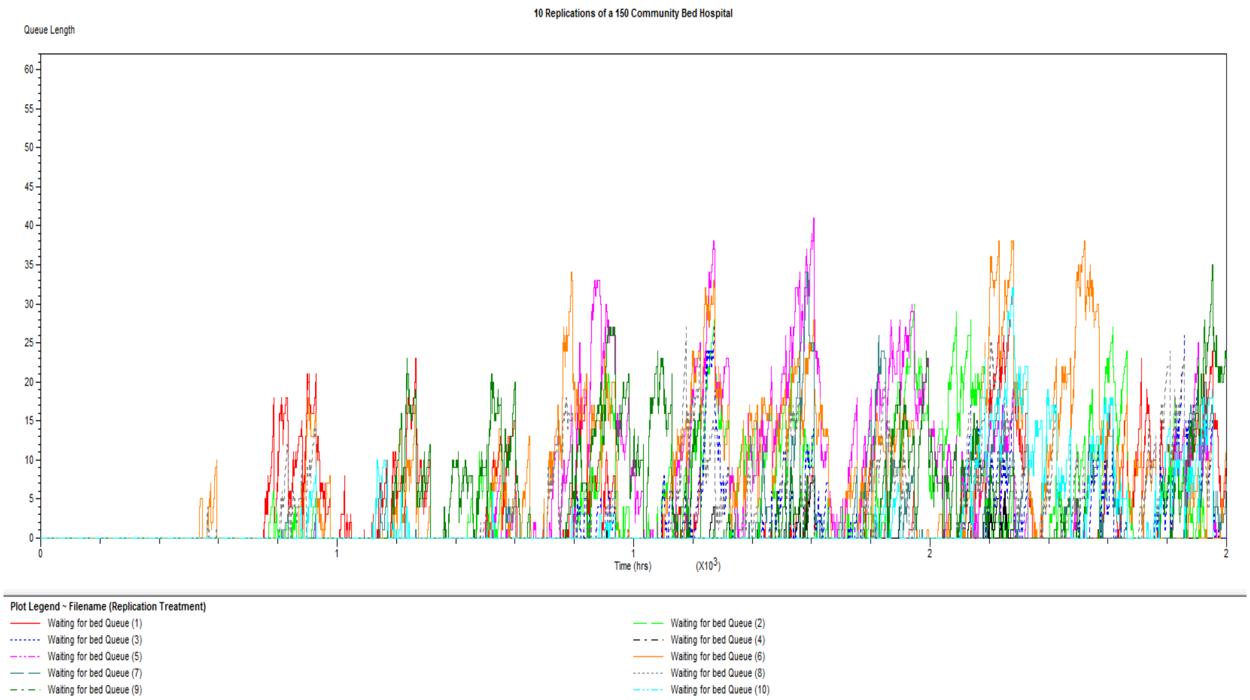


Figure 5 Queue length of a 150 bed community hospital with 10 replications

From the two graphs, first of bed utilization and the second of the queue length of patients waiting for a bed, we are able to estimate a warm up period that is believed to be satisfactory. In the graph of bed utilization, we can see that the percentage of beds being utilized reaches 100% quite rapidly and in all replications within 500 hours or 20.83 days. The queue length of the 10 different replications has many peaks which is believed to be random and reaches a steady state by half way point in the graph, 1000 hours or 41.67 days. To be conservative, our warm up period was extended to 60 days in all the simulation runs within this study to create a system where the hospital is in a steady state.

3.1.1.3 Replication Length

A single replication simulation run requires a longer replication length in order to find a performance measure with a desirable confidence interval. Under a single replication, the data becomes dependant when computing the standard error of a mean. To solve this problem, batch means could be used by splitting the single replication into a number of batches, with means considered to be independent of each other (Banks *et al*. 2005). The batch means are in essence a method to provide measures that are comparable to the means of a simulation with multiple replications. ARENA automatically batches single replications in sizes which attempt to make the data uncorrelated. ARENA attempts to compute a 95% confidence interval through batch means automatically and creates half widths for the output statistics. ARENA does not use data from the warm up period when calculating batch means and will not report a half width if the internal checks done through the program signal that the batch means collected were correlated (Kelton *et al.* 2007).

The method that ARENA uses to batch data is by forming 20 batches when enough data is collected. A time persistent statistic will form a batch with the average over 0.25 base time units. As the simulation is continuingly collecting data, once 20 batches are made, ARENA continues to count batches with the same batch sizes until 40 batches exist. At this point, the 40 batches are reformed by combining the means of batch 1 and 2, 3 and 4, and so on until 20 batches exist. The 20 batches have twice as many points compared to the original 20 batches, and the simulation program continues to create the 21st batch with the new batch size. Once 40 batches are made, they are again formed into 20 newer batches with again double the points of data. This method is used based on the reason that it is not more advantageous to continue to collect data and increase the number of batches which are more likely to produce correlated batch means if the batches are originally too small. (Kelton *et al. I2007)*

Original models that were used in the early stages of this study used 5 replications with a 5 year replication length. As we transitioned into a 1 replication model, we converted all the replications to a single simulation run of 25 years. A 25 year simulation length allowed the data collected to have batches that were believed to be unbiased, independent and identically distributed due to the conservative lengthening of the simulation. ARENA also producing values of half widths with a 95% confidence interval for each of the statistical outputs also confirmed the chosen replication length was sufficient.

The replication length in each of the simulations conducted in this study was set to 9185 days, which is 25 years plus 60 days of warm up. This allows the replication length to fully incorporate 25 years of data.

3.1.1.4 Replication Start Date and Base Time Units

In order to have a standard between replications there was a need to pick a replication start date since the arrival rates of patients depended on the day of the week. January 2, 2012 was chosen as the start date, but more importantly, the simulation starting day of the week was Monday. The base time unit in this study that fit with all the different arrival rates and discharge times is hours.

3.1.2 Uncontrollable Parameters

Uncontrollable parameters were the values in the model that were believed to be fixed and uncontrollable in the hospitals current state. Within a given situation, the UP, uncontrollable parameters would in most cases be set based on a number circumstances including the area a hospital is located, the types of patients served, type of facilities available, and access to certain technologies. Some of the uncontrollable parameters were the type of hospital (community versus referral), percentage of ED and NonED patients, patient length of stay, and the arrival rate of ED patients.

Every simulation was categorized using a shorthanded description of the model using brackets and periods to separate categories within the parameters. For uncontrollable parameters the categories were listed in order based on the type of hospital, then the percentage of ED and NonED patients, length of stay, and the ED admission arrival rate.

The following is an example of this short hand representation describing a hospital as a community hospital, with 70% ED and 30% NonED patients, a length of stay with a lognormal distribution with the mean being 111.36 hours with a standard deviation of 167.04 hours, while using the Baystate distribution of ED patients.

UP[Comm.70ED.30NED.LOGN(111.36,167.04)BLOS.B-SdistribEDarrival]

3.1.2.1 Type of Hospital

Creating two types of hospitals, a tertiary referral hospital and a local community hospital would allow this study to be applicable to a larger population of hospitals in the country. In our study, a tertiary referral hospital was categorized as a hospital able to accommodate referrals from lower levels of care, that can treat more complex clinical conditions through specialized personnel, and advanced technologies (Hensher *et al.* 2006). Community hospitals were considered to be smaller in size, treating a larger portion of their patients admitted through the emergency department. It would be nearly impossible to fit every health care facility or system in specific categories, but there were major differences in the size and patient type distribution that was addressed. This study allows a general comparison of different size hospitals while also considering the difference in their patient makeup. Often times, a community hospital would be located in a rural area while a referral hospital is in an urban setting.

A study done by HCUP, Healthcare Cost and Utilization Project categorized the number of beds between small, medium, and large size hospitals between regions, and location. Using the values found in the HCUP's data, 150 beds was chosen to represent the size of a large community hospital and a small/medium referral hospital. In order to compare community and referral hospitals it was important the two different hospital types shared the same number of beds. A smaller community hospital with 75 beds was also considered while a 300 bed referral hospital was created as well. The representation of community hospitals having 75 and 150 beds while referral hospitals with 150 and 300 beds allowed a symmetric increase in size while also being able to consider the different type of patients that were admitted more effectively.

3.1.2.2 Hospital Patient Make Up

Once the size of the different hospitals was determined, the patient make up of each hospital was considered. In this study, there are two different types of patients admitted into the hospital, ED and NonED patients. Hospitals in Massachusetts were examined in order to create the standard patient spread for each type of hospital by categorizing hospitals to be either community or referral. Each hospital's percent of admissions from the ED was factored into the baseline values. An assumption was made that the remainder of patients that were admitted would be considered as NonED patients.

Mass Hospitals FY10						
Local Hospitals	ED volume	ED Inpt Admits	ED Obs Admit	Total Inpt Discharges	% ED Inpt Admits	Discharges/day
Baystate Franklin	29,203	2,722	925	4,292	63.4%	11.8
Baystate MaryLane	15,684	1,127	603	1,493	75.5%	4.1
Baystate Medical	112,447	19,833	7,612	37,988	52.2%	104.1
Berkshire Medical - Birkshire	56,514	8,152	2,153	10,775	75.7%	29.5
Cooley	36,735	6,416	895	9,161	70.0%	25.1
Harrington	35,707	2,954	1,555	4,056	72.8%	11.1
Holyoke	42,533	4,858	2,043	6,691	72.6%	18.3
Mercy	76,582	7,177	2,178	12,131	59.2%	33.2
Noble	27,567	2,485	2	3,475	71.5%	9.5
Total Mass	3,093,778	468,635	115,455	851,154	55.1%	2331.9
Referral Hospitals	ED volume	ED Inpt Admits	ED Obs Admit	Total Inpt Discharges	% ED Inpt Admits	Discharges/day
Beth Israel	55,046	19,431	6,807	41,595	46.7%	114.0
Boston Medical Center	127,643	18,382	6,249	30,251	60.8%	82.9
Brigham & Womens	56,437	13,427	6,361	51,754	25.9%	141.8
Childrens - Boston	47,560	NA	NA	18,147		49.7
Mass General	89,587	21,826	3,180	50,337	43.4%	137.9
Tufts	41,437	8,279	906	21,075	39.3%	57.7
U Mass Memorial 22029 Univ 2329	134,346	26,266	6,236	45,328	57.9%	124.2

Table 1 Mass hospital percentage of admission in 2010

Source: Inpatient hospital discharge database, 2011, Division Health Care Finance and Policy

Efficiency of ED utilization in Massachusetts 2012, Division Health Care Finance Policy

The average for % ED Inpatient Admits for the local community hospitals resulted in 70.1% which was rounded to 70%. 70% of patients admitted through the emergency department would result in 30% of patients admitted as NonED patients. The same process was taken for the referral hospitals which resulted in ED patients averaging 45.7% which was rounded down to 45% and of the patients admitted into a referral hospital, 55% would be NonED patients. The following table gives a breakdown of the baseline values used for the different types of hospitals used in this study. The percent spread of each type of hospital does not change throughout this study.

% Admissions for ED/Non ED		
	% from ED	% Non ED / Elective Admissions
Community Hospitals	70%	30%
Tertiary Hospitals	45%	55%

Table 2 Baseline percent admission for community and referral hospitals

3.1.2.3 Length of Stay (LOS)

The method of determining a patients length of stay was using existing data from Baystate Medical Center, finding a distribution, and applying national numbers. The point of this study is to provide a general relationship between different types of hospitals and the admission of patients on a scale that could represent a majority of existing hospitals. Due to our objectives, it was important when possible not to use data specific to any given hospital.

Ozen *et al.* 2012 collected data from Baystate Medical Center in Springfield Massachusetts on the length of stay of patients from the time they received a bed until they were discharged for a six month period. Time stamps were taken for four different types of patients, ED admits that had no surgery, ED admits who needed surgery, NonED admits needing surgery, and NonED admits non needing surgery. The LOS for each type of patient was heavily skewed right with the tail reaching times much further away from the majority of the data points. The following is a graph from their research showing the length of stays for NonED patients not needing surgery.

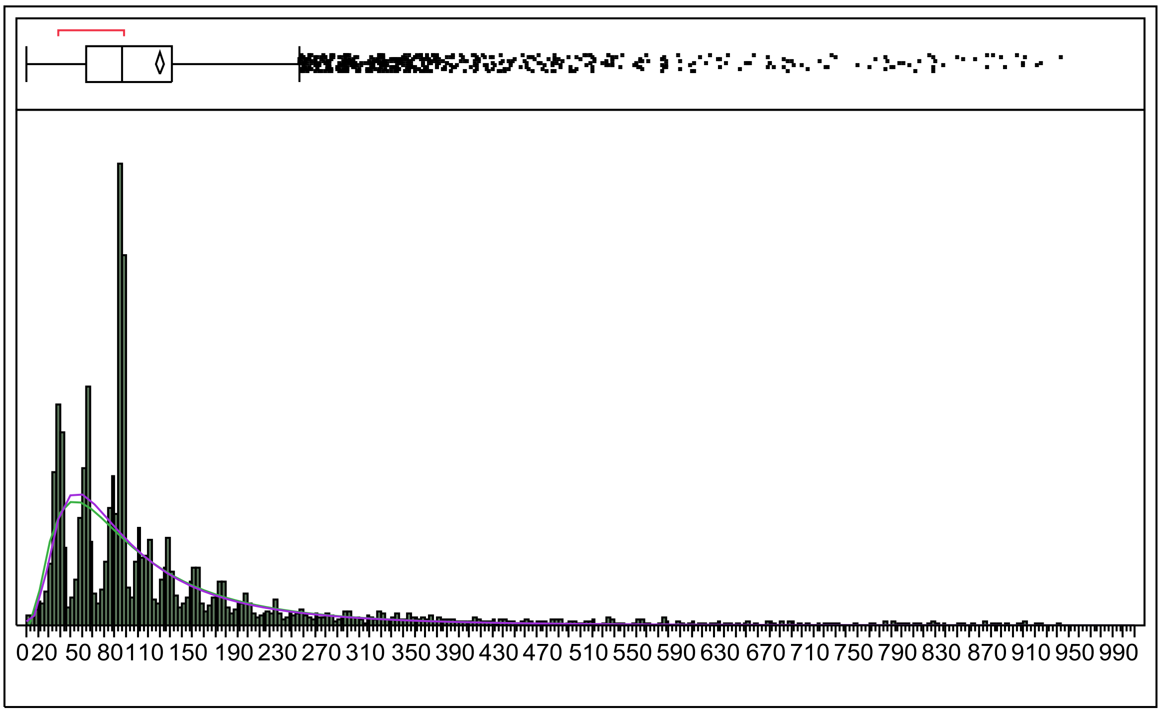


Figure 6 Length of stay distribution of NonED patients not needing surgery Asli 2012

The distributions with heavy right skews were best choices: we looked at johnson, lognormal, and Glog distributions. After analyzing the different distributions that would fit a skewed LOS, it was determined that using a lognormal distribution would best allow the input of national data on length of stay requiring only two parameters, the mean and standard deviation. Again, the use of national data allows this study to be more viable for a broader range of hospital systems.

National averages on the length of stay of patients were obtained from the 2010 HCUP Nationwide Inpatient Sample (NIS) , a database of hospital inpatient stays, the largest inpatient care database publically available in the United States.

NIS's length of stay is calculated by subtracting the date of admission from the date of discharge. Same day stays are therefore counted with a length of stay of 0. The average length of stay for inpatients from the 2010 HCUP NIS data came out to 4.64 days with a standard deviation of 6.96 days. Since the simulation's base time units is in hours, we converted the values resulting in an average LOS of 111.36 hours with a standard deviation of 167.04 hours.

The length of stay baseline value used in our simulation model was a lognormal distribution having a mean of 111.36 and a standard deviation of 167.04 hours. In order to confirm in our ARENA software, a one year simulation run exporting the LOS values was conducted using the input lognormal(111.36, 167.04) for the LOS value. The following graphs shows the output values as the bar graph compared to the lognormal distribution shown as the blue line.

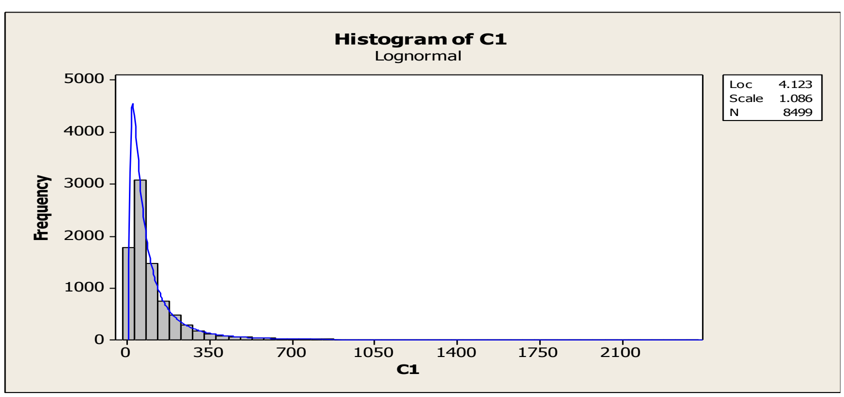


Figure 7 LOS lognormal distribution compared to ARENA LOS exported data

ARENA exported data represented as bar graph, lognormal distribution represented with blue line

The location and scale parameters of the lognormal are the mean and standard deviation of the natural logarithm where the log of the lognormal distribution would be normally distributed. The location and scale parameter can be found using the E[X] as the expected value of the distribution and the Var[X] being the variance (standard deviation^2).

$$\mu = \ln(\mathrm{E}[X]) - \frac{1}{2}\ln\left(1 + \frac{\mathrm{Var}[X]}{(\mathrm{E}[X])^2}\right),$$
$$\sigma^2 = \ln\left(1 + \frac{\mathrm{Var}[X]}{(\mathrm{E}[X])^2}\right).$$

Figure 8 Equations of lognormal location and scale parameters

Calculations finding the location and scale parameters

Mean = 111.36 SD = 167.04 Mean^2 = 12401.0496 SD^2 = Var = 27902.3616

μ = ln(111.36) - (1/2) * ln(1+ (27902.3616/12401.0496)) = 4.1234

σ^2 = ln(1+ (27902.3616/12401.0496)) = 1.1787m =

σ = $\sqrt{1.1787}$ = 1.08567

However, in ARENA we are able to input the mean and standard deviation of the lognormal directly. The one year simulation run had an average of 108.04 hours and a standard deviation of 147.468. By also best fitting the exported values of the LOS to a distribution, we obtained the following lognormal, which confirmed that the input parameters of the LOS distribution was indeed a skewed right lognormal distribution that would converge to the baseline values of 111.36 hours with a standard deviation of 167.04 hours if ran for a longer period of time. LOS in our model represented the time the patient spent in the system from the moment they entered until the time they are ready to be discharged.

