ABSTRACT

SLOCUM, RYAN FIELD. Improving Chemotherapy Infusion Operations through the Simulation of Scheduling Heuristics. (Under the direction of Dr. Thom Hodgson and Dr. Javad Taheri).

Over the last decade, the healthcare industry has experienced a substantial shift from inpatient care to outpatient services as the ability to provide timely, safe outpatient care has increased. Due to the variety of treatments, volatility of drugs, and variable patient conditions, chemotherapy delivery is among the most complex treatments administered in an outpatient setting. However, there has been a dramatic movement away from inpatient chemotherapy treatments, such that nearly 90% of all infusions are now administered outpatient. This shift has challenged oncology clinics to make chemotherapy treatment as widely available as possible, while attempting to treat all patients within a fixed period of time. Many oncology clinics attempt to maximize throughput by overbooking appointments, which has resulted in excessively large waiting times for patients without necessarily reducing the probability of incurring overtime hours. The methods discussed in this paper examine various scheduling heuristics with a goal of reducing the average patient waiting time by 20% and the average amount of nurse overtime by 25%.

The study is broken down in to three components: data analysis, simulation structure, and scheduling results. Historical data from the chemotherapy clinic was used to determine the average patient arrival time, the number of patients treated each day and how frequently the various chemotherapy regimens were administered. Chemotherapy regimen data was used to determine the average infusion length and the probability of a patient requiring lab work prior to treatment. There were several ancillary processes, ranging from the phlebotomy station through the chemotherapy pharmacy, that were essential to modeling the system. In the absence of historical data, anecdotal evidence from the clinic's staff was used to determine appropriate distributions.

Using the values and distributions derived during data analysis, a Monte Carlo simulation of the chemotherapy clinic was built using Visual Basic for Applications (VBA). The simulation examined the impact of altering the current schedule, where all patients arrive at 8:00 AM, to a schedule that assigned patients to two or three different appointment times based on the expected length of their chemotherapy infusion.

The results found multiple scheduling policies that could be easily implemented at the Durham VAMC chemotherapy clinic with the best solutions reducing average patient waiting time by 24% and reducing average nurse overtime by 66%. As the ability to detect cancer increases and the treatment protocols improve life expectancy, demand for chemotherapy services will continue to increase. Outpatient chemotherapy clinics willing to carefully examine their existing scheduling policies will be the most likely to efficiently and effectively meet the demands of a growing field.

Improving Chemotherapy Infusion Operations through the Simulation of Scheduling Heuristics

by
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BIOGRAPHY

Captain Ryan Field Slocum graduated from the United States Military Academy in 2006 with a Bachelor of Science in Operations Research and was commissioned as a Second Lieutenant in the United States Army Infantry Corps.

After completing U.S Army Airborne School, Ranger School, and the Mechanized Leaders Course, his first assignment was with the 1st Battalion, 67th Armor Regiment, 2nd Brigade Combat Team, 4th Infantry Division in Fort Carson, Colorado. He deployed in support of Operation Iraqi Freedom from 2008-2009, where he served as an infantry platoon leader and as a company executive officer.

Upon his redeployment from Iraq, Ryan began his second assignment with the 5th Ranger Training Battalion at Camp Merrill in Dahlonega, Georgia, where his unit was responsible for training future Rangers on mountain warfare tactics and techniques. He spent two years in the mountains of Dahlonega, where he was the commander of Headquarters and Headquarters Company for 15 months.

Following graduation, Ryan will join the United States Military Academy Department of Mathematical Sciences as an instructor for three years.

ACKNOWLEDGMENTS

To my wife, Danielle, thank you for your love and continued support over the last seven years. You always made sure I had plenty of time to focus on my work, as well as my golf swing. I always knew you were a talented multi-tasker, but you have made running a household, working a full-time job, and juggling a newborn baby look so easy. I want to reassure you that your efforts have not gone unnoticed—now that you have a firm grasp on life, the Army is rewarding you with your fifth move in seven years.

To my father, Bob Slocum, thank you for raising such a cohesive family and for always putting your kids first. You were the best teacher a son could ever ask for. Although our time together here in Raleigh was cut short, I will always be grateful for the four months we had together.

To my brother, Wes Slocum, and sister-in-law, Mandy Slocum, thank you for serving as a constant source of motivation throughout this process. I am amazed by the patience and strength you exude while taking Drew to his chemotherapy appointments. It is hard to imagine waiting three or four hours to start a chemotherapy infusion with an infant, and my sincere hope is that this research will encourage clinics to reexamine their scheduling policies so that long waits become the exception instead of the norm.

To Dr. Thom Hodgson, thank you for your patience, support, and ridicule. You have been an outstanding mentor throughout this process and I thank you for making this an enjoyable, challenging experience.

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CHAPTER 1

INTRODUCTION

In 1930, Congress authorized the President to establish the Veteran's Administration (VA), in order to provide care for the men and women who served this country. While the VA provides a wide range of services to Veterans nationwide, its healthcare system is arguably the most important and most costly service. Since its creation, the VA healthcare system has expanded from 54 hospitals to 153 hospitals, 909 community based outpatient clinics, and 135 nursing home clinics. VA Medical Centers (VAMCs) provide full spectrum services, ranging from routine outpatient services to emergency care to specialized services such as oncology, neurology, and prosthetics. Typically, VA hospitals are co-located adjacent to medical schools, allowing experienced physicians to provide excellent care to veterans while training the next generation of medical providers.

This paper will focus specifically on improving scheduling for the outpatient chemotherapy clinic at the Veteran's Affairs Medical Center in Durham, North Carolina. The Durham VAMC provides care to over 200,000 veterans across 26 counties in North Carolina. However, since not all VAMCs are capable of providing oncology services, the Durham VAMC treats patients traveling from northern South Carolina, southern Virginia, and as far east as the North Carolina coastal counties.

The chemotherapy clinic is open 250 days a year and it will administer more than 3,500 doses of chemotherapy in 2013. The clinic is staffed with five chemotherapy certified nurses that cycle patients through 14 infusion chairs throughout the day. The clinic administers over 80 different chemotherapy regimens (regimens refer to the combination of one or more drugs) and provides ancillary services such as phlebotomies and blood transfusions. While some infusions take 15 minutes, others take upwards of six to eight hours—yet in each case, the patient is told to arrive at 8:00 am for treatment. This practice has resulted in very long wait times for the patients and significant overtime hours for the nursing staff.

The daily process for the chemotherapy clinic consists of three major phases: lab work, pharmacy processing, and the chemotherapy infusion.

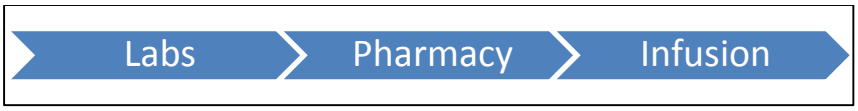

Figure 1- 1: Three phases of chemotherapy delivery

When patients arrive to the clinic, their first stop is the phlebotomy station. The phlebotomy station is staffed with two phlebotomists, one arriving at 6:00 AM and the other arriving at 7:30 AM. Patients are called in to the phlebotomy station on a first come, first served basis. The phlebotomist draws multiple blood samples, which are then escorted to the hospital's main lab. Lab tests are required because providers must ensure their patients can safely receive chemotherapy. Chemotherapy drugs are fundamentally toxic to the body and typically work by either destroying cells or preventing cell replication. The drugs are unable to differentiate between good cells and cancer cells, which are both affected during chemotherapy treatments, so lab tests are essential for determining whether a patient can withstand their next round of treatment. Once the main lab completes the testing, the patient's doctor will review the results to ensure the patient can tolerate treatment. If the patient is healthy enough for treatment, the doctor will notify the attending nurse to submit the patient's chemotherapy order to the pharmacy. If the patient is not a viable candidate for treatment, the doctor will either postpone treatment to a later date or they may supplement the patient with a blood transfusion, platelets, etc.

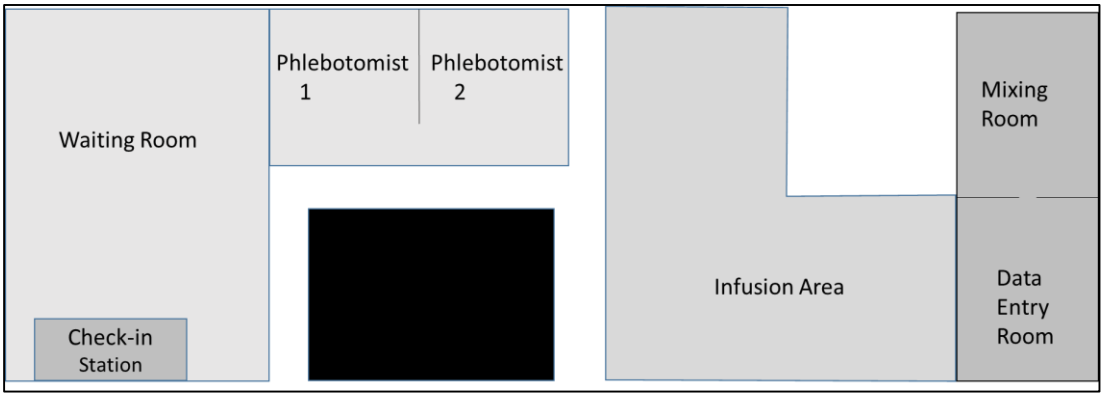

Figure 1- 2: Diagram of the Durham VA Medical Center Chemotherapy clinic

Unlike many VAMCs, the Durham clinic has a dedicated pharmacy located next to the infusion clinic. The pharmacy is staffed with two pharmacists who rotate between working in the hospital's main pharmacy and the chemotherapy pharmacy. The pharmacy operates as two single serve processes in series. The order starts with one pharmacist entering all of the patient and order information and printing out drug labels. Once data entry is complete, the second pharmacist will gather all of the necessary supplies to mix the drug in the neighboring "clean room" under a ventilation hood. Once the drug has been prepared, the pharmacy delivers the chemotherapy drugs to the infusion clinic. The pharmacy processes drug orders on a first in, first out basis, unless one of the nurses asks the pharmacists to bump an order to the front of the line (typically for patients with very long infusion times).

While the nurses wait for their patients' lab results and chemotherapy drugs from the pharmacy, they collect vital signs and administer chemotherapy pre-medication drugs, which must be taken at least 30 minutes prior to starting an infusion. Once the nurses receive their patients' chemotherapy drugs, the process is fairly deterministic since they are pumped in to the patients' blood stream at a predetermined rate. Occasionally patients experience adverse reactions to the chemotherapy drugs, which can delay or prematurely end a treatment, but these instances are very rare.

VAMCs are at a significant disadvantage when it comes to controlling their patient flow. In many cases, patients rely on VA sponsored buses to get to the hospital; and unlike most community hospitals, some patients will be traveling over three hours for their appointment. As a result, VAMCs are reluctant to enforce strict adherence to appointment times and will generally do everything in their power to treat patients whenever they arrive. However, by telling every patient to arrive at 8:00 AM the chemotherapy clinic cannot effectively control the order in which patients are treated.

When every patient is scheduled to arrive at 8:00 AM, the clinic ensures the lab, pharmacy, and nursing staff will be fully utilized in the morning and the staff rarely waits on patients to arrive; however, patients spend significantly more time in the system waiting for service. Furthermore, this is not necessarily the most efficient scheduling method as it creates a longer queue at the phlebotomy station, which may delay lab results for certain patients. When patients with short infusions get their lab results ahead of those patients with long infusions, the pharmacy builds a backlog of orders that

are tail heavy with long infusions. Now, instead of starting a five-hour infusion at 10 AM, the nurses might not be able to start the infusion until 12 PM.

As a population of patients, veterans with cancer are one of the last demographics that should spend hours waiting for service. The goal of this project was to build a simulation of the clinic to examine how various scheduling heuristics affected the average waiting time in the system (measured from the time a patient checks in until the patient starts his/her chemotherapy infusion) and the clinic's annual overtime cost. The first step was to build a simulation that accurately models the current system, when every patient was told to arrive at 8:00 AM. The simulation used a combination of historical data and anecdotal evidence from the clinic's staff to model various service times. A collaborative effort from the nursing staff, pharmacy, and doctors verified that the system is modeled correctly, and historical overtime data was used to validate the simulation's construction. Once the base schedule simulation was built, the method of paired comparisons examined the impact of each proposed schedule against the current schedule and pairwise substitutions were made until the best scheduling solution was identified.

The next Chapter will examine existing literature and common techniques for clinical scheduling. Chapter 3 discusses the data analysis used to determine the appropriate input values and distributions, followed by Chapter 4 which discusses the Visual Basic for Applications (VBA) simulation structure. The research results are listed in Chapter 5, conclusions in Chapter 6, and Chapter 7 concludes with a discussion of future research for scheduling outpatient chemotherapy delivery.

CHAPTER 2

LITERATURE REVIEW

Nearly 90% of all oncology patients will be treated in an ambulatory (outpatient) setting over the course of their battle with cancer, which is why many professionals in the oncology and hematology field have realized a need for improved efficiency (Williamson, 2008). Although some outpatient clinics operate twenty-four hours a day, most mirror normal business hours, which presents the challenge of treating every patient within a limited period of time. Unlike the inpatient setting, outpatient nurses cannot pass their patient off to the next shift. Most infusion clinics tend to front load all of their appointments in an effort to reduce overtime hours, but this can result in long wait times for patients. Studies show that cancer patients tend to value quality of care above all other factors; however, excessive waiting times have become the most prevalent source of dissatisfaction (Thomas et al, 1997). However, quality of care and excessive wait times are not a zero sum game, which is why many researchers are attempting to find ways to improve outpatient chemotherapy scheduling techniques.

2.1 GENERAL SCHEDULING

The primary goal for chemotherapy clinics is to maximize the utilization of its infusion chairs so that the clinic can treat as many patients as possible in a single day without exceeding normal business hours. The current policy at the Durham VA clinic is an example of the simplest block scheduling techniques. In this case, the number of blocks, k, equals 1, and the number of patients assigned to that block, n, is equal to the total number of patients scheduled on that day. This technique is designed to minimize the service providers' idle times, but it typically comes at the expense of the patient whom experiences longer waiting times for service (Gupta and Denton, 2007).

The other end of the spectrum regarding block scheduling is to set the number of blocks equal to the number of patients, such that $k = n$, and the length of time allocated to each block k is equal to the expected mean service time for each n (Welch and Bailey, 1952). This type of schedule has several drawbacks, primarily that it works best for a single server process (which the chemotherapy clinic is not), and its complexity can be very challenging for schedulers to execute.

A common practice for primary care doctors is to use a "multiple-block/fixed interval rule" (Cayirli and Veral, 2003). Using this rule, clinics assign multiple patients identical appointment

times, which are spread out across equal intervals throughout the day. For example, three patients could be assigned appointment times at 8:30, and three more patients would be assigned appointments at 9:00. This works particularly well in primary care or general practice settings because the mean service time is usually small (less than 15 minutes), but the wide range of chemotherapy infusion times may prohibit chemotherapy clinics from using fixed intervals.

2.2 CHEMOTHERAPY SCHDULING

Very few outpatient services in the healthcare field are as complex as the delivery of chemotherapy because there are multiple ancillary processes that work together before a patient can start their treatment. Depending on the processing capacity and variability of those ancillary services (phlebotomists, lab technicians, and pharmacists), it can be extremely difficult to develop an accurate appointment system. Some clinics encourage pre-infusion appointments, allowing the providers to review lab results 24-48 hours prior to a patient's chemotherapy infusion, thereby eliminating the uncertainty of those processes, but this is not practical for VA hospitals since many of their patients travel a great distance for treatment. Much of the reviewed literature focused exclusively on the infusion phase of outpatient chemotherapy clinics, which is a significant simplification because it eliminates the uncertainty, variability, and delays of the lab and pharmacy phases (Chabot and Fox (2005), Delaney et al. (2002), and Turkcan et al. (2010))

One of the most significant advances in chemotherapy scheduling was the development of a meaningful patient classification system (Chabot and Fox, 2005). Gerri Chabot and Mary Fox developed acuity levels that represented a combination of the total amount of treatment time and the nursing attention each patient would require based on their prescribed chemotherapy regimen, where the acuity value ($1, 2, \dots, n$) was equal to the total treatment time divided by thirty minutes. Patients were scheduled using a multiple-block/variable interval system, with each nurse treated as a single-server and intervals were blocked off according to patient acuity levels. Chabot and Fox recognized that acuity levels did not eliminate the complexities involved in scheduling chemotherapy patients, but if clinics included acuity levels during the scheduling process they would be able to better quantify a nurse's workload.

Ayten Turkcan attempts to build on Chabot and Fox's work by developing algorithms and heuristics in a 2-stage integer program to minimize patient treatment delays and staff overtime, while maximizing staff utilization (Turkcan et al., 2010). In order to balance nurse workloads, the integer

program included each patient's acuity level, A_i, and for each nurse, the sum of their patient's total acuity was required to be less than or equal to a predetermined value, A^{max}. While this study provides the most detailed analysis of chemotherapy operations, yielding one of the best optimization methodologies in its field, it only examines the infusion phase of the outpatient chemotherapy treatment process. Without addressing the lab and pharmacy phases, Turkcan's planning and scheduling model cannot be implemented.

Of the few studies that have reached implementation and tested their algorithms or models, most are too specific to a particular clinic or hospital, thus their findings cannot be replicated elsewhere (Hendershot et al. (2005), Kallen et al. (2012), Belter et al. (2012)). Several clinics have attempted to create fast-tracking programs that assign a higher priority to patients with shorter infusion times or patients that require minimal nursing attention. These are logical strategies; however, their success is entirely dependent on pharmacy capacity, and neither of the studies discuss how to best schedule these appointments.

Seth Eisenberg highlights a common issue with many outpatient chemotherapy deliver systems, which is particularly evident at the Durham VAMC: nurses are involved in the scheduling appointments. Instead of focusing solely on providing care, some nurses have an active role establishing appointments and balancing their patient load (Eisenberg, 2009). When nurses manage appointments independently, clinics lose the ability to control patient flow through the system.

