ABSTRACT

WOODALL, JONATHAN C. Models for Optimizing Resource Allocation in a Cancer Center. (Under the direction of Dr. Brian Denton.)

Cancer centers are the central hub of the health care system for most cancer patients. Patients visit to receive consultations with their oncologists and treatment. Medical advances and an aging population have resulted in patient volumes steadily increasing over time, a trend that is expected to continue. Some studies indicate a simultaneous increase in demand and potential decrease in the supply of nurses, which has created pressure on healthcare managers and administrators to improve efficiency of oncology services. Process improvements could help improve patient access and at the same time increase revenue to providers. Additional potential benefits include a more predictable, manageable, and evenly distributed workload for employees, as well as reduced waiting times for patients. This thesis focuses on the development and validation of a discrete event simulation model for a large medical center. We discuss the most important aspects of cancer center operations, the model building and validation process, and we provide examples of several research questions related to predicting bottlenecks in a cancer center and designing monthly, daily, and weekly nurse schedules.

We use our simulation model to conduct experiments based on the planned design of a new cancer center in order to predict bottlenecks in the patient flow process. We find that treatment chairs and nurses are frequently a major bottleneck in the treatment center. We formulate a mixed integer programming (MIP) model to optimize the allocation of treatment center nurses in a monthly and weekly scenario, which can provide inputs to the simulation model. The MIP has the objective of minimizing shortage hours in the treatment center, and is subject to existing scheduling constraints. We allow the MIP to select from a series of full-time and part-time nurses to find an optimal solution. We examine three potential staffing levels of nurses to reflect a best, most likely, and worst case scenario, and we find that the addition of part-time nurses significantly reduces the number of shortage hours. Furthermore, we find that only a small number of part-time nurses are needed, as increases in part-time nurses improve shortage hours with diminishing returns. We formulate and use a simulation-optimization model to study daily nurse schedules. The simulation-optimization model determines daily nurse arrival times that minimize average waiting time for patients. By comparing with schedules generated manually after consulting experts, we show that

the simulation optimization model can generate moderate improvements. We also show that the ad-hoc scheduling approach taken by experts at the cancer center often yields good schedules.

Models for Optimizing Resource Allocation in a Cancer Center

by
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BIOGRAPHY

Jonathan was born in Orlando, Florida, where he spent much of his childhood. He and his family moved to Raleigh, NC, shortly before he started high school, where he currently lives. Jonathan received his B.S. in Industrial Engineering from NC State University in December 2009, graduating with Magna Cum Laude honors.

Jonathan recently spoke at the INFORMS Healthcare conference in Montreal, Canada, presenting much of this thesis work. Professionally, Jonathan has had several internships over his time in college, interning with Progress Energy and the Duke Medical Center, working with process development and analysis. Jonathan has also been involved with simulation projects through NC State, working with UNC Chapel Hill and the Mayo Clinic on simulation projects. He recently began working a full-time job at Duke Medicine as a management engineer.

Jonathan was recently married to his beautiful bride, Catherine, and in his free time enjoys taking walks through the park and along the beach with her. He is also an avid Carolina Hurricanes and Tampa Bay Rays fan, and is actively involved at his church.

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This thesis was funded by the Duke Cancer Institute. I appreciate their funding of this project, which has led to me accepting a full time position at Duke Medicine working in the Performance Services Department. I appreciate the support Duke has shown me in finishing up my education and helping me grow as a professional.

Finally, I would like to thank my beautiful bride, Catherine, for all of her support, encouragement, love, and care throughout the writing of this thesis. This thesis would not exist if not for her continual encouragement to press on and complete the task that had been given me.

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Chapter 1: Introduction

Recent years have seen many medical advances, particularly in the area of heart disease. These advances have resulted in fewer patients dying of heart disease, and overall increase in life expectancy. However, as a consequence of these improvements, there have been increases in the likelihood of cancer diagnosis over the course of a patient's lifetime. In many countries cancer is, or is rapidly becoming, the leading cause of death. As a result, patient demand for cancer center services has been steadily increasing, and is expected to continue to increase (Erikson et al., 2007). Furthermore, this is expected to lead to significant shortage in oncology.

Cancer centers are the central hub of the health care system for most cancer patients. Patients attend cancer centers to receive consultations with their oncologists and treatment for cancer. Increasing patient demand has created patient and staff scheduling challenges. From the patient perspective, high demand often results in long waiting times. This can be in the form of direct waiting (waiting on site to see a provider or receive treatment) or indirect waiting (waiting for a scheduled appointment). From the staffing perspective, high demand results in higher resource utilization, and congestion that can be frustrating for providers. In a high-demand environment, variation in patient mix can result in portions of the cancer center, or parts of the day, being overloaded, while other areas, or times of day, are underutilized. From the provider perspective, process improvement can allow for more patient throughput, and thus more revenue. It can also mean less stress for employees (and ultimately lower turnover) as the workload becomes more evenly distributed, predictable, and manageable. Therefore, process improvements can help bridge the gap between supply and demand for oncology services. Furthermore, reduced waiting time is associated with more timely treatment, which may result in improved health for patients served by the cancer center.

Process improvement opportunities at cancer centers can be challenging to identify due to the large number of patients served, multiple stages of health services delivered to patients, complex patterns of care and provider workflows, and the highly uncertain nature of daily demand and patient flow through the clinic. Patient flow varies in terms of the interactions patients have with various clinics, labs, pharmacy, radiology, and the treatment center. Each step of the process

involves many different resources and processes, each with differing amounts of variation, and the potential to be a bottleneck in the overall process.

In this thesis we use quantitative models to investigate ways to improve the efficiency of a cancer center. The main focus of this thesis is on the development of a validated simulation model at a cancer center. The model is used to forecast the success of potential process improvements. This predictive ability allows decision-makers the ability to systematically look at many potential alternatives for improvement and identify the best route for improvement. Furthermore, the simulation model is used to recommend design decisions for a new cancer center, and to predict the effect of resource allocation decisions prior to the use of the new cancer center.

Our simulation model was built to represent a particular cancer center at a large academic medical center. However, the insights we draw from our study are applicable to other cancer centers. We begin by describing a conceptual model of a cancer center. Next, we describe the various parts of the discrete event simulation model, development of a non-stationary Poisson arrival process to represent the randomness and unpredictability of patient arrivals, methods for fitting input distributions of process variability, and validation of the model. The model combines the interaction of multiple clinics, the oncology treatment center (OTC), central labs, radiology (where scans are performed for patients), and the pharmacy. Furthermore, it includes complexities of all the various employees responsible for caring for patients along with their work schedules.

We use the simulation model to identify common bottlenecks in the patient flow process at a cancer. We further combine the simulation model with optimization methods to design and analyze nurse schedules for the OTC, which is an important part of the overall cancer care process. Monthly and weekly schedules are determined using a mixed integer program, assuming three nurse staffing levels reflecting a best, most likely, and worst case scenario. Varying shift length combinations are also considered in developing schedules, including both full-time and part-time nurses working 10-hour, 8-hour, or 4-hour shifts. Next, a simulation-optimization approach is used to compute nurse arrival times during the day to minimize patient waiting time.

The simulation model is also used to evaluate two planning scenarios for a new hypothetical cancer center. We conduct a series of experiments using the simulation model for predictive purposes to determine likely bottlenecks in the new cancer center, and to be used for contingency planning with regard to design decisions and nurse staffing and scheduling decisions.

The remainder of this thesis is organized as follows. In Chapter 2, we provide general background on cancer center operations and a review of the relevant literature on applications of discrete event simulation models to cancer centers and other related health services. In Chapter 3 we discuss a conceptual model of the patient flow process, and we describe the development of our discrete event simulation model and its validation. In Chapter 4 we describe the use of the simulation model to investigate nurse scheduling in the patient OTC. In Chapter 5 we investigate the use of our simulation model to represent a new cancer center for future capacity planning and prediction of potential bottlenecks. Finally, in Chapter 6, we summarize our most significant findings and we discuss opportunities for future research.