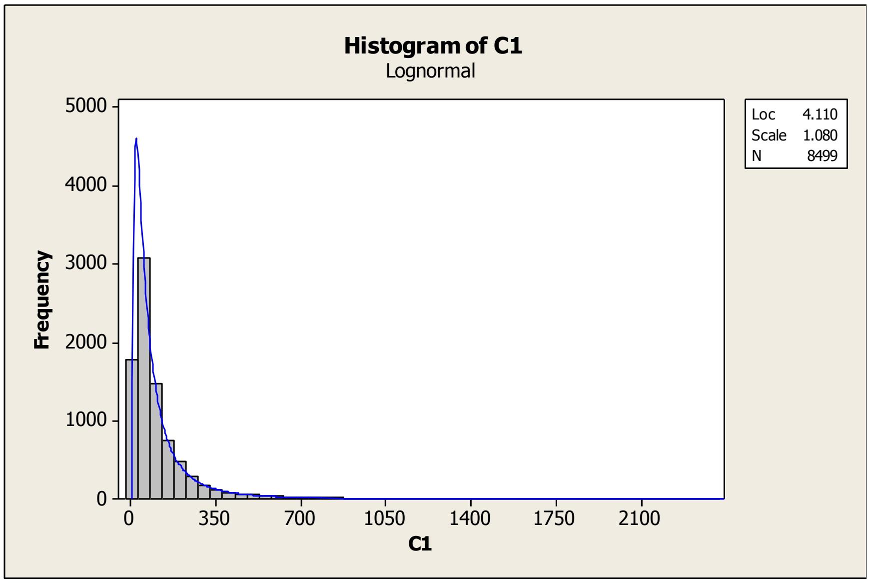


Figure 9 ARENA LOS exported values best fitted to a lognormal distribution

3.1.2.4 Weekly Arrival Rate

In order to create a crowded hospital system considering the given length of stay alongside the number of beds available, Little's Law was used to determine the weekly arrival rate of patients. Little's Law states that under steady state conditions, the number of beds in the system will equal the average rate of arrivals times the average time spent in the system.

Little's Law

L = # of Beds in the system

λ = Average number of patients arriving per unit time

W = Average time spent in the system, length of stay

$$L = \lambda W$$

Example of using Little's Law in our study

The following shows the arrival rate of a community hospital with 150 beds. λ is the average arrival rate of both ED and NonED patients into the system.

$L = 150$ Beds

$W = LOS = 4.64$ days

$L = \lambda * W$

$\lambda = L / W = 150/4.64 = 32.33$ patients per day

Due to the different arrival rate schedules, the arrival rate was converted to a weekly arrival rate by taking $\lambda * 7$.

Average arrival rate per week = $\lambda * 7 = 32.33$ patients per day $* 7 = 226.29$ patients per week

# of Beds in the Hospital	Average daily arrival rate of patients	Average weekly arrival rate of patients
75	16.16	113.15
150	32.33	226.29
300	64.66	452.59

Table 3 Arrival rate chart based on hospital size

The number of patients arriving per week whether a community or referral hospital does not change based on the type of hospital when considering a 150 bed system. Both 150 Bed hospital systems, community and referral will see an average weekly arrival of 226.29 patients.

3.1.2.5 ED Patient Arrival Distribution

The hourly distribution of ED patients were determined to be an uncontrollable parameter because hospitals cannot restrict or determine when patients are able to receive care. Emergency departments are open 24/7 and patients arrive throughout the day Monday through Sunday unscheduled and also random. Admission arrival rates into the hospital from the emergency department have been collected from Baystate Medical in Springfield, Massachusetts by hour of the day for each day of the week over a 6 month period. The daily arrival of patients being admitted from the ED followed a consistent trend shown below.

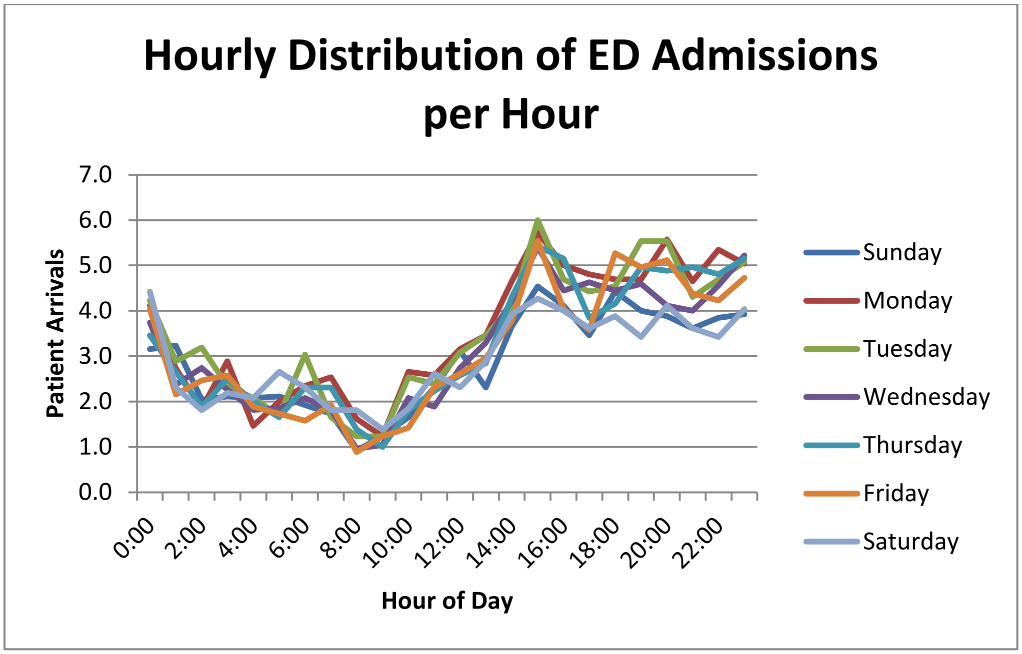


Figure 10 Average patient arrival for ED patients each day of the week at Baystate Medical Center

The arrival process of patient admission for different departments generally follows a Poisson process (Bekker and Koeleman 2011). The arrival rate for ED patients are often considered to follow a Poisson distribution. The data also would indicate that the inter-arrival rate for ED patients by hour of the day follows an exponential distribution, giving the arrival rate of hospital admissions by hour of the day from the ED a Poisson distribution. The actual percentiles of ED arrivals per hour is compared to the percentiles of a Poisson distribution using the actual mean indicate that the arrival rate of ED patients is Poisson distributed.

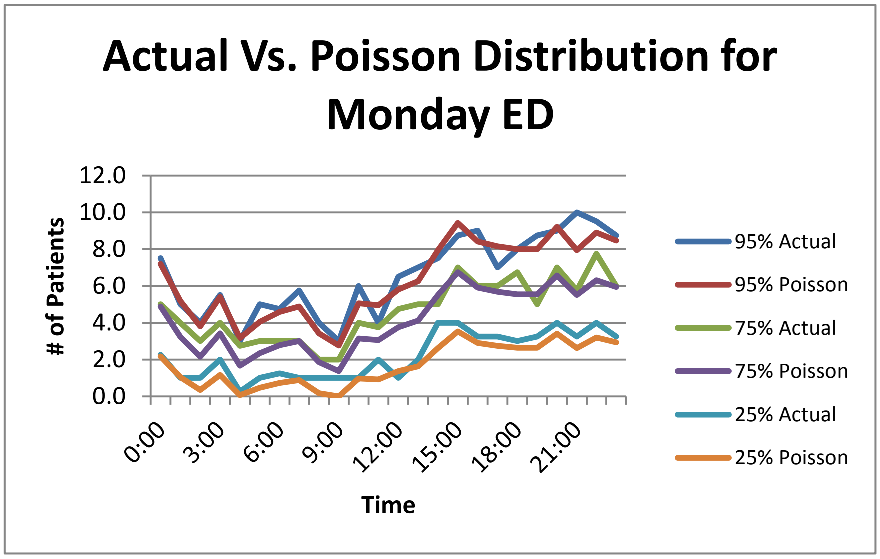


Figure 11 ED admission comparing actual distribution to a Poisson distribution on Mondays at Baystate Medical Springfield Massachusetts

In order to create a simpler model for this study, there was an assumption that each day of the week could be represented by a single distribution of ED arrivals by taking the average of the entire week. From the average, a single distribution of the percentage of patients arriving per hour for ED patients was created shown in the following graph. This graph shows based on the daily arrival rate of ED patients admitted into the hospital, the number of patients by percentage admitted each hour that was used in this study. For example, 5% of the daily ED admits will arrive at midnight. We also see from this distribution that there is a larger number of ED patients admitted between 3pm - 12am. The ED hourly admission distribution was used as the baseline values for the distribution of ED patient arrivals on average throughout the day.

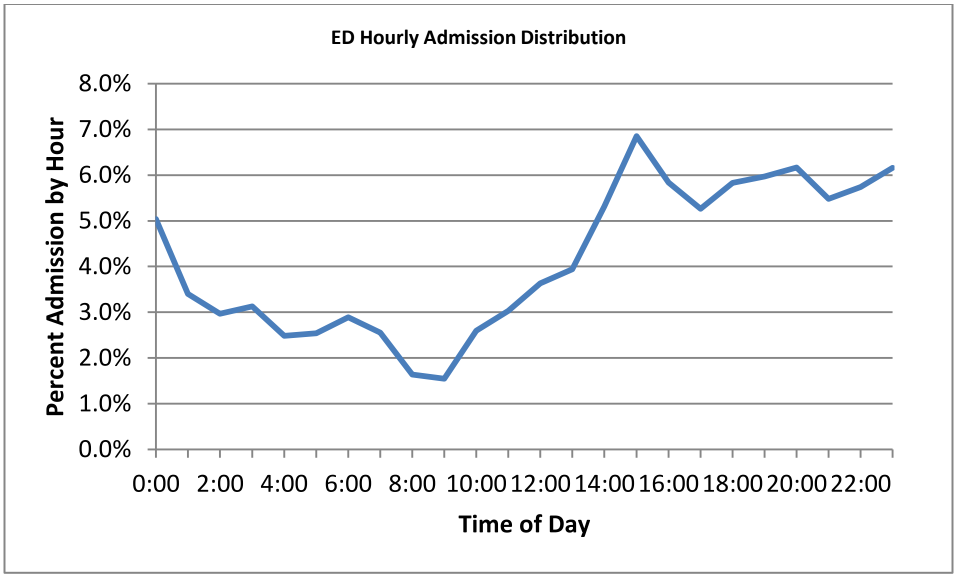


Figure 12 Average ED admission by percent of the daily arrival rate per hour

Since the arrival rate of ED patients into the hospital follows a Poisson distribution, the input data into the simulation was conducted as a stochastic component of the model. The baseline values depended on the total weekly volume of patients admitted through the ED but follow the same hourly distribution each day. In our simulation model, both the total admissions as well as the arrival rate following a Poisson distribution was checked. The daily arrival rate of patients was found by taking the weekly arrival rate and using the percentage of ED patients based on the type of hospital and dividing by the number of days that ED patients could be admitted per week.

<u>Example of Finding the Daily Arrival Rate of ED patients for a 150 Bed Community/Referral Hospital</u>

Average weekly arrival rate of patients for a 150 bed hospital found using Little's Law = 226.29 patients

% of patients admitted from the ED in a community hospital = 70%

Average weekly arrival of ED patients in a 150 bed community hospital = 226.29 * 70% = 158.405 patients

Average daily arrival of ED patients in a 150 Bed community hospital = 158.405/7 = 22.629

Average weekly arrival of ED patients in a 150 bed referral hospital = 226.29 * 45% = 101.832 patients

Average daily arrival of ED patients in a 150 bed referral hospital = 101.832/7 = 14.547 patients

Using the daily arrival rate of ED patients, the hourly arrival rate percentage was multiplied to the average daily arrival rate to find the hourly admission rate of ED patients. The total number of patients arriving in the simulation by hour was compared to the theoretical estimate. From the data we can conclude that the schedule used in the simulation is accurate by the total number of ED patients admitted into the hospital by hour of day.

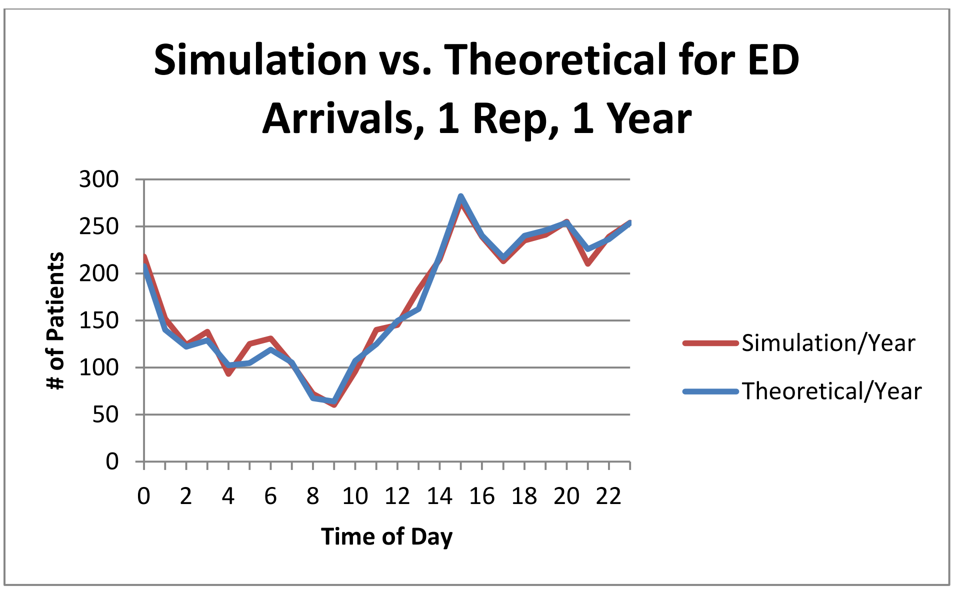


Figure 13 Comparison of the number of ED patients being admitted in a 1 year simulation run compared to the theoretical value

To verify that the input schedule in the simulation for the ED admission rate is Poisson distributed, the number patients arriving for every hour of the day was found in a 1 year simulation run. The number of patients arriving for each hour was counted and compared to the likeliness of that event based on the Poisson distribution. Six different hours of the day were checked where two of them can be found in the following table. Over a year period, the results show that the simulation is indeed showing an ED arrival rate that is Poisson distributed.

# Patients arriving within the hour	% of event based on Poisson distribution	# of times event occurred in simulation	% the event occurred in the simulation
12am - 1am			
0	0.565	207	0.567
1	0.322	110	0.301
2	0.092	38	0.104
3	0.017	8	0.022
4	0.002	2	0.005
12pm - 1pm			
0	0.663	249	0.682
1	0.273	91	0.249
2	0.056	22	0.060
3	0.008	2	0.005
4	0.001	1	0.003

Table 4 Two hours with percentages of events occurring with a Poisson distribution compared to actual events during a 1 year simulation run

In this study, there were four different ED arrival rates, all being Poisson distributed, with an hourly distribution based on the daily arrival rate found using Little's Law and the type of hospital being studied. The number of patients being admitted while following the ED distribution is random as it is in hospitals throughout this country. Within the short hand representation describing the values used within a particular simulation run, B-SdstribEDarrival stands for the Bay State ED arrival distribution used to find the percentage of patients arriving each hour of the day.

3.1.3 Controllable Parameters (CP)

Controllable parameters are the values that were considered to be controllable within a hospital's management. Such parameters involve values regarding the number of beds, NonED admission rates, allowable discharge hours, the bed turn over time, and patient priority.

The shorthanded description of the simulation model's values for the controllable parameters are listed in order by the number of beds, NonED admission days, the hours available for patient discharge, the length of time for the bed turn over time, and patient priority.

CP[150Bed.Mon-Fri(even)NEDarrival.8am-8pmDisCh.Tria(45,60,75)BtoT.FCFS] would represent a model that has 150 beds, allows NonEd patients to arrive Monday through Friday, 8am-8pm available patient discharge hours, a triangular distribution of min, mean, max values of 45, 60, and 75 minutes of time for a bed to be cleaned, and a first come first serve (FCFS) patient priority system.

3.1.3.1 Number of Beds

The number of beds in the simulation is considered to be controllable because hospitals are able to increase or decrease the number of beds which exist. Changing the number of beds may be restricted to the space available as well as financial constraints, however, we felt the number of beds within a hospital in general, is flexible.