The volume of existing research regarding outpatient chemotherapy scheduling demonstrates the significant need for improvement, yet the vast majority of the research results cannot be implemented due to either an oversimplification of the problem or the complexity of the model. The few studies that reached implementation were generally designed for a specific subset of patients or the system required a resource capacity that could not be widely replicated. A simple and easy to implement heuristic that clinics could use as a guideline for scheduling chemotherapy appointments would be an invaluable tool.

CHAPTER 3

MODEL DEFINITION AND DATA ANALYSIS

The first step towards modeling the system was to build a network flow diagram that mapped a patient's movement through the clinic from their arrival through their departure. Appendix A illustrates how patients move through the Durham VAMC chemotherapy clinic. By looking at the flow diagram, it became evident which entities, attributes, processes, and resources are necessary to model the system.

First, the only entities in the system are the patients. The number of patients that entered the clinic varies from day to day, as does the type of chemotherapy regimens administered. The attributes that characterize each unique patient are:

1) Arrival Time
2) Chemotherapy Regimen

Both of these attributes are sampled from an appropriate distribution, which will be discussed in the sections below. Next, there are several sub-attributes that characterize a patients treatment requirements based on his/her chemotherapy regimen:

1) Appointment Time
2) Length of the Infusion
3) Labs required prior to receiving an infusion
4) Probability of needing labs

Under the current system, every patient's appointment time was 8:00 AM; however, adding the appointment time as an attribute allows the simulation to test scheduling heuristics that bring specific patient populations in at alternate appointment times.

The processes for this model are listed below and their corresponding processing times will be discussed in the following sections:

Processes
Blood Draw
Lab Processing
Wait on Chemotherapy Orders
Data Entry

Mix Chemotherapy Drugs
Chemotherapy Infusion

The resources for this model are listed below, along with their current capacity:

Resource	Capacity
Phlebotomist	1-2
Data Entry Pharmacist	1
Mixing Pharmacist	1
Nurse	3-4

Notice that the lab process does not have an assigned resource, because the clinic does not have the ability to process labs internally. Instead, lab processing times are modeled purely as a delay rather than a process that seizes a resource during its delay. Similarly, the process of waiting on chemotherapy orders is modeled purely as a delay.

With the system clearly defined, the remaining sections will discuss the distributions the model uses to simulate the chemotherapy clinic.

3.1 ARRIVAL TIME ANALYSIS

Although every patient is scheduled for an 8:00 AM appointment, the daily variance in arrival times is significant. Some patients try to "game" the system, knowing that if they show up early they can be the first patient in the queue, whereas other patients are indifferent to their arrival time because they know that their infusion will be an all-day event. It is difficult to quantify the impact of these beliefs or to account for them in a simulation, and it is probably unrealistic to assume patients would display the same behavior if the clinic used a meaningful appointment system. However, without having data to the contrary, all simulations follow the same arrival time distribution, regardless of the appointment time.

To model the patient arrival times, the simulation uses historical check-in times from the patients at the clinic. The earliest arrival time from the sample data is 6:30 AM and the latest is 10:20. However, there are only two patients who arrived after 10:00 AM and occasionally nurses tell their patients with shorter infusions to come later in the morning. Since these two data points are significant outliers (60 minutes greater than the next latest arrival time), it is reasonable to assume that these patients were not instructed to arrive at 8:00 AM, therefore they are excluded from the sample population.

The rest of the data points are scaled by subtracting the sample time from 6:30, where 6:30 is the earliest data point in the set. This step converts each data point from a time to the number of minutes it is from the lower bound (6:30).

The sample size of historical arrival times is limited due to a high cost of procuring the data and frequency of corrupt data samples. Since the number of data points is less than 500, the Sturgis rule is used to determine the appropriate number of bins in the histogram. The Sturges' rule states the number of bins to use is equal to J, where J is calculated using the following equation:

$$J = 1 + 3.3 * log_{10} * n$$
$$n = total\ number\ of\ observations$$
$$J = 1 + 3.3 * log_{10} * (72) \sim 7$$

Based on this parameter, and the exclusion of two outlier points, Arena's Input Analyzer tool creates the following histogram.

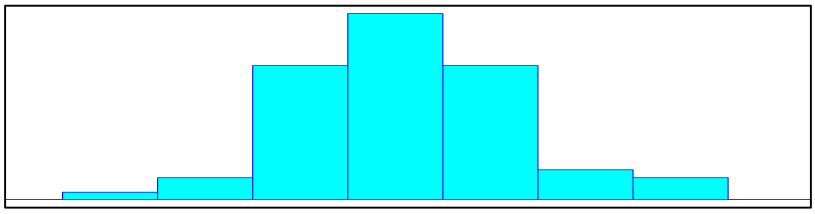

Figure 3- 1: Histogram of patient arrival times

The "best fit" function in Arena's Input Analyzer determines that the best fit for this data is a normal distribution; however, since the normal distribution is unbounded, it could provide unreasonable arrival time values that would skew the simulation's results. In this situation, a bounded distribution is appropriate because there is a clearly defined start time and if the patient arrives too late, they will be denied treatment. The uniform distribution is not appropriate for this data, but the triangular or beta distributions may work. After analyzing both options, the beta distribution is selected to model patient arrival times.

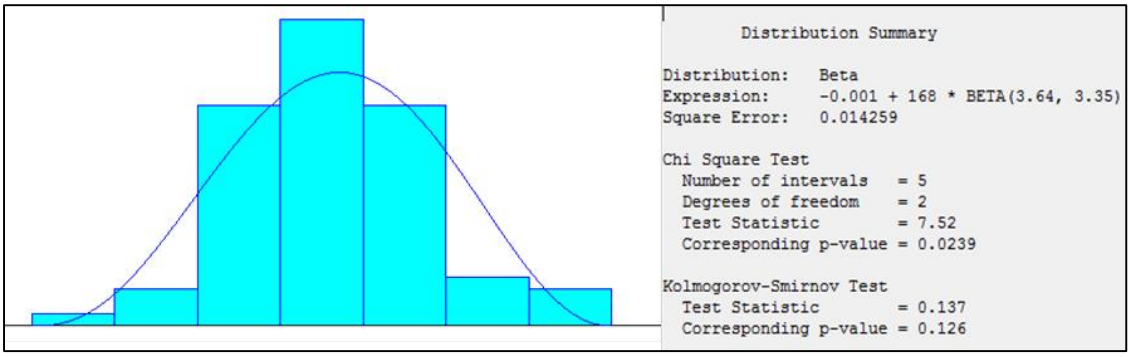

Figure 3- 2: Arena's Input Analyzer best fit for patient arrival times

This beta distribution tracks the histogram reasonably well in the body; however, the 2nd and 6th intervals are clearly overestimated. Since the Kolmogorov-Smirnov test statistic of 0.137 is acceptable and the P-value is acceptable, we will move use the beta distribution for this model and conduct sensitivity analysis to evaluate how sensitive the simulation is to the selected arrival time distribution. The expression "$168 * Beta(3.64, 3.35)$" is used to sample each patient's arrival time.

3.2 PATIENT DISTRIBUTION

In looking at the average number of patients that visited the chemotherapy clinic, a strong correlation emerges between the number of nurses scheduled to work on a given day and the number of patients that were treated. Historical data from January – October of 2013 revealed that 82.7% of the time there were four nurses on the schedule and 17.3% of the time there were 3 nurses on the schedule. There were three instances when the clinic operated with two nurses; however those days were limited to the 2nd, 3rd, and 4th of January, therefore they were excluded from the sample population. The average number of patients treated on a given day is reflected in the following chart:

Table 3- 1: The average number of patients treated and nurses working

Nurses	Probability	Avg. # Patients	STDEV
3	17.3%	12.1	2.190
4	82.7%	14.7	2.682

The number of patients who received treatment at the clinic when there are 3 nurses on the schedule is significantly different than the number of patients who are treated when there are four nurses on the schedule. After separating the sample data, Arena's Input Analyzer tool determined that the best fit for both sets is the normal distribution. Since the normal distribution could yield results outside of the historical lower and upper bounds, the beta distribution is selected.

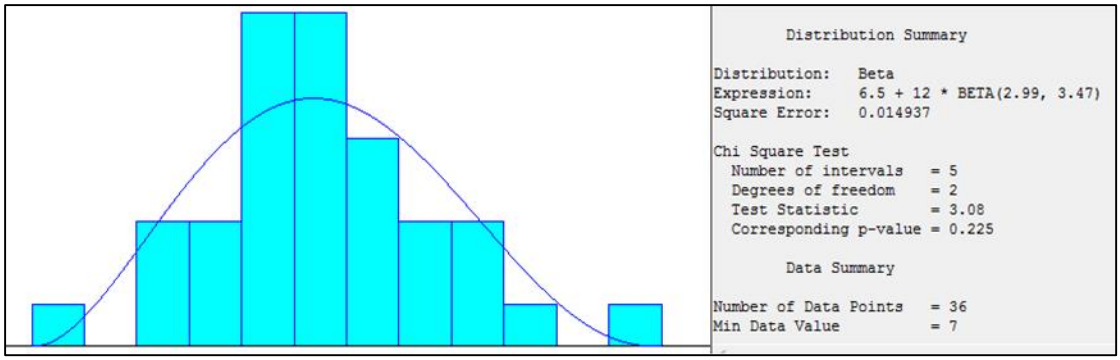

Figure 3- 3: Best fit for the number of patients scheduled for treatment with three nurses.

The beta distribution shown above is not a great fit for the histogram representing the patient population when three nurses are scheduled, which is like a result of only having 36 sample points. The beta distribution for the patient population when four nurses are scheduled looks like a much better fit, which is confirmed with a P-value of 0.474.

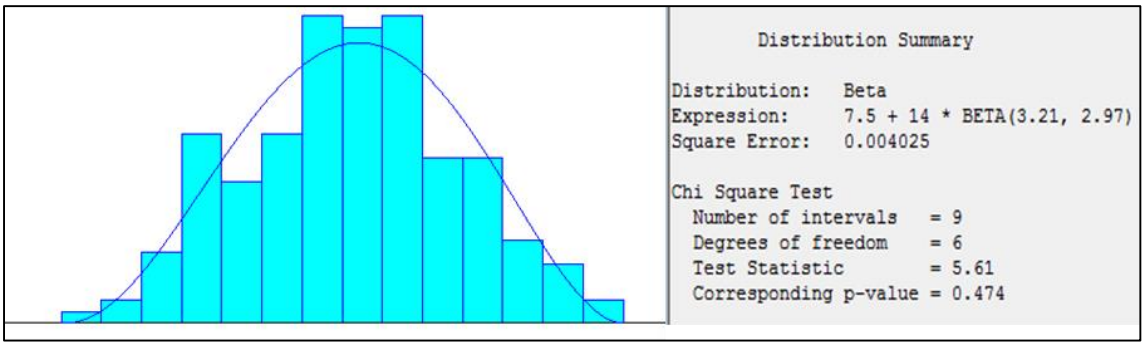

Figure 3- 4: Best fit for the number of patients scheduled for treatment with four nurses

Obviously, a beta distribution is a continuous distribution that would result in non-integer solutions when the inverse CDF method is used to randomly sample from the distribution. The following expressions are used to model the number of patient's that are treated each day (INT is the VBA command to round the resulting sample to the nearest integer value):

$INT(7 + 11 * Beta(2.42\ , 2.85))$ *When there are 3 nurses scheduled to work

$INT(7.5 + 14 * Beta(3.21\ , 2.97))$ *When there are 4 nurses scheduled to work

3.3 PHLEBOTOMY STATION

The phlebotomy station is the first queue that patients enter when they arrive to the clinic. The clinic has two phelobomists and under the current schedule, one works from 6:00 AM until 2:00 PM and the other works from 7:30 AM until 3:30 PM.

The average amount of time required to draw a patients blood is 5 minutes, although some patient's veins are more challenging than others, in which case a phlebotomist could spend up to 10 minutes trying to access a vein. After 10 minutes of trying to find a vein, the phlebotomist typically directs the patient to the infusion room where a specialist will come to draw their blood.

The difficulty in modeling the phlebotomy station is that chemotherapy patients represent less than half of the patients that come through the station each day. Hematology and oncology patients that are scheduled to meet with their doctor also use the clinic's phlebotomy station, and chemotherapy patients are not given priority. From personal observations, there are rarely two phlebotomists in the office at the same time, as one is either absent, on break, or completing administrative work instead of drawing blood samples.

The simulation assumes a constant service time of 10 minutes throughout the day, which is double the average service time during these periods. Sensitivity analysis is conducted in Section 4.6 to determine how sensitive the simulation is to this assumption. By using a service time of double the average service time, the model attempts to account for the impact non-chemotherapy patients would have on the phlebotomy queue length and waiting time.

3.4 LAB RESULTS

Each chemotherapy regimen attacks cancer cells differently, but the general concept is that chemotherapy drugs work by killing cells during a specific phase of the cell cycle —unable to

differentiate between good cells and cancer cells. Therefore, doctors require lab tests to determine whether a patient can withstand their next round of chemotherapy. The most common tests prior to receiving chemotherapy are complete blood count (CBC) tests and chemistry (Chem-7) tests. CBC tests measure a patient's ability to recover from an infection or blood loss, while the Chem-7 tests indicates whether a patient's metabolism will be able to clear the chemotherapy drugs adequately.

At the VA, over 95% of the regimens required both of these tests. Historically, nurses found the Chem-7 test results generally take longer to receive than the CBC test results. Without access to historical lab result times, the simulation estimated the lab result waiting times with a beta distribution. Anecdotal evidence from the nursing staff suggests that the fastest they can get both test results is 45 minutes, the mode is 70 minutes, and the longest amount of time they have waited is 150 minutes. The nurses also believe the average time they spend waiting for lab results is 75 minutes. Using this information, a beta distribution can be derived using the following system of equations:

$$Let\ a = 45, m = 70, b = 150, and\ E[t] = 75$$

$$\boldsymbol{EQ\ 1}\text{: }\boldsymbol{Mode}$$

$$\frac{(\alpha_1 - 1) * b + (\alpha_2 - 1) * a}{(\alpha_1 + \alpha_2 - 2)} = m$$

$$\boldsymbol{EQ\ 2}\text{: }\boldsymbol{Mean}$$

$$\frac{\alpha_1 * b + \alpha_2 * a}{\alpha_1 + \alpha_2} = \mu$$

$$\alpha_1 = 3.143 \text{ and } \quad \alpha_2 = 7.857$$

$$Time\ waiting\ for\ lab\ results \sim 45 + 105 * Beta(3.143, 7.857)$$

3.5 CHEMOTHERAPY ORDERS

Occasionally, a patient's lab results will be ready but the nursing staff does not have chemotherapy orders to give the pharmacy. When this happens, the nurse has to locate the patient's provider and ask them for chemotherapy orders. VA hospitals have not switched to electronic orders, thus the doctor must provide hard copy orders for every patient. This can be particularly challenging at the Durham VA hospital, because often times its oncologists spend several days each week at the Duke University Hospital.

The frequency of these delays is unclear, therefore the simulation uses anecdotal evidence to capture the process. According to the nursing staff, they have to track down orders for 25% of their patients. The lower bound for this delay is zero minutes, since it is possible for the doctor to deliver orders simultaneously with the lab results. The nurses agreed that the mode is roughly 10 minutes and the upper bound is 120 minutes; however, the most common waiting time is 20 minutes. Based on this information, and applying a similar system of equations outlined in Section 3.4, the following beta distribution is derived to model this delay:

$$Time\ to\ Locate\ Chemotherapy\ Orders \sim 120 * Beta(1.6667, 8.3333)$$

3.6 PHARMACY PROCESS

The pharmacy operates as two single server queues in series, where the first stage is the data entry phase and the second stage is the mixing phase. There are not two dedicated pharmacists that support the chemotherapy clinic, rather the hospital rotates its 14-16 pharmacists between the main pharmacy and the chemotherapy pharmacy to ensure all of their employees are capable of supporting either assignment and to limit the amount of exposure the pharmacists have to potentially harmful drugs.

Typically, the senior pharmacist in the chemotherapy room is responsible for the data entry portion of the process because it requires significant attention to detail and if the pharmacy makes a mistake, it usually occurs during data entry. For this simulation, the data entry phase refers to the time interval starting when the pharmacy receives the order until the time the mixing pharmacist enters the "clean room" to mix the drugs. During this phase, the pharmacist reviews the order and dosage calculations, enters the patient information, enters the drug data, and prepares a layout of drugs and mixing solutions. Once all of this is complete, both pharmacists review the layout together to verify that the order is correct—this ends the data entry phase. Typically, this process takes approximately 20 minutes, with a lower bound of 15 minutes and an upper bound of 25 minutes. This process is modeled with the following beta distribution:

$$Data\ Entry\ process = 15 + 10 * Beta(4, 4)$$

The next phase is the mixing phase, which begins when the mixing pharmacist enters the clean room. The mixing pharmacist carries all of the drugs to the ventilation hood and proceeds to mix all of the drug orders under the hood thereby reducing his/her exposure to the drugs. While some

of the drugs take longer to dissolve in the saline solution than others, this process normally takes approximately 15 minutes, with a lower bound of 5 minutes and an upper bound of 25 minutes. It is modeled with the beta distribution below:

$$Chemotherapy\ Mixing\ process = 5 + 20 * Beta(4, 4)$$

3.7 CHEMOTHERAPY REGIMEN DATA

Initially, one may think that the type of cancer, whether it be colon, lung, or pancreatic would be important to the simulation, but it turns out to be largely irrelevant. Instead, knowing which treatment regimen a patient is on provides much more useful information, because the regimen dictates the expected infusion length, probability of needing labs, and determines which labs are required prior to treatment.