Chapter 2: Cancer Center Background and Literature Review

Section 1: Overview of Cancer Center Operations

Patients visit cancer centers for many reasons such as referrals from primary care physicians due to suspicion of cancer, second opinions, consultation on treatment type and location, check-up consultations while undergoing treatment, and follow-up consultations upon completion of treatment. The location in which patients visit doctors is called the *clinic*. Most cancer centers have clinics organized based on type of cancer (e.g. breast, prostate, lung). A second major part of a cancer center is the *treatment center,* or *OTC*. The OTC is the location in which patients who have been diagnosed with cancer receive chemotherapy treatment. The goal of chemotherapy is to attempt to cause the cancer to go into remission. Chemotherapy can be received in the form of an *injection* or an *infusion*, where medicine is dripped intravenously into the patient (referred to as an *IV*). Patients may also receive radiation treatment for their cancer, though hospitals vary on whether this location is near or far from the OTC.

There are additional locations in the cancer center that play key roles. One is *radiology*, the location in which radiation imaging scans are performed. Another is the location of the *central labs,* where patient blood tests and other lab tests are processed. Most patients who receive chemotherapy or a consultation with an oncologist must have blood drawn. Blood counts are an important part of diagnosis, and they must be reviewed prior to receiving chemotherapy. This can pose a constraint on patient flow through the cancer center, as treatment cannot start until the blood draw has been processed by the lab, and the patient is deemed able to receive the specified treatment.

The *pharmacy* is the central location that mixes the drugs used for chemotherapy prior to the patient's treatment. However, the pharmacy typically will not mix drugs for a patient until the lab results have been reviewed and the patient has checked in to the OTC and been cleared for treatment by their oncologist. The reason for delaying mixing drugs is that the drugs are very expensive and have a short lifetime once mixed. Therefore, it must be ensured the patient will actually use the drug before it is mixed.

Section 2: Data Analysis and Barriers to Efficient Patient Flow

The large number of interacting areas of the cancer center, and natural variation in the time to complete activities creates a large amount of uncertainty and variability in the patient flow process. As mentioned, there are also challenges posed by a steady increase in patient demand for cancer center services. Figure 2.1 below illustrates the increase in patient volume seen in the OTC over the time from which all arrival data in the model came specifically. A linear trend line has been added to illustrate the increase in patient volume over the time period. The combination of increasing demand for cancer center services and a large number of interacting areas in the cancer center creates significant challenges in managing patient flow. Therefore, it is of particular interest to cancer center management to examine how to best to reduce the negative impacts of this uncertainty. While our data does not cover the span of an entire year, and thus may not capture seasonality in patient arrivals, expert opinion of OTC administration staff has indicated that patient volume has steadily increased over time. For example, July 2009 had less volume than July 2010, and each corresponding month as well.

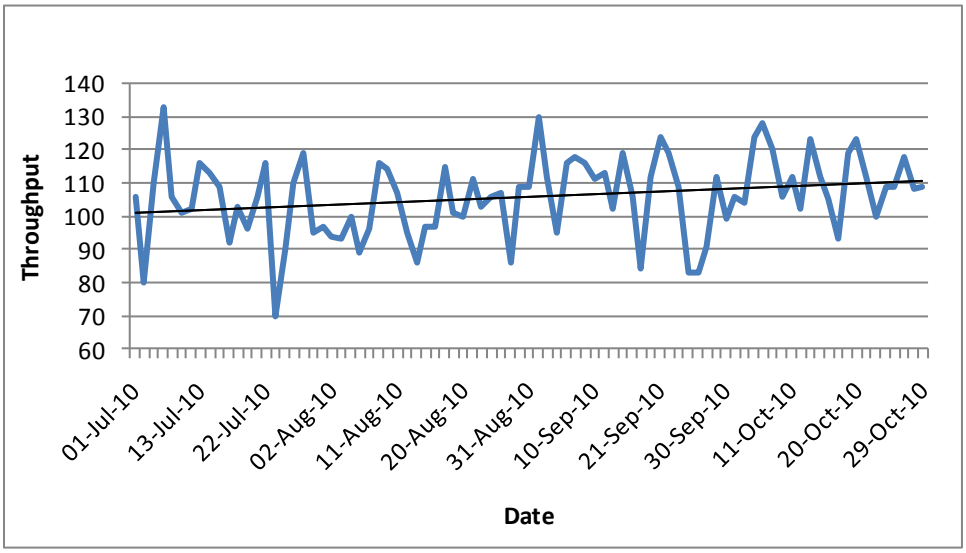

Figure 2.1: Diagram of total patient throughput by day in the treatment center.

Patient arrivals vary depending upon day of week. For example, Figure 2.2 below shows the average throughput in the oncology OTC for each day of the week, with 95% confidence intervals noted by the red bars based on historical arrival data from the time period of July-October 2010. The graph shows some variation across weekdays, with Wednesday being the busiest day, and Friday being the least busy day. The difference in average expected throughput from Wednesday to Friday is approximately 20 patients. This day-to-day variation further complicates planning and resource allocation decisions. The variation in daily demand at the OTC is largely driven by the clinic arrivals in the cancer center. Clinic arrivals are in turn driven by the days in which oncologists practice in clinic. This day-to-day variation in OTC patient volumes is also consistent with expert opinion, and is the case year-round, as patient volume is driven by oncologist availability rather than demand for services, since in this case, the demand far exceeds the supply.

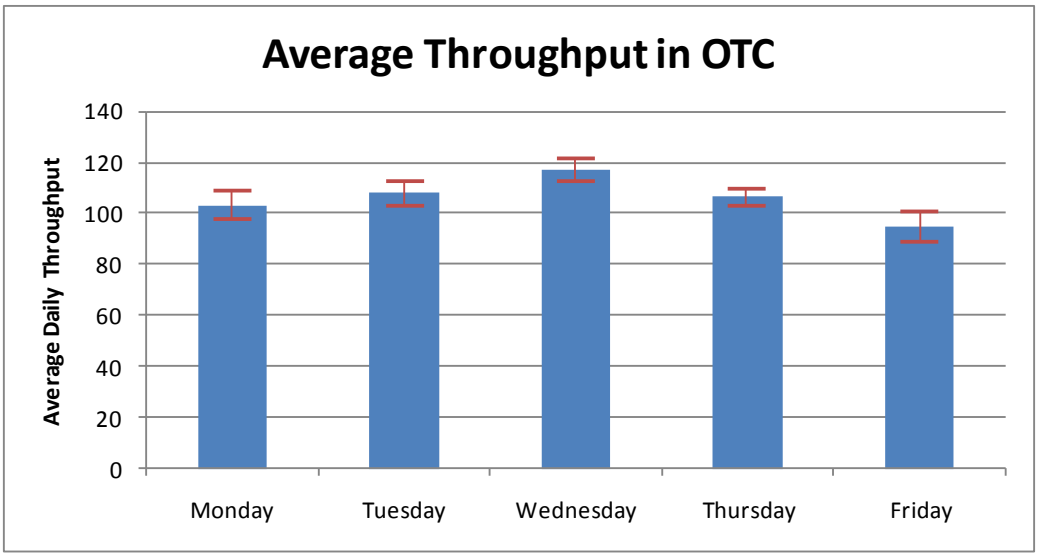

Figure 2.2: Average daily throughput numbers in the treatment center by day of week. Bars indicate 95% Confidence Intervals.