The baseline values within this study for the number of beds is covered in section 3.1.3.1 Type of Hospital. There are 3 different sizes of hospitals with different number of beds. Community hospitals will have 75 beds and 150 beds while referral hospitals will be studied with bed sizes of 150 and 300 beds.

3.1.3.2 NonED Admission Rates

NonED patients are admitted into the hospital outside of the emergency department. The admission is considered to be controllable due to the hospital's ability to cancel, delay, and schedule in advanced when the patients are admitted. In this study, the baseline values for NonED admission rates was a Monday through Friday schedule with a uniform distribution over ten hours from 8am-6pm. A baseline of 5 days of NonED allowable admission days is used due to the data from Baystate Medical showing the majority of NonED admits being admitted on weekdays. Weekend admissions were not included in this study.

Like the method used to find the daily arrival rates for ED patients, the percentage of NonED of the weekly arrival rate was multiplied then used to find the daily arrival rate based on the number of allowable days for NonED admissions. A Mon-Fri NonED admission schedules has 5 allowable admission days. The daily arrival rate for 5 NonED arrival days equals the weekly arrival of NonED patients divided by 5.

<u>Example of Finding the Daily Arrival Rate of NonED patients for a 150 Bed Community/Referral Hospital</u>

Average weekly arrival rate of patients for a 150 bed hospital found using Little's Law = 226.29 patients

% of NonED patients admitted in a **community** hospital = 30%

% of NonED patients admitted in a **referral** hospital = 55%

Average weekly arrival of NonED patients in a 150 bed community hospital = 226.29 * 30% = 67.887 patients

Average daily arrival of NonED patients in a 150 Bed community hospital = 67.887/5 = 13.577

Average weekly arrival ofNon ED patients in a 150 bed referral hospital = 226.29 * 55% = 124.46 patients

Average daily arrival of NonED patients in a 150 bed referral hospital = 124.46/5 = 24.892 patients

Using the daily arrival rate of NonED patients based on the type and size of the hospital, the number of patients arriving each day would be distributed evenly over 10 hours from 8am – 6pm. For a 150 bed community hospital, the number of patients arriving each hour on average would equal to 10% of the daily arrival rate of 13.577, or 1.358 patients per hour from 8am – 6pm.

Although the number arrival of NonED patients is considered controllable, the element of randomness was still applied to the arrival of patients through a Poisson distribution varying the number of arrivals per hour of the day based on the given mean.

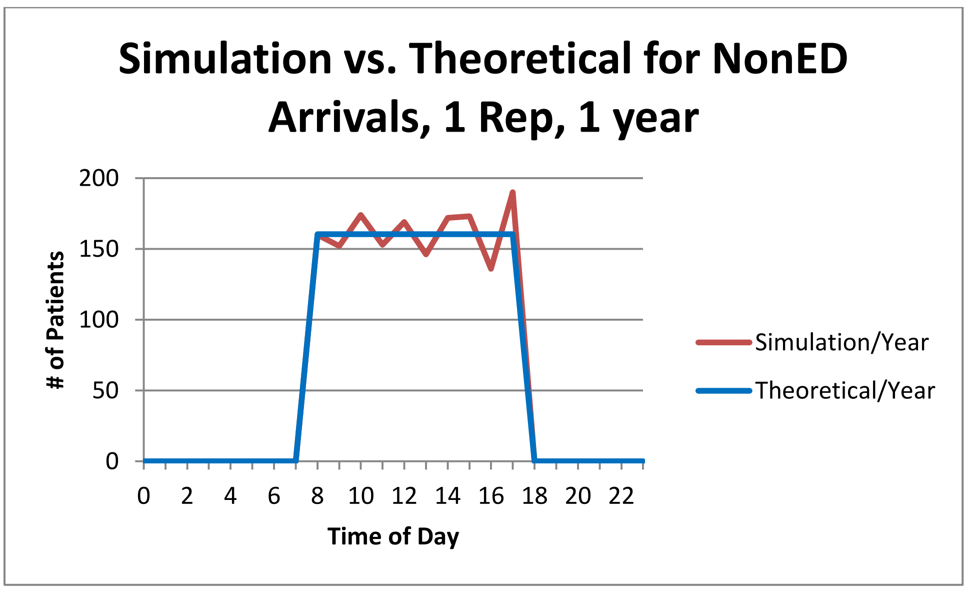


Figure 14 The arrival rate of NonED patients comparing the theoretical and simulation values

The graph above shows the number of patients expected in a given year as well as the number of patients simulated to arrive by the software. In all the different simulation runs, the uniform distribution and the number of hours NonED patients arrive is unchanged.

3.1.3.3 Patient Discharge Hours

The baseline values for when patients are allowed to be discharged (DisCh) from the hospital once their length of stay is completed was set between 8am – 8pm. A patient who completes their care based on their assigned length of stay during the available discharge hours will proceed to exit the hospital freeing a bed in its process. However, for patients whose care is completed outside the discharges hours will wait until the start of the discharge period the following day, for the baseline being 8am. Hospitals have certain times when patients can be discharged based on the resources available and was set based on the recommendation of physicians.

3.1.3.4 Bed Turnover Time

Bed turnover time (BtoT) in the model represents the time between patient discharge and the time the bed is ready for a new admitted patient. There are many processes within a hospital involving nurses, doctors, administrators, and workers in order to coordinate an efficient turnover of beds. In order to find data for the time it takes to turnover a bed, the values for the bed cleaning time from Baystate Medical Center were used. Bed cleaning time from Baystate Medical represents the time contacted to the time cleaned and ready to admit.

Mean	58.7
Median	59
Min	44
5%	49
10%	51
90%	65
95%	68
Max	71

Table 5 Baystate Medical Center bed cleaning time statistics

Incorporating the min, mean, and max values of the data from Baystate, the model's BtoT was determined as a triangular distribution with a minimum of 45 minutes, a mean of 60 minutes, and a maximum of 75 minutes (Tria(45,60,75)BtoT). Although, one disparity from the data and the BtoT distribution of the model is that the time between a patient discharge and the time to signal the bed to be cleaned is missing. The models bed turnover time is efficient in signaling that a bed is ready to be cleaned instantaneously and provides a general time frame of how long it would take to have the bed prepared for a new patient.

3.1.3.5 Patient Priority

Patient safety is of utmost importance and patients with more critical conditions are usually seen before those who are able to wait. Considerations of both the NonED and ED admitted patients were also considered into the development of the best priority baseline value. However, in order to provide a general model, priority is given to the longest waiting patient. A first come first serve (FCFS) approach is conducted where the patient with the earliest arrival time is given the next available bed. A FCFS model does not consider how critical a patient is or where the patients are admitted from (ED or NonED).

3.2 Modified Parameters

A major portion of this study involved the effects of changing parameters from their baseline values and their impacts on the model. Key parameters were chosen and studied to help understand their relationship to both ED and NonED patient waiting times. As parameters were modified, only the modified parameter changed while keeping all other baseline parameters consistent. The degree in which a parameter affected the hospital system is also compared to the different types of hospitals within this study.

3.2.1 Patient Discharge Times

The baseline for the patient discharge time in this study is from 8am – 8pm. When a patients length of stay is completed outside the values of the discharge time parameter, the patient must wait, occupying the bed they received care until the start of the next discharge period. By creating changes in this parameter, the question of how might extending the time allowed for patients to leave affect patient waiting times. We assume if we allow a longer period of time for patients to be discharged, there would be fewer patients waiting to leave and thus improve waiting time by allowing more patients to be admitted faster. However, by how much, and to what degree is increasing the time of allowable discharge have on waiting times. Also, is there a greater effect for hospitals that are larger or have a larger portion of their patients from the ED?

These questions were considered when modifying the patient discharge times. The scenarios chosen are the baseline value of 8am-8pm, 8am-12am, and a 24 hour model. The change in this parameter would provide insight into the effects of the discharge times and the benefits of a hospital increasing the available hours for patients to be discharged.

3.2.2 Allowable days of arrival for NonED patients

The allowable days of arrival for NonED patients is considered controllable by the hospital system due to patients being scheduled for admission. By changing the allowable days of arrival for NonED patients show how a change in the number of days hospitals operate affects patient waiting times. The baseline value for NonED arrival days is a 5 day, Monday through Friday admission schedule. The other values used for this parameter is to restrict and expand the allowable days of arrival to 4, 6, and 7 days. A 4 day schedule would restrict patients to arrive Mon-Thurs, and increasing to a 6 and 7 day schedule, NonED patients arrive Mon-Sat and Mon-Sun respectively.

The average weekly arrival of NonED patients arriving however is not changed even with the change in the allowable days of arrival for NonED patients and instead is spread accordingly based on the number of days scheduled. A 4 day schedule will have a greater number of patients arriving each day on average than a 5 day schedule while a 6 and 7 day will have fewer patients. The average weekly arrival rate would be divided by the number of days scheduled to find the daily arrival rate for each change in schedule. For example, a 150 bed community hospital will have an average weekly arrival of 67.887 patients.

<u>Example of average arrival rate for 4,5,6 days of arrival for NonED patients</u>

Average daily arrival of NonED patients for 5 arrival days = 67.887/5 = 13.577 patients
Average daily arrival of NonED patients for 4 arrival days = 67.887/4 = 16.972 patients
Average daily arrival of NonED patients for 6 arrival days = 67.887/6 = 11.315 patients
Average daily arrival of NonED patients for 7 arrival days = 67.887/7 = 9.698 patients

The hourly arrival of NonED patients like the baseline case will arrive evenly distributed over a 10 hour period from 8am-6pm. The change in NonED days of arrivals is also compared to the type of hospital to see if the change in the allowable days of NonED arrivals has a greater effect based on the makeup of patients or the size of hospital.

3.2.3 Patient length of stay

Although a patient's length of stay is considered uncontrollable in that many of the procedures and time required serving a patient is essential, in light of new technology, or changes to the process of serving a patient, changing the average length of stay was studied. The baseline value of 111.36 hours following a lognormal distribution with a standard deviation of 167.04 hours is used and compared to different averages. Average LOS values in increments of 4.8 hours were simulated giving averages of 106.56, 101.76 hours. The distribution and standard deviation in being lognormal with a standard deviation of 167.04 hours did not change with the modification of this parameter. The values were chosen based on an increment of .2 days and with the question of how such changes would affect patient waiting times.

3.3 ARENA Model

The simulation package used in this study is ARENA, a discrete event simulation software created by Rockwell Automation. The model was built from the ground up, incorporating all the baseline parameters to create a system that is able to reflect a general hospital system with stochastic input variables and exporting data that is able to provide valuable insights into patient waiting time. The model is able to adjust the different parameters used in this study. A general flow within the model can be seen in the figure below.

Figure 15 Basic flow of patients in the model

3.3.1 Patient Arrival

In this study, there are two types of patients, ED and NonED patients who are both represented as two different types of entities within ARENA. Both types of patients were created with separate create modules with an arrival rate based on a schedule which is specified for each patient type. ED patients have a 24 hour schedule where each hour has a specified arrival rate mean signaling the average number of patients to arrive in that hour with a Poisson distribution. NonED patients have a schedule consisting of 168 hours, a full week with the average number of patients to arrive for each hour. A full week schedule is needed to be created due to the differences in NonED days of arrival, where for the baseline case, the schedule consisted of values of 0 starting in hour 115 (6pm Friday) through hour 168 (Midnight on Sunday).

Every patient entering the system is assigned a number of attributes to help identify characteristics for that patient. The assign modules used to assign the attribute values immediately followed the create module. The attributes assigned consisted of the day of week, hour of day, day of year that the patient arrived as well as being assigned the time of completed care. The time of completed care is given by TNOW + LOGN(111.36, 167.04), which gives a simulation time based on the current time (TNOW) that the patient arrived with a lognormal distribution with mean and standard deviation of 111.36 and 167.04 hours added. This will give every patient a specified time during the simulation when their LOS is completed. Once a patient arrives and is assigned the given attributes needed to identify the patient, both ED and NonED patients enter the same waiting for bed queue.

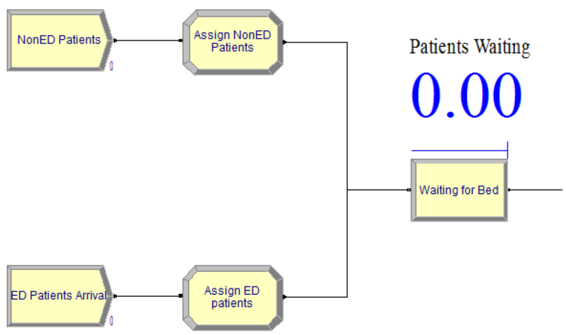


Figure 16 Arrival process of ED and NonED patients in ARENA

3.3.2 Waiting for Bed Queue

The waiting for bed queue holds both ED and NonED patients until either their LOS is completed or an available bed is ready to be occupied by a patient. ED and NonED patients fill the queue as they arrive and the queue serves as the access point before being admitted into the hospital. For ED patients, the waiting for bed queue would represent a patient boarding in the ED, waiting to be admitted into the hospital. The command within the waiting for bed queue hold module is a condition which checks for the number of beds being currently occupied. If the number of beds occupied is less than the total number of beds available within the hospital, patients are released to fill the empty beds. No additional simulation time is counted from the point of release from the queue until the patient occupies a bed due to the way time between events within ARENA occur instantaneously.

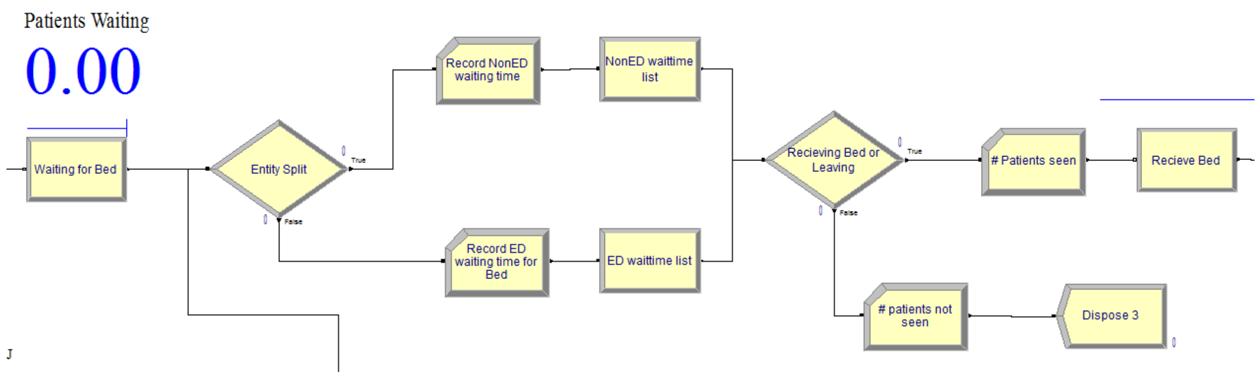


Figure 17 Waiting for bed process in ARENA model

In this study, an important method of distinguishing the LOS to equal the total time in the system was determined to provide the best method of utilizing the different parameters used to study patient waiting times. The national LOS values and standard deviation representing the time of admission to the time of discharge includes the time in bed along with waiting time and discharges gave further reason to create a model with the LOS as the total time spent in the system.

A method of finding patients with completed LOS values that are still waiting in the waiting for bed queue had to be created using dummy entities with search and remove modules. A create module is used creating dummy entities every 15 minutes checking the waiting for bed queue for patients ready to leave the system without being admitted into the hospital. Patients with their time of completed care exceeding the current simulation time are determined as patients ready to leave since their entire LOS is taken while waiting for a bed. The number of dummy entities created equaled half the number of patients in the waiting for bed queue. This method assumes that in any given 15 minute span, less than half of the patients waiting for a bed will have their length of stay duration exceed the current simulation time.

Once dummy entities are created, they proceed to a search module checking the waiting for bed queue from the first patient in line until a patient ready to leave the system is found. If a patient with an exceeded LOS is found, that patient is removed from the waiting for bed queue through the remove module and proceeds through the model similar to a patient being released due to an open bed.

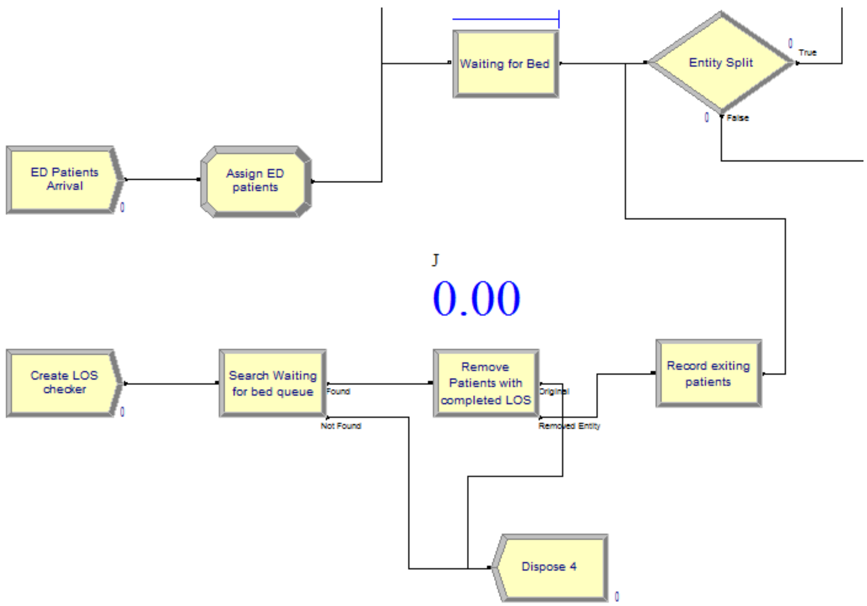


Figure 18 **Dummy variables created to search and remove patients with completed LOS**

All patients leaving the waiting for bed queue will be split based on entity type to record separate statistics on waiting time for ED and NonED patients. Patients leaving the queue due to an exceeded time of completed care will have a waiting time equal to their entire LOS value. Once a patient enters the receiving bed or leaving decide module after the waiting time stats are recorded, the patients will be directed to either leave the system or to occupy a bed. If the current time is less than the time of completed care which is the time the patient arrived plus their LOS value, the patient will occupy a bed. However, if the patient's arrival time plus LOS is greater than the current simulation time, being patients who were removed from the waiting for bed queue with the remove module will not receive a bed and exit the system.