Fortunately, the clinic's electronic calendar lists each patient by their corresponding chemotherapy regimen, so it is possible to query the database for a list of all patient appointments from 1 January 2013 to 1 July 2013. After sorting the results, the query yields the following results:

Table 3- 2: Frequency each chemotherapy regimen was administered

Regimen	Count
0.45 NSS	1
0.9 NSS	5
1 UNIT BLOOD	5
2 UNITS BLOOD	38
2 UNITS BLOOD + PLATELET	4
5-FU	3
ABVD	29
ADO-TRASTUZUMAB EMTANSINE	9
Ancillary Therapy	102
AZACITADINE(Vidaza)	34
BENDAMUSTINE HCL	16
BEP	13
BEVAC/CAPEC	3
BEVACIZUMAB	17
BLEOMYCIN	1
CARBO/DOCET	32
CARBO/ETOPO	19
CARBO/IRINO	17
CARBO/PACLI	83
CARBO/PACLI/BEVAC	9
CARBO/PEMET	17
CARFILZOMIB	34
CISPL/5-FU	1
CISPL/DOCET	34
CISPL/ETOPO	23
CISPL/GEMCI	7
CISPL/PEMET	8

Regimen	Count
CISPLATIN	13
CISPLATIN >75MG/M2	42
CYCLO/DOXOR	6
CYCLO/VELC	26
DECITABINE	58
DOCET/HERCE/PETUZ	4
DOCET/ZOMET	12
DOCETAXEL	56
DOXORUBICIN HCL	3
EOX	16
EPIRUBICIN	6
ETOPOSIDE	122
FC	40
FCR	21
FERRLECIT	3
FOLFIRI/OX	9
FOLFOX	21
GEMCITABINE HCL	54
HERCEPTIN	16
IFOSF/DOXOR	3
IRINO/BEVAC	10
IRINO/PANIT	1
IRINOTECAN HCL	24
IRON DEXTRAN	5
IV Medication	10
IVIG-GAMMUNEX	8
IXABEPILONE	3

Regimen	Count
Magnesium 1 gram	1
OXALI/BEVAC	21
OXALI/BEVAC 1st dose	34
OXALIPLATIN	59
PACLI/CARBO	8
PACLITAXEL	3
PAMIDRONATE >60 min	9
PANIT/IRINO	9
PANITUMUMAB	2
PEMETREXED	46
PLATELET	4
R-CHOP	18
R-CVP	2
R-EPOCH	4
R-ESHAP	3
RICE	4
RITUX/BENDA	39
RITUX/CYCLOS	1
RITUX/FLUDA/CYCLO	6
RITUX/VELC	1
RITUXAN	30
VELCA/PAMID	17
VELCA/ZOMET	41
VELCADE	84
VENOFER	47
ZOMETA	180
Total Patients	1829

However, this data was not entirely accurate. Sometimes nurses erroneously label patients with multiday treatments. For example, the FCR/FC regimen is a three day treatment, in which the first day the patient receives FCR followed by two days of FC. Logically, this means that the number of FC treatments should be twice the number of FCR treatments. However, the values listed above show that there were 47 FCR treatments and only 14 FC treatments. After discussing this anomaly with the nursing staff, they agreed that sometimes patients are not accurately added to the electronic calendar. There are two other regimens that were frequently mislabeled: carbo/etopo and cispl/etopo. The carbo/etopo regimen is a five-day treatment that administers carbo/etopo on day one, followed by four days of etoposide. The cispl/etopo regimen is a three-day treatment that consists of one day of cispl/etopo followed by two days of etoposide. After making the necessary scaling adjustments, the corresponding probability mass function (PMF) and cumulative distribution function (CDF) for the clinic's chemotherapy regimen distribution is shown below:

Table 3- 3: Probability Mass Function and Cumulative Distribution Function values

PMF	CDF	Regimen	Count
0.00055	0.00055	0.45 NSS	1
0.00273	0.00328	0.9 NSS	5
0.00273	0.00601	1 UNIT BLOOD	5
0.02078	0.02679	2 UNITS BLOOD	38
0.00219	0.02898	2 UNITS BLOOD + PLATELET	4
0.00164	0.03062	5-FU	3
0.01586	0.04647	ABVD	29
0.00492	0.05139	ADO-TRASTUZUMAB EMTANSINE	9
0.05577	0.10716	Ancillary Therapy	102
0.01859	0.12575	AZACITADINE(Vidaza)	34
0.00875	0.13450	BENDAMUSTINE HCL	16
0.00711	0.14161	BEP	13
0.00164	0.14325	BEVAC/CAPEC	3
0.00929	0.15254	BEVACIZUMAB	17
0.00055	0.15309	BLEOMYCIN	1
0.01750	0.17059	CARBO/DOCET	32
0.01039	0.18097	CARBO/ETOPO	19
0.00929	0.19027	CARBO/IRINO	17
0.04538	0.23565	CARBO/PACLI	83
0.00492	0.24057	CARBO/PACLI/BEVAC	9
0.00929	0.24986	CARBO/PEMET	17
0.01859	0.26845	CARFILZOMIB	34
0.00055	0.26900	CISPL/5-FU	1
0.01859	0.28759	CISPL/DOCET	34
0.01258	0.30016	CISPL/ETOPO	23
0.00383	0.30399	CISPL/GEMCI	7
0.00437	0.30837	CISPL/PEMET	8
0.00711	0.31547	CISPLATIN	13
0.02296	0.33844	CISPLATIN >75MG/M2	42
0.00328	0.34172	CYCLO/DOXOR	6
0.01422	0.35593	CYCLO/VELC	26
0.03171	0.38764	DECITABINE	58
0.00219	0.38983	DOCET/HERCE/PETUZ	4
0.00656	0.39639	DOCET/ZOMET	12
0.03062	0.42701	DOCETAXEL	56
0.00164	0.42865	DOXORUBICIN HCL	3
0.00875	0.43740	EOX	16
0.00328	0.44068	EPIRUBICIN	6
0.06670	0.50738	ETOPOSIDE	122
0.02187	0.52925	FC	40
0.01148	0.54073	FCR	21
0.00164	0.54237	FERRLECIT	3
0.00492	0.54729	FOLFIRI/OX	9
0.01148	0.55878	FOLFOX	21
0.02952	0.58830	GEMCITABINE HCL	54
0.00875	0.59705	HERCEPTIN	16
0.00164	0.59869	IFOSF/DOXOR	3
0.00547	0.60416	IRINO/BEVAC	10
0.00055	0.60470	IRINO/PANIT	1
0.01312	0.61782	IRINOTECAN HCL	24
0.00273	0.62056	IRON DEXTRAN	5
0.00547	0.62603	IV Medication	10
0.00437	0.63040	IVIG-GAMMUNEX	8
0.00164	0.63204	IXABEPILONE	3
0.00055	0.63259	Magnesium 1 gram	1
0.01148	0.64407	OXALI/BEVAC	21
0.01859	0.66266	OXALI/BEVAC 1st dose	34
0.03226	0.69492	OXALIPLATIN	59
0.00437	0.69929	PACLI/CARBO	8
0.00164	0.70093	PACLITAXEL	3
0.00492	0.70585	PAMIDRONATE >60 min	9
0.00492	0.71077	PANIT/IRINO	9
0.00109	0.71186	PANITUMUMAB	2
0.02515	0.73701	PEMETREXED	46
0.00219	0.73920	PLATELET	4
0.00984	0.74904	R-CHOP	18
0.00109	0.75014	R-CVP	2
0.00219	0.75232	R-EPOCH	4
0.00164	0.75396	R-ESHAP	3
0.00219	0.75615	RICE	4
0.02132	0.77747	RITUX/BENDA	39
0.00055	0.77802	RITUX/CYCLOS	1
0.00328	0.78130	RITUX/FLUDA/CYCLO	6
0.00055	0.78185	RITUX/VELC	1
0.01640	0.79825	RITUXAN	30
0.00929	0.80755	VELCA/PAMID	17
0.02242	0.82996	VELCA/ZOMET	41
0.04593	0.87589	VELCADE	84
0.02570	0.90159	VENOFER	47
0.09841	1.00000	ZOMETA	180

The majority of these regimens are administered intravenously (IV) or intra-arterially with an infusion pump. This process differs from the traditional gravity-fed process which is used for hydration fluids or units of blood, because it allows nurses and doctors to control the rate of flow in to a patient's body. As a result, nurses and doctors can make reasonably accurate predictions regarding how long an infusion will take based on the regimen. Furthermore, a regimen's infusion rate is not doctor dependent—there is an "industry" standard for oncology that prescribes the appropriate infusion rate for every chemotherapy drug. The clinic's nursing staff filled in the infusion time chart shown below.

Table 3- 4: Average infusion length for each chemotherapy regimen (h:mm)

Regimen	Infusion Time
0.45 NSS	0:30
0.9 NSS	1:00
1 UNIT BLOOD	1:30
2 UNITS BLOOD	3:00
2 UNITS BLOOD + PLATELET	3:30
5-FU	2:00
ABVD	0:55
ADO-TRASTUZUMAB EMTANSINE	0:30
Ancillary Therapy	0:20
AZACITADINE(Vidaza)	0:05
BENDAMUSTINE HCL	1:00
BEP	5:00
BEVAC/CAPEC	1:30
BEVACIZUMAB	1:30
BLEOMYCIN	1:05
CARBO/DOCET	1:30
CARBO/ETOPO	1:30
CARBO/IRINO	2:00
CARBO/PACLI	3:30
CARBO/PACLI/BEVAC	4:30
CARBO/PEMET	1:10
CARFILZOMIB	1:40
CISPL/5-FU	4:00
CISPL/DOCET	5:00
CISPL/ETOPO	5:00
CISPL/GEMCI	4:30
CISPL/PEMET	4:10

Regimen	Infusion Time
CISPLATIN	4:00
CISPLATIN >75MG/M2	4:00
CYCLO/DOXOR	1:20
CYCLO/VELC	1:10
DECITABINE	1:00
DOCET/HERCE/PETUZ	3:00
DOCET/ZOMET	1:15
DOCETAXEL	1:00
DOXORUBICIN HCL	0:20
EOX	2:20
EPIRUBICIN	0:20
ETOPOSIDE	1:00
FC	1:30
FCR	5:00
FERRLECIT	1:00
FOLFIRI/OX	5:40
FOLFOX	0:10
GEMCITABINE HCL	0:30
HERCEPTIN	1:00
IFOSF/DOXOR	2:00
IRINO/BEVAC	2:30
IRINO/PANIT	4:30
IRINOTECAN HCL	1:30
IRON DEXTRAN	7:40
IV Medication	1:00
IVIG-GAMMUNEX	4:00
IXABEPILONE	3:00

Regimen	Infusion Time
Magnesium 1 gram	1:00
OXALI/BEVAC	3:00
OXALI/BEVAC 1st dose	3:30
OXALIPLATIN	2:00
PACLI/CARBO	3:30
PACLITAXEL	3:00
PAMIDRONATE >60 min	1:30
PANIT/IRINO	2:30
PANITUMUMAB	3:00
PEMETREXED	0:10
PLATELET	0:20
R-CHOP	6:00
R-CVP	6:00
R-EPOCH	8:00
R-ESHAP	6:00
RICE	5:00
RITUX/BENDA	5:00
RITUX/CYCLOS	5:30
RITUX/FLUDA/CYCLO	6:30
RITUX/VELC	1:10
RITUXAN	4:00
VELCA/PAMID	1:35
VELCA/ZOMET	0:17
VELCADE	0:05
VENOFER	2:00
ZOMETA	0:15

In some cases, a regimen's infusion rate can be increased on subsequent visits, assuming the patient did not experience any adverse reactions to the drug during their previous infusion. For example, the chemotherapy regimen consisting of Fludarabine Cyclophosphamide Rituximab (FCR) takes 4.5 hours to complete if it is the patient's first infusion; but because nurses can double the infusion rate of Rituximab during subsequent infusions, it may only take 2.5 hours for some patients to complete the infusion. The clinic's electronic calendar often overlooks whether a patient is receiving their first dose or subsequent dose of FCR, therefore this simulation assumes all FCR appointments are first-time appointments. This is another source of bias in the model which will inflate the average overtime values.

One of the ways the simulation attempts to schedule patients is based on the expected length of their infusion. The simulation breaks the various infusions lengths in to four categories: Quick, Short, Intermediate, and Long. A quick infusion is one that requires less than 1 hour of chair time. Quick infusions account for 49.3% of all infusions. A short infusion is one that takes between 1 and 2 hours. Short infusions account for 21.4% of all infusions. Intermediate infusions are those that take

between 2 and 4 hours, and account for 18% of all infusions. Long infusions are those that take greater than 4 hours to administer and they account for 11.3% of all infusions.

The type of chemotherapy regimen that a patient is prescribed dictates the probability of needing labs when they arrive for treatment. Although labs are required prior to any patient receiving chemotherapy, labs are only required on the first day of treatment for patients receiving multiday infusions. For example, a patient that is on the FCR/FC regimen will have labs drawn on the first day of treatment when they receive FCR, but on days two and three the patient will come straight back to the infusion clinic and the nurses will give the pharmacy their chemotherapy order. In this example, the probability of needing labs for FCR is 1 and the probability of needing labs for FC is 0. Similarly, for a five day treatment such as Decitabine, a patient will only have labs drawn on 20% of their visits. Table 3-5 shows the probability of labs for all chemotherapy regimens administered in the last year.

Table 3- 5: The probability of a patient requiring lab tests

Regimen	Pr[Labs]	Regimen	Pr[Labs]	Regimen	Pr[Labs]
0.45 NSS	1.00	CISPLATIN	1.00	Magnesium 1 gram	1.00
0.9 NSS	1.00	CISPLATIN >75MG/M2	1.00	OXALI/BEVAC	1.00
1 UNIT BLOOD	1.00	CYCLO/DOXOR	1.00	OXALI/BEVAC 1st dose	1.00
2 UNITS BLOOD	1.00	CYCLO/VELC	1.00	OXALIPLATIN	1.00
2 UNITS BLOOD + PLATELET	1.00	DECITABINE	0.20	PACLI/CARBO	1.00
5-FU	1.00	DOCET/HERCE/PETUZ	1.00	PACLITAXEL	1.00
ABVD	1.00	DOCET/ZOMET	1.00	PAMIDRONATE >60 min	1.00
ADO-TRASTUZUMAB EMTANSINE	1.00	DOCETAXEL	1.00	PANIT/IRINO	1.00
Ancillary Therapy	1.00	DOXORUBICIN HCL	1.00	PANITUMUMAB	1.00
AZACITADINE(Vidaza)	0.14	EOX	1.00	PEMETREXED	1.00
BENDAMUSTINE HCL	0.50	EPIRUBICIN	1.00	PLATELET	1.00
BEP	1.00	ETOPOSIDE	0.20	R-CHOP	1.00
BEVAC/CAPEC	1.00	FC	0.00	R-CVP	1.00
BEVACIZUMAB	1.00	FCR	1.00	R-EPOCH	1.00
BLEOMYCIN	1.00	FERRLECIT	1.00	R-ESHAP	1.00
CARBO/DOCET	1.00	FOLFIRI/OX	1.00	RICE	1.00
CARBO/ETOPO	0.20	FOLFOX	1.00	RITUX/BENDA	1.00
CARBO/IRINO	1.00	GEMCITABINE HCL	1.00	RITUX/CYCLOS	1.00
CARBO/PACLI	1.00	HERCEPTIN	1.00	RITUX/FLUDA/CYCLO	1.00
CARBO/PACLI/BEVAC	1.00	IFOSF/DOXOR	1.00	RITUX/VELC	1.00
CARBO/PEMET	1.00	IRINO/BEVAC	1.00	RITUXAN	1.00
CARFILZOMIB	1.00	IRINO/PANIT	1.00	VELCA/PAMID	1.00
CISPL/5-FU	1.00	IRINOTECAN HCL	1.00	VELCA/ZOMET	1.00
CISPL/DOCET	1.00	IRON DEXTRAN	1.00	VELCADE	1.00
CISPL/ETOPO	0.20	IV Medication	1.00	VENOFER	1.00
CISPL/GEMCI	1.00	IVIG-GAMMUNEX	1.00	ZOMETA	1.00
CISPL/PEMET	1.00	IXABEPILONE	1.00		

Due to patients with consecutive days of treatment, each day is not independent from the previous day. Since this model only simulates one day at a time, it was important to include the probability of a patient requiring labs in order to account for the impact multiday patients have on the system. These patients are typically the first to have their pharmacy orders placed because they are able to bypass the lab phase and their chemotherapy orders are on hand from the previous day. If the model assumed patients always required labs the pharmacy would rarely receive orders before 9:00 AM, which is unrealistic.

CHAPTER 4

SIMULATION STRUCTURE

This chapter will discuss the desired outputs from the simulation and how to structure the model to yield those outputs. To build an accurate and appropriate simulation of the chemotherapy clinic, it is important to understand the stochastic nature of the problem. The clinic is an example of a transient process. The system essentially starts anew each morning when the first patient arrives and stops when the last patient leaves, therefore it never has an opportunity to reach a steady state behavior.

Since the system resets each day, the Monte Carlo method is a logical choice for this simulation. This Monte Carlo experiment simulates a single day in the chemotherapy clinic *n* number of times and reports the specified descriptive statistics with respect to the types of patients treated, average patient wait time, and any overtime incurred by the nursing staff.

4.1 DESCRIPTIVE STATISTICS

One of the fundamental aspects of modeling is identifying the outputs of interest. For the Chemotherapy clinic, there are several areas of interest. First of all, it is important to collect patient information regarding demand for services. The simulation needs to answer questions like: How many patients are treated each day and how many infusions by category are administered? In order to forecast future demand, it is also important to include the mean and standard deviation of quick, short, intermediate, and long infusions administered on any given day.

One of the Durham VAMC's primary focal points is on improving patient care. Considering that cancer patients typically have weakened immune systems, reducing the amount of time they spend in the hospital would be a significant step toward improving patient care. Therefore, the simulation needs to track the average waiting time in the system, along with the minimum and maximum waiting times in the system (these times were not representative of an individual patient, rather they represent the average waiting time on any given day).

While examining the average waiting time in the system, it is beneficial to examine the components that contribute to the unexpectedly large wait times. Hence, the simulation results separate the average wait time into two subcomponents: average lab processing time and average

waiting time for the pharmacy to process orders. Including these subcomponents made it easy to identify the bottlenecked processes and measure the effectiveness of each proposed scheduling policy against the base schedule.

The simulation also needs to measure the amount of overtime the nursing staff works each day. The policy for treating patients whose infusions are not complete by 4:00 PM is for two nurses to stay until the last patient departs. Whether there are six patients or only one patient completing their infusions, two nurses must stay until the last patient leaves. To calculate the amount of overtime the nursing staff works on any given day, the simulation uses the following equation:

$$Max[(Last\ Patient's\ Departure - 16{:}00) * 2, 0]$$

This is critical because overtime hours are the only performance statistic that the chemotherapy clinic keeps track of, which means it is the only measure available to validate the simulation.