Patient flow patterns in the cancer center differ depending upon the type of patient. In general, a patient receiving treatment will start at one of the clinics, have labs drawn and processed, and will finish at the OTC. However, patients may be classified in several different ways. For

instance, some patients visit the cancer center only for a clinic visit. Of the patients solely receiving a clinic visit, some will have labs and/or radiology, others will not. Some patients are return visits and some are new visits; new visits tend to have longer service times in the clinic. Some patients may go from the clinic to the OTC on the same day, while others may return on a different day for treatment. This variation in patient flow further contributes to uncertainty in resource utilization from day to day.

Of the patients arriving to the OTC, some arrive after visiting other portions of the cancer center and others arrive directly. However, all patients receiving treatment must have their blood drawn to verify they are healthy enough to receive the chemotherapy. Since all blood specimens must be taken within 24 hours of treatment, patients arriving directly must either have had labs drawn the day before at an approved off-site location or must visit one of the labs in the cancer center to have their blood drawn. If review of the blood work indicates patients are not healthy enough to receive treatment, their physician is contacted either to approve the treatment or change the *regimen* (strength and type of drug) used. Upon receiving treatment, patients generally leave the facility, although they may occasionally have to visit radiology or the clinic afterwards.

Figure 2.3 below illustrates the wide variety of types of patient flow and classifications within the cancer center. The pie chart shows the varying sources of arrivals into the OTC. The largest contributors to OTC throughput are the surgical oncology and hematology oncology clinics, as well as the independent arrivals formed by the collection of scattered arrivals from other clinics in the hospital or direct into treatment. These arrivals do not require a clinic visit, but require labs on or off-site within 24 hours of treatment. Bottlenecks in source clinics can significantly affect the process flow of patients into the OTC. Surgical oncology and hematology oncology are important in particular as they supply such a large percentage of the patient volume.

Figure 2.4 below shows a pie chart of the punctuality of patient arrivals into the OTC. Arrivals are deemed “on-time” if the patient arrived within 30 minutes of the scheduled arrival time. Likewise, early patients are designated as patients arriving for treatment more than 30 minutes before the scheduled treatment time, and late patients are designated as patients arriving more than 30 minutes after the scheduled treatment time. As illustrated in Figure 4, less than 50% of

patients arrive within 30 minutes of the scheduled time. Therefore punctuality varies significantly and is a substantial source of uncertainty in patient arrivals to the OTC throughout the day.

Similar pie charts are also provided for arrival punctuality at each of the clinics in Appendix 1. However, the interpretation of these charts differs for the clinic. In the clinic, the scheduled appointment time is the time expected to see the oncologist. For patients requiring lab draws or radiology scans, it is expected that they arrive an hour early for their appointment. Thus, a large percent of patients arrive early. One conclusion that can be drawn from the charts is that late arrivals are not as significant an issue in the clinics, as the number of arrivals that are more than 30 minutes late is approximately 5%. However, if these late patients require lab draws or radiology scans, they can potentially cause significant patient flow inefficiencies even if they are small in number.

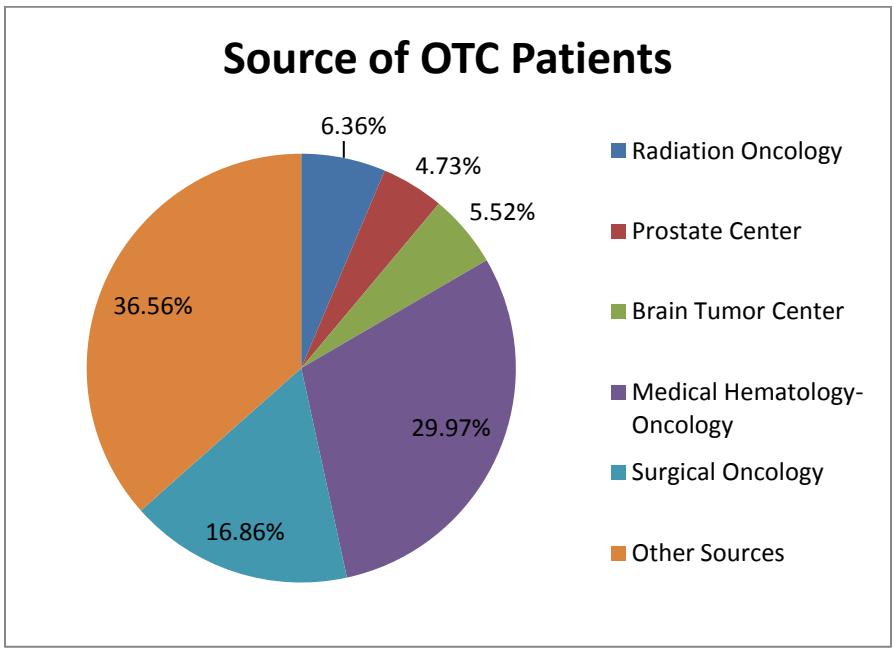

Figure 2.3: Percentage breakdown of the source of patients in the treatment center.

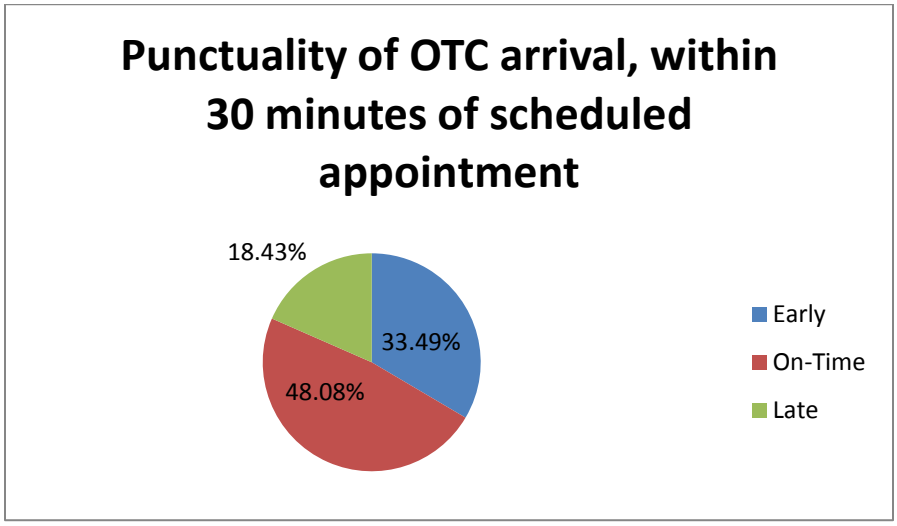

Figure 2.4: Pie Chart showing the punctuality of treatment center arrivals.

Figure 2.5 below illustrates the interaction between early and late arrivals within the OTC. It plots the average number of scheduled patients versus the actual number of arrivals over varying times of the day. Furthermore, it shows the time-varying nature of arrival rates into the OTC. The graph shows that the sum total of patient arrivals during the day is similar to the number scheduled; however, we observe a larger number of arrivals in the early hours of the day than expected, and in the late morning and early afternoon, fewer than expected. This is possibly caused by a tendency for afternoon patients to arrive earlier than scheduled. Furthermore, it is possible that in the lunch hours as nurses take lunch breaks, OTC administration plans for fewer patient arrivals when in reality it appears arrivals do not slow down over that time frame. Additionally, the information provided from Figures 2.4 and 2.5 seem to indicate that while punctuality of a specific patient is uncertain, the early patients and late patients approximately balance and may help cancel each other out. No-shows and cancellations are not modeled, as the data used to populate the model with patient arrivals excluded no-shows and cancellations. Thus, we model patient arrivals and scheduled patient arrivals based only on the historical throughput of those patients actually arriving (the data in Figure 2.5 also excludes no-shows and cancellations for both lines).