3.3.3 Patient Receives Care in Bed

As beds become available and patients are released from the waiting for bed queue to be admitted into the hospital, the entities seize a bed resource and enter a hold module titled receive care in bed. This hold module holds patients until their time of completed care exceeds the current simulation time. The time patients spend in this hold module is their LOS value determined by the lognormal distribution minus the time they waited in the waiting for bed queue. Once a patient completes their LOS value in the hold module, the patients are released into the waiting to leave discharge queue.

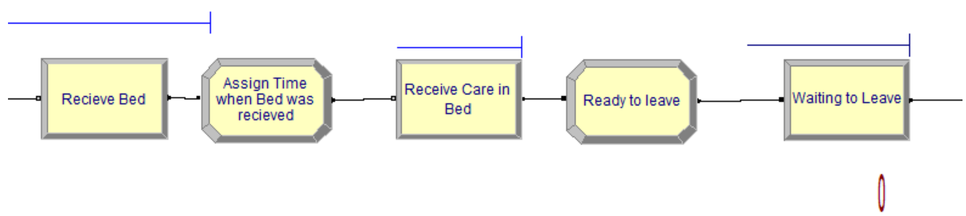


Figure 19 Patients receiving a bed in the ARENA model

3.3.4 Patient Discharge

Once a patient's LOS is completed based on their arrival time and LOS value compared to the current simulation time, patients will enter the waiting to leave process module. The waiting to leave process module allows patients to proceed if and only if a discharge resource is available based on the discharge schedule. The baseline discharge schedule is 8am-8pm which allows patients to be discharged if a patient enters the waiting to leave process module between the discharge hours. Patients will be held in the process module if the patient entered the module outside the discharge window until the start of the discharge schedule the following day. The discharge resources can represent staff of the hospital needed to discharge patients or could even represent the pickup party not being available. Although the entity representing the patient is discharged as the entity passes through the waiting to leave process module, the bed is yet to be available for another patient.

The entity continues to a bed clean up delay module with a delay using a triangular distribution with min, mean, and max values of 45, 60, and 75 minutes. Once the bed is cleaned, statistics on the times available are recorded and the bed is released by the release bed module. As the entity passes through the release bed module, the bed resource is freed and is able to be utilized by the next patient waiting in line. The entities are then disposed of finally completing the simulation cycle representing the admission discharge process created through the ARENA simulation software.

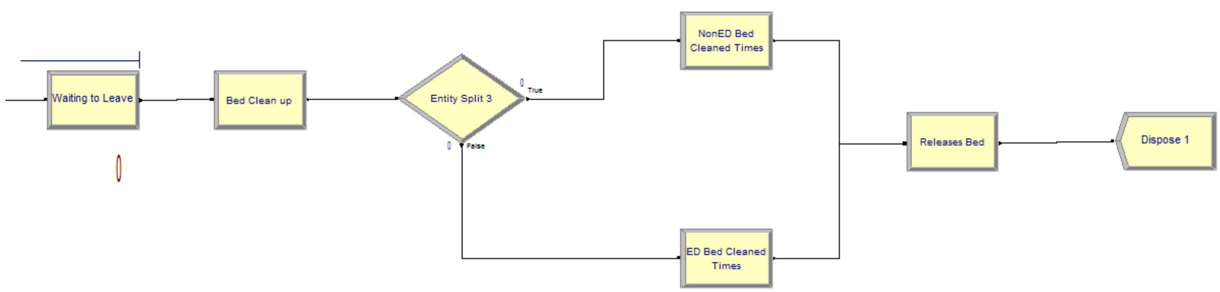


Figure 20 Discharge process in ARENA simulation

CHAPTER 4

RESULTS

4.1 Baseline Parameters

When comparing the different types of hospitals and bed sizes using the baseline values, there is significant variation in the waiting times throughout the week and by the hour of day of the patient's bed request.

A hospitals makeup of patients has an effect on patient waiting time when comparing wait time values based on the day of week and hour of day the bed is requested. Referral hospitals for both ED and NonED patients have a steeper rise in waiting time starting from Wednesday through Friday.

Increasing the number of beds from 75 to 150 significantly decreases both ED and NonED waiting times, however, such results are not reflected in an increase of 150 to 300 beds in a referral hospital. Economies of scale however seems to play a role in the hospitals within a community hospital due to the percentage of patients of NonED patients arriving on weekdays compared to a referral hospital which creates a more congested hospital towards the end of the week. By increasing a referral hospital to 1200 beds allows ED and NonED patient wait times to decrease significantly. This may show that a referral hospital's percentage of ED and NonED patients may create a congested hospital which is hard to alleviate during the weekends compared to community hospitals.

By comparing hospitals with the same total number of beds at 150, a community hospital has shorter waiting times for NonED patients compared to a referral hospital. There is not significant evidence to say that ED patients wait less, however the average value found is lower than the referral hospital.

All figures show a 95% confidence interval.

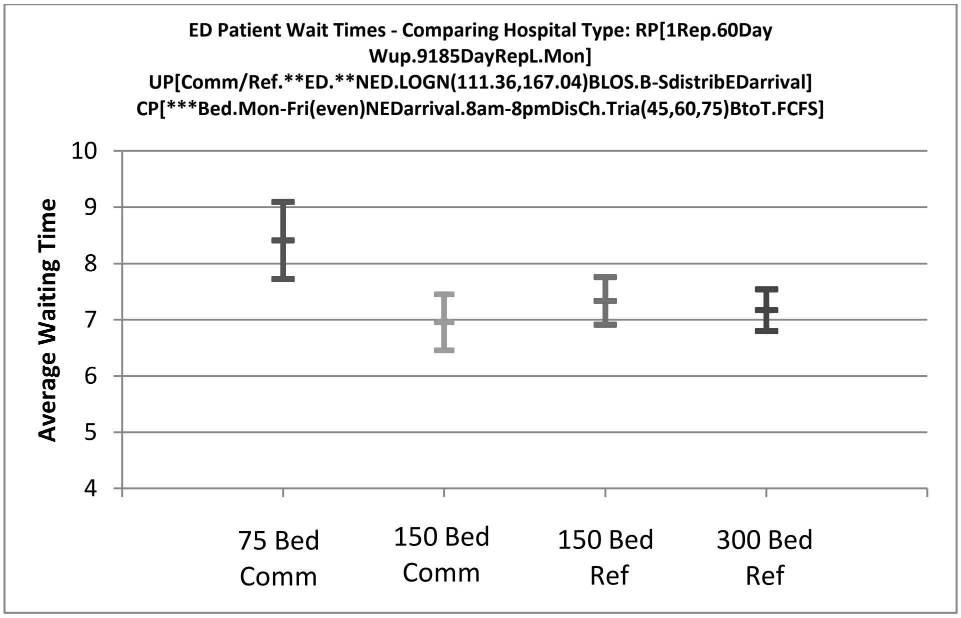


Figure 21 ED patient wait time comparing hospital types with baseline values

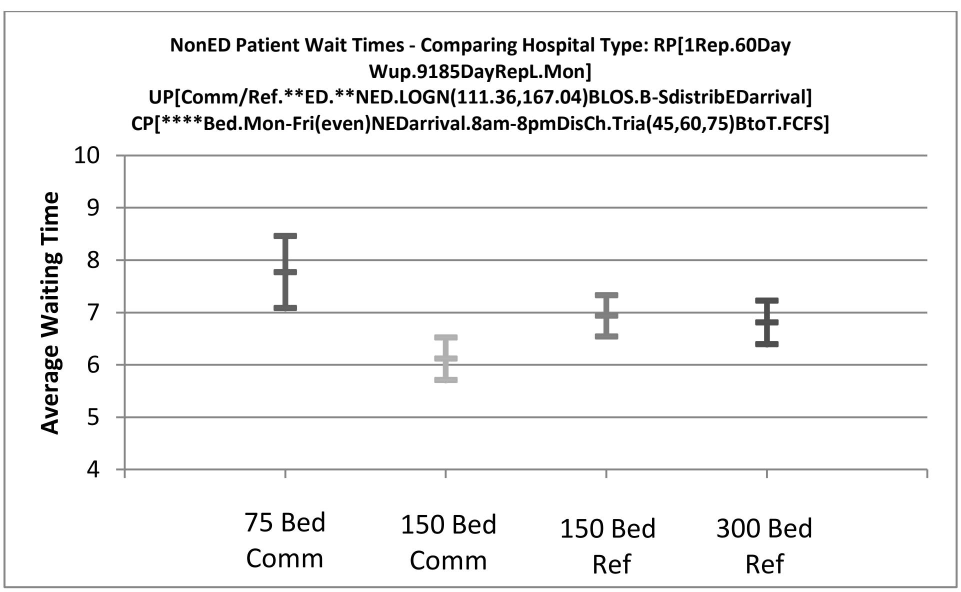


Figure 22 NonED patient wait time comparing hospital types with baseline values

ED		75 Bed Comm	150 Bed Comm	150 Bed Ref	300 Bed Ref
	Upper 95th	9.091	7.452	7.749	7.537
	Average	8.404	6.953	7.33	7.165
	Lower 95th	7.717	6.454	6.911	6.793
NonED					
	Upper 95th	8.454	6.521	7.328	7.221
	Average	7.767	6.112	6.933	6.805
	Lower 95th	7.08	5.703	6.538	6.389

Table 6 ED and NonED waiting times comparing hospital types using baseline values

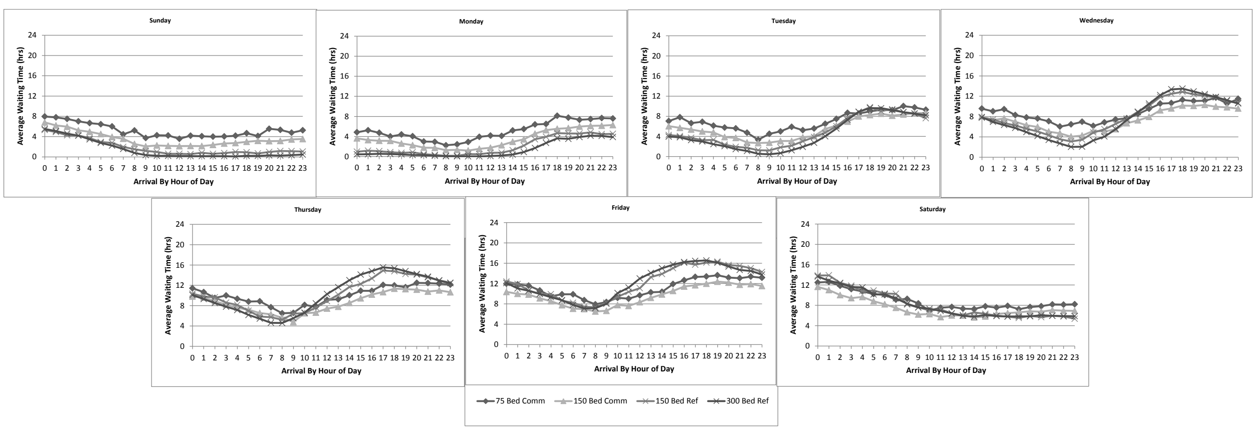


Figure 23 ED wait time by day and hour of bed request comparing hospital types using baseline values

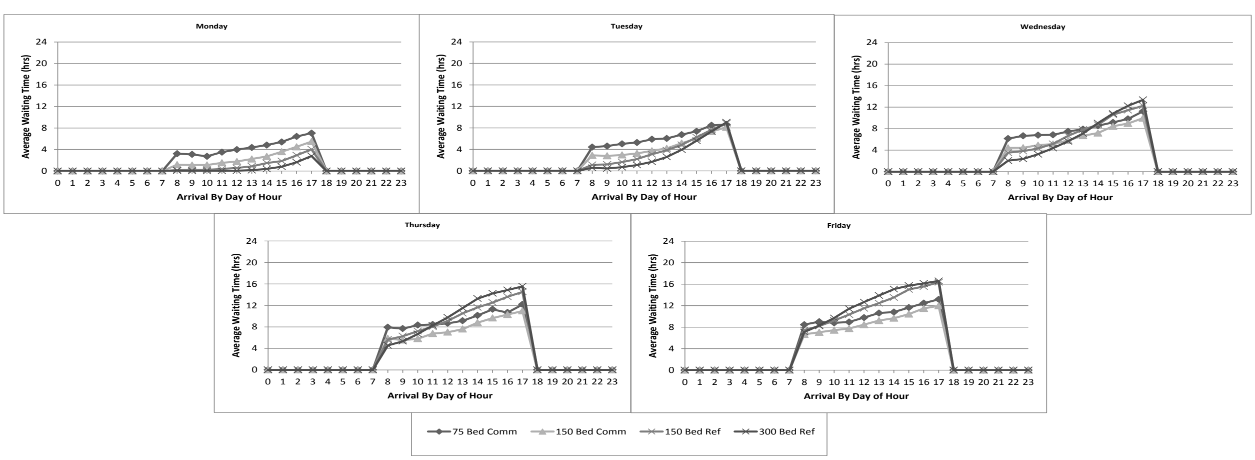


Figure 24 NonED wait time by day and hour of bed request comparing hospital types using baseline values

4.2 Peaks and Valleys

The simulation of the hospital admission system using the values in our study creates a steady state system which has significant variation in delay times due to the high peaks of queue lengths. The standard deviation of the LOS distribution being greater than the mean will cause a wide range of different LOS values and may cause such variation in the queue length.

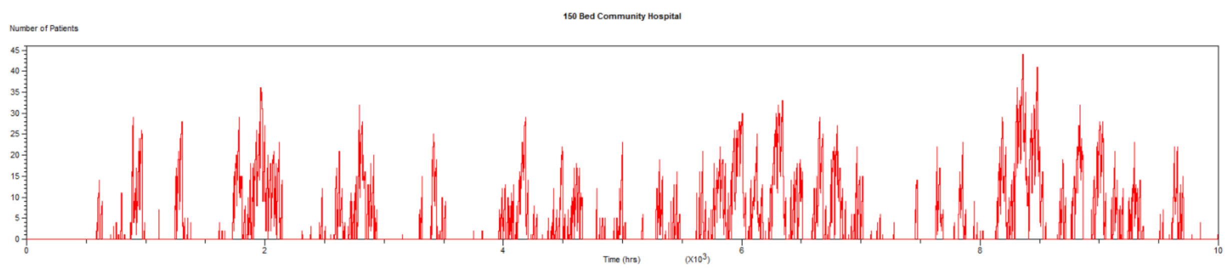


Figure 25 150 bed community hospital queue length for baseline values from time 0 to 10000 hours

4.3 Patient Discharge Times

Patient waiting time decreases as the hours available for discharge increases. There is significant results where each hospital case shows a decrease in waiting times from an 8am-8pm discharge times (baseline) to a 24 hour discharge period for both ED and NonEd patients.

A change in discharge period from 8am-8pm to 8am-12am gives only certain hospitals and patient types lower average waiting times with significant results as is the same from an 8am-12am to a 24 hr discharge period.

All figures show a 95% confidence interval.