The simulation captures data to determine the average amount of overtime based on the number of patients treated each day, as well as the average wait time in the system based on the number of patients scheduled. It is logical to expect the average amount of overtime to increase as the number of patients treated increases, and this statistic quantifies the impact each additional patient has on the system.

4.2 PAIRED COMPARISONS

When a simulation uses random sampling to compare two different schedules, it can be challenging to prove that one schedule is statistically better than the other, without running a very large number of iterations. To illustrate this problem, examine the two patient lists in Table 4-1.

Table 4- 1: Illustrates the different patient lists for two different iterations.

Sample 1 (n = 14)

Patient	Regimen	Infusion Length	Arrival
1	GEMCITABINE HCL	0:30	7:23
2	CISPL/DOCET	5:00	8:18
3	2 UNITS BLOOD	3:00	8:16
4	VELCA/ZOMET	0:17	8:09
5	ABVD	0:55	7:37
6	VELCADE	0:05	8:20
7	CISPLATIN > 75MG/M2	4:00	9:02
8	VELCADE	0:05	6:42
9	ZOMETA	0:15	7:32
10	FCR	5:00	8:17
11	ANCILLARY THERAPY	0:20	7:56
12	DOCETAXEL	1:00	7:24
13	IV MEDICATION	1:00	8:02
14	CARBO/PACLI	3:30	7:22

Sample 2 (n = 14)

Patient	Regimen	Infusion Length	Arrival
1	DECITABINE	1:00	6:54
2	GEMCITABINE HCL	0:30	8:08
3	ZOMETA	0:15	8:27
4	2 UNITS BLOOD	3:00	7:51
5	ZOMETA	0:15	7:39
6	OXALIPLATIN	2:00	7:47
7	FC	1:30	7:42
8	CISPL/GEMCI	4:30	7:36
9	CARBO/PACLI/BEVAC	4:30	6:42
10	CARBO/PACLI	3:30	9:13
11	ANCILLARY THERAPY	0:20	7:35
12	CISPLATIN	4:00	7:45
13	CARBO/DOCET	1:30	7:44
14	CARBO/PACLI/BEVAC	3:30	8:00

Both of these randomly sampled days have 14 patients, yet the types of infusions the patients receive and the patient arrival times are fairly different. The average infusion length for sample 1 is 106 minutes and the average arrival time is 7:52 AM. The average infusion length for sample 2 is 130 minutes and the average arrival time is 7:47 AM. Although sample 2 has a longer average infusion length, it results in 50 minutes of overtime whereas sample 1 results in 4 hours of overtime. These two iterations appear similar at first, but the results differ significantly. This example highlights a frequent occurrence when simulations use random sampling techniques, which can lead to skewed results; consequently, the number of iterations, *n*, must be very large to overcome the variance inherent in random sampling.

One way of reducing this issue is to use a technique known as paired comparisons. This method takes identical inputs, and runs them through the same sequence of events. The clinic's simulation does this by creating a patient list with the base schedule (all patients scheduled for 8:00 AM appointments) and shifting the selected patient population by a specific amount of time. Table 4-2 provides an example of a potential scheduling policy, where the number of blocks, *k*, is two, and the interval length separating the two blocks is three hours.

Table 4- 2: An example of a k = 2 scheduling policy

Patient Population	**Appointment Time**
Patients with infusions greater than 90 minutes	8:00 AM
Patients with infusions less than or equal to 90 minutes	11:00 AM

By applying the paired comparison method, the simulation generates the patient lists and arrival times shown below in Table 4-3. Notice the patient list is identical and the patients' arrival times with respect to their appointment time is scaled according to the proposed policy's interval length. This simulation applies the same randomly sampled arrival time value from the base schedule to the proposed schedule, instead of resampling from the beta distribution discussed in Section 3.1. If the patient arrives 15 minutes early for their 8:00 AM appointment in the base schedule, that patient will be 15 minutes early for their 11:00 AM appointment in the proposed schedule.

Table 4- 3: Paired comparison example

Patient	Regimen	Infusion Length	Appt Time	Arrival Time		Patient	Regimen	Appt Time	Arrival Time
1	FC	1:30	8:00	7:55	→	1	FC	11:00	10:55
2	VELCA/ZOMET	0:17	8:00	7:50	→	2	VELCA/ZOMET	11:00	10:50
3	CISPL/GEMCI	4:30	8:00	7:50		3	CISPL/GEMCI	8:00	7:50
4	ABVD	0:55	8:00	7:59	→	4	ABVD	11:00	10:59
5	RITUX/BENDA	5:00	8:00	7:50		5	RITUX/BENDA	8:00	7:50
6	AZACITADINE(Vidaza)	0:05	8:00	7:52	→	6	AZACITADINE(Vidaza)	11:00	10:52
7	R-CHOP	6:00	8:00	8:06		7	R-CHOP	8:00	8:06
8	IRON DEXTRAN	7:40	8:00	7:45		8	IRON DEXTRAN	8:00	7:45
9	IV Medication	1:00	8:00	7:54	→	9	IV Medication	11:00	10:54
10	CARBO/PACLI	3:30	8:00	7:52		10	CARBO/PACLI	8:00	7:52
11	ETOPOSIDE	1:00	8:00	8:10	→	11	ETOPOSIDE	11:00	11:10

This ensures the integrity of the comparisons and it eliminates the need to run an exceedingly large number of iterations to definitively declare one policy better than another.

It is important to realize the remainder of the simulation does not share identical sampling values. The blood draw, lab testing, and pharmacy processes contain randomness that is not identical for both schedules. Realistically, a blood sample drawn at 9:00 AM may take more or less time to process than a sample drawn at 12:00 PM, so it is reasonable to determine the processing times for these procedures by resampling from the distributions discussed in Chapter 3.

4.3 VISUAL BASIC SIMULATION

The software this simulation uses is a combination of Microsoft Excel and Visual Basic for Applications (VBA). While several other programs were considered, VBA's ability to store each iteration's output in a cumulative spreadsheet eases the comparison process between various scheduling heuristics. It is also a program that most administrators are comfortable with, which may allow them to manipulate and display the simulation results as they see fit.

4.3.1 PATIENT CREATION

Each iteration begins by randomly determining the number of nurses that will be scheduled for that day. In VBA, this is done by calling on a random number generator, "RND," and executing a vertical lookup to determine the number of nurses (based on the historical data presented in Section 3-1). The next step is to determine the number of patients that will receive infusions, which is correlated with the number of nurses working. This portion of the simulation calls on an "IF" statement that reads:

$$
\begin{aligned}
&If\ numNurses = 3\ Then\\
&\quad numPatients = INT(7 + 11 * Beta(2.42\ , 2.85))\\
&Else\\
&\quad numPatients = INT(7.5 + 14 * Beta(3.21\ , 2.97))\\
&End\ if
\end{aligned}
$$

With the number of nurses and patients determined, the next step is to assign each patient a chemotherapy regimen from the CDF shown in Section 3.7, as well as all of the regimen's corresponding attributes to the patient. The corresponding attributes include the infusion length, necessary labs, probability of needing labs, and the appointment time. Each patient's chemotherapy regimen is determined using a "FOR" loop that generates a random number (listed as the Regimen ID on the spreadsheet) and then the simulation uses a vertical lookup to determine the name of the regimen and all of its sub-attributes. This portion of the simulation produces the data shown in Table 4-4.

Table 4- 4: VBA patient generation list

Patient	Regimen ID	Regimen	Labs Required	Pr[Labs]	Infusion Length	Appt Time
1	0.0885885	Ancillary Therapy	CBC, Ferritin, Iron Saturation	1.0	0:20	8:00
2	0.3611163	DECITABINE	Chem-7, CBC	0.2	1:00	8:00
3	0.8443843	VELCADE	Chem-7, CBC	1.0	0:05	8:00
4	0.9684536	ZOMETA	Chem-7	1.0	0:15	8:00
5	0.5570014	FOLFOX	Chem-7, CBC	1.0	0:10	8:00
6	0.6012463	IRINO/BEVAC	Chem-7, CBC	1.0	2:30	8:00
7	0.2252803	CARBO/PACLI	Chem-7, CBC	1.0	3:30	8:00
8	0.3740575	DECITABINE	Chem-7, CBC	0.2	1:00	8:00
9	0.0052879	1 UNIT BLOOD	CBC	1.0	1:30	8:00
10	0.8164892	VELCA/ZOMET	Chem-7, CBC	1.0	0:17	8:00

The next step for the simulation is to determine the arrival times for each patient. Section 3.1 explained that patient arrival times follow a beta distribution, with respect to their appointment time. The beta distribution is shifted to reflect a 6:30 AM start time and the distribution is applied using the following expression:

$$For\ i = 1\ to\ numPatients$$
$$\quad Arrival_i = 6{:}30 + 168 * Beta(3.64\ ,3.35)$$
$$Next\ i$$

The processes outlined above complete the submodule "Call PatientList ()" (Appendix E-1). Once the patient list is determined, the simulation copies the data and pastes it to two separate worksheets. First, it pastes the data on the "current model" worksheet, then it pasted the data on the "scheduled model" worksheet. The underlying code for the "scheduled model" worksheet modifies the data by executing a vertical lookup to determine the proposed appointment time for each corresponding chemotherapy regimen, rather than assuming each patient is scheduled to arrive at 8:00 AM. Then, it adjusts the patient's arrival time using the following statement:

$$For\ i = 1\ to\ numPatients$$
$$\quad NewArrival_i = (ApptTime_i - 8{:}00) + Arrival_i$$
$$Next\ i$$

After this step, both the base schedule and the proposed scheduled have the exact same patient list and the patient arrival times have been scaled according to their designated appointment times. From this point through the end of the iteration, the coding for the simulation is identical for both models (See Appendices E-2 and E-3).

4.3.2 LAB PROCESS

Appendix A shows that the first process that a patient encounters is the phlebotomy station where their blood is sampled and sent for processing in the main hospital laboratory. However, some patients return for consecutive days of treatment; therefore they may skip the phlebotomy and lab process all together. The earliest a patient can arrive is 6:30 AM and the first phlebotomist arrives at 6:00 AM, thus if the patient requires testing, they will move directly in to the phlebotomy station.

$$
\begin{aligned}
&If\ NeedLabs_1 = 0\ Then\\
&\quad BloodDrawComplete_1 = Arrival_1\\
&Else\\
&\quad BloodDrawComplete_1 = Arrival_1 + 10\ minutes\\
&End\ if
\end{aligned}
$$

For the remaining patients, the simulation must check to see if the phlebotomy station is available before processing the next patient. To do this, the simulation uses a variation of Lindley's Recursion method to determine the waiting time for each subsequent patient passing through the phlebotomy station. If the phlebotomy station is empty when the second patient arrives, they could move directly in for service. If the phlebotomist is still working on the first patient, then the second patient cannot enter until the first patient departs. Since each patient was sorted according to their arrival time, the following pseudo-code shows how phlebotomy service times were assigned.

$$
\begin{aligned}
&For\ i = 2\ to\ numPatients\\
&\quad If\ NeedLabs_i = 0\ Then\\
&\quad\quad BloodDrawComplete_i = Arrival_i\\
&\quad Else\\
&\quad\quad BloodDrawComplete_i = Max[Arrival_i, BloodDrawComplete_{i-1}] + 10\\
&\quad End\ if\\
&Next\ i
\end{aligned}
$$

Once a patient moves through the phlebotomy station, the next step in the simulation is lab processing. Similarly, if a patient is returning for a consecutive day of treatment, they did not require lab testing. As discussed in Section 3.4, the simulation assumes the amount of time it takes to receive the final lab result can be modeled with a beta distribution. For each patient, the time until their lab results are received is calculated using the following logical expression:

$$
\begin{aligned}
&For\ i = 1\ to\ numPatients \\
&\quad If\ NeedLabs_i = 0\ Then \\
&\quad\quad LabResults_i = BloodDrawComplete_i \\
&\quad Else \\
&\quad\quad LabResults_i = BloodDrawComplete_i + (45 + 105 * Beta(3.143, 7.857)) \\
&\quad End\ if \\
&Next\ i
\end{aligned}
$$

After the labs are processed, there is a chance that the nursing staff has not received the doctor's chemotherapy orders, in which case the nurse must locate the doctor and wait for them to produce the drug orders. The probability of this delay is 25% and the length of the delay is modeled with a beta distribution based on anecdotal evidence. The simulation uses the following logic to simulate the delay:

$$
\begin{aligned}
&For\ i = 1\ to\ numPatients \\
&\quad If\ NeedLabs_i = 0\ Then \\
&\quad\quad OrdersWait_i = 0 \\
&\quad Else\ if\ RND < .75\ Then \\
&\quad\quad OrdersWait_i = 0 \\
&\quad Else \\
&\quad\quad ChemoWait_i = 120 * \text{Beta}(1.48,4.36) \\
&\quad End\ if \\
&Next\ i
\end{aligned}
$$

4.3.3 PHARMACY PROCESS

The next process in the clinic is to physically order the chemotherapy drugs with the pharmacy. The Durham VAMC uses hardcopy orders, which are placed in the window separating the chemotherapy pharmacy and the infusion clinic. The pharmacy is the last queuing process in the model and since it operates as a series of single-server queues, the same recursion method that was used to determine patient flow through the phlebotomy station is used to determine each chemotherapy order's flow through the pharmacy. First, the simulation identifies the time that the chemotherapy orders were received by taking the sum of the lab results time and any delay caused by waiting for chemotherapy orders. The simulation then sorts the data set from earliest chemo order time to the latest order time. The first order to reach the pharmacy moves directly in to the data entry process, if the order time is greater than 8:00. The pseudo code looks like the following expression:

$$DataEntryComplete_1 = Max[ChemoOrdered_1, 8{:}00] + (15 + 10 * Beta(4,4))$$

$$For\ i = 2\ to\ numPatients$$
$$DataEntryComplete_i = \text{Max}[ChemoOrdered_i, DataEntryComplete_{i-1}] + (15 + 10 * Beta(4,4))$$
$$Next\ i$$

The mixing process mirrors the data entry process, but it does not require the 8:00 AM conditions check used on the first patient's order. Since the range of the processing times for data entry and mixing overlap, it is possible for the second order to pass through data entry before the mixing pharmacist finishes the first order. To ensure the mixing pharmacist is available before the next job starts, the same recursion method is applied. Its pseudo-code looks like the following expression:

$$MixingComplete_1 = DataEntryComplete_1 + (5 + 20 * Beta(4,4))$$
$$For\ i = 2\ to\ numPatients$$
$$MixingComplete_i = \text{Max}[DataEntryComplete_i, MixingComplete_{i-1}] + (5 + 20 * Beta(4,4))$$
$$Next\ i$$

4.3.4 INFUSION PROCESS

When the pharmacy completes a drug order, the mixing pharmacist delivers the drugs to the infusion clinic through the window. The attending nurse receives the drugs and verifies the drug order and patient information with a second nurse. If there is an infusion chair available for the patient, this process typically takes between five and ten minutes, after which the nurse starts the infusion. However, Section 4.2 showed that sometimes the clinic treats as many as twenty patients, in which case only the first fourteen patients are guaranteed to start their infusion immediately.

To address the possibility of patients waiting for an infusion chair to vacate, the simulation maintains a running count of available chairs. It subtracts one available chair each time a patient arrives, and adds one available chair when a patient departs. If the number of available chairs is zero, the simulation uses a while loop to delay the patients infusion start time until a chair becomes available.

Once each patient begins their infusion, their departure time is calculated by adding their infusion start time with their infusion length that was populated during the initial patient creation.

4.3.5 DESCRIPTIVE STATISTICS

Once each patient has completed their infusion, the simulation calculates the daily descriptive statistics discussed in Section 4.1. First, it determines each patient's waiting times for the various phases of the clinic. It determines the lab waiting time by subtracting the lab completion time from the patient's arrival time. It determines the pharmacy waiting time by subtracting the chemo received time from the chemo ordered time. These values are averaged at the end of each iteration and recorded in a table.

The simulation also analyzes the infusion data (categories of infusions) for each iteration and stores the information in the same table mentioned above. Then it calculates whether the nursing staff worked any overtime hours for that iteration. Table 4-5 is an example of the simulation's output for a single iteration.

Table 4- 5: Simulation output table

Base Schedule	
Nurses	4
Patients	14
Infusion Data	
0-1 HR	6
1-2 HR	2
2-4 HR	3
> 4 HR	2
Avg. Wait Time	3:07
Wait on Lab	1:09
Wait on Pharmacy	1:33
Overtime hours	2:34

Proposed Schedule	
Nurses	4
Patients	14
Infusion Data	
0-1 HR	6
1-2 HR	2
2-4 HR	3
> 4 HR	2
Avg. Wait Time	2:27
Wait on Lab	1:05
Wait on Pharmacy	1:01
Overtime hours	1:03

The simulation takes this data and stores all of it on the "Stats" worksheet in a single row. Then it clears the existing data from the base schedule and the proposed schedule worksheets and runs another iteration of the simulation. The loop consisting of running an iteration, storing the iterations

descriptive statistics, and clearing the worksheets continues for as many iterations as the user specified on the main menu page (Appendix E-4).

4.3.6 SIMULATION RESULTS

Once the simulation completes its last iteration, the simulation produces a side-by-side comparison of the two schedules on the "Results" worksheet. It uses the data stored on the "Stats" worksheet to produce four tables. The first table shows the patient and nurse data, summarizing the number of patients that were treated and the average number of treatments administered by category (since the number patient and nursing data is identical for both schedules it is displayed in a single table).

Table 4- 6: Nurse and patient summary statistics

	AVERAGE	MIN	MAX	STDEV
Nurses	3.794	3	4	0.405
Patients	13.719	7	21	2.747
Infusion Data				
0-1 HR	6.732	0	15	2.273
1-2 HR	1.947	0	8	1.352
2-4 HR	3.480	0	11	1.747
> 4 HR	1.560	0	7	1.216

While the average number of patients treated on any given day could be derived from looking at the historical data, the average number of patients for each category of infusions was unknown. This simulation shows the average number of long infusions (> 4 hours) is only two per day, but the maximum value was eight patients. This is a significant deviation from the average, and as a result, the clinic is likely to incur signficant overtime. Since each iteration is stored on the same worksheet, it is easy to examine the consequences of scheduling eight long infusions on the same day. In this particular example, over the course of 7,500 iterations, the average amount of overtime given there were eight long infusions under the base schedule was 6.3 hours, whereas under the proposed schedule the average amount of overtime was only 3.4 hours.