Figure 2.5 also shows important information surrounding the timing of patient demand. We observe the peak arrival rate running between 9 and 11 am. Considering it generally takes between 30 minutes to an hour to process a patient prior to actually being called back into the treatment room, the residual effect has peak volume from a nursing perspective between the hours of 9:30 am until 2 or 3 pm. This graph also shows the time-varying arrival rate into the OTC, with the large majority of arrivals taking place in the mid to late morning and early afternoon hours, and significantly fewer arrivals on the tails of the day. From a staffing perspective, it is best to have the most help during the busy hours. Of particular concern is the lunch break hours; demand for nurses builds up during those hours when it is time for nurses to take lunch breaks. We checked the results of this graph with nurses and administrators in the OTC, who verified that this graph is consistent with their experience in the cancer center. Furthermore, peaks of patients are seen in the mid to late morning and early afternoon hours with consistency according to this expert opinion.

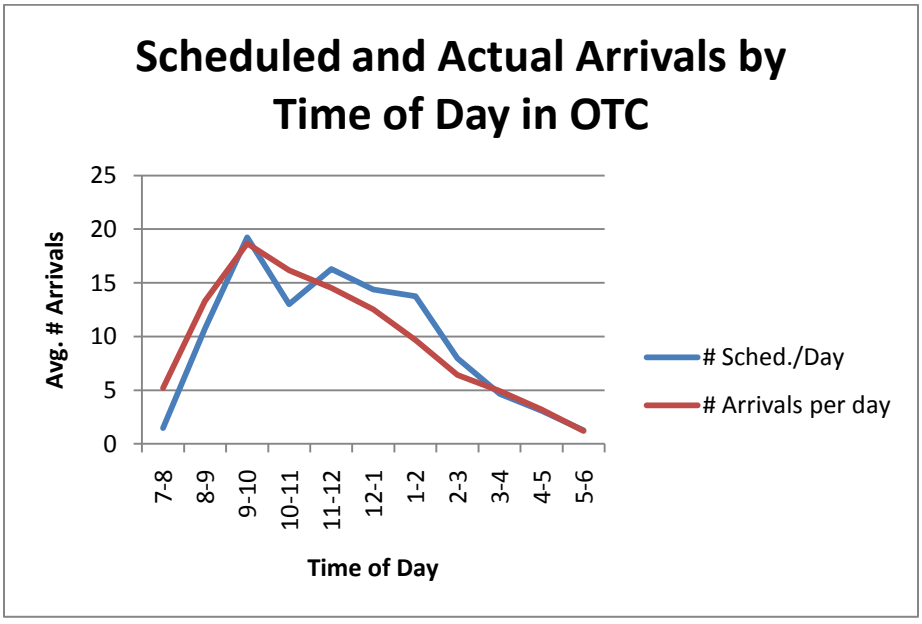

Figure 2.5: Analysis of average number of patient arrivals in the treatment center by time of day for a given day of the week.

Section 3: Literature Review

This literature review has two goals. First, to provide an overview of simulation modeling, citing some recent reviews of applications of discrete event simulation to healthcare. Second, to review the literature on the application of discrete event simulation in health care settings, focusing particularly on cancer centers.

Reviews of the Simulation Literature

A number of literature reviews pertaining to simulation modeling have been conducted in recent years. The most recent is Gunal and Pidd (2010). They conducted a systematic review of the use of discrete event simulation in a health care setting, noting an increase in the use of simulation modeling from 2004. They seek to identify where the research has been centered, particularly in the past several years, detailing a wide range of applications and objectives for these models. They also provide an analysis of potential weaknesses in these models as well as other potential areas of research. They break their review into five major categories: emergency departments (the most common), inpatient facilities of specific hospital wards, outpatient clinics, other hospital units (e.g. pharmacies, surgical suites, screening centers), and whole hospital simulations. Models tend to be designed for these specific applications, and are rarely used to show interactions of other major entities in the hospital. They report a lot of work on patient appointment scheduling. They cite one of the major weaknesses of simulation research as a lack of results able to be generalized for all hospital systems.

Brailsford (2007) also provides an overview of simulation modeling uses, including system dynamics as well as discrete event simulation. She highlights the benefits of using discrete event simulation and system dynamics in differing modeling circumstances. She identifies three major types of simulations: Level 1 (models of the human body such as disease models and cancer progression models), Level 2 (operational and tactical models at the unit level for patient flows and identification of bottlenecks), and Level 3 (strategic long range planning models). Level 2 is reported to be the most frequent application of simulation modeling in healthcare, and is largely built using discrete event simulation.

Another literature review was conducted by Eldabi, Paul, and Young (2007), with a focus on future uses of simulation modeling and the challenges of successful implementation in practice. The authors discuss why implementation rates are low, and possible ways to improve simulation implementation. They conducted a survey of academic experts and professionals in healthcare and found most professionals and academic experts see the benefits of simulation modeling, particularly in whole system approaches that focus on the full and interactive complexity of health care delivery. They also identified hesitancy towards simulation due to the lack of simulation software capability, data quality, and discomfort with modeling tools in the medical community. They cite improved communication and use of whole system approaches as two possible solutions for increased implementation. Brailsford (2007) also identifies a low rate of reported implementation in simulation modeling, and seeks to identify possible solutions for increased implementation. She identifies commonalities in projects with successful implementation as having a stakeholder involved at the institution being studied, studying a high priority problem at that institution, and having a detailed data description. Ideas for future success of simulation modeling are identified as generalizing results for broader cases and combining system dynamics with discrete event simulation to capture the benefits of both approaches to simulation modeling. Many of Brailsford's findings are consistent with Gunal and Pidd (2010). For example, among the challenges of applying simulation to healthcare, she identifies the difficulty in translating results beyond a single application to multiple interacting hospital entities, and the amount of data needed to build a trustworthy model.

The work presented in this thesis falls within the Level 2 modeling described by Brailsford (2007). We seek to identify bottlenecks and improve patient flow in the cancer center. However, our work extends beyond the single outpatient clinic genre described by Gunal and Pidd (2010). We do not take a complete whole system (whole hospital) approach, but within the cancer center, we do take a whole system approach. We consider all the different clinics, the treatment center, and all areas involved in processing patients including the central labs facility, radiology, and pharmacy. While our work is motivated by a specific cancer center, many of the insights from this research can be generalized to other cancer centers.

Review of Cancer Center Models

This thesis examines resource allocation decisions for a cancer center. Therefore, in the remainder of this literature review we focus on simulation of cancer centers via optimization methods or discrete event simulation.

Santibáñez et al. (2009) examine a cancer center at British Columbia Cancer Agency. They focus on the interaction of several cancer clinics with a focus on the combination of operations, planning, and resource allocation. They seek to simultaneously reduce patient wait times and increase patient throughput. They highlight scenarios that include operational factors (clinic start time, use of faculty such as residents/fellows), appointment scheduling (order of appointment type in sequence of day, allowed appointment length increase, scheduling of add-ons), and resource allocation (use of pooled clinic resources versus designated resources). They found that significant process improvement required multiple changes to the existing process. They point out that one of the most effective ways to improve efficiency is by improving clinic on-time starts.

Another discrete event simulation study for a cancer center was performed by Sepúlveda et al. (1999). They model the MD Anderson cancer center in Orlando, Florida, including the oncology clinic, treatment center, and pharmacy to inform design and process improvement decisions. They also model pre-processed patients, which includes scheduling some patients for advance lab processing the day before for treatment. They use their simulation model to examine three scenarios: a layout scenario, a scheduling alternative scenario, and a new building scenario. Expert opinion was used to validate the model, as data was unavailable for certain portions of the study and statistical validation could not be completed. It is worth noting that the authors successfully implemented recommendations from their model. Results of the analysis led to moving the pharmacy location next to the treatment center, which freed up space for additional space in the clinic and lab areas that improved efficiency in the clinic. The movement of the pharmacy location did not affect the treatment center, as the chairs were found to be the limiting resource. The scheduling analysis showed that the number of patients seen per day could increase by up to 20% without affecting the closing time of the facility by modifying the patient arrival schedule. Schedules were altered to bring more short-term patients during slow portions of the day and a few less in the

later, busier portions. A second simulation model was built to model a new, increased capacity facility, and it was determined one of the wait rooms did not have sufficient capacity and bottlenecks were identified and analyzed.