4.3.1 75 bed community hospital

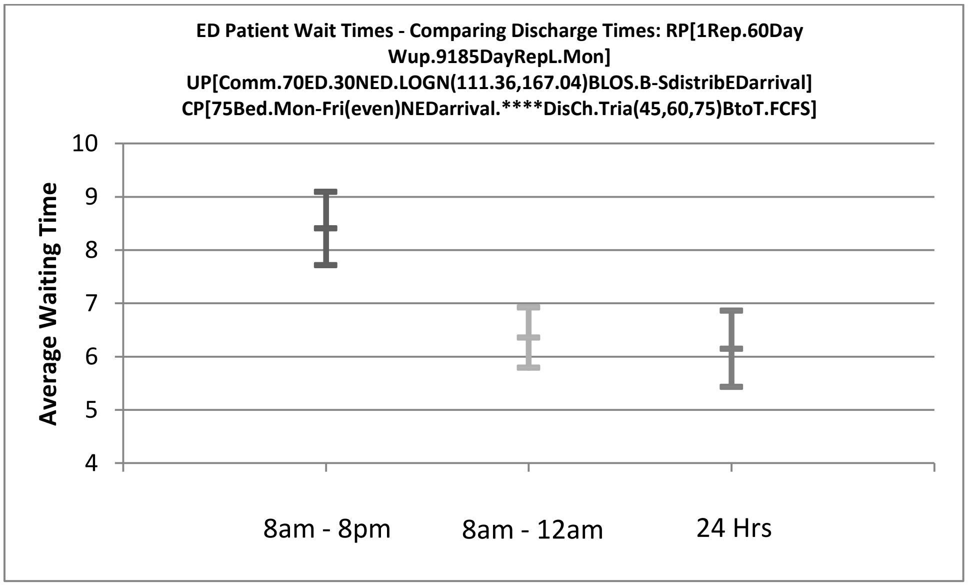


Figure 26 ED patient wait times comparing discharge times for a 75 bed community hospital

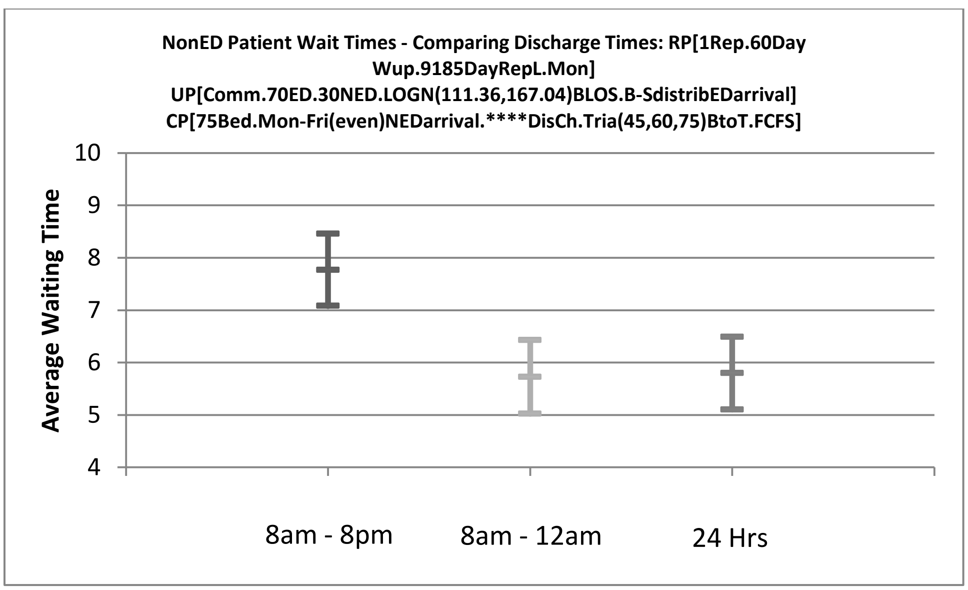


Figure 27 NonED patient wait times comparing discharge times for a 75 bed community hospital

ED			8am - 8pm	8am - 12am	24 hrs
	Upper 95th		9.091	6.918	6.8614
	Average		8.404	6.354	6.146
	Lower 95th		7.717	5.79	5.4306
NonED					
	Upper 95th		8.454	6.429	6.486
	Average		7.767	5.726	5.794
	Lower 95th		7.08	5.023	5.102

Table 7 ED and NonED wait times comparing discharge times for a 75 bed community hospital

4.3.2 150 bed community hospital

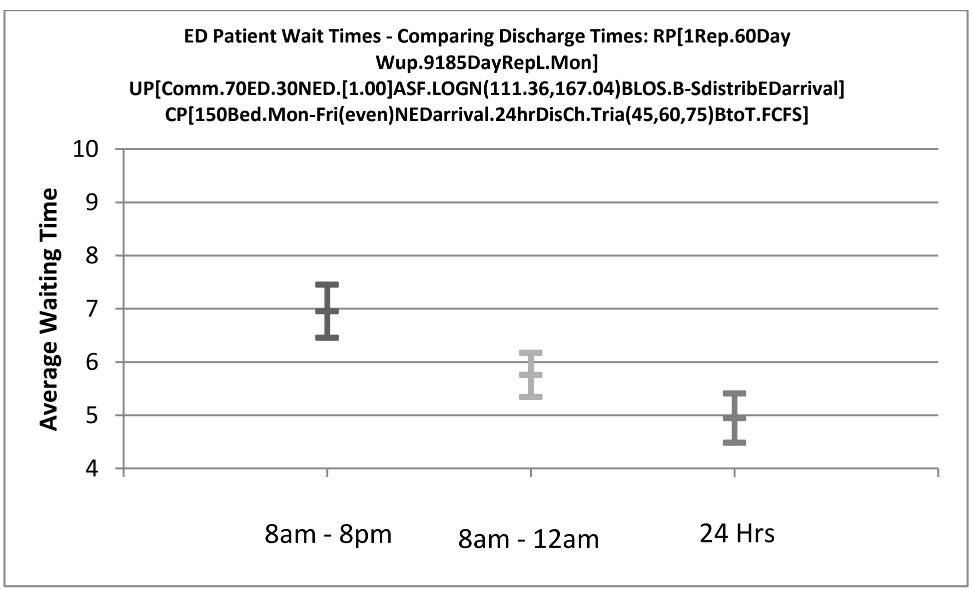


Figure 28 ED patient wait time comparing discharge times for a 150 bed community hospital

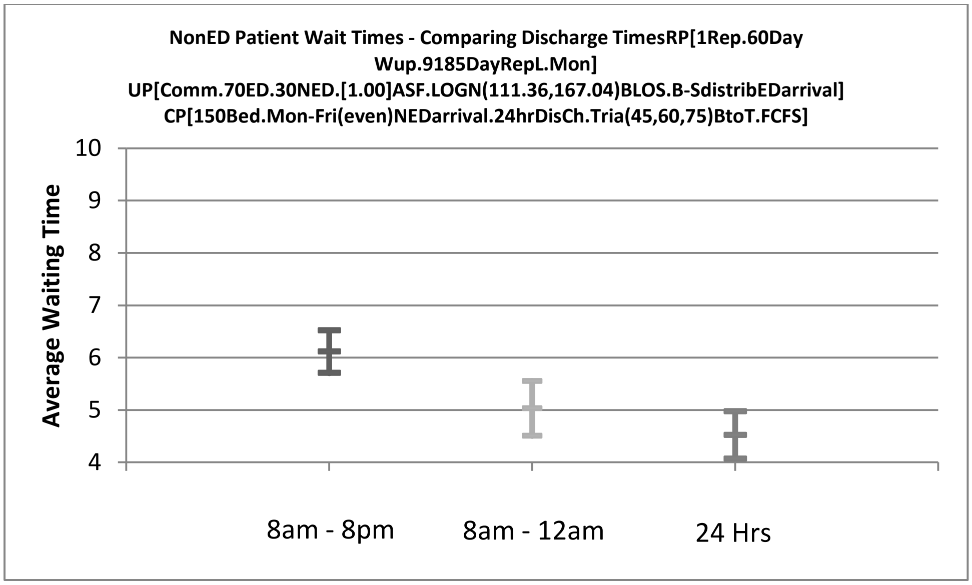


Figure 29 NonED patient wait time comparing discharge times for a 150 bed community hospital

ED		8am - 8pm	8am - 12am	24 hrs
	Upper 95th	7.452	6.171	5.404
	Average	6.953	5.756	4.941
	Lower 95th	6.454	5.341	4.478
NonED				
	Upper 95th	6.521	5.554	4.973
	Average	6.112	5.03	4.521
	Lower 95th	5.703	4.506	4.069

Table 8 ED and NonED wait times comparing discharge times for a 150 bed community hospital

4.3.3 150 bed referral hospital

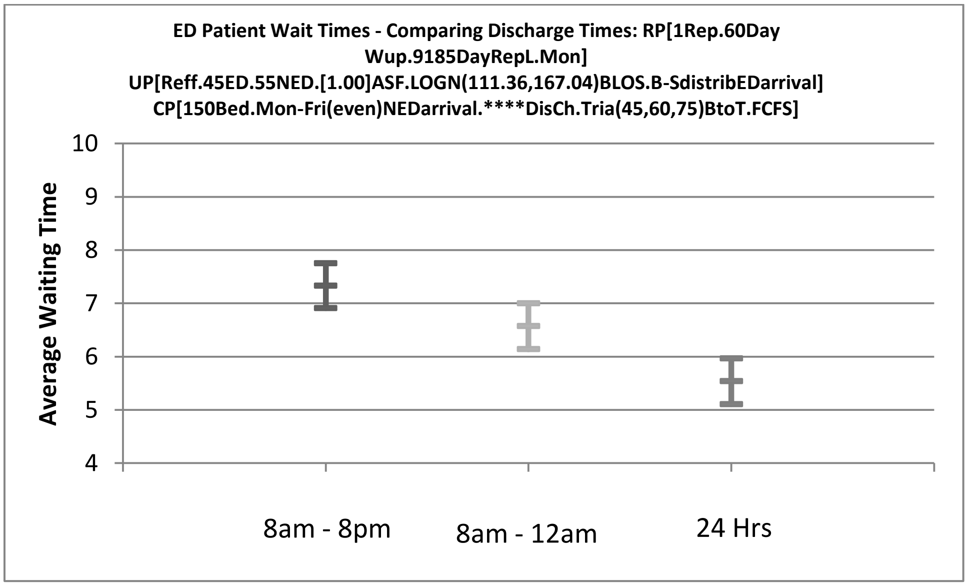


Figure 30 ED patient wait time comparing discharge times for a 150 bed referral hospital

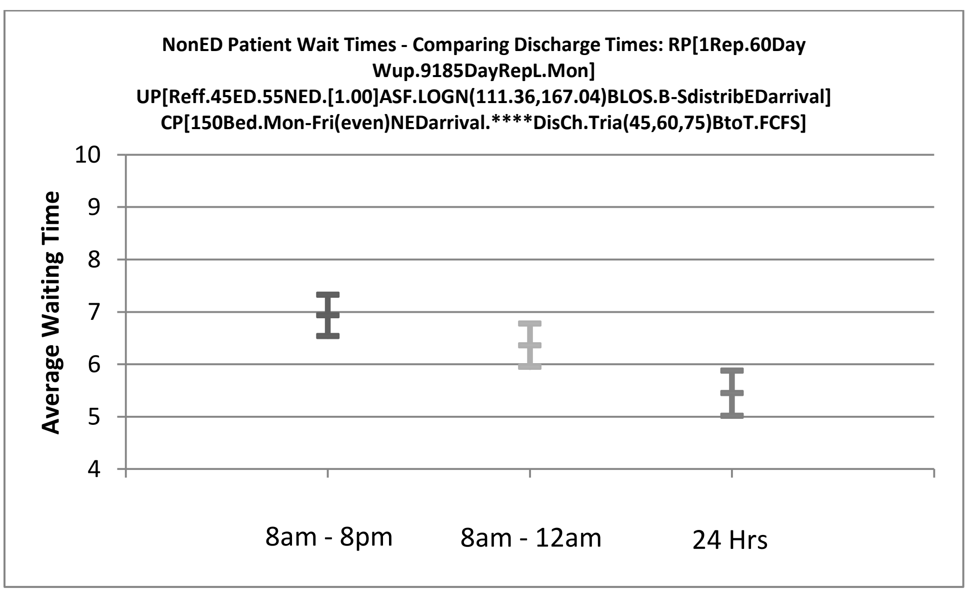


Figure 31 NonED patient wait time comparing discharge times for a 150 bed referral hospital

ED			8am - 8pm	8am - 12am	24 hrs
	Upper 95th		7.749	7.001	5.9675
	Average		7.33	6.57	5.538
	Lower 95th		6.911	6.139	5.1085
NonED					
	Upper 95th		7.328	6.777	5.876
	Average		6.933	6.362	5.446
	Lower 95th		6.538	5.947	5.016

Table 9 ED and NonED patient wait time comparing discharge times for a 150 bed referral hospital

4.3.4 300 bed referral hospital

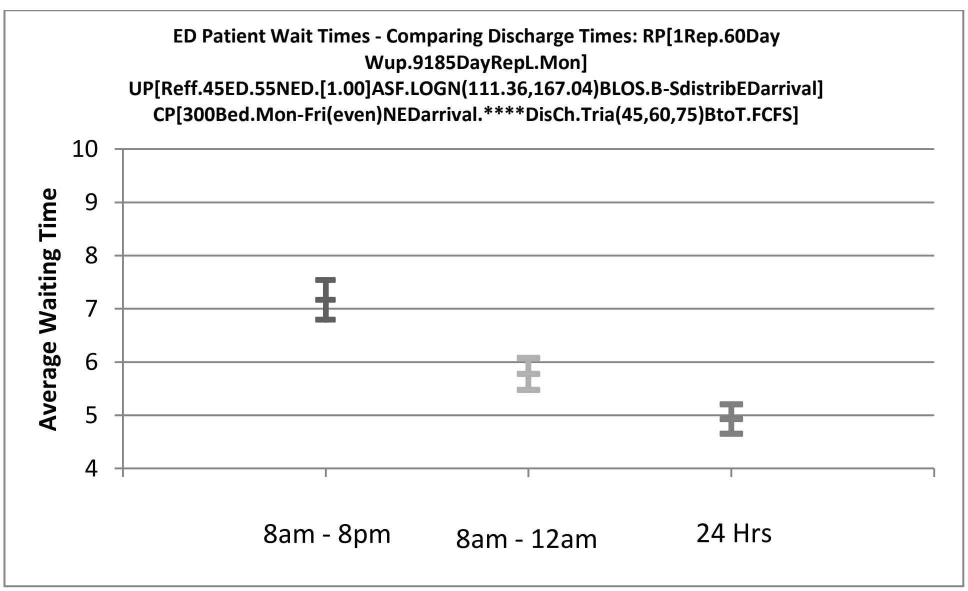


Figure 32 ED patient wait time comparing discharge times for a 300 bed referral hospital

**** 8am-12am results and confidence interval is found manually**

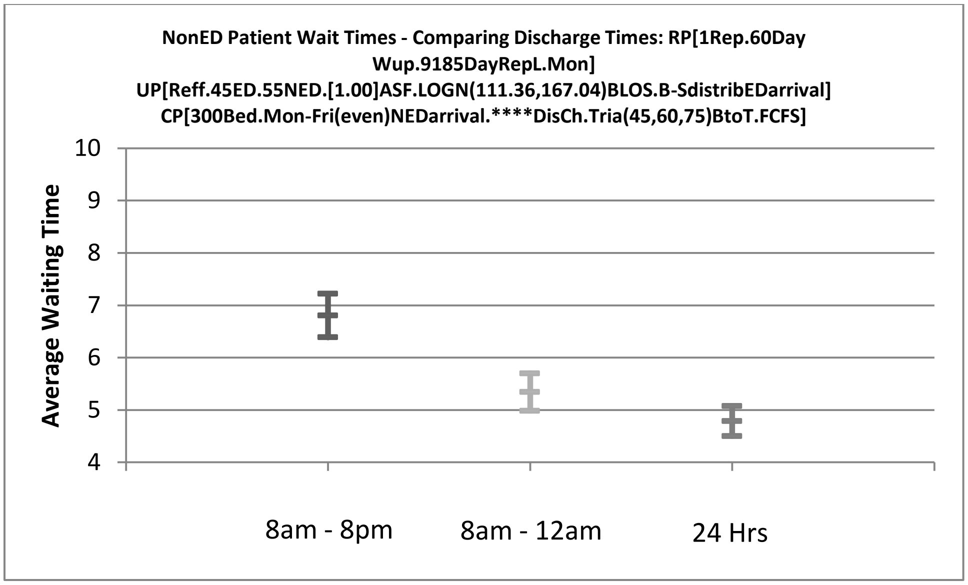


Figure 33 NonED patient wait time comparing discharge times for a 300 bed referral hospital

ED		8am - 8pm	8am - 12am	24 hrs
	Upper 95th	7.537	6.076*	5.203
	Average	7.165	5.775*	4.926
	Lower 95th	6.793	5.474*	4.649
NonED				
	Upper 95th	7.221	5.7	5.077
	Average	6.805	5.343	4.79
	Lower 95th	6.389	4.986	4.503

Table 10 ED and NonED patient wait time comparing discharge times for a 300 bed referral hospital

4.4 Allowable day of arrival for NonED patients

When comparing the different allowable days of arrival for NonED patients, there is significant difference in NonED patient waiting times when there is 2 additional days of arrival for NonED patients. A Mon-Thurs and Mon-Sat comparison shows significant results as does a comparison of a Mon-Fri (baseline) compared to a Mon-Sun NonED arrival schedule.

A one day increase in NonED arrival schedule from a Mon-Fri to a Mon-Sat shows a decrease in waiting times for NonED patients for the 150 bed community, 150 bed referral, and 300 bed referral hospitals. However, the change in the Mon-Fri to a Mon-Sat NonED schedule cannot determine if the waiting time for NonED patients is lower due to the average falling within the confidence interval for a 75 bed community hospital.

The waiting time for ED patients is not significantly affected by a change in NonED arrivals. The number of patients arriving per week remains the same even with the different days of arrival for NonED patients.

All figures show a 95% confidence interval.