The simulation also analyzes the effectiveness of each proposed schedule. This research focused on two major performance objectives: reducing overtime hours and reducing the average

waiting time in the system. In terms of reducing the average amount of waiting time, the scheduling heuristic affects the lab process and the pharmacy process by staggering patient arrival times. In terms of reducing the average overtime, the scheduling heuristic uses appointment times to prioritize a subset of the patient population, ensuring the pharmacy processes the longest infusions first. Table 4-7 compares the proposed schedule with the base schedule and computes the system improvement.

Table 4- 7: Proposed schedule's effect on the system.

	System Improvement
Wait Time	27%
Lab	7%
Pharmacy	39%
Overtime	62%

In this example, the average amount of time patients spent waiting for their chemotherapy infusion to start was reduced by 21% and the average nurse overtime was reduced by 59%. It also shows the proposed schedule reduced time spent waiting for lab results by 6% and the average waiting time for the pharmacy to process chemotherapy orders was reduced by 34%.

The simulation also provides information regarding the average amount of overtime, given a specific number of patients are scheduled for treatment. Figure 4-1 shows the average amount of overtime the nurses worked, based on the number of patients that were treated. Clearly, the proposed schedule significantly reduces the average overtime that the nurses worked. In many cases, the proposed schedule reduced the average overtime by more than 50%. For example, when 20 patients received treatment at the clinic following the base schedule, the nursing staff averaged nearly six hours of overtime. However, when the clinic followed the proposed schedule, the nursing staff averaged only two and a half hours of overtime—a 54% reduction. As the number of treated patients increases, the importance of treating patients in the correct order also increases.

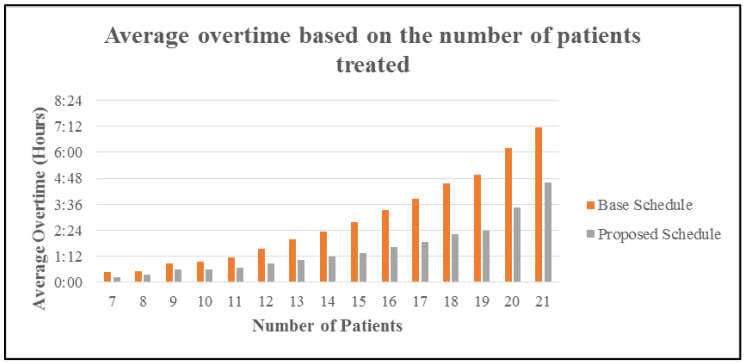

Figure 4- 1: Average overtime comparisons

The simulation also produces a graphic illustrating the impact that the number of patients treated has on the average waiting time in the clinic. Once again, the proposed schedule clearly reduces the patient waiting times, but the changes are not nearly as drastic, because scheduling cannot reduce the processing times for ancillary services. Without reducing the service times for each process leading up to the patient starting their infusion, even the optimal schedule will reach a lower-bound with respect to the average waiting time.

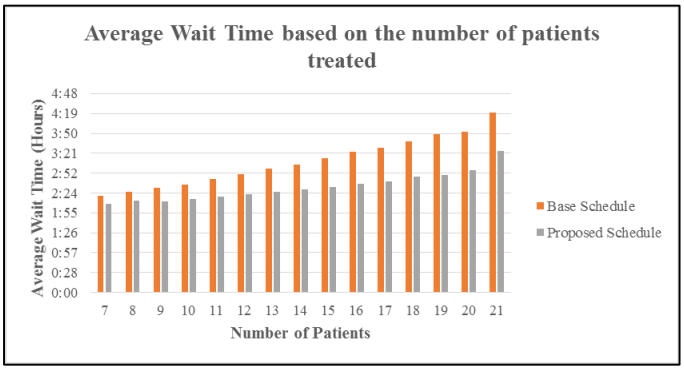

Figure 4- 2: Average waiting times comparisons.

4.4 VERIFICATION

This model uses a mix of historical data and anecdotal evidence to simulate the clinic's daily activities. Chapter 3 explained the inputs that were used to create the model, but it is equally important to verify that the simulation is constructed correctly. Multiple staff members from the clinic reviewed the system flow diagram (Appendix A), and verified the logic flow and decisions that occurred throughout the different phases of the system. There were some processes that were intentionally omitted from this model due to the rarity of their occurrences (appointment no-shows, adverse reactions to chemotherapy infusions, etc.); the nurses, pharmacists, and doctors all agreed that those processes were unnecessary to include.

4.5 VALIDATION

There are several output statistics that validate the construction of this simulation, including the number of patients treated, wait time statistics, processing times, and overtime data. Over the course of twenty replications of the simulation using 7,500 iterations, the average number of patients who were treated each day was 13.7, which matches the historical output. Also, the minimum (7) and maximum (21) fall within the lower and upper bounds of the clinic's historical values.

The processing times for lab results and the pharmacy match the anecdotal times presented by the nursing staff and the pharmacists. Additionally, personal observations of the chemotherapy clinic confirm that the simulation's backlog of chemotherapy orders at the data entry process is very indicative of true behavior.

Historical overtime data is also used to validate the simulation's output. In 2012, the infusion clinic tallied 460 overtime hours, and the nursing staff was on pace to log more than 500 overtime hours in 2013. This equates to roughly two hours of overtime each day. However, it is important to keep in mind that this model contains several biases. First of all, it assumes the longest possible treatment times for each chemotherapy regimen, which will inflate the overtime values. For example, Rituximab is a drug that takes 4 hours to infuse for a patient's first dosage, but subsequent doses are infused in 2 hours; however, this model treats each rituximab order as a four hour dose. Secondly, if a patient with a long infusion time arrives late (after 9:00 AM), the nursing staff typically asks the pharmacy to move that patient's order to the front of the line, allowing the patient to complete his/her infusion before 4:00 PM. This type of action occurs frequently, but this model does not allow for

infusions to break the first in first out protocol. Lastly, some chemotherapy regimens require pre-hydration fluids and post-hydration fluids, which are included in the total treatment time represented in Table 3-4. If the nursing staff does not expect the patient to finish their treatment before 4:00 PM, sometimes they are able to administer the post-hydration fluids simultaneously with the chemotherapy infusion. This is another source of bias that causes this model to overestimate the annual overtime.

Aside from the modeling biases that inflate the simulation's estimated overtime values, all other output values closely mirror the true system's values. Therefore, we can confidently state that the simulation accurately models the true system.

4.6 SENSITIVITY ANALYSIS

In the absence of historical data, this simulation used anecdotal evidence several times to estimate appropriate service time distributions. Although the staff at the Durham VAMC chemotherapy clinic has many years of experience, sometimes one's perception of "average time" can be skewed by rare outliers. For this reason, it was important to conduct thorough sensitivity analysis on the inputs that relied exclusively on anecdotal evidence. These inputs included: the phlebotomy station, lab processing, probability of waiting on chemotherapy orders, time spent waiting on chemotherapy orders, pharmacy data entry, and chemotherapy preparation. Since the number of observations used to model patient arrival times was relatively small, it was also included in the sensitivity analysis.

In order to determine how sensitive the simulation was to a specific input, each input was manipulated individually. If an input was insensitive to a large change, then it was reasonable to assume it would also be insensitive to a small change. Table 4-8 shows simulation results after each input was scaled by +/- 20%.

Table 4- 8: Based Schedule Sensitivity analysis results

Base Schedule (k = 1)

Input	-20%	Base	+20%	
Phlebotomy Time	3:03	3:05	3:07	Wait Time
	-1.1%	*N/A*	*1.1%*	
	2:25	2:26	2:29	Over Time
	-1%	*N/A*	*2%*	
Lab Processing Time	3:00	3:05	3:12	Wait Time
	-2.7%	*N/A*	*3.8%*	
	2:20	2:26	2:37	Over Time
	-4%	*N/A*	*8%*	
Data Entry Time	2:43	3:05	3:30	Wait Time
	-11.9%	*N/A*	*13.5%*	
	1:38	2:26	3:34	Over Time
	-33%	*N/A*	*47%*	
Probability of Waiting on Chemotherapy Orders	3:04	3:05	3:06	Wait Time
	-0.5%	*N/A*	*0.5%*	
	2:22	2:26	2:30	Over Time
	-3%	*N/A*	*3%*	

Base Schedule (k = 1)

Input	-20%	Base	+20%	
Wait Time for Chemotherapy Orders	3:03	3:05	3:07	Wait Time
	-1.1%	*N/A*	*1.1%*	
	2:25	2:26	2:30	Over Time
	-1%	*N/A*	*3%*	
Chemotherapy Preparation Time	3:02	3:05	3:09	Wait Time
	-1.6%	*N/A*	*2.2%*	
	2:21	2:26	2:32	Over Time
	-3%	*N/A*	*4%*	
Arrival Rate	3:14	3:05	2:58	Wait Time
	4.9%	*N/A*	*-3.8%*	
	2:16	2:26	2:43	Over Time
	-7%	*N/A*	*12%*	

These results indicate that of the six inputs derived entirely from anecdotal evidence, the simulation was only sensitive to data entry time distribution. The phlebotomy station was a fairly small delay in overall process, so it makes sense that its impact on the system's performance is small. Lab processing times, the probability of waiting for chemotherapy orders, and the wait time for chemotherapy orders were modeled purely as a delay, which means increasing or decreasing this input parameter merely changed how long it takes for each chemotherapy order to reach the pharmacy phase. Since none of these processes altered the order in which the pharmacy processed the orders, there was very little effect on the system. Similarly, since the main backlog of chemotherapy orders occurred at the data entry process, changes to the chemotherapy mixing distribution was unlikely to have a substantial impact on the system since it was downstream from the data entry process.

Knowing the data entry process was the biggest bottleneck in the system, it made sense for it to be the most sensitive input. With respect to the average wait time in the system, the data entry parameter was moderately sensitive to a 20% increase or decrease. Increasing the average processing time by 20% resulted in a 13% increase in the average wait time and decreasing the parameter resulted in an 11% decrease in wait time. The average overtime value was very sensitive to changes in the data entry distribution. Reducing the data entry time reduced the average queue length, and consequently made a substantial reduction in overtime (-33%). Increasing the data entry time

increased the average queue length and delayed the average start time for each patient's infusion. With each patient starting their infusion later in the day, the average overtime increased from 2:26 to 3:34 (+47%).

The last input parameter that was tested is the arrival time distribution. Due to the high cost of procuring historical data, the sample size was limited to 72 observations. This histogram clearly lends itself to a bell-shaped distribution, and Section 3.1 explained why a bounded distribution was used; however, it is possible that the small sample size underestimated or overestimated the variability and/or centrality of the distribution. Examining the effects of altering the current input by +/-20% revealed a negative correlation between wait time and overtime. Reducing the parameter by 20% decreased the variability and shifted the centrality to the left. With patients arriving earlier and closer together the average wait time increased by 4.9%, but the average overtime decreased by 7%. Conversely, when the distribution was increased by 20% the variability increased and the centrality shifted to the right. This increased the inter arrival times between patients thereby reducing the average wait time by 3.8%, but the later arrival times increased the average overtime by 12%.

Overall, the base schedule was only sensitive to one input distribution. However, it was also worth examining whether the proposed schedules from Sections 5.1 and 5.2 would be equally sensitive to changes. Appendix D shows the sensitivity analysis for the best $k = 2$ and $k = 3$ policy, and compares each of them with the base schedule. Despite the significant changes, both proposed scheduling policies significantly outperformed the based schedule.

CHAPTER 5

RESULTS

The goal of this project was to identify a scheduling policy for the chemotherapy clinic that reduced the average patient wait time by 20% and the average overtime by 25%. The VAMC nursing staff had several suggestions for potential scheduling policies, some of which were more complicated than others, but ease of implementation was among the most important screening criteria for each proposed scheduling policy. With the simulation fully built and validated, the next step was to determine the best scheduling policy.

This research focused on two different scheduling policies. The first policy was a fixed-block scheduling approach where $k = 2$. This would be the easiest scheduling technique to implement, but it might be challenging to adequately shape patient arrivals with only two appointment slots. Next, the simulation tested a fixed-block scheduling where $k = 3$. This option would still be fairly easy to implement, and it would provide the clinic greater flexibility and control while assigning appointment times.

5.1 TWO APPOINTMENT POLICIES

The two-appointment policy categorized patients based on their chemotherapy regimen's expected infusion length and assigned them one of two potential appointment times. The first appointment was at 8:00 AM and the simulation tested the impact of several different times for the second appointment. Under this policy, there were two variables that effected results: the patient population and the appointment time.

The patient population refers to the patients (or chemotherapy regimens) that received an alternate appointment time. For example, if the patient population was 60 minutes, then all patients with infusion lengths less than or equal to 60 minutes were selected for the second appointment time.

The second variable was the appointment time for the designated patient population. Under the two appointment approach, the entire selected patient population received the same appointment time, which ranged between 8:00 AM and 4:00 PM. If the appointment time was too close to 8:00 AM, then there was very little change from the base schedule. Similarly, if the appointment time was

too late in the afternoon, the proposed schedule resulted in increased overtime hours by the nursing staff.

In order to find the best scheduling policy, pairwise switches between the patient population and the appointment times were conducted until the best schedule was identified. The patient populations that were tested are listed in Table 5-1, along with their corresponding percentage of the total population. This table shows that when the 30 minute patient population was selected, 68% of the appointments were scheduled at 8:00 AM and 32% received the alternate appointment time.

Table 5- 1: Numbering system for the Patient Populations

Number	Patient Population	% of Total Population
1	30 minutes	32%
2	60 minutes	49%
3	90 minutes	61%
4	120 minutes	71%

Table 5-2 shows the appointment times the simulation tested. These times were initially selected arbitrarily and simulations confirmed that the lower bound for each combination of patient populations and appointment times did not include a boundary point (Appointment 1 or 6).

Table 5- 2: Numbering system for proposed appointment times

Number	Appointment Time
1	10:30 AM
2	11:00 AM
3	11:30 AM
4	12:00 PM
5	12:30 PM
6	1:00 PM

Proposed schedules are referred to as schedule *i-k*, where *i* represents the patient population from Table 5-1 and *j* represents the appointment time listed in Table 5-2. Each schedule was simulated with n = 7,500 iterations. Using a smaller number of iterations (n = 2,500 and n = 5,000) yielded

nearly identical results; however, the tail ends of the patient distribution were not sufficiently represented.

The research started by testing the 30 minute patient population. This was the smallest subset of patients, accounting for only 32% of the historical appointment volume. The results for these simulations are listed below in Table 5-3.

Table 5- 3: Simulation results for patient population 1

Schedule	Patient Population	Appointment Time	Wait Time Reduction	Overtime Reduction
1-1	30 Minutes	10:30 AM	17.30%	49.32%
1-2	30 Minutes	11:00 AM	18.40%	49.32%
1-3	30 Minutes	11:30 AM	20.00%	50.00%
1-4	30 Minutes	12:00 PM	19.53%	47.26%
1-5	30 Minutes	12:30 PM	20.54%	41.10%
1-6	30 Minutes	1:00 PM	20.54%	29.45%

Although the 10:30 AM appointment made a significant improvement with respect to overtime, it had the lowest reduction in waiting time. The 10:30 AM appointment was sufficiently spaced to prevent the pharmacy from processing quick infusions before long and intermediate infusions, but it does not allow the pharmacy queue to diminish before the second appointment's chemotherapy orders arrive.

Schedules 1-5 and 1-6 indicate that appointment times after 12:30 PM may increase the likelihood of overtime; however, since the only infusions arriving late in the day are quick infusions (30 minutes or less) the decreased effectiveness was less significant. The remaining three schedules (1-2, 1-3, and 1-4) present a trade-off between reduced wait time and reduced overtime Given the nearly identical wait time reductions, the clinic would likely select the policy with the greatest overtime reduction (1-3).

By changing the patient population to infusions less than or equal to 60 minutes, 49% of the clinic's infusions were schedule to arrive at the alternate appointment time. The results for schedules 2-*j* are listed in Table 5-4.

Table 5- 4: Simulation results for patient population 2

Schedule	Patient Population	Appointment Time	Wait Time Reduction	Overtime Reduction
2-1	60 Minutes	10:30 AM	18.11%	57.53%
2-2	60 Minutes	11:00 AM	21.08%	60.27%
2-3	60 Minutes	11:30 AM	22.70%	57.53%
2-4	60 Minutes	12:00 PM	23.24%	48.88%
2-5	60 Minutes	12:30 PM	23.78%	33.80%
2-6	60 Minutes	1:00 PM	23.78%	9.59%

These results confirmed that scheduling patients to arrive at 10:30 AM was not optimal because it did not provide enough separation from the 8:00 AM appointments. Also, schedules 2-5 and 2-6 confirmed that appointment times later than 12:30 PM increase the likelihood of overtime.

The remaining schedules made significant impacts on the system, well beyond the project's initial goals. Schedules 2-2 and 2-3 offer the greatest reduction in overtime, with fairly close reductions in average wait time. Appendix B lists the lower and upper bounds for each output statistic and at the 95% level of confidence, the average overtime confidence intervals overlap for schedules 2-2 and 2-3; consequently, neither schedule can be deemed statistically superior to the other. The average wait time confidence intervals do not overlap, therefore schedule 2-3 is statistically better than schedule 2-2. Schedule 2-3 dominates schedule 1-3 with respect to the average waiting time and the average overtime, therefore it was the best candidate moving forward.

Next, the simulation tested schedules where patients with infusion lengths less than or equal to 90 minutes were selected for an alternate appointment time. This patient population accounted for 61% of the total population and it further reduced the risk of short infusions being processed before long and intermediate infusions. The results for these simulation are shown below in Table 5-5.