Turkcan, Zeng, and Lawley (2010) examined operations planning and scheduling in the setting of a cancer center. Instead of simulation, they used deterministic mixed integer programming models. Specifically, they use two MIPs in combination to plan patient chemotherapy treatment over a certain length of time, such that the same patient returns for multiple treatments over a sequence of days. The first integer program determines the amount of resources and acuity level required for the patient, and the second integer program seeks to determine the best time to schedule the patient for treatment subject to the constraint the nurse cannot exceed a certain acuity level for the day. Staffing levels were also examined to determine the optimal allocation of resources. They find nurse time to be the limiting resource, and basic guidelines for an optimization model include the following: a) Estimating an acuity level should be based upon nurse experience or from time studies; b) The impact of delays in receiving treatment on patient health should be quantified; and c) Parameters on planning problem should be carefully chosen so as to not drive the nurse utilization to unreasonably high levels.

Our study differs from the above references studies in the following ways. Compared with Santibáñez et al. (2009) and Sepulveda et al. (1999), our primary focus is on the treatment center, optimal design of treatment center nurse schedules, and running experiments on specific anticipated bottlenecks for a hypothetical new cancer center. We also use both discrete event simulation and simulation-optimization for nurse schedules. Furthermore, in contrast to all of the aforementioned studies, we assume patient arrival patterns do not change and seek the best ways to staff in light of patient arrival behavior. Compared with Turkcan et al. (2010), we use discrete event simulation in addition to a deterministic model. Thus, we model many sources of uncertainty in the patient arrival and flow process. Our model provides a detailed representation of overall patient flow on a daily basis rather than focusing on multiple-day planning of individual patient schedules. We also differ in that our MIP model is focused on allocating nurses optimally subject to the criteria of certain daily nursing hour requirements driven by patient demand.

Chapter 3: Simulation Model Design and Validation

Section 1: Introduction

In this section we describe our conceptual model of patient flow with respect to the major elements of the cancer center including the clinic, labs, pharmacy, and the OTC. We provide a description of the typical steps a patient goes through at the cancer center. Diagrams are provided to aid the understanding of basic process flow.

We begin with a high level overview of patient flow. Figure 3.1 below illustrates the patient flow between major entities within the cancer center. Patients typically arrive into one of the cancer clinics, including surgical oncology, hematology oncology, brain tumor, and prostate cancer clinics. Within the clinic, patients have blood specimens drawn and sent to central labs for processing. Additionally, other patients may go to radiology for a scan after checking in to the clinic and prior to oncologist consultation. After finishing in the clinic, some patients go to the treatment center for chemotherapy. When the results from the blood specimens are ready, central labs sends the information to the charge nurse in the treatment center and to pharmacy for mixing the drug. The treatment center process starts when the pharmacy has finished mixing the drug.

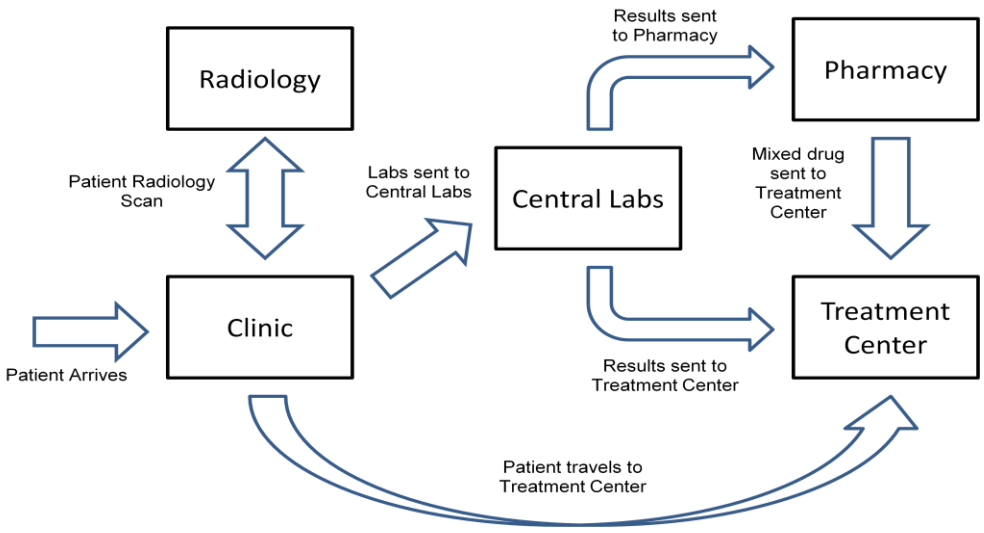

Figure 3.1: Flow chart showing the high-level patient flow through the cancer center.

Clinic Flow

Figure 3.2 illustrates the basic process flow of a patient entering the clinic. Patients are provided an appointment time for arrival at the cancer center in advance of their visit. On the day of their appointment, patients arrive to the clinic at a reception area for check-in. For most patients the clinic is the first stop of the day (in a small number of cases, radiology scans or treatment are scheduled first). The length of time for check-in varies by clinic. A receptionist is required to complete check-in so the total time at check-in may include some waiting time if a queue develops for the receptionist.

After checking in, most patients wait in the waiting room until a phlebotomist is available to draw blood to send to the lab for processing. Some patients also visit radiology after receiving their blood draw and prior to entering the clinic; if not, the patient skips this step in the process and waits to be called back to an examination room. Once blood has been drawn and, if necessary, radiology labs completed, the patient is called back to an exam room by a nurse. Once in the room, the nurse takes the patient's vitals, reviews medical history, and preps the patient for the oncologist consultation. If a room is not available, patient vitals are taken prior to the nurse bringing the patient back to the examination room, provided a resource is available to take vitals. In such cases, there are dedicated employees (vitals specialists) specifically for taking vitals that help reduce the amount of time the nurse spends with the patient in an effort to prepare the patient for consultation more quickly. If nurses are not engaged with other work, they may also help take vitals while waiting for the examination room to become available. Blood work is processed at central labs in parallel to the nurse subsequent clinic processes.

After the nurse has finished with the patient, the oncologist comes into the exam room for a consultation. After the consultation, patients move to a reception area for check-out, which also requires a receptionist. Check-out times vary by clinic. After checking-out, some patients are finished for the day while others continue on to the treatment center. For those patients destined for the treatment center, an oncologist must enter the order for the treatment regimen into an automated order system to communicate the order to the treatment center and pharmacy.