4.4.1 75 bed community hospital

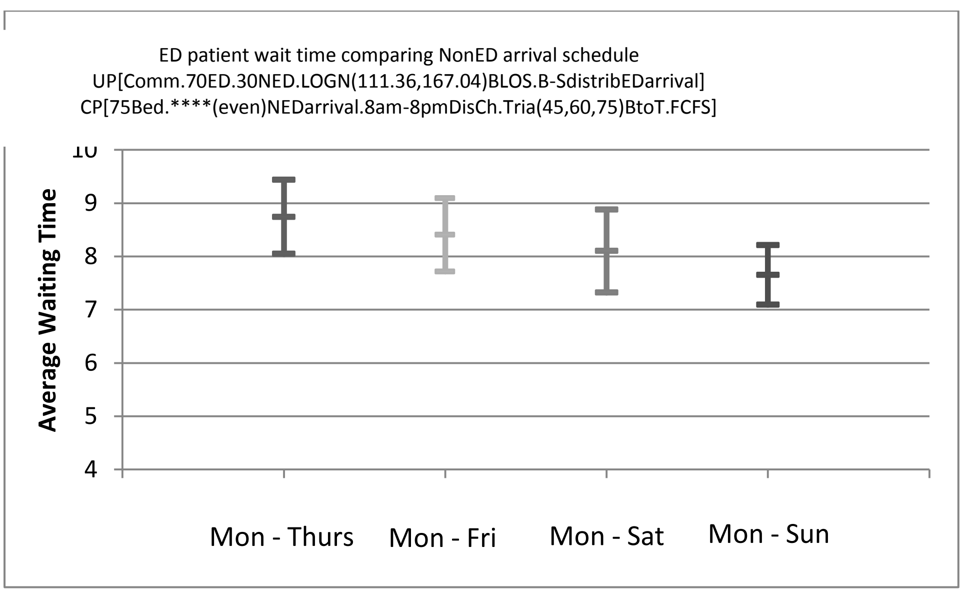


Figure 34 ED wait time comparing NonED arrival schedule for a 75 bed community hospital

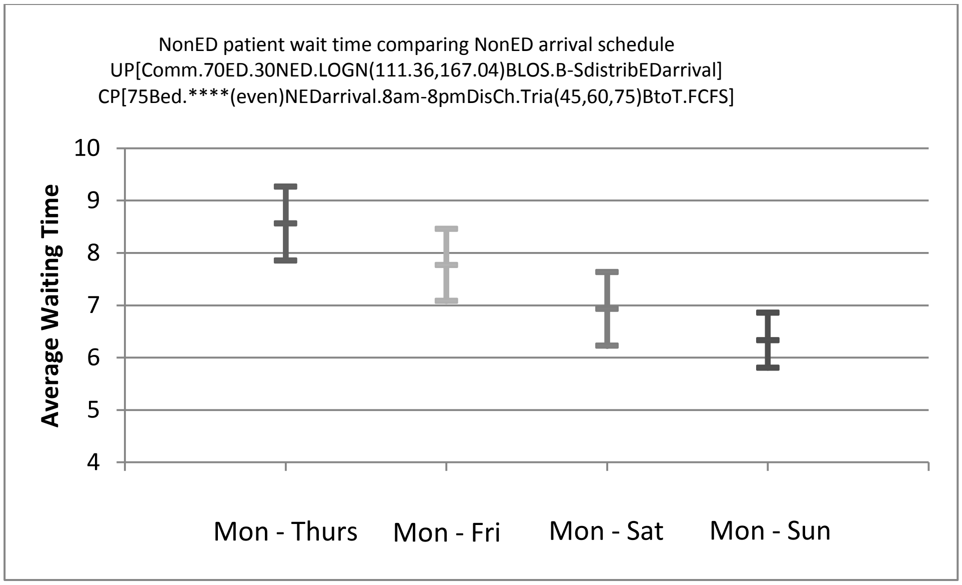


Figure 35 NonED wait time comparing NonED arrival schedule for a 75 bed community hospital

ED		Mon - Thurs	Mon - Fri	Mon - Sat	Mon - Sun
	Upper 95th	9.431	9.091	8.877	8.209
	Average	8.737	8.404	8.098	7.65
	Lower 95th	8.043	7.717	7.319	7.091
NonED					
	Upper 95th	9.263	8.454	7.631	6.853
	Average	8.558	7.767	6.927	6.329
	Lower 95th	7.853	7.08	6.223	5.805

Table 11 ED and NonED wait time comparing NonED arrival schedule for a 75 bed community hospital

4.4.2 150 bed community hospital

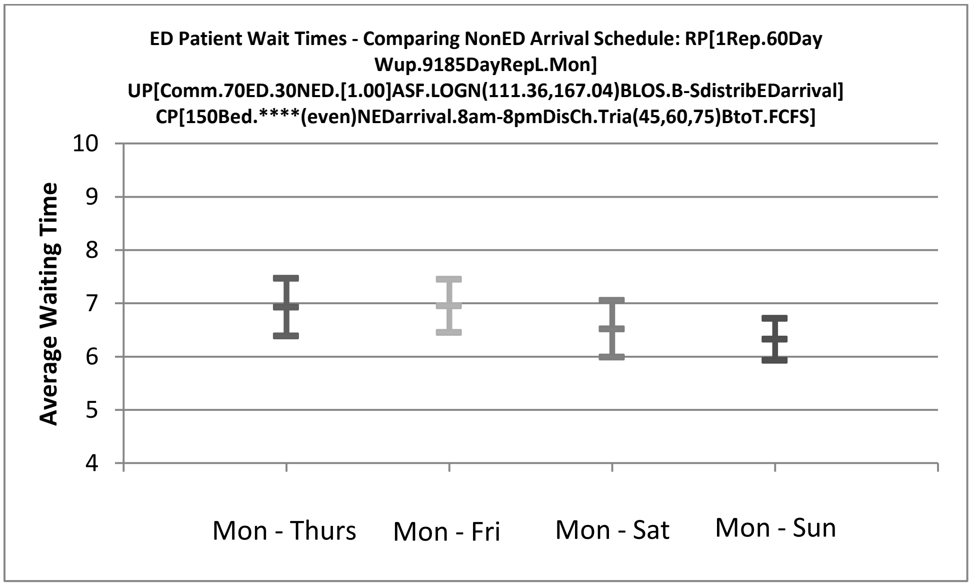


Figure 36 ED patient wait time comparing NonED arrival schedule for a 150 bed community hospital

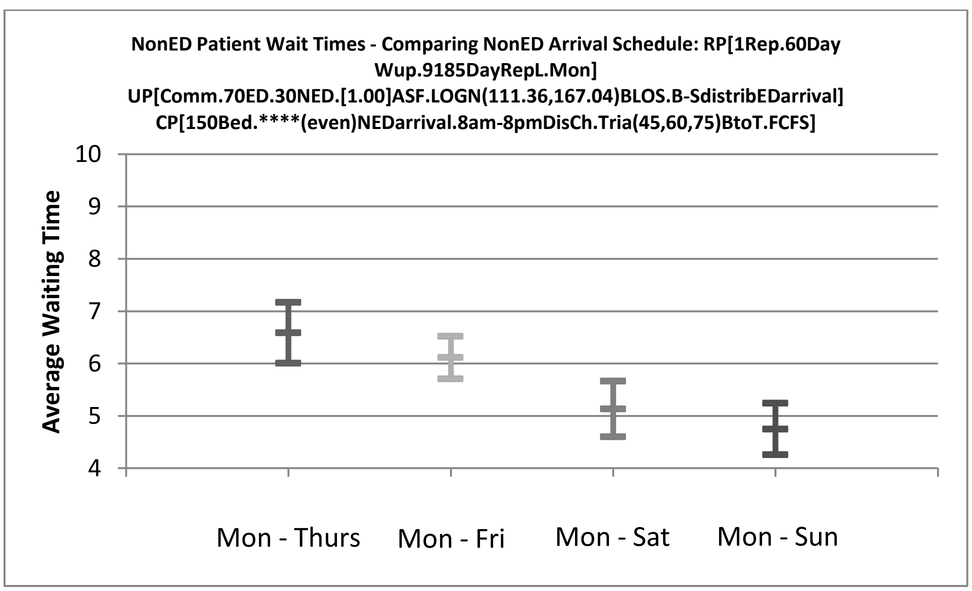


Figure 37 NonED patient wait time comparing NonED arrival schedule for a 150 bed community hospital

ED			Mon - Thurs	Mon - Fri	Mon - Sat	Mon - Sun
	Upper 95th		7.466	7.452	7.053	6.718
	Average		6.926	6.953	6.521	6.325
	Lower 95th		6.386	6.454	5.989	5.932
NonED						
	Upper 95th		7.166	6.521	5.662	5.24
	Average		6.584	6.112	5.129	4.747
	Lower 95th		6.002	5.703	4.596	4.254

Figure 38 ED and NonED patient wait time comparing NonED arrival schedule for a 150 bed community hospital

4.4.3 150 bed referral hospital

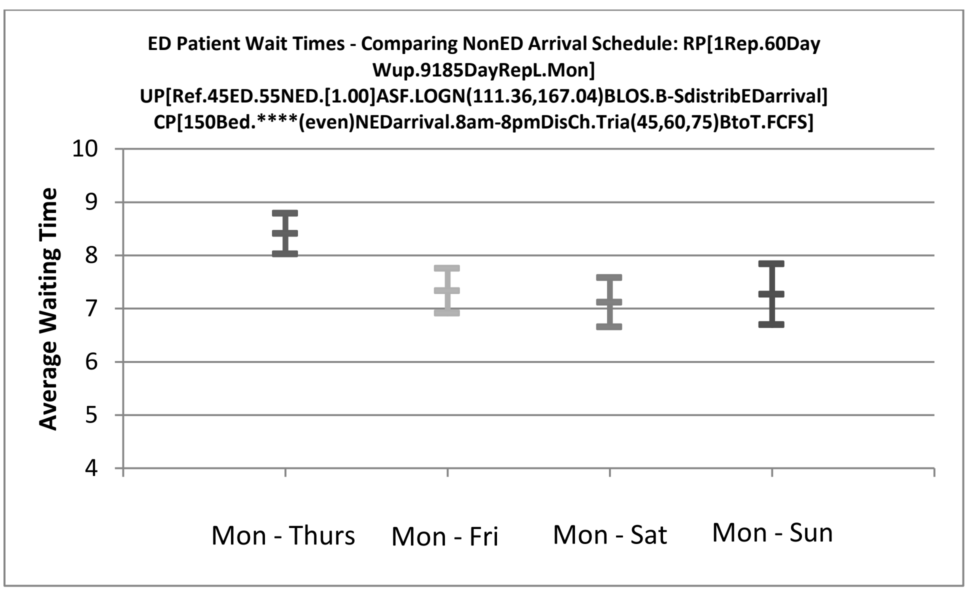


Figure 39 ED patient wait time comparing NonED arrival schedules for a 150 bed referral hospital

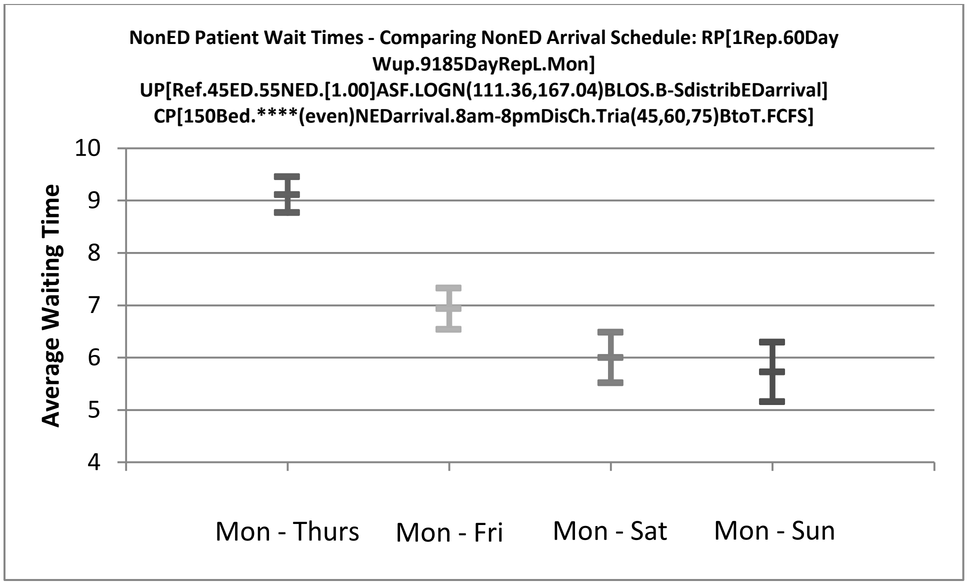


Figure 40 NonED patient wait time comparing NonED arrival schedule for a 150 bed referral hospital

ED			Mon - Thurs	Mon - Fri	Mon - Sat	Mon - Sun
	Upper 95th		8.787	7.749	7.577	7.832
	Average		8.405	7.33	7.115	7.261
	Lower 95th		8.023	6.911	6.653	6.69
NonED						
	Upper 95th		9.452	7.328	6.4823	6.294
	Average		9.109	6.933	6	5.726
	Lower 95th		8.766	6.538	5.5177	5.158

Table 12 ED and NonED patient wait time comparing NonED arrival schedule for a 150 bed referral hospital

4.4.4 300 bed referral hospital

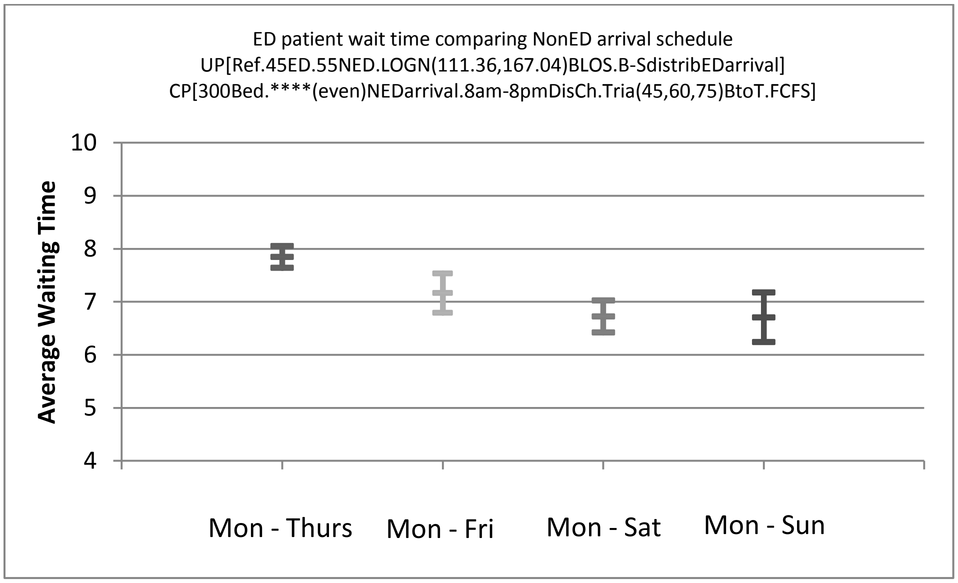


Figure 41 ED patient wait time comparing NonED arrival schedule for a 300 bed referral hospital

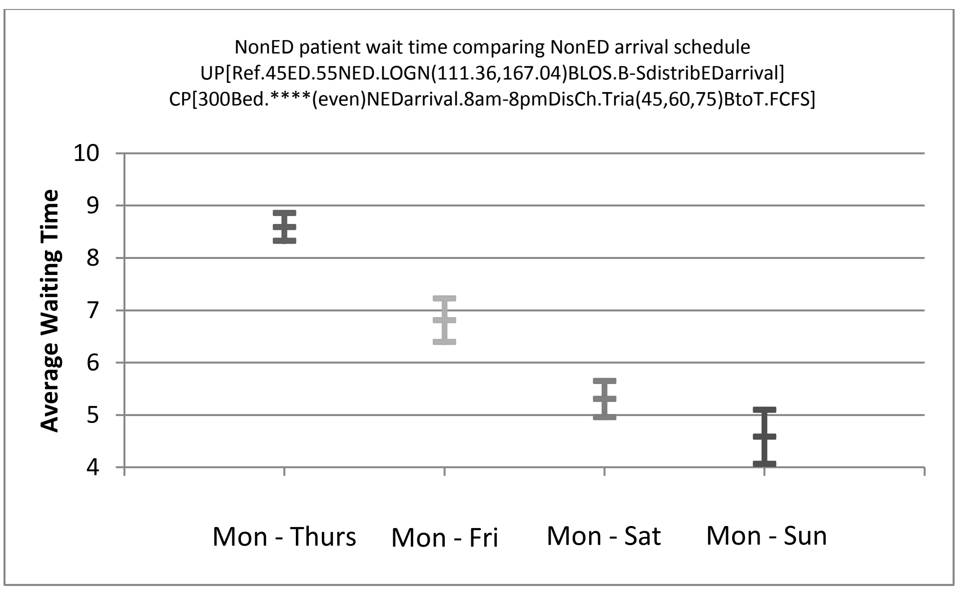


Figure 42 NonED patient wait time comparing NonED arrival schedule for a 300 bed referral hospital

ED			Mon - Thurs	Mon - Fri	Mon - Sat	Mon - Sun
	Upper 95th		8.048	7.537	7.022	7.172
	Average		7.842	7.165	6.719	6.705
	Lower 95th		7.636	6.793	6.416	6.238
NonED						
	Upper 95th		8.854	7.221	5.642	5.097
	Average		8.587	6.805	5.299	4.579
	Lower 95th		8.32	6.389	4.956	4.061

Table 13 ED and NonED patient wait time comparing NonED arrival schedule for a 300 bed referral hospital

4.5 Patient length of stay

A decrease in the average LOS by 4.8 hours shows significant decrease in patient waiting times for both ED and NonED patients in all hospitals types studied with starting LOS values of 111.36 and 106.56 hours.