Table 5- 5: Simulation results for patient population 3

Schedule	Patient Population	Appointment Time	Wait Time Reduction	Overtime Reduction
3-1	90 Minutes	10:30 AM	17.84%	60.96%
3-2	90 Minutes	11:00 AM	21.00%	59.59%
3-3	90 Minutes	11:30 AM	23.24%	52.05%
3-4	90 Minutes	12:00 PM	22.80%	34.25%
3-5	90 Minutes	12:30 PM	23.78%	8.90%
3-6	90 Minutes	1:00 PM	23.78%	-23.97%

Clearly the two best schedules under this policy are 3-1 and 3-2, and the remaining four schedules lose effectiveness as the appointment time is pushed later in the day. Appendix B shows the confidence intervals for the average amount of overtime for these two schedules overlap, thus neither schedule was statistically better than the other for that metric. Schedule 3-2 did a better job of reducing the average patient waiting time, therefore it was the best schedule in this subset.

Last, the simulation tested schedules where patients with less than or equal to 120 minute infusions were assigned to the alternate appointment time. These schedules brought in 71% of the patient population at an alternate appointment time. It reserved the 8:00 AM appointments for patients with intermediate and long infusions, but the uneven distribution of patients scheduled for later appointments was likely to increase the average overtime. The results listed in Table 5-6 show that increasing the patient population size to 120 minutes did not improve the results.

Table 5- 6: Simulation results for patient population 4

Schedule	Patient Population	Appointment Time	Wait Time Reduction	Overtime Reduction
4-1	120 Minutes	10:30 AM	17.84%	56.85%
4-2	120 Minutes	11:00 AM	19.67%	43.15%
4-3	120 Minutes	11:30 AM	20.54%	21.92%
4-4	120 Minutes	12:00 PM	20.86%	-6.16%
4-5	120 Minutes	12:30 PM	20.80%	-43.15%
4-6	120 Minutes	1:00 PM	21.62%	-79.45%

Figure 5-1 shows the results of all 24 schedules tested, and 20 of the proposed policies outperformed the base policy (annotated with the red dashed line). This figure illustrates that as the percentage of the total population that is assigned to the second appointment slot increases, the results become more increasingly sensitive to the appointment time. Notice the 30 minute patient population line is relatively flat, whereas the 120 minute population is severely sloped.

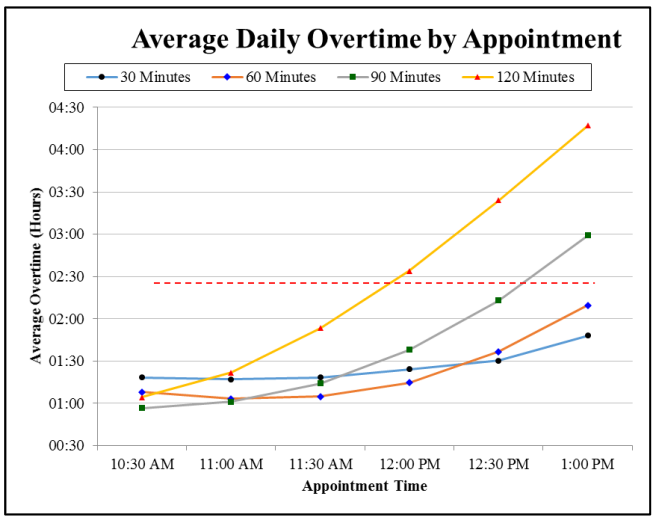

Figure 5- 1: Average overtime statistics for all proposed schedules

In terms of the average patient waiting time in the system, the best results occurred when the patient populations were split relatively evenly between the two appointments. Figure 5-2 shows that when the populations were not split evenly (30 minute and 120 minute patient populations), patient waiting times were higher, regardless of the interval between the two appointment times.

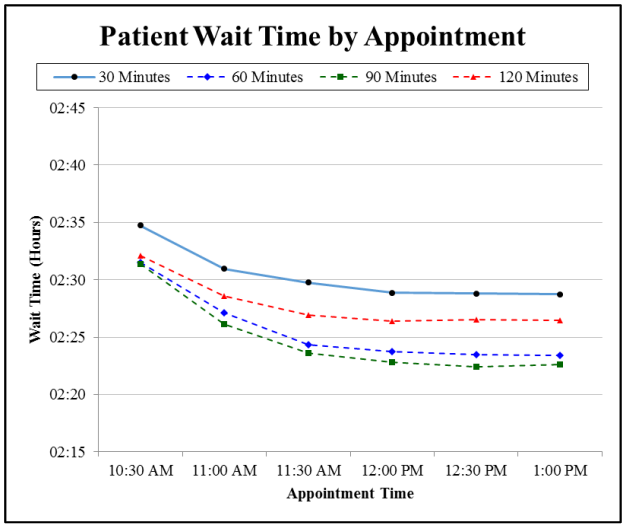

Figure 5- 2: Average patient waiting times for all proposed schedules

Based on the results of this section, there were multiple schedules that drastically improved the clinic's performance. Figure 5-3 shows the six best $k = 2$ schedules with respect to overtime reduction and wait time reduction, making it easy to visually compare each schedule.

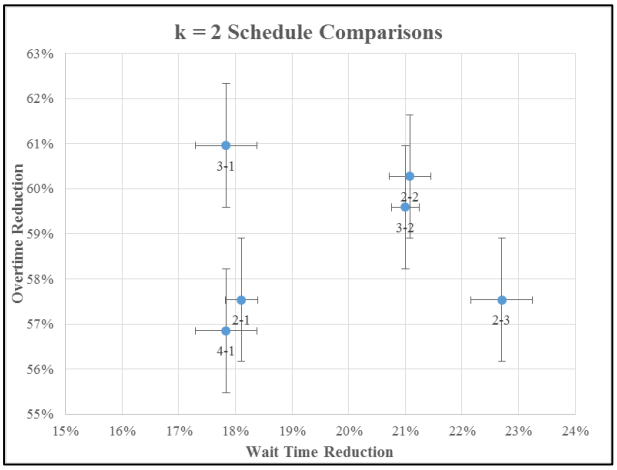

Figure 5- 3: Comparison of the best k = 2 schedules

Schedules 2-1, 3-1, and 4-1 all made significant improvements with respect to overtime, but none of them met the initial goal to reduce the average wait time by 20%. Schedules 2-2 and 3-2 produced nearly identical results, and since the confidence intervals for both overtime and wait time reduction overlap, neither is statistically better than the other. Schedule 2-3 provided the greatest reduction in wait time (22.7%), and while its overtime reduction confidence interval overlaps with schedule 3-2, it does not overlap with schedule 2-2.

Consequently, there is not a single dominant schedule. Instead, there is a trade-off between the schedule that maximizes overtime reduction and the schedule that maximizes wait time reduction. Without knowing the clinic's preferences or weighting values for overtime reduction versus wait time reduction, we are unable to determine which they should adopt. However, assuming the clinic's first priority is to reduce overtime, our recommendation is to implement schedule 2-2 which reduced the average overtime by 60% and average wait time by 21%.

5.2 THREE APPOINTMENT POLICIES

The two appointment policy is the simplest to implement, but it is worth exploring the impact of a three appointment policy to see if the results justify increasing the scheduling complexity. Based on the results in Section 5.1, it is clear that the best block scheduling policies shared two traits: the patient populations were evenly distributed across the appointment times and the fixed-intervals were sufficiently spread out (although small fixed-intervals continue to reduce overtime, they unnecessarily increase patient waiting times). The following patient populations were selected to test the three appointment policy since they are relatively evenly distributed and this methodology would be easy for the clinic to implement.

Table 5- 7: Break down of infusion lengths for k=3 policies

Population #	Patient Population	% of Total Population
1	$t > 120\ Minutes$	32.42%
2	$30 < t \leq 120\ Minutes$	35.59%
3	$t \leq 30\ Minutes$	31.99%

Section 5.1 explored several alternatives for the best fixed-interval length when $k = 2$, and in doing so it showed that a fixed-interval less than or equal to two and a half hours was suboptimal because it did not sufficiently stagger patient arrivals, thus increasing the average waiting time in the system. However, it is important to note that this scenario differs from Section 5.1 because a smaller percentage of patients will arrive during each fixed-interval. Previously, the intersection of the first appointment time and the second appointment time accounted for 100% of the patient population. When $k = 3$, the intersections between the first and second appointment times and the second and third appointment times will each account for 67% of the patient population, therefore a smaller interval between the appointment times may not increase average wait time.

Section 5.1 also showed that for all patient population sizes, appointment times after 12:30 PM increases average overtime in the clinic. Using this information, the following schedules were nominated for testing:

Table 5- 8: List of k = 3 schedules that will be tested

	***k = 3* Schedule Number**					
Patient #	1	2	3	4	5	6
1	8:00 AM	8:00 AM	8:00 AM	8:00 AM	8:00 AM	8:00 AM
2	9:30 AM	9:30 AM	10:00 AM	10:00 AM	10:30 AM	10:30 AM
3	11:00 AM	11:30 PM	11:30 AM	12:00 PM	12:00 PM	12:30 PM

The results for these simulations validated the assumption that increasing the number of fixed blocks would improve the overall system performance. The results listed Table 5-9 show the best schedules were 3, 4, and 5.

Table 5- 9: Simulation results for k = 3 schedules

Schedule #	Avg. Wait Time Reduction	Avg. Overtime Reduction
1	19.71%	63.67%
2	21.98%	64.93%
3	22.43%	66.05%
4	24.25%	66.01%
5	24.64%	66.00%
6	26.39%	61.47%

Schedule 3 had the greatest reduction in the average overtime but due to overlapping confidence intervals shown in Appendix C, neither schedule 2, 3, 4, nor 5 can be deemed statistically superior to the other. Figure 5-4 plots the overtime reduction and wait time reduction for all four schedules.

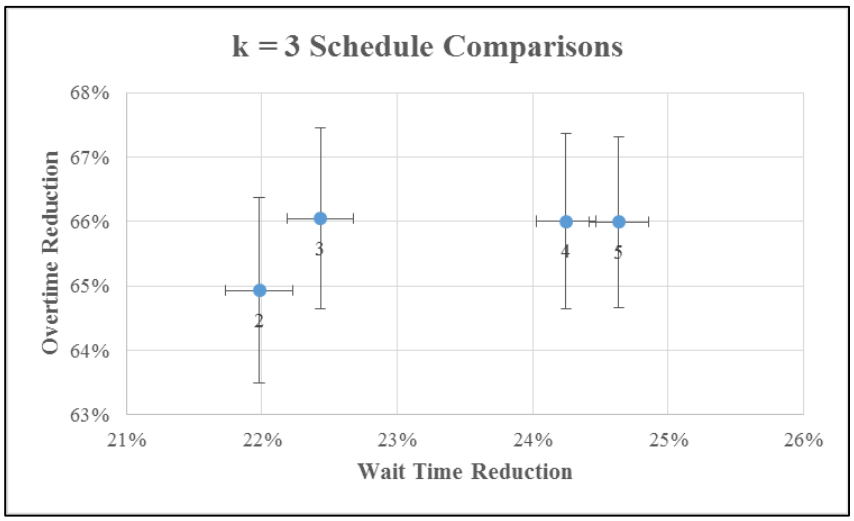

Figure 5- 4: Comparison of the best k = 4 Schedules

Figure 5-4 makes it clear that schedules 4 and 5 dominate the other $k = 3$ schedules. In this case, both 4 and 5 have nearly identical overtime reduction values and their wait time reduction values are very close, which is indicated by their overlapping confidence intervals.

Since neither schedule 4 nor schedule 5 proved to be statistically superior to the other, both are equally valid selections for implementation; however, the schedule 4's even two hour spacing between appointment times may be more aesthetically pleasing to nurses, patients, and administrators. Applying this schedule reduced the average overtime by 66% and it reduced the average patient waiting time by 24%. These results outperform the best $k = 2$ schedule by 6% in terms of overtime reduction and 3% in terms of wait time reduction.

CHAPTER 6

CONCLUSIONS

This research examined two scheduling policies that could be easily implemented at the Durham VAMC chemotherapy clinic. When $k = 2$, the best policy was schedule 2-2, which assigned all patients with less than or equal to 60 minute infusions an appointment time of 11:00 AM. This schedule reduced the average waiting time in the system by 21% and it reduced the average overtime by 60%.

When $k = 3$, the best policy was schedule 4, which assigned 12:00 PM appointments for patients with infusion lengths less than or equal to 30 minutes, 10:00 AM appointments for patients with infusion lengths between 31 minutes and 120 minutes, and 8:00 AM appointments for patients with infusion lengths greater than 120 minutes. This schedule reduced the average waiting time in the system by 24% and it reduced the average overtime by 66%.

With respect to minimizing overtime costs, the optimal scheduling solution for this problem is to prioritize patients using a Longest Infusion Time (LIT) heuristic. Though this is the optimal solution, it is not practical because appointments are created, changed, and canceled over a rolling horizon, such that the daily patient volume may not be finalized until the day of treatment. Instead, chemotherapy clinics can apply a standardized fixed-block scheduling technique to shape the patient arrivals such that the longest infusion times arrive first and the shortest infusion times arrive last. Increasing the number of blocks, k, increases the likelihood of achieving LIT order, but it also increases the scheduling complexity.

Figure 6.1 shows how the current $k = 1$ policy processes chemotherapy orders in the pharmacy. In this example, the various infusion categories are widely intermixed, and longest treatments were processed 9^{th}, 10^{th}, and 17^{th}. By failing to prioritize longer infusions, the clinic worked 3.7 hours of overtime.

Sequence of Chemotherapy Orders in to the Pharmacy																
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**
$k=1$	60	90	90	100	70	140	120	20	240	240	95	120	90	17	210	10	240

quick	$t \leq 60$	short	$60 < t \leq 120$	intermediate	$120 < t < 240$	long	$t \geq 240$

Figure 6- 1: Pharmacy sequence when k = 1.

When the best $k = 2$ schedule from Section 5.1 was applied to the same patient list with identical service times, the chemotherapy order sequence changed significantly. There was a visibly better grouping among long and intermediate infusions, but there were several short infusions dispersed throughout the sequence. This schedule resulted in zero overtime hours and the last patient completed his/her infusion at 3:59 PM.

Sequence of Chemotherapy Orders in to the Pharmacy																
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**
$k=2$	100	140	120	240	95	240	210	240	120	90	70	20	60	90	10	90	17

quick	$t \leq 60$	short	$60 < t \leq 120$	intermediate	$120 < t < 240$	long	$t \geq 240$

Figure 6- 2: Pharmacy sequence when k = 2.

Finally, when the best $k = 3$ schedule from Section 5.2 was applied, there was a noticeably better grouping of long and intermediate infusions first, short infusions in the middle, and quick infusions at the end. Under this schedule, there was zero overtime and the last patient completed their infusion at 3:52 PM.

Sequence of Chemotherapy Orders in to the Pharmacy																
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**
$k=3$	140	240	240	210	240	90	100	120	70	95	60	90	90	120	20	10	17

quick	$t \leq 60$	short	$60 < t \leq 120$	intermediate	$120 < t < 240$	long	$t \geq 240$

Figure 6- 3: Pharmacy sequence when k = 3.

The current policy intends to maximize utilization earlier in the day, but the blind approach of treating each patient the same, despite the varying degrees of acuity and infusion lengths, has clearly been detrimental to the system. Although some patients struggle with appointment punctuality and there is a high degree of variability every day, the chemotherapy clinic should not overlook an educated approach to shaping their daily patient inflow. Outpatient clinics have a fixed amount of time to treat all of their patients and clinics like the VA (those that operate with a two-staged single server pharmacy) must prioritize patients with the longest infusion times or they will continue to experience significant overtime costs.

With respect to reducing the average patient wait time, the optimal scheduling policy under the current conditions would ensure that as soon as the data entry pharmacist completes one order, the next order would arrive. This is unrealistic due to the variability of the lab process. Instead, a practical solution is to stagger appointment times such that there will be a constant flow of chemotherapy orders into the pharmacy, as opposed to the current method which produces a massive influx of orders between 9:00-10:30 AM. This staggering policy needs to adequately separate the fixed-blocks of patients, without creating large idle periods in the pharmacy or increasing overtime.

The proposed schedules reduced the average wait time in the system predominantly by staggering the flow of chemotherapy orders into the pharmacy. In the example shown above, there was a significant difference in the average queue length for the three policies. Reducing the average number of jobs waiting in the queue is the most effective method for reducing the average waiting time in the system. The results for all three schedules are listed in Table 6.1.

Table 6- 1: The impact of increasing k on queue length and waiting time.

	Average # of orders in the pharmacy queue	**Average Waiting Time**
k =1	4.625	3:28
k =2	2.3125	2:26
k =3	1.4375	2:13

As the value of *k* continues to increase, the average number of orders in the queue will continue to decrease until it reaches a lower bound. Due to the variability in the amount of time it takes to receive lab results, the lower-bound is unlikely to reach zero.

Without addressing other aspects of the system (phlebotomy station, lab processing, waiting for chemotherapy orders, and pharmacy operations), the average wait time in the system will also reach a lower-bound. The lower-bound for patients that require labs is the sum of the average service times prior to starting their infusion. In this simulation, that value equals 2:05. Patients that do not require labs move directly to the pharmacy process and have a lower-bound of 35 minutes. Based on the data listed in Tables 3-3 and 3-5, the probability of a randomly selected patient requiring lab work is 0.8607 and the probability that the patient does not require lab work is 0.1393; therefore, the average waiting time in the system has a lower bound of 1:52. Despite the simplistic nature of the scheduling policies selected from Section 5.1 and Section 5.2, both do a very good job of approaching the lower-bound.

VA hospitals and community hospitals that treat a high volume of Medicaid or Medicare patients may have little incentive to change their current practices. Generally speaking, they do not have to compete for business and their monetary compensation for treatment is low, therefore providers may be largely indifferent to patient waiting times. But as the population of veterans grows from over a decade of war, access to healthcare increases throughout the country as a result of the Affordable Care Act, and oncology treatment protocols increase patient life expectancies the demand for chemotherapy services will likely outpace supply. Administrators would be wise to seek out cost-free solutions, like scheduling, that can reduce operating costs and improve patient care.