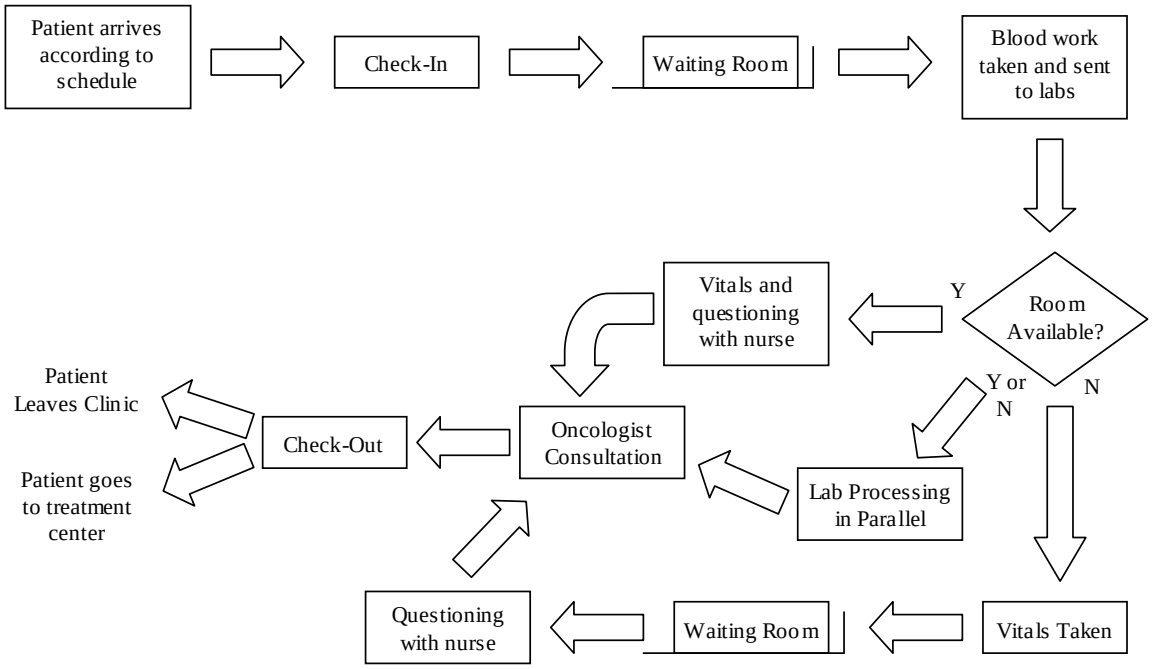

Figure 3.2: Flow Chart of the major steps in the clinic patient flow process.

Pre-Treatment Flow

Figure 3.3 illustrates the treatment center process prior to the patient receiving treatment. Patients arrive into the OTC either directly from one of the clinics or in follow-up to prior visits. In either case, upon arrival at the treatment center, patients must first go through a check-in process. A receptionist pulls the patient's chart and brings it to the charge nurse to notify the charge nurse the patient has arrived. Once the patient checks-in, he or she must wait until several other processes have been completed to ensure the drug is ready to be administered and clearance for treatment has been provided by the oncologist. If the charge nurse deems the health of the patient to be inadequate for the treatment, then the oncologist must be contacted. The charge nurse then receives approval to carry on with the treatment, or instructions on reducing the strength of the regimen. Additionally, if the order has not been entered by the oncologist, the charge nurse must contact the oncologist about the order. Once this process is complete, the pharmacy begins mixing the drug.

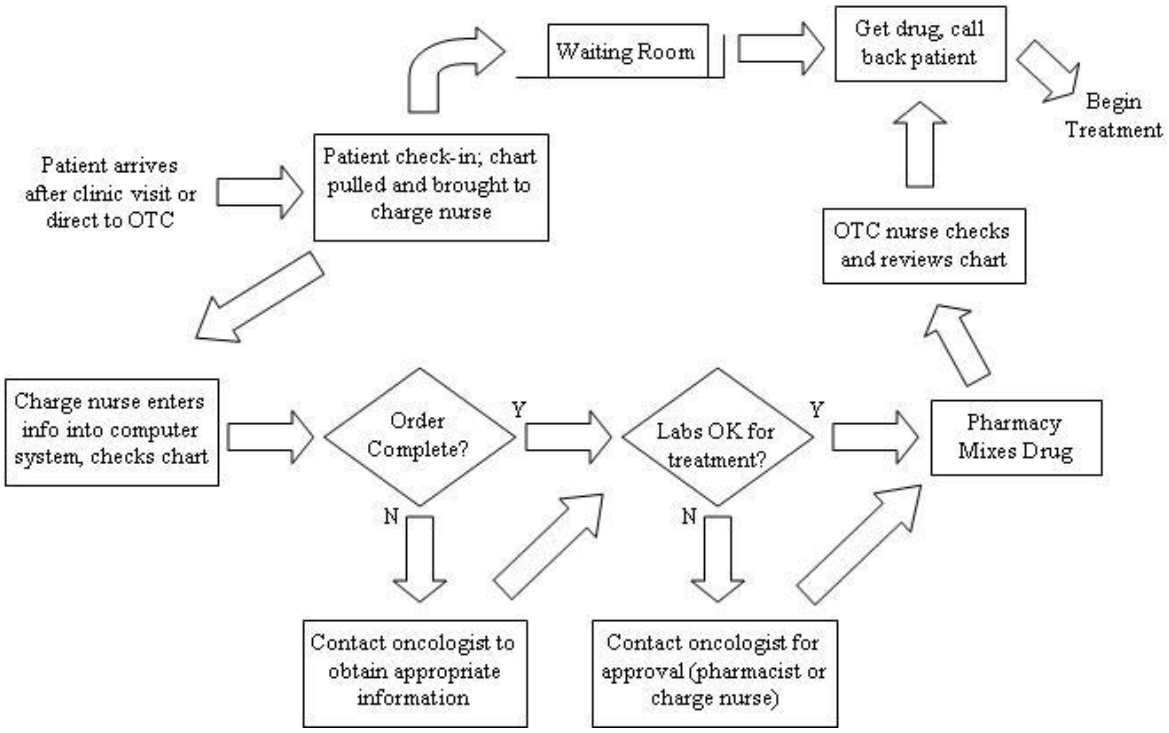

Figure 3.3: Flow chart of treatment center process prior to treatment being initiated.

Once the order has been verified and the lab results approved, the pharmacy can begin to mix the drug. The pharmacist reviews the order and may contact the physician before mixing the drug. When the pharmacist approves, the order is printed and brought back to pharmacy technicians for mixing. The drug is mixed and then reviewed by a pharmacist in the *clean room,* the room where the technicians work, before being sent to the treatment center. Next, a treatment center nurse picks up the patient's chart, locates the patient's drug, reviews the blood results, and then retrieves the patient from the waiting room for treatment.

Treatment Center Flow Following Pre-Treatment

Figure 3.4 illustrates the process flow in the treatment center after all pre-treatment work has been completed. Once pre-treatment is complete, a nurse brings the patient back to a treatment chair or bed. Beds are typically used for older patients and patients with longer treatment times, although there is no functional difference between beds and chairs. For this

reason, we refer to the combination of beds and chairs as chairs throughout the remainder of the thesis. Of the two treatment types, injections and infusions, injections are much shorter. Thus patients receiving injections are typically allocated a chair. Prior to injection the nurse reviews and discusses the appropriate medical history with the patient and provides relevant information about the injection to the patient. Once the injection is complete, the patient is free to leave. There is no discharge process following this step.

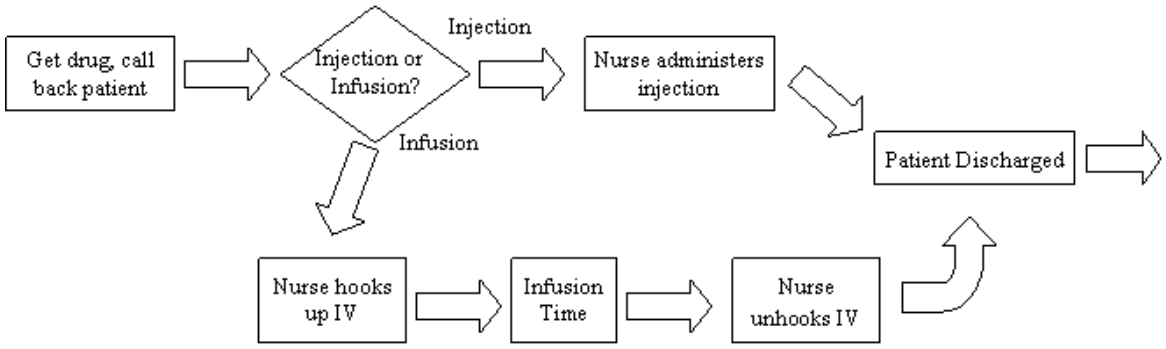

Figure 3.4: Flow Chart of treatment center flow process following treatment.