4.5.1 75 bed community hospital

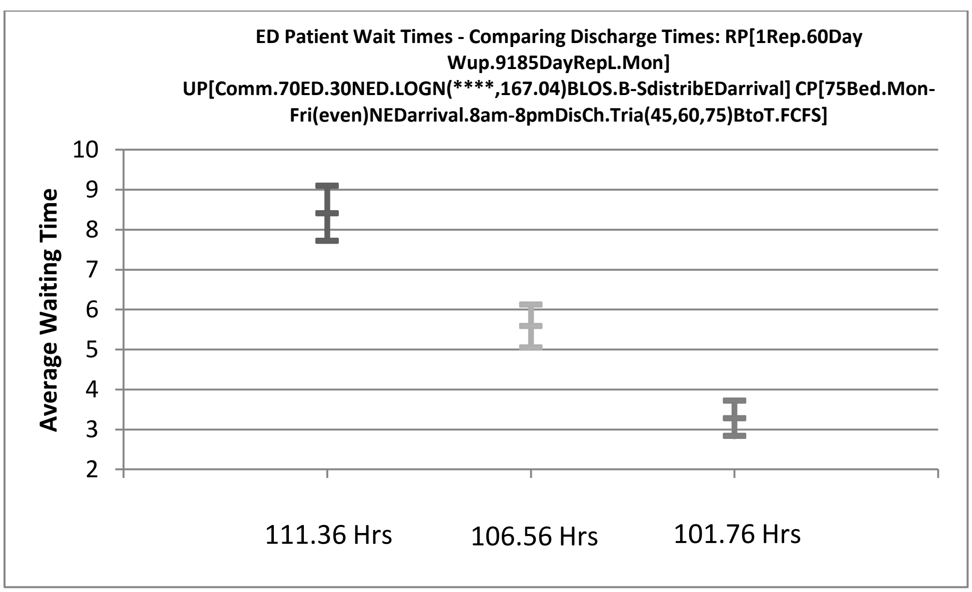


Figure 43 ED patient wait time comparing LOS for a 75 bed community hospital

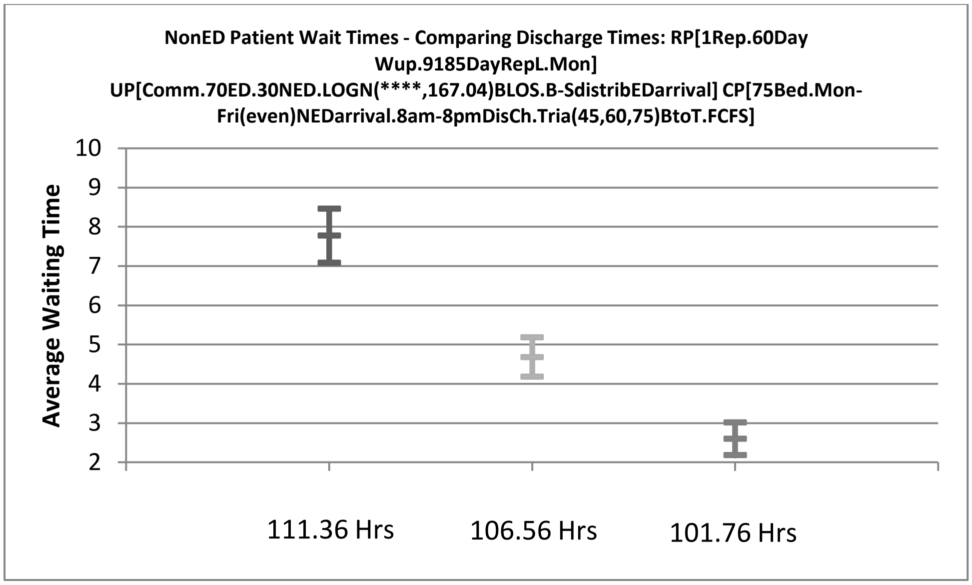


Figure 44 NonED patient wait time comparing LOS for a 75 bed community hospital

ED			111.36	106.56	101.76
	Upper 95th		9.091	6.116	3.718
	Average		8.404	5.581	3.275
	Lower 95th		7.717	5.046	2.832
NonED					
	Upper 95th		8.454	5.175	3.009
	Average		7.767	4.677	2.594
	Lower 95th		7.08	4.179	2.179

Table 14 ED and NonED patient wait time comparing LOS for a 75 bed community hospital

4.5.2 150 bed community hospital

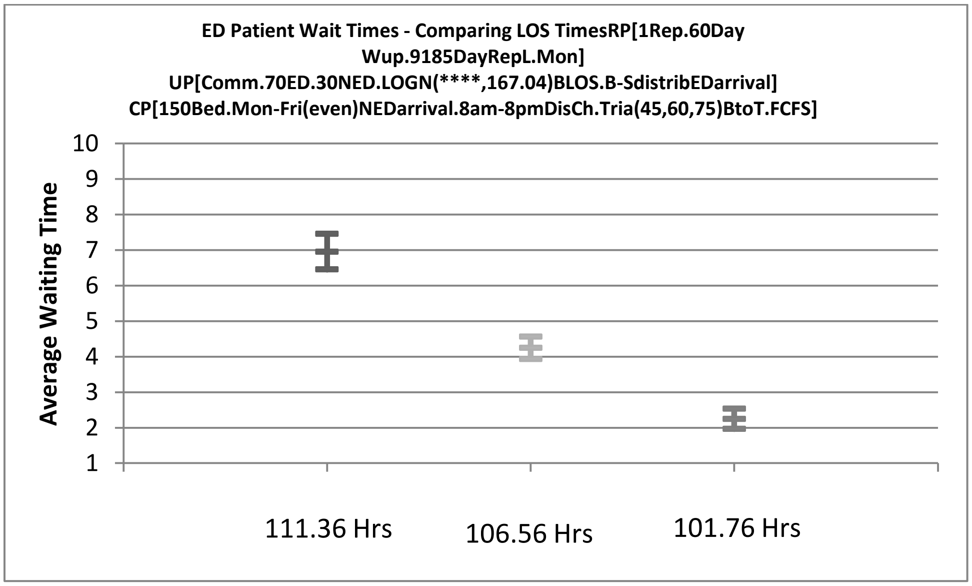


Figure 45 ED patient wait time comparing LOS for a 150 bed community hospital

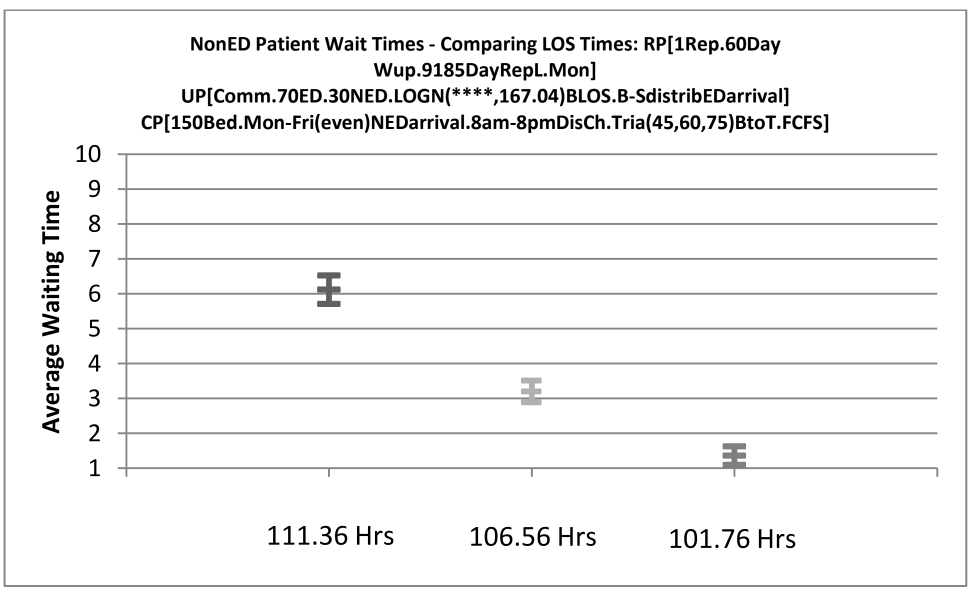


Figure 46 NonED patient wait time comparing LOS for a 150 bed community hospital

ED			111.36	106.56	101.76
	Upper 95th		7.452	4.558	2.528
	Average		6.953	4.244	2.246
	Lower 95th		6.454	3.93	1.964
NonED					
	Upper 95th		6.521	3.51	1.624
	Average		6.112	3.199	1.357
	Lower 95th		5.703	2.888	1.09

Table 15 ED and NonED patient wait time comparing LOS for a 150 bed community hospital

4.5.3 150 bed referral hospital

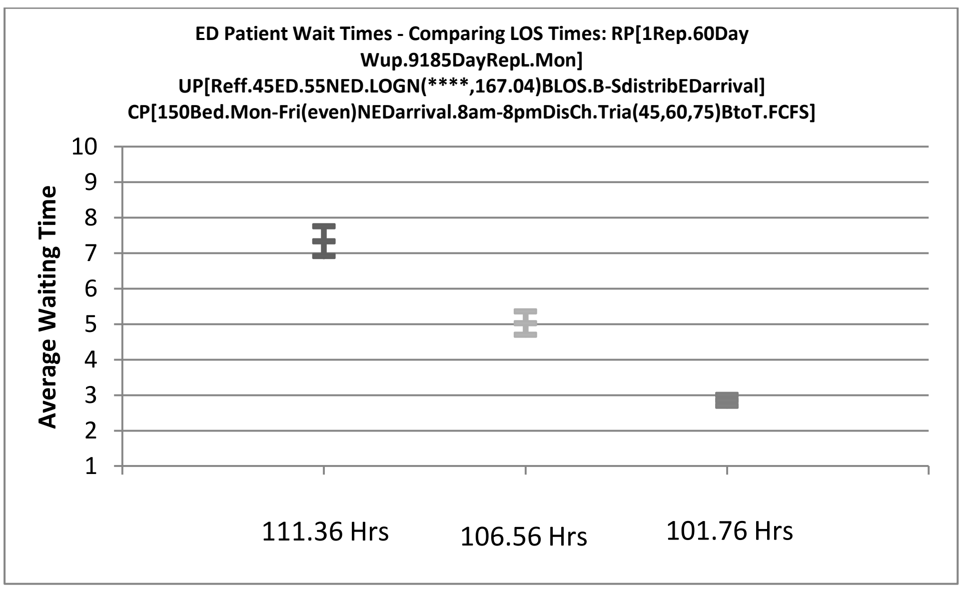


Figure 47 ED patient wait time comparing LOS for a 150 bed referral hospital

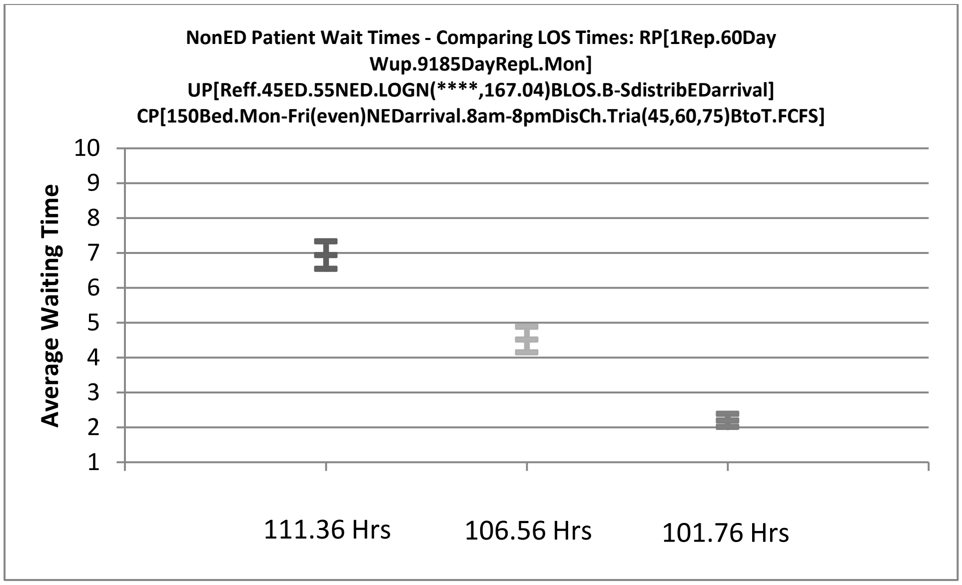


Figure 48 NonED patient wait time comparing LOS for a 150 bed referral hospital

ED		111.36	106.56	101.76
	Upper 95th	7.749	5.352	3.004
	Average	7.33	5.025	2.851
	Lower 95th	6.911	4.698	2.698
NonED				
	Upper 95th	7.328	4.879	2.38
	Average	6.933	4.514	2.193
	Lower 95th	6.538	4.149	2.006

Table 16 ED and NonED patient wait time comparing LOS for a 150 bed referral hospital

4.5.4 300 bed referral hospital

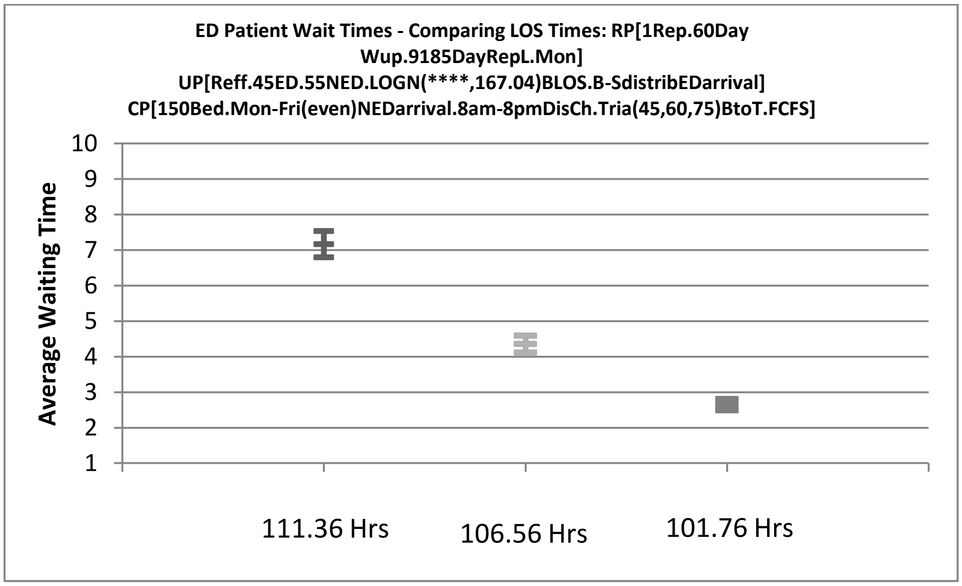


Figure 49 ED patient wait time comparing LOS for a 300 bed referral hospital

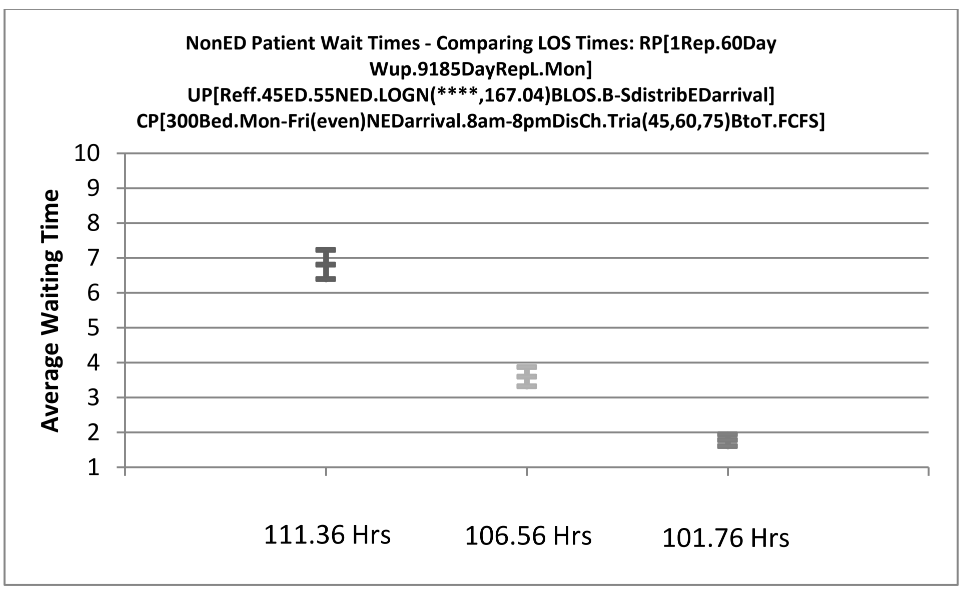


Figure 50 NonED patient wait time comparing LOS for a 300 bed referral hospital

ED			111.36	106.56	101.76
	Upper 95th		7.5365	4.589	2.807
	Average		7.165	4.351	2.648
	Lower 95th		6.7935	4.113	2.489
NonED					
	Upper 95th		7.221	3.868	1.948
	Average		6.805	3.593	1.775
	Lower 95th		6.389	3.318	1.602

Table 17 ED and NonED patient wait time comparing LOS for a 300 bed referral hospital

CHAPTER 5

DISCUSSION

5.1 Summary of Results

Four different hospital models have been created to represent a range of different types of hospitals in the United States. Each of our 4 hospital models (75 bed community, 150 bed community, 150 bed referral, 300 bed referral) have high bed occupancy with significant average waits for bed placement for both ED and NonED admissions. The modeled hospitals are often in a state of full capacity with every bed filled, creating a gridlock like behavior, which is when the patients in the model experience delays.

Even in steady state, there are significant random variations in average bed waiting times due to the peaks and valleys of the queue length. Such peaks and valleys will affect the entire hospital system in that a peak in the queue length will cause peaks in waiting time and peaks in the duration the hospital remains in gridlock. The peaks and valleys occur due to the method of creating the arrival rate and the lognormal distribution of length of stay values with a standard deviation that is greater than the mean.