CHAPTER 7

FUTURE RESEARCH

This research focused on a system that was specific to the Durham VA Medical Center, and even within this niche example, there are several possibilities for continued research. The VAMC's current scheduling practice is driven by the nursing staff, which is to say that there is not a centralized scheduler for the clinic. With five different nurses in the clinic scheduling appointments, no one looks at the clinic's total acuity on any given day. As a result, some days the clinic treats 4-8 Zometa patients (the most common patient type and arguably the easiest treatment to administer), while other days are filled with complex and lengthy infusions. This problem presents the opportunity to develop a scheduling program that forecasts each patient's future appointments and distributes the clinic's daily acuity levels. This would contribute to the effectiveness of the heuristic developed in this paper, because it performs best when the patient populations are evenly distributed between the two (or three) appointment times.

This research could also be improved upon by examining the effects of increasing the pharmacy capacity. Under the current system, the pharmacy delivers chemotherapy drugs to the infusion clinic every 20-30 minutes. As a result, by the time the 14th patient receives their drugs, it has been 4.5 hours since the first patient started their infusion. The single-server pharmacy inadvertently staggers infusion start times such that by the time the 15th patient arrives, the probability of a patient waiting for an available infusion chair is extremely small. The current heuristic may become problematic, because increasing the rate of output from the pharmacy could result in patients waiting for an available infusion chair. In this case, reserving one or two infusion chairs for patients with quick infusions may alleviate this problem, but it certainly warrants further research.

This research provides a starting point for future chemotherapy clinic simulations. Simulations may be the best tool for administrators to evaluate the impact of policy and staffing decisions without interrupting patient care, therefore a generalized modeling tool could be an invaluable asset to health systems engineering.

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APPENDICES

APPENDIX A

CHEMOTHERAPY INFUSION CLINC FLOW DIAGRAM

The following flow diagram depicts a patient's movement through the Durham VAMC chemotherapy clinic. This flow diagram is a simplified representation of the true system. It does not include rare events, such as unfavorable lab results or adverse reactions to the chemotherapy infusion.

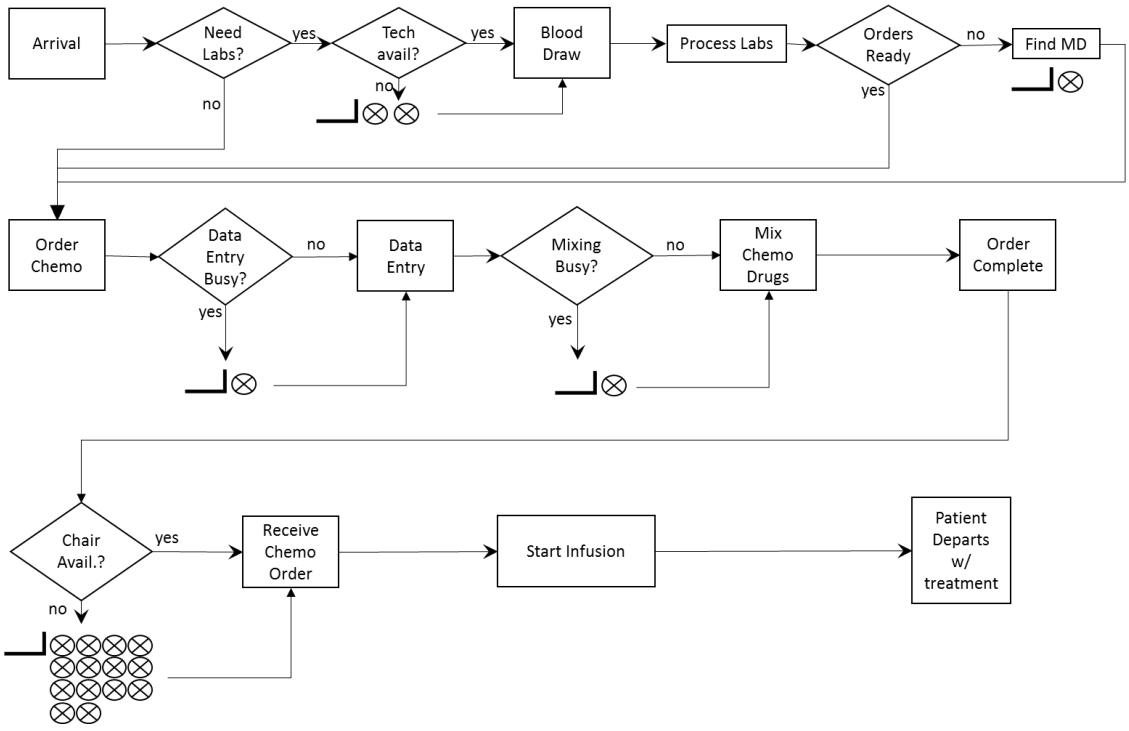

Figure A- 1: Infusion Clinic Patient Flow Diagram

APPENDIX B

K = 2 SIMULATION RESULTS

The table below contains the simulation results for all of the k = 2 schedules that were tested during this research. Each schedule was simulated with 7,500 iterations.

Table B- 1: VBA simulation results for k = 2 schedules

i-j	Patient Pop.	Appt Time	Wait Time	%	Half Width	Lower	Upper	Overtime	%	Half width	Lower	Upper
Base	All	8:00	3:05	n/a	0:00			2:26				
1-1	30 Minutes	10:30	2:33	17.30%	0:00	2:32	2:33	1:14	49.32%	0:02	1:12	1:17
1-2	30 Minutes	11:00	2:30	18.40%	0:00	2:29	2:30	1:14	49.32%	0:02	1:12	1:17
1-3	30 Minutes	11:30	2:28	20.00%	0:00	2:28	2:29	1:13	50.00%	0:02	1:11	1:16
1-4	30 Minutes	12:00	2:28	19.53%	0:00	2:27	2:28	1:17	47.26%	0:02	1:14	1:19
1-5	30 Minutes	12:30	2:27	20.54%	0:00	2:27	2:28	1:26	41.10%	0:02	1:24	1:29
1-6	30 Minutes	13:00	2:27	20.54%	0:00	2:27	2:28	1:43	29.45%	0:02	1:41	1:45
2-1	60 Minutes	10:30	2:31	18.11%	0:00	2:30	2:32	1:02	57.53%	0:02	1:00	1:04
2-2	60 Minutes	11:00	2:26	21.08%	0:00	2:26	2:27	0:58	60.27%	0:02	0:56	1:00
2-3	60 Minutes	11:30	2:23	22.70%	0:00	2:22	2:23	1:02	57.53%	0:02	1:00	1:04
2-4	60 Minutes	12:00	2:22	23.24%	0:00	2:21	2:22	1:14	48.88%	0:02	1:12	1:16
2-5	60 Minutes	12:30	2:21	23.78%	0:00	2:21	2:21	1:36	33.80%	0:02	1:33	1:38
2-6	60 Minutes	13:00	2:21	23.78%	0:00	2:21	2:22	2:12	9.59%	0:02	2:10	2:14
3-1	90 Minutes	10:30	2:32	17.84%	0:00	2:31	2:32	0:57	60.96%	0:02	0:54	0:59
3-2	90 Minutes	11:00	2:26	21.00%	0:00	2:25	2:26	0:59	59.59%	0:02	0:57	1:01
3-3	90 Minutes	11:30	2:22	23.24%	0:00	2:22	2:23	1:10	52.05%	0:02	1:08	1:12
3-4	90 Minutes	12:00	2:22	22.80%	0:00	2:21	2:22	1:36	34.25%	0:02	1:34	1:38
3-5	90 Minutes	12:30	2:21	23.78%	0:00	2:21	2:22	2:13	8.90%	0:02	2:11	2:15
3-6	90 Minutes	13:00	2:21	23.78%	0:00	2:21	2:22	3:01	-23.97%	0:02	2:58	3:03
4-1	120 Minutes	10:30	2:32	17.84%	0:00	2:32	2:33	1:03	56.85%	0:01	1:01	1:05
4-2	120 Minutes	11:00	2:28	19.67%	0:00	2:28	2:29	1:23	43.15%	0:02	1:21	1:25
4-3	120 Minutes	11:30	2:27	20.54%	0:00	2:26	2:27	1:54	21.92%	0:02	1:52	1:56
4-4	120 Minutes	12:00	2:26	20.86%	0:00	2:25	2:26	2:35	-6.16%	0:02	2:33	2:38
4-5	120 Minutes	12:30	2:26	20.80%	0:00	2:26	2:26	3:29	-43.15%	0:02	3:26	3:31
4-6	120 Minutes	13:00	2:25	21.62%	0:00	2:25	2:26	4:22	-79.45%	0:02	4:19	4:24

APPENDIX C

K = 3 SIMULATION RESULTS

The table below contains the simulation results for all of the k = 3 schedules that were tested during this research. Each schedule was simulated with 7,500 iterations.

Table C- 1: VBA simulation results for k = 3 schedules

	1st Appt	2nd Appt	3rd Appt	Wait Time	%	Half Width	Lower	Upper	Overtime	%	Half width	Lower	Upper
Base	8:00	n/a	n/a	3:05	-	-	-	-	2:26	-	-	-	
1	8:00	9:30	11:00	2:28	19.71%	0:00	2:28	2:29	0:53	63.67%	0:02	0:50	0:55
2	8:00	9:30	11:30	2:24	21.98%	0:00	2:23	2:24	0:51	64.93%	0:02	0:49	0:53
3	8:00	10:00	11:30	2:23	22.43%	0:00	2:23	2:23	0:49	66.05%	0:01	0:47	0:51
4	8:00	10:00	12:00	2:20	24.25%	0:00	2:19	2:20	0:49	66.01%	0:01	0:47	0:51
5	8:00	10:30	12:00	2:19	24.64%	0:00	2:19	2:19	0:49	66.00%	0:01	0:47	0:51
6	8:00	10:30	12:30	2:16	26.39%	0:00	2:15	2:16	0:56	61.47%	0:01	0:54	0:58

APPENDIX D

SENSITIVITY ANALYSIS

D.1 K = 2 SENSITIVITY ANALYSIS RESULTS

The following table shows the sensitivity analysis for Schedule 2-2 from Section 5.1. The left side of Table D-1 shows the schedule's sensitivity to changes from the current distributions, and the right side of the table compares the schedule against the base schedule's average wait time (3:05) and average over time (2:26). At worst, the proposed schedule outperformed the base schedule by reducing the average wait time 14.6% and the average overtime by 37%.

Table D- 1: Sensitivity Analysis Results for Schedule 2-2 (k=2)

	Schedule 2-2 (k = 2)				Schedule 2-2 vs. the Base Schedule		
Input	**-20%**	**Base**	**+20%**		**-20%**	**Base**	**+20%**
Phlebotomy Time	2:20	2:23	2:25	Wait Time	24.3%	22.7%	21.6%
	-24.3%	*N/A*	*1.1%*				
	1:01	1:02	1:07	Over Time	58.2%	57.5%	54.1%
	-2%	*N/A*	*8%*				
Lab Processing Time	2:15	2:23	2:34	Wait Time	27.0%	22.7%	16.8%
	-4.3%	*N/A*	*5.9%*				
	0:52	1:02	1:20	Over Time	64.4%	57.5%	45.2%
	-16%	*N/A*	*29%*				
Probability of Waiting on Chemotherapy Orders	2:21	2:23	2:24	Wait Time	23.8%	22.7%	22.2%
	-1.4%	*N/A*	*0.7%*				
	0:59	1:02	1:06	Over Time	59.6%	57.5%	54.8%
	-5%	*N/A*	*6%*				
Wait Time for Chemotherapy Orders	2:21	2:23	2:25	Wait Time	23.8%	22.7%	21.6%
	-1.4%	*N/A*	*1.4%*				
	1:01	1:02	1:07	Over Time	58.2%	57.5%	54.1%
	-2%	*N/A*	*8%*				
Data Entry Time	2:12	2:23	2:38	Wait Time	28.6%	22.7%	14.6%
	-7.7%	*N/A*	*10.5%*				
	0:47	1:02	1:32	Over Time	67.8%	57.5%	37.0%
	-24%	*N/A*	*48%*				
Chemotherapy Preparation Time	2:20	2:23	2:27	Wait Time	24.3%	22.7%	20.5%
	-2.1%	*N/A*	*2.8%*				
	0:58	1:02	1:06	Over Time	60.3%	57.5%	54.8%
	-6%	*N/A*	*6%*				
Arrival Rate	2:27	2:23	2:20	Wait Time	20.5%	22.7%	24.3%
	2.8%	*N/A*	*-2.1%*				
	0:50	1:02	1:22	Over Time	65.8%	57.5%	43.8%
	-19%	*N/A*	*32%*				

D.2 K = 3 SENSITIVITY ANALSYIS RESULTS

The following table shows the sensitivity analysis results for Schedule 4 from Section 5.2. The left side of Table D-2 shows the schedule's sensitivity to changes from the current distributions, and the right side of the table compares the schedule against the base schedule's average wait time (3:05) and average over time (2:26). At worst, the proposed schedule outperformed the base schedule by reducing the average wait time 15.7% and the average overtime by 49.3%.

Table D- 2: Sensitivity Analysis Results for Schedule 4 (k=3)

Schedule 4 (k = 3)					Schedule 4 vs. the Base Schedule		
Input	**-20%**	**Base**	**+20%**		**-20%**	**Base**	**+20%**
Phlebotomy Time	2:17	2:20	2:22	Wait Time	25.9%	24.3%	23.2%
	-2.1%	*N/A*	*1.4%*				
	0:47	0:49	0:52	Over Time	67.8%	66.4%	64.4%
	-4%	*N/A*	*6%*				
Lab Processing Time	2:11	2:20	2:31	Wait Time	29.2%	24.3%	18.4%
	-6.9%	*N/A*	*7.9%*				
	0:40	0:49	1:10	Over Time	72.6%	66.4%	52.1%
	-18%	*N/A*	*43%*				
Probability of Waiting on Chemotherapy Orders	2:18	2:20	2:21	Wait Time	25.4%	24.3%	23.8%
	-1.4%	*N/A*	*0.7%*				
	0:47	0:49	0:51	Over Time	67.8%	66.4%	65.1%
	-4%	*N/A*	*4%*				
Wait Time for Chemotherapy Orders	2:17	2:20	2:22	Wait Time	25.9%	24.3%	23.2%
	-2.1%	*N/A*	*1.4%*				
	0:48	0:49	0:52	Over Time	67.1%	66.4%	64.4%
	-2%	*N/A*	*6%*				
Data Entry Time	2:08	2:20	2:36	Wait Time	30.8%	24.3%	15.7%
	-8.6%	*N/A*	*11.4%*				
	0:36	0:49	1:14	Over Time	75.3%	66.4%	49.3%
	-27%	*N/A*	*51%*				
Chemotherapy Preparation Time	2:16	2:20	2:23	Wait Time	26.5%	24.3%	22.7%
	-26.5%	*N/A*	*-22.7%*				
	0:48	0:49	0:53	Over Time	67.1%	66.4%	63.7%
	-2%	*N/A*	*8%*				
Arrival Rate	2:22	2:20	2:18	Wait Time	23.2%	24.3%	25.4%
	1.4%	*N/A*	*-1.4%*				
	0:36	0:49	1:10	Over Time	75.3%	66.4%	52.1%
	-27%	*N/A*	*43%*				

APPENDIX E

VBA SOURCE CODE

The following sections contain all of the Visual Basic for Applications (VBA) source code that is used to create the simulation. The simulation contains four major VBA modules: Patient Creation, Base Schedule, Proposed Schedule, and Loop Construction.

E.1 SOURCE CODE FOR PATIENT CREATION

```
Sub PatientList()
    Sheets("CurrentModel").Select

    Dim i As Integer
    Dim numPatients As Integer, numNurses As Integer

    numNurses = Application.VLookup(Rnd, Sheets("Regimens").Range("L2:M3"), 2, True)
    Range("C30") = numNurses

    If numNurses = 3 Then
       numPatients = Int(7 + 11 * Application.WorksheetFunction.Beta_Inv(Rnd, 2.42, 2.85))
    Else: If numNurses = 4 Then numPatients = Int(7.5 + 14 *
Application.WorksheetFunction.Beta_Inv(Rnd, 3.21, 2.97))
    End If

    Range("C31") = numPatients

    For i = 1 To numPatients
          Cells(i + 4, 1) = i
          Cells(i + 4, 2) = Rnd

          Dim vRegimen As Variant
                vRegimen = Application.VLookup(Cells(i + 4, 2),
          Sheets("Regimens").Range("A2:G81"), 2, True)
          Cells(i + 4, 3) = vRegimen

          Dim vLabs As Variant
          vLabs = Application.VLookup(Cells(i + 4, 2), Sheets("Regimens").Range("A2:G81"), 6,
True)
          Cells(i + 4, 4) = vLabs

       Dim vInfusion As Variant
       vInfusion = Application.VLookup(Cells(i + 4, 2), Sheets("Regimens").Range("A2:G81"), 5,
True)
             Cells(i + 4, 5) = vInfusion
```

```
    Cells(i + 4, 5) = Format(Cells(i + 4, 5), "hh:mm")
        Cells(i + 4, 7) = (168 * Application.WorksheetFunction.Beta_Inv(Rnd, 3.64, 3.35)) / (24 *
    60) + (6.5                                  / 24)
    Cells(i + 4, 7) = Format(Cells(i + 4, 7), "hh:mm")

  Next i

  Range("A4:G32").Select
  Selection.Copy
  Sheets("ScheduledModel").Select
  Range("A4").Select
  ActiveSheet.Paste
  Range("H7").Select

End Sub
```