Infusions follow a similar process. Initially, there is time required for the nurse to prepare the patient. Activities involved in preparation include the review of medical history, discussion of necessary medical information about the treatment, connecting the IV, and taking vitals. Once this is complete, infusion begins (the common terminology is that the drug is *dripping* at this point). Once infusion has begun, the nurse is free to prepare other patients and is no longer required to be continuously present with the patient at the chair or bed unless the patient needs help, has questions, or needs an IV changed to a different drug (in cases where multiple drugs are part of the regimen). Based on expert opinion from nursing administration in the OTC, we assume that a nurse can care for at most four patients at a time, though this number depends on acuity level of the patient and skill set and experience of the nurse, which can vary greatly. Infusions are scheduled in different categories, depending upon approximate expected length of treatment (e.g., 1 hour, 3

hours, and 5 hours). Once the infusion is complete, the nurse disconnects the IV and discharges the patient. There is no formal check-out process at the center.

Grouping of Resources in the Treatment Center

In the treatment center, chairs and beds are used on a first-come first-serve basis regardless of patient type. However, the nurses are often organized into *pods* by *disease based groups* (DBGs). In general, nurses serve patients from within their own DBG. However, nurses can help out in other DBGs when necessary. There are five major DBG classifications: *Breast/Gynecology*, *Gastrointestinal and Genitourinary* (GI/GU), *Hematology Oncology* (HOA*), Lung/thoracic*, and off-service. *Off-service patients* are various disease and regimen types that can be served by any of the nurses (though most typically HOA). All other DBGs have designated nurses to serve those patient types. Patient volume by disease type varies by day of the week, as does total treatment center throughput, and schedules of nurses. Other than nurses, chairs and beds, resources in the treatment center include the charge nurse and the receptionists for check-in.

Sources of Uncertainty

Most clinic visits, lab draws, and radiology scans take place prior to a patient receiving treatment, and thus can cause variability and uncertainty in arrivals. It is difficult to schedule patients in the treatment center, as the amount of time in each of the prior steps in the cancer center is uncertain. Although patients are generally punctual in their arrival to the cancer center, there is considerable uncertainty in the arrivals to the treatment center. Bottlenecks in patient flow through the clinic can cause delays in arrival times to the treatment center. Possible bottlenecks in the clinic process can include wait times at any of the check-in or check-out stations, delays waiting for a room to become available, delays waiting for the oncologist, and delays in waiting for a phlebotomist to draw blood. Radiology can also be a bottleneck (the radiology area operates independently and services other clinics as well). To compensate for these potential bottlenecks, clinic appointments may be scheduled far in advance of treatment center appointments. As a result, in some cases variation and uncertainty in clinic flow times may cause a patient to go to the treatment center earlier than anticipated as well.

After the patient arrives at the treatment center, there are additional possible bottlenecks that may delay the patient in receiving treatment. Delays take place when the pharmacy becomes overloaded and the pharmacists and technicians are unable to keep up with orders. Another source of delay can occur if the regimen order is not completed and signed off in the automated order entry system by the oncologist, or if the lab results indicate the patient is not healthy enough for his or her treatment regimen. In such cases, the charge nurse must call and contact the oncologist, who may be busy with other activities in or out of clinic. Sometimes it can take more than an hour to get in touch with the oncologist. All of these variables and possible delays can have a large impact on patient flow in the treatment center, and make planning to meet demand a challenge.

Section 2: Methods

We built our simulation model based on the above conceptual model using Rockwell's simulation software, Arena version 11. We run the model separate for each day of the week because of the significant variation in patient arrival rates in each of the clinics by day of week. Thus, there are five variants of the simulation model in which the input streams are changed based on the day of the week. Preliminary work in developing the model included collecting sample observation times for services provided in all parts of the cancer center. Process maps representing the patient flow process were developed based upon these observations and interviews with subject matter experts. Collaborative work with subject matter experts yielded assumptions for process times where data did not exist or was not immediately available. Additional model data including the number of resources (nurses, doctors, chairs/rooms, receptionists, phlebotomists, etc.) and associated schedules came from a variety of sources, including computer information systems and expert interviews including oncologists, administrators, and nurses for the clinic, treatment center, and pharmacy.

Once data collection was complete, a prototype version of the simulation model was developed. The initial model included major processes within the cancer center including clinics, labs, radiology, pharmacy, and the treatment center. The model was built to include the primary clinics that cancer patients flow through. Some other smaller clinics that send patients to the treatment center were treated as a separate random arrival feeding directly into the treatment center. This arrival stream also includes the small proportion of patients arriving directly into the treatment center. Major components of the simulation model are as follows.

Patient Arrivals

Cancer centers typically schedule patient arrivals; however, using a deterministic schedule of arrivals in the simulation model was found to be unrealistic because there is considerable uncertainty in the arrival process. This occurs for a variety of reasons including patient behavior, and the dependencies patients may have on other upstream parts of the care process. Therefore, we decided to use observed arrival times to fit an appropriate stochastic process for arrivals, based

on the mean number of arrivals through various parts of the day. We used a non-stationary Poisson arrival process because patient arrival rates vary significantly over the course of a day. These arrivals were generated in the model based on historic data from the time period of July 2010 through October 2010. An additional benefit to modeling arrival processes in this manner is the ease in translation for future volume increases, when arrival schedules may not be developed yet.

Our approach is consistent with other studies. For example, Swartzman (1970) performed several statistical tests in a large hospital to determine appropriate ways to model patient arrivals. He concluded that in the case of unscheduled arrivals, a time-varying Poisson arrival rate most closely described arrivals. While our arrivals are not unscheduled, we apply the same principle with our time-varying arrival rate being defined by the number of arrivals over a given period of time based on historical data.

We used the arrival schedule feature in Arena 11 to define the non-stationary Poisson arrival process for each clinic based upon historical arrivals. This feature allows the user to enter in expected arrival rates over user-defined intervals of time. Hourly throughput rates were input for various blocks of time throughout the day. The average expected arrival rate by each half-hour of the day was calculated from the historical data. Arrivals begin at 7:00 am and end at 5:30 pm. The arrival rate for each half-hour was calculated as an equivalent hourly rate for entering the Poisson process into Arena 11.

Table 3.1 is a sample of the arrival calculations that were made for one of the clinics on Thursday; a similar process was used for each of the clinics. Throughput calculations can also be found for every clinic and every day in Appendix 2. Separate processes were fit for each day of the week. The first column indicates the time slot; the second column contains the mean number of arrivals over the 18 Thursdays in the data set. The “E[Arrivals/half-hour]” column represents the expected throughput for that particular half-hour time block over the 18 Thursdays in the data set. These values were then converted into an hourly throughput level (“Arrivals/Hour” Column), which were the values used to define the arrival schedule in Arena.

Patient arrivals are generated for multiple clinics, which ultimately become arrivals into the OTC. Patient arrivals are also generated for patients directly to the treatment center from other sources. These other sources include the collection of various other clinics not explicitly represented in our simulation model, patients not required to visit an oncologist in the clinic prior to receiving treatment, and patients arriving directly from radiation oncology.

Patient flow process

All components of the patient flow process described in Section 1 of this chapter are included in the simulation model. However, we made some simplifying assumptions in our model. The central labs and radiology are both modeled as general delays with no resources. This means that the length of time a patient spends processing is merely a random sample from the probability distribution of the flow time. We made this assumption for two reasons: 1) the time spent waiting in either of these two areas is accounted for in the historical data used to represent these resources; and 2) the radiology and central labs serve patients from across the entire hospital, and thus, modeling resources and specific process times without the entire patient flow does not make sense.