By studying the effects of different parameters in the hospital system, steps were taken to understand the admission process and its effects on patient waiting time. Increasing the allowable discharge time from 12 hours (8 AM to 8 PM) to 24 hours a day significantly shortens average waiting time for both ED and NonED admissions. An increase from 12 hours (8 AM to 8 PM) to 16 hours (8 AM to 12 AM) showed a significant decrease in patient waiting time for only certain types of hospitals and patients. Spreading the same number of NonED admissions over two additional days significantly reduces average waiting time for NonED patients but not for patients admitted from the emergency department. Increasing the number of allowable arrival days for NonED patients from the baseline to include an additional day provided significant lower waiting times for NonED patients except for the 75 bed community hospital and again waiting time for ED patients did not decrease.

Reducing the overall average hospital length of stay (even by 0.2 days) has the greatest impact on reducing ED and NonED waiting time for bed placement in hospitals with high bed occupancy. As the other parameters fail to show significant results for all types of patients and all hospital types within this study, a decrease in LOS significantly lowers waiting time for all patient types and hospitals. Reducing the LOS of a patient may be the greatest means to lowering patient waiting time and improving the overall quality of health care based off the results of our model. Decreasing the LOS can be accomplished by improving the method of patient throughput, possibly improving a certain process, using better signals, improved technology, etc.

The model in this study provides insight into the hospital admission process based on the assumptions in representing a component of the health care system. Although simplified in many aspects, we believe that invaluable information can be learned through the model on the admission process of hospitals and how ED and NonED patients compete for beds. Using simulation will not guarantee real life results but provide an approach to tackle the inefficiencies that plague our health systems today. In combination with the results from studies such as this one, with physicians, health care providers, researchers, there is no doubt that progress will be made to eventually find methods of creating a health care system that is efficient, sustainable, and provide higher quality care.

5.2 Transparency and Validation

Transparency and validation of a model is required for readers to gain confidence in the model's results and implications on the process being simulated. Transparency is the method that shows how a model's structure, equations, parameter values, and assumptions can be reviewed to provide sufficient information which gives the reader the ability to see the model's accuracy, limitations, and potential applications. Validation judges the model's accuracy in the ability to provide the correct results if the process was run in an actual health care setting. Transparency shows what and how the model is run while validation will determine how well. (Eddy *et al.* 2012)

Throughout the process of this study, and the collection of data, every component of our model is transparent with the intent of providing all the necessary information to show the model's purpose, sources of information, structure, and results to the best of our knowledge. Many of the details are covered in the methods section of this study with the reasons and method of applying the data to our model. Many of the model's technical aspects are also covered in the methods section describing how the model was built and structured to reflect the admission system of ED and NonED patients. By providing a transparent model, we hope that the model's intent to provide information on the model's accuracy, limitations and potential solutions for a hospital admission system will be understandable and valid.

5.2.1 Face Validity

Face validity is subjective, where the inputs and outputs of a model reflect the current understanding of experts of the study (Eddy *et al.* 2012). By looking at the results of our model, increasing the duration of the discharge process, decreasing the length of stay, and leveling the arrival days of NonED patients should decrease patient waiting time based on how they affect patient throughput. The model behaves in such a way that the clinical experts of the health care process should agree with the trends of the results. For example, by increasing the discharge process, when patient's time of care is completed, there is a greater chance that their LOS is completed within the discharge time period allowing for a faster turnaround of beds.

5.2.2 Verification

Verification examines the internal consistency of a model which inspects the accuracy of mathematical calculations and implementation of the model (Eddy *et al.* 2012). As this study uses a commercial simulation package, more emphasis was taken to verify the inputs and if the correct values were used during the simulation runs. A great deal of rigor was applied when first building the model, to make sure that each input variable provided the proper values which would create a hospital admission system that reaches steady state and causes waiting for two different types of patients. The patient's length of stay was individually calculated by creating a separate model with just a process module having a delay with a lognormal distribution with a mean of 111.36 hours and a standard deviation of 167.04 hours. The model was run for one year, and the exported LOS values was best fitted to a distribution with an average of 108.04 and standard deviation of 147.47 hours. The skewed right lognormal distribution that was obtained from the test confirmed the validity of the LOS input variable as the distribution is believed to converge to a mean of 111.36 and S.D of 167.04 hours seen in Figure 3.7.

Comparing the theoretical and simulation for the number of arrivals based on the hour of day was conducted for both ED and NonED patients seen in Figures 3.11 and 3.12. The arrival of patients also needed to be Poisson distributed and was verified by counting the number of patients arriving each hour of the day. Over a one year period, the percent of an event in the number of patients arriving in a single hour of day was compared to the percentage of times the event occurred in the simulation. Two different hours of the day for ED patients is shown in Table 3.4 comparing the percentage of the Poisson distribution based off of the mean arrival and the percentage of the event occurring in the simulation. Through checking the total number of patients arriving by hour and checking the percentage of the number of events occurring, the arrival rate of patients arriving matches what we wanted to do.

The ARENA simulation model was also built in portions, validating the model by component, making sure that each section was validated and functioned properly. The pieces of the model was broken into the arrival process, waiting for bed process, removing patients with completed LOS, bed process, and finally the discharge process. The most difficult hurdle when creating the model was the implementation of finding patients with completed LOS due to the need of two conditions for a single queue that also checks every patient. The problem was that the waiting for bed hold module could only check for a number of conditions for the first patient in line. If the first patient happened to have a large LOS, the queue would increase without any patients leaving even if a patient's LOS was complete while in queue. This scenario was undesirable, being the reason dummy entities were created to check for patients with completed LOS while in the queue explained in the methods section 3.3.2.

Due to our model's extensive verification of the input parameters, we are confident that the model is behaving and creating an instance of the health care admission process given the assumptions of the model. Also many of the same input variables were highlighted in Lowery (1996) who explained steps into creating a hospital admission system through simulation.

5.2.3 Cross Validation

Cross validation is the method of comparing results of other models that addresses similar problems to our study (Eddy *et al.* 2012). Helm *et al.* (2009) showed that by reducing variability through a more flexible system showed improvements in hospital efficiency. Distributing patient demand improved patient flow be decreasing waiting time through a discrete simulation model by June *et al.* (1999). Bekker and Koeleman (2011) using a quadratic programming model shows how smoother admissions stabilizes bed occupancy levels where the more even distribution of elective admissions throughout the week provide a decrease in variability and bed demand. Although the admission of NonED is steady throughout a day in our model, by spreading the number of days in which NonED patients arrive, which spreads the arrival of patients throughout the week more evenly, lowers NonED waiting time and improves hospital efficiencies.

Other studies from May *et al.* (2011) have also shown that the stochastic element of arrivals and duration of procedures creates significant deviations which are also observed in the study as random arrivals and LOS durations create a system of peaks and valleys. The conceptual model by Asplin *et al.* (2003) found that a delay in the discharge process could be a factor causing inpatient boarding in the ED, which is also seen in our study as the discharge process is able to relieve some of the pressures and decrease patient waiting times.

5.2.4 External Validation

External validation uses the results of the study and compares them to the data of actual events within the industry and can be also applied to components of the model (Eddy *et al.* 2012). A study done by Boston Medical Center showed the importance of elective surgery scheduling in our study NonED admissions and its impacts on bottlenecks within the system. Addressing NonED arrivals and decreasing daily patient volumes had significant impact on lowering NonED waiting times.

The Chartis Group (2007) had similar results who found the benefits of optimizing patient throughput and its improvement of the hospitals overall system. There are definitely differences between the Chartis Group and the work done through the models of this study, but the overall theme of improving throughput in essence is the same as decreasing a patients LOS, which has significant reduction in waiting time for both ED and NonED patients. A high variability in the LOS can often create a hospital admission system unable to avoid high rates of cancelations due to operational difficulties in Gallivan *et al.* (2002). Gallivan *et al.* (2002) findings are validate how in this study, the high standard deviation of the LOS of patients creates an often gridlocked hospital with very high bed utilization. The NHS Institute for Innovation and Improvement also stated that reducing LOS releases capacity in the system and emphasized a proactive approach to decrease patient LOS through predictive discharge methods, visual triggers, nurse led discharges, and a greater need for patient awareness of the discharge process.

Forster *et al.* (2003) conducted an observational study of a 500 bed acute care teaching hospital which shows the peaks and valleys that exist within a hospital system confirmed that our results' own peaks and valleys can be common in a congested hospital.

5.3 Limitations

An extensive discussion on the limitations of a simplified admission and discharge process provides a deeper understanding of simulation and its limitations to model or predict the health care process. Such a discussion is not meant to highlight how the software falls short of reality but to help understand the limitations of the model and provide foundation and motivation for improvement.

5.3.1 Input parameters

As the length of stay was used to represent the time of the patient's bed request until the time of completed care, there were some limitations in representing the true LOS value. The LOS national mean value represents the days stayed overnight which does not factor in how long in hours the patients stayed in a bed, or when they were discharged. The national average is found using units in days stayed overnight where in the simulation, the average is converted into hours. If a patient arrives at 8 AM and is discharged the next day 8 PM, although having a LOS of 36 hours, the amount of time the LOS value contributed to the national mean is still the same as a patient arriving the same day at 5 PM and being discharged the next day at 9 AM (16 hours), each being 1 day. Converting the LOS from the average number of overnights into what was used as the LOS in our study is a limitation to be considered in future studies.

The LOS is used as a national average and doesn't distinguish LOS values for the different types of patients. Both ED and NonED patients use the same LOS distribution but also there is even more of a limitation in that an actual hospital has many more different types of patients and types of beds utilized with varying LOS values.

The method of creating a hospital with only two types of patients (ED and NonED) is clearly far from reality since a hospital has many different types of patients. The arrivals of NonED patients is also assumed to arrive with an even hourly distribution with no arrivals on the weekends for the baseline case. We believed that NonED arrivals on weekends were negligible relative to the number of weekday arrivals. Also, the hourly distribution of ED patient admission was used from Baystate Medical Center and represents the average hourly arrival of ED patients but was not found using the average of every hospital. However, we believe that there are similarities between EDs throughout the United States and using the data from Baystate Medical Center was the only way to gain access to the hourly admission rate.

Correlation could also exist in a 1 replication simulation run. Although using the batch mean method attempts to create an unbiased standard error by treating each batch as if independent, there will be some correlation between the values and the points on the boundaries of a batch (Banks 2005, Kelton 2007).

The bed turnover time in the model used values from Baystate Medical Center which equals the bed cleaning time. There is a difference in that the model lacks the time it takes for a staff member to notice and request for a bed clean from the point a patient is discharged.

There is also a limitation of creating the arrival rates of ED and NonED patients using Little's Law with L, as the number of beds in the system. Little's Law gives an arrival rate of patients with L being the number of patients in the entire system, however, our model includes a waiting time queue creating a system with more than L patients. This assumes that the arrival rate of patients may in fact be less than what the system can possibly handle. However, the use of Little's Law was to initially find an appropriate arrival rate of patients to create a system that has patients waiting for beds.

5.3.2 ARENA Limitations

The ARENA simulation model is a discrete event simulation software with the ability to model processes but is set to behave in the way the software was built which may result in limitations that should be considered.

In ARENA, time between events happen instantly as discrete events, so in our model, when a bed is available, a patient is placed in the bed instantaneously and there is no delay in this process. Such a process takes into account many of the resources and networks involved in the hospital and are simplified from a real hospital admission process.

The simulation doesn't take into account situations in hospitals when idle beds exist, when beds are unavailable for use based on them not being cleaned after discharge. There is also no signal process, no delay, nor any problems with cleaning staff availability or willingness, such as nurse aversion. Beds are also cleaned as soon as a patient is discharged and made ready for the next patient in the waiting for bed queue.

All patients waiting to leave or ready to be discharged will leave based only on the timeframe of the allowable discharge hours. In the model, there are no staff requirements, nor any additional precautions for a patient's LOS completed outside the allowable discharge hours. If there is a queue which builds up the waiting to leave queue due to the hour of day being outside the allowable discharge hours, every patient in the queue will be discharged together at the start of the following day's discharge window. The patient discharge process becomes instantaneous within the discharge window.

The waiting for bed queue is assumed to hold patients in a first come first serve manor with no priorities, no critical patients, or differentiation between the arrivals of each patient besides the time that they arrive.

5.3.3 System Limitations

Our study is also limited by how the model was created with a set of assumptions which give certain system limitations.

The LOS was configured in the model to represent the patients time from bed request until the point of completed care ready to be discharged. However, if the LOS of patients were completed outside the discharge window, the patient's time in the system is extended until discharged. A 24 hour discharge period would represent a better representation of the average 4.6 LOS value.

Another limitation that is of concern is the use of Little's Law as the source of creating the arrival rate of patients within this system. We would like to acknowledge the shortcomings of using Little's Law in a system that has time varying elements as is shown to be biased when using time varying arrival rates and long service times (Kim and Whitt, 2012). The input variables are all time varying in that the discharge process and arrival rates depend not only the hour of day but also the day of the week. Kim and Whitt (2012) discuss a Time-Varying Little's Law (TVLL) that may prove to be a better method of creating a more realistic system, however their study used only constant, linear, quadratic, and sinusoidal arrival rates.

The number of beds considered is also limited to the four types of hospitals created for this study to represent a wide range of hospitals. The arrival rate of patients per day is found through Little's Law which creates a crowded system with a hospital that has high utilization for the entirety of the simulation. The use of this arrival rate assumes that the hospital in the study is in a state of grid lock, with high bed occupancy. Within the model, there is no set of actions performed based on the state of the hospital which would occur in the real world. Grid lock hospitals can perform actions such as speeding up discharges or canceling scheduled surgeries, etc. in order alleviate the crowded hospital system.

The model is also limited to the 2 types of hospitals with the set percentages of ED and NonED patients between the referral and community hospitals. There is no sensitivity analysis done to see the differences in ED and NonED percentages like a 80:20 ED:NonED or a 55:45 ED:NonED make up.

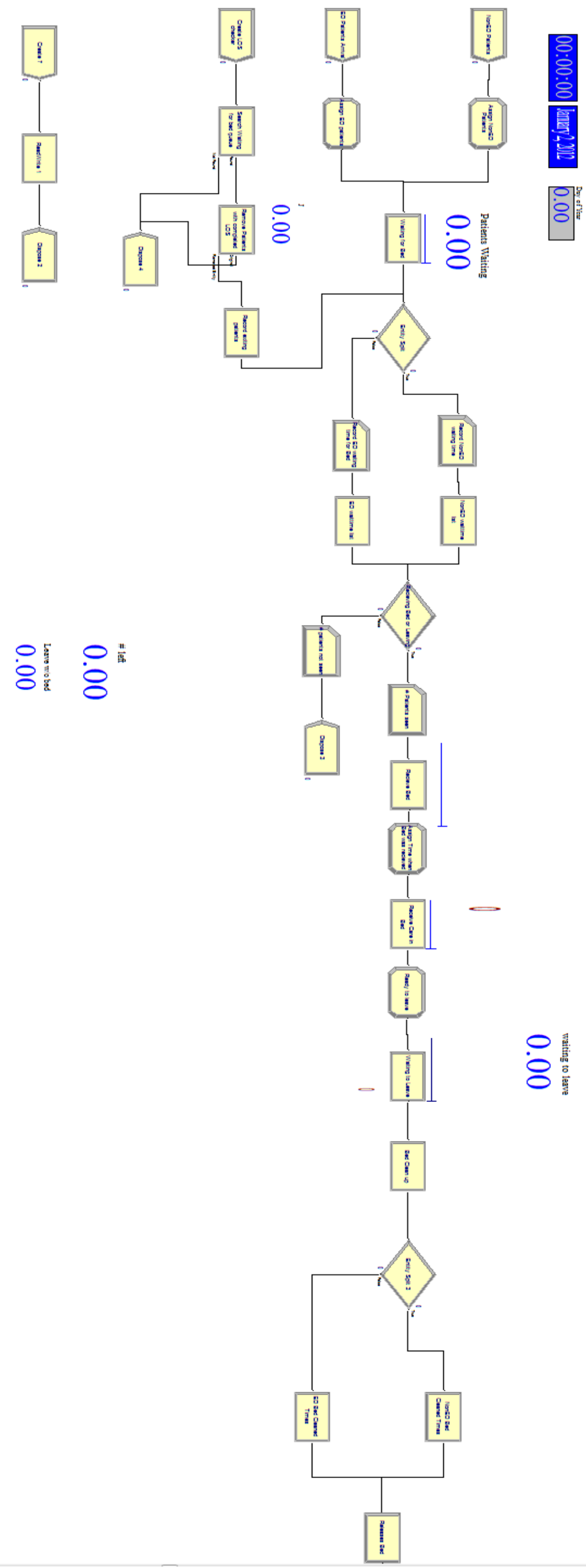
These are some of the limitations within this study and provide insights into the model and the assumptions that were made.

CHAPTER 6

CONCLUSION

There is a common theme in the literature and in our study which points to the importance of patient flow and improving throughput as the best way to combat the extensive waiting times that exist in the healthcare admission process. (Haraden and Resar (2004), Boston Medical Center (2004), Kloehn (2004)) Understanding the admission process would provide benefits to explaining how the system behaves and solve critical bottlenecks. Simulation is not a perfect representation of the real world and how the real system behaves, but is able to help provide insights into the health care system. However, use of discrete event simulation models have become more relevant in the literature to analyze health care systems (Jacobson *et al.* 2006), and the results from this study can provide healthcare decision makers with a deeper understanding of the relationships of the various input parameters. Although there are many challenges ahead, there are future opportunities to implement novel industrial engineering and operations research techniques to improve the health care system (Gupta and Denton (2008)). The stochastic and dynamic nature of the industry as policies and technology continually change, improvements in the method of providing care must be addressed to build a lasting and efficient high quality system.

APPENDIX: FULL ARENA MODEL



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