E.2 SOURCE CODE FOR THE BASE SCHEDULE

```
Sub BaseSchedule()

Dim i As Integer
Dim numPatients As Integer
numPatients = Sheets("CurrentModel").Cells(31, 3).Value

For i = 1 To numPatients
      'Appt time
      Cells(i + 4, 6) = 1 / 3
      Cells(i + 4, 6) = Format(Cells(i + 4, 6), "hh:mm")

      'Need Labs?
      Cells(i + 4, 9) = Rnd
          If Cells(i + 4, 9) > Application.VLookup(Cells(i + 4, 2),
                Sheets("Regimens").Range("A2:G81"), 7, True) Then
                Cells(i + 4, 9) = 0
          Else: Cells(i + 4, 9) = 1
          End If
Next i

Dim oneRange As Range
Dim aCell As Range
Set oneRange = Range("A4:z38")
Set aCell = Range("G4")
oneRange.Sort Key1:=aCell, Order1:=xlAscending, Header:=xlYes
```

```
'Code for the blood draw queue
Dim j As Integer
j = 1
    If Cells(j + 4, 9) = 0 Then
       Cells(j + 4, 10) = Cells(i + 4, 7)
    Else: Cells(j + 4, 10) = Cells(j + 4, 7) + 10 / (60 * 24)
    End If

For j = 2 To numPatients
    If Cells(j + 4, 9) = 0 Then
       Cells(j + 4, 10) = Cells(j + 4, 7)
   Else
       Cells(j + 4, 10) = Application.Max(Range("J:J"), Cells(j + 4, 7)) + 10 / (60 * 24)
   End If
Next j

'time until lab results are back
Dim k As Integer
For k = 1 To numPatients
   If Cells(k + 4, 9) = 0 Then
      Cells(k + 4, 11) = Cells(k + 4, 7)
   Else
      Cells(4 + k, 11) = Cells(4 + k, 10).Value + (45 + 105 *
      Application.WorksheetFunction.Beta_Inv(Rnd, 3.143, 7.857)) / (24 * 60)
   End If
Next k

'time spent waiting on orders
Dim z As Integer
For z = 1 To numPatients
   If Cells(4 + z, 9).Value = 0 Then
      Cells(4 + z, 12) = 0
    Else: If Rnd > 0.75 Then Cells(4 + z, 12) = (120 * Application.WorksheetFunction.Beta_Inv(Rnd,
       5 / 3, 25 / 3)) / (24 * 60)
   End If
Next z

Dim twoRange As Range
Dim bCell As Range
Set twoRange = Range("A4:z38")
Set bCell = Range("K4")
```

```
twoRange.Sort Key1:=bCell, Order1:=xlAscending, Header:=xlYes

‘chemo ordered
Dim m As Integer
For m = 1 To numPatients
   If Cells(4 + m, 9) = 0 Then
     Cells(4 + m, 13) = Application.Max(Cells(4 + m, 7) + 0.00208, 1 / 3)
   Else
      Cells(4 + m, 13) = Application.Max(Cells(4 + m, 11) + Cells(4 + m, 12) + 0.00208, 0.33333)
   End If
Next m

'chemo data entry complete
Dim p As Integer
p = 1
     Cells(4 + p, 14) = Cells(4 + p, 13).Value + ((15 + 10 *
          Application.WorksheetFunction.Beta_Inv(Rnd, 4, 4)) / (60 * 24))
For p = 2 To numPatients
     Cells(4 + p, 14) = Application.Max(Cells(4 + p, 13), Cells(3 + p, 14)) + ((15 + 10 *
          Application.WorksheetFunction.Beta_Inv(Rnd, 4, 4)) / (60 * 24))
Next p

'the first patient goes straight through the process
Dim s As Integer
s = 1
     Cells(4 + s, 15) = Cells(4 + s, 14).Value + ((5 + 20 *
          Application.WorksheetFunction.Beta_Inv(Rnd, 4, 4)) / (60 * 24))

'first patient receives chemo order
     Cells(4 + s, 16) = Cells(4 + s, 15) + 0.00208

'tallly the patient number
Cells(4 + s, 17) = s

'All other patients go through a queuing process
For s = 2 To numPatients
     Cells(4 + s, 15) = Application.Max(Cells(4 + s, 14), Cells(3 + s, 15)) + ((5 + 20 *
          Application.WorksheetFunction.Beta_Inv(Rnd, 4, 4)) / (60 * 24))

     'receive chemo
     Cells(4 + s, 16) = Cells(4 + s, 15) + 0.00208
```

```
    'patient number
    Cells(4 + s, 17) = s
Next s

'start infusions for the first 14 patients
Dim q As Integer

If numPatients <= 14 Then
    For q = 1 To numPatients

        'Start infusion
        Cells(4 + q, 20) = Cells(4 + q, 16)
        'complete infusion
        Cells(4 + q, 21) = Cells(4 + q, 20) + Cells(4 + q, 5)
      Next q
Else
  For q = 1 To 14
        'Start infusion
        Cells(4 + q, 20) = Cells(4 + q, 16)
        'complete infusion
        Cells(4 + q, 21) = Cells(4 + q, 20) + Cells(4 + q, 5)
   Next q
End If

For q = 15 To numPatients
      'vacated chairs
      Cells(4 + q, 18) = Application.CountIf(Range("u5:u" & (4 + q)), "<" & Cells(4 + q, 16))
      'avialable chairs
      Cells(4 + q, 19) = 14 - ((Cells(4 + q, 17) - 1) - Cells(4 + q, 18))
      'if available chairs, then start infusion
  If Cells(4 + q, 19) >= 1 Then
     Cells(4 + q, 20) = Cells(4 + q, 16)

   Else
     'wait until a chair is availabe to start the next infusion
     While 14 - ((Cells(4 + q, 17) - 1) - Application.CountIf(Range("u5:u" & (4 + q)), "<" & Cells(4
           + q, 16))) < 1
        Cells(4 + q, 16) = Cells(4 + q, 16) + 10 / (24 * 60)
     Wend
   ‘start infusion
   Cells(4 + q, 20) = Cells(4 + q, 16)
```

```
End If

'complete infusion
Cells(4 + q, 21) = Cells(4 + q, 20) + Cells(4 + q, 5)
Next q

'wait time in system
Dim w As Integer

For w = 1 To numPatients
    'lab processing time
    Cells(4 + w, 22) = Cells(4 + w, 11) - Cells(4 + w, 10)

    'pharmacy time
    Cells(4 + w, 23) = Cells(4 + w, 16) - Cells(4 + w, 13)

    'total waiting time
    Cells(4 + w, 25) = Cells(4 + w, 20) - Cells(4 + w, 7)
Next w

'Daily infusion statistics
Cells(33, 3) = Application.CountIf(Range("E5:E35"), "<.041667")
Cells(34, 3) = Application.CountIf(Range("E5:E35"), "<.083333") - Cells(33, 3).Value
Cells(35, 3) = Application.CountIf(Range("E5:E35"), "<.166667") - Cells(33, 3).Value - Cells(34,
               3).Value
Cells(36, 3) = Application.CountIf(Range("E5:E35"), ">.166667")

'Daily lab wait
Dim dailyLabwait As Double
dailyLabwait = WorksheetFunction.Average(Range("v5:v30"))
Cells(39, 3) = dailyLabwait


'Daily orders wait
  Dim dailyOrdersWait As Double
    If Application.Count(Range("L5:L35")) > 1 Then
        dailyOrdersWait = Application.WorksheetFunction.Average(Range("l5:l30"))
    Else
        dailyOrdersWait = WorksheetFunction.Max(Range("L5:L35"))
    End If
Cells(40, 3) = dailyOrdersWait
```

```
‘Daily pharmacy wait
Dim dailyPharmaWait As Double
dailyPharmaWait = WorksheetFunction.Average(Range("w5:w30"))
Cells(41, 3) = dailyPharmaWait

‘Daily Wait time in the system
Dim dailyWait As Double
dailyWait = WorksheetFunction.Average(Range("y5:y30"))
Cells(38, 3) = dailyWait

'Daily overtime in the system
If WorksheetFunction.Max(Range("u5:u35")) > 0.67 Then
    Cells(43, 3) = (WorksheetFunction.Max(Range("u5:u35")) - 0.666667) * 2
Else
    Cells(43, 3) = 0
End If

End Sub
```

E.3 SOURCE CODE FOR THE PROPOSED SCHEDULE

```
Sub ProposedSchedule()

Dim i As Integer
Dim numPatients As Integer
numPatients = Sheets("CurrentModel").Cells(31, 3).Value

For i = 1 To numPatients
    'Appt time
    Dim vAppointment As Variant
    vAppointment = Application.VLookup(Cells(i + 4, 2), Sheets("Regimens").Range("A2:G81"),
                    3, True)
    Cells(i + 4, 6) = vAppointment
    'Arrival time
    Cells(i + 4, 8) = Cells(i + 4, 7) + (Application.VLookup(Cells(i + 4, 2),
                    Sheets("Regimens").Range("A2:G81"), 3, True) - 1 / 3)
    Cells(i + 4, 9) = Rnd
      If Cells(i + 4, 9) > Application.VLookup(Cells(i + 4, 2),
        Sheets("Regimens").Range("A2:G81"), 7, True) Then
         Cells(i + 4, 9) = 0
      Else: Cells(i + 4, 9) = 1
      End If
```

```
Next i
Dim oneRange As Range
Dim aCell As Range
Set oneRange = Range("A4:z38")
Set aCell = Range("G4")
oneRange.Sort Key1:=aCell, Order1:=xlAscending, Header:=xlYes

'Code for the blood draw queue
Dim j As Integer
j = 1
    If Cells(j + 4, 9) = 0 Then
       Cells(j + 4, 10) = Cells(i + 4, 7)
    Else: Cells(j + 4, 10) = Cells(j + 4, 7) + 10 / (60 * 24)
    End If

For j = 2 To numPatients
    If Cells(j + 4, 9) = 0 Then
       Cells(j + 4, 10) = Cells(j + 4, 7)
   Else
       Cells(j + 4, 10) = Application.Max(Range("J:J"), Cells(j + 4, 7)) + 10 / (60 * 24)
   End If
Next j

'time until lab results are back
Dim k As Integer
For k = 1 To numPatients
   If Cells(k + 4, 9) = 0 Then
      Cells(k + 4, 11) = Cells(k + 4, 7)
   Else
      Cells(4 + k, 11) = Cells(4 + k, 10).Value + (45 + 105 *
      Application.WorksheetFunction.Beta_Inv(Rnd, 3.143, 7.857)) / (24 * 60)
   End If
Next k

'time spent waiting on orders
Dim z As Integer
For z = 1 To numPatients
   If Cells(4 + z, 9).Value = 0 Then
      Cells(4 + z, 12) = 0
    Else: If Rnd > 0.75 Then Cells(4 + z, 12) = (120 * Application.WorksheetFunction.Beta_Inv(Rnd,
       5 / 3, 25 / 3)) / (24 * 60)
```

```
   End If
Next z

Dim twoRange As Range
Dim bCell As Range
Set twoRange = Range("A4:z38")
Set bCell = Range("K4")
twoRange.Sort Key1:=bCell, Order1:=xlAscending, Header:=xlYes

‘chemo ordered
Dim m As Integer
For m = 1 To numPatients
   If Cells(4 + m, 9) = 0 Then
      Cells(4 + m, 13) = Application.Max(Cells(4 + m, 7) + 0.00208, 1 / 3)
   Else
       Cells(4 + m, 13) = Application.Max(Cells(4 + m, 11) + Cells(4 + m, 12) + 0.00208, 0.33333)
   End If
Next m

'chemo data entry complete
Dim p As Integer
p = 1
     Cells(4 + p, 14) = Cells(4 + p, 13).Value + ((15 + 10 *
          Application.WorksheetFunction.Beta_Inv(Rnd, 4, 4)) / (60 * 24))
For p = 2 To numPatients
     Cells(4 + p, 14) = Application.Max(Cells(4 + p, 13), Cells(3 + p, 14)) + ((15 + 10 *
          Application.WorksheetFunction.Beta_Inv(Rnd, 4, 4)) / (60 * 24))
Next p

'the first patient goes straight through the process
Dim s As Integer
s = 1
     Cells(4 + s, 15) = Cells(4 + s, 14).Value + ((5 + 20 *
          Application.WorksheetFunction.Beta_Inv(Rnd, 4, 4)) / (60 * 24))

'first patient receives chemo order
     Cells(4 + s, 16) = Cells(4 + s, 15) + 0.00208

'tallly the patient number
Cells(4 + s, 17) = s
```

```
'All other patients go through a queuing process
For s = 2 To numPatients
    Cells(4 + s, 15) = Application.Max(Cells(4 + s, 14), Cells(3 + s, 15)) + ((5 + 20 *
        Application.WorksheetFunction.Beta_Inv(Rnd, 4, 4)) / (60 * 24))

    'receive chemo
    Cells(4 + s, 16) = Cells(4 + s, 15) + 0.00208

    'patient number
    Cells(4 + s, 17) = s
Next s

'start infusions for the first 14 patients
Dim q As Integer

If numPatients <= 14 Then
    For q = 1 To numPatients

        'Start infusion
        Cells(4 + q, 20) = Cells(4 + q, 16)
        'complete infusion
        Cells(4 + q, 21) = Cells(4 + q, 20) + Cells(4 + q, 5)
      Next q
Else
  For q = 1 To 14
        'Start infusion
        Cells(4 + q, 20) = Cells(4 + q, 16)
        'complete infusion
        Cells(4 + q, 21) = Cells(4 + q, 20) + Cells(4 + q, 5)
   Next q
End If

For q = 15 To numPatients
      'vacated chairs
      Cells(4 + q, 18) = Application.CountIf(Range("u5:u" & (4 + q)), "<" & Cells(4 + q, 16))
      'avialable chairs
      Cells(4 + q, 19) = 14 - ((Cells(4 + q, 17) - 1) - Cells(4 + q, 18))
      'if available chairs, then start infusion
  If Cells(4 + q, 19) >= 1 Then
     Cells(4 + q, 20) = Cells(4 + q, 16)
```

```
    Else
      'wait until a chair is availabe to start the next infusion
      While 14 - ((Cells(4 + q, 17) - 1) - Application.CountIf(Range("u5:u" & (4 + q)), "<" & Cells(4
            + q, 16))) < 1
          Cells(4 + q, 16) = Cells(4 + q, 16) + 10 / (24 * 60)
      Wend
    ‘start infusion
    Cells(4 + q, 20) = Cells(4 + q, 16)
End If

'complete infusion
Cells(4 + q, 21) = Cells(4 + q, 20) + Cells(4 + q, 5)
Next q

'wait time in system
Dim w As Integer

For w = 1 To numPatients
     'lab processing time
     Cells(4 + w, 22) = Cells(4 + w, 11) - Cells(4 + w, 10)

     'pharmacy time
     Cells(4 + w, 23) = Cells(4 + w, 16) - Cells(4 + w, 13)

     'total waiting time
     Cells(4 + w, 25) = Cells(4 + w, 20) - Cells(4 + w, 7)
Next w

'Daily infusion statistics
Cells(33, 3) = Application.CountIf(Range("E5:E35"), "<.041667")
Cells(34, 3) = Application.CountIf(Range("E5:E35"), "<.083333") - Cells(33, 3).Value
Cells(35, 3) = Application.CountIf(Range("E5:E35"), "<.166667") - Cells(33, 3).Value - Cells(34,
               3).Value
Cells(36, 3) = Application.CountIf(Range("E5:E35"), ">.166667")

'Daily lab wait
Dim dailyLabwait As Double
dailyLabwait = WorksheetFunction.Average(Range("v5:v30"))
Cells(39, 3) = dailyLabwait
```

```
'Daily orders wait
   Dim dailyOrdersWait As Double
      If Application.Count(Range("L5:L35")) > 1 Then
         dailyOrdersWait = Application.WorksheetFunction.Average(Range("l5:l30"))
      Else
         dailyOrdersWait = WorksheetFunction.Max(Range("L5:L35"))
      End If
Cells(40, 3) = dailyOrdersWait

'Daily pharmacy wait
Dim dailyPharmaWait As Double
dailyPharmaWait = WorksheetFunction.Average(Range("w5:w30"))
Cells(41, 3) = dailyPharmaWait

'Daily Wait time in the system
Dim dailyWait As Double
dailyWait = WorksheetFunction.Average(Range("y5:y30"))
Cells(38, 3) = dailyWait

'Daily overtime in the system
If WorksheetFunction.Max(Range("u5:u35")) > 0.67 Then
      Cells(43, 3) = (WorksheetFunction.Max(Range("u5:u35")) - 0.666667) * 2
Else
      Cells(43, 3) = 0
End If

End Sub
```

E.4 SOURCE CODE FOR THE MAIN MENU

```
Public Sub RunSimulation_Click()

    Dim n As Integer

    For n = 1 To Cells(2, 2).Value
       Sheets("CurrentModel").Range("A4:AA40").ClearContents
       Sheets("ScheduledModel").Range("A4:AA40").ClearContents

       Call PatientList
       Sheets("CurrentModel").Select
       Call Iteration1
       Sheets("ScheduledModel").Select
       Call Iteration2
```

```
        Sheets("Stats").Cells(n, 1) = Sheets("CurrentModel").Cells(30, 3).Value
        Sheets("Stats").Cells(n, 2) = Sheets("CurrentModel").Cells(31, 3).Value
        Sheets("Stats").Cells(n, 3) = Sheets("CurrentModel").Cells(33, 3).Value
        Sheets("Stats").Cells(n, 4) = Sheets("CurrentModel").Cells(34, 3).Value
        Sheets("Stats").Cells(n, 5) = Sheets("CurrentModel").Cells(35, 3).Value
        Sheets("Stats").Cells(n, 6) = Sheets("CurrentModel").Cells(36, 3).Value
        'wait
        Sheets("Stats").Cells(n, 7) = Sheets("CurrentModel").Cells(38, 3).Value
        Sheets("Stats").Cells(n, 8) = Sheets("CurrentModel").Cells(39, 3).Value
        Sheets("Stats").Cells(n, 9) = Sheets("CurrentModel").Cells(40, 3).Value
        Sheets("Stats").Cells(n, 10) = Sheets("CurrentModel").Cells(41, 3).Value
        'ot
        Sheets("Stats").Cells(n, 11) = Sheets("CurrentModel").Cells(43, 3).Value

        'Scheduled System Statisitics
        'wait
        Sheets("Stats").Cells(n, 13) = Sheets("ScheduledModel").Cells(38, 3).Value
        Sheets("Stats").Cells(n, 14) = Sheets("ScheduledModel").Cells(39, 3).Value
        Sheets("Stats").Cells(n, 15) = Sheets("ScheduledModel").Cells(40, 3).Value
        Sheets("Stats").Cells(n, 16) = Sheets("ScheduledModel").Cells(41, 3).Value
        'ot
        Sheets("Stats").Cells(n, 17) = Sheets("ScheduledModel").Cells(43, 3).Value

    Next n

    Call results

Application.ScreenUpdating = True

End Sub
```