Upon arrival in each clinic, patients are designated as either new or returning patients based upon historical frequency of each patient type. Patients are also designated as being *port* or *peripheral stick* for their labs upon entry into the clinic, as this varies the amount of time the blood draw process takes. A *port* patient is a patient with an IV access tube already attached, usually in the chest area. A *peripheral stick* patient is a patient whose blood is drawn through veins in the arm in a traditional manner.

Table 3.1: Arrivals per hour calculations for each time block in a clinic on Thursday.

# Thursdays	18	E[Thursday Arrivals	109.33
half-hour	counts	E[Arrivals]/half-hour	Arrivals/Hour
7-7:30	55	3.06	6.11
7:30-8	111	6.17	12.33
8-8:30	136	7.56	15.11
8:30-9:00	148	8.22	16.44
9:00-9:30	195	10.83	21.67
9:30-10:00	186	10.33	20.67
10:00-10:30	175	9.72	19.44
10:30-11:00	162	9.00	18.00
11:00-11:30	126	7.00	14.00
11:30-12:00	75	4.17	8.33
12:00-12:30	77	4.28	8.56
12:30-1:00	96	5.33	10.67
1:00-1:30	79	4.39	8.78
1:30-2:00	99	5.50	11.00
2:00-2:30	70	3.89	7.78
2:30-3:00	71	3.94	7.89
3:00-3:30	51	2.83	5.67
3:30-4:00	30	1.56	3.11
4:00-4:30	19	0.00	0.00
4:30-5:00	4	0.00	0.00
5:00-5:30	2	0.11	0.22

Preparatory work prior to the oncologist visit consists of two pieces: recording vitals, and pre-consult assessment and briefing. Vitals can be performed by either a vitals specialist or a nurse. We assume vitals specialists perform a piece of the preparatory work in cases when the nurse and room are unavailable. This occurs at a small location next to the phlebotomy area. In such cases, the patient returns to the waiting room after having vitals taken, and when the nurse and room become available, the nurse will bring the patient to the exam room and finish preparatory work prior to the consult. Otherwise, the nurse retrieves the patient and completes the full preparatory process in the exam room, provided a room is available.

We assume patients have an equal probability of seeing any oncologist in the clinic. Each oncologist is assumed to have the same number of exam rooms and mean patient volume. These assumptions were made to simplify construction of the model and due to delays in obtaining the necessary oncologist patient volume information by day of week.

After consultation with a patient, the oncologist enters the chemotherapy order into the computer system for the treatment center and pharmacy. In some cases the order is not entered, subsequently requiring the charge nurse to call the oncologist later in the process to verify the order. To reflect this in the simulation model, each order has a certain probability of requiring nurse follow-up. Probability estimates are based on historical data, and can be found in Table 3.4. Finally, a clinic check-out process is modeled. In some cases, patients do not go through the check out process if they are willing to schedule future appointments by e-mail or phone. We model certain percentages of patients skipping the check-out process based on expert opinion of frequency of occurrence, denoted in Table 3.3 as % late tray patients.

In the treatment center, the time for the charge nurse to evaluate a chart is broken into two parts. The first part is the time it takes the charge nurse to review the order and enter the necessary information. We assume all patients undergo this process initially. The second part is the time required for the charge nurse to review labs and follow-up with the oncologist. This occurs with a certain probability based on the results of a time study. Thus, some patients randomly encounter a second stage to the chart check process for contacting the oncologist. The pharmacy process is also broken down into two parts based upon a time study. The first part is for the pharmacist to check the order and labs and process the paperwork, and the second part is for the technicians to mix the drug. Finally, we assume the scheduled treatment time is a random variable with a discrete 5-point distribution based on current scheduling templates. The value of this distribution can be found in Appendix 3.

Scheduling of Resources

Resources in the model are modeled as capacity resources. Schedules are input into the model based on how many employees of each type are working at any given point in time, rather

than specific start and end times for each employee. While the capacity schedule is developed from an actual staff arrival schedule, this subtle difference means staffing levels are modeled from the patient perspective in the sense that the patient is only concerned with how many staff members are available at any given point in time at any given location. Thus, the simulation model has capacity schedules derived from employee schedules. Resources include check-in and check-out receptionists for all clinics, phlebotomists for some of the clinics (some clinics model lab draws as a general delay because patients receive lab draws off clinic-site), nurses and oncologists for each of the clinics (we assume each oncologist has one nurse and three exam rooms after consulting with the administrative manager), exam rooms, receptionists at the treatment center check-in, a charge nurse, nurses by DBGs, treatment chairs, and beds. Many of the resources are available according to predefined schedules. A complete list detailing every employee schedule can be found in the Appendix 4.

Nurses in the treatment center are modeled uniquely to capture their role in both direct and indirect care that results from starting and monitoring patients. We assume that each nurse working has six *capacity units* available. In the simulation model, this means that for each nurse, there are six units available to be distributed for use by patients. In order for a patient to begin an infusion (direct care time), we require at least 3 units of nurse to be available and unused. Thus, a patient in direct care for start-up uses 3 units of nurse. Once the nurse finishes start-up and moves to a monitoring role with the patient, 2 units of the nurse are freed (1 unit is still in use). Doing so restricts the number of patients a nurse can serve at one time to 4 as desired. For example, if 3 units of nurse are being used, then 3 units are available to start a new patient. Suppose a new patient is now serviced. Once that patient has completed start-up, 4 units of nurse are being used, meaning there are only 2 units of nurse available, an insufficient amount to begin a fifth patient. Thus, we restrict the number of patients to 4 per nurse.

Methodology for Determining Service Time Probability Distributions

Probability distributions were used to represent the length of time for various process steps. Specific probability distributions were selected based upon the data or expert opinion, depending on the amount of data available. For processes with extensive and reliable data, distributions were

fit using standard statistical data fitting techniques using Arena 11 Input Analyzer, all of which can be found in Appendix 3. Criteria for selecting distributions were visual inspection and the results of chi-square and Kolmogorov-Smirnov tests. Additional consideration was given to the squared error of the fit. For processes with unreliable or no data, probability distributions were fit in two ways; time studies and expert opinion. As time permitted and as it was possible, time studies were performed to collect data for fitting distributions, as described in the paragraph below.

In total, three time studies were performed: one for the pharmacy process in two parts (pharmacist processing time and drug mixing time), one for the check-out time at one of the clinics, and one for the length of the chart check by the charge nurse in the OTC. The pharmacy time study was performed over several days working with both pharmacists and pharmacy technicians during the summer of 2010. A time study for check-out at one of the clinics was performed on September 21, 2010. The time study recorded when the patient walked up to the counter as the beginning of check-out and the time the patient walked away from the counter as the end of check-out. A time study for the charge nurse chart check was performed on October 5, 2010. This time study captures the length of time it takes for a patient chart to be processed, with the start of processing occurring when the charge nurses begins examining the chart, and ending when the charge nurse has placed the chart on the front counter for pickup by the OTC nurse. We broke chart check times into two categories, depending upon the situation. The first category is a normal or routine chart check, meaning the nurse does not have to call externally to complete examination of the chart. The second category is a special case chart check, defined by the charge nurse calling the patient's oncologist either because the patient's blood specimen indicated the patient should not receive chemotherapy for health reasons or because the oncologist did not approve the chemotherapy order in the computer system.

Table 3.2 contains a list of probability distributions used (in some cases constant) in the model for service times, with the exception of some of the distributions developed based on expert opinion (these are described in Table 3.4). Most of the service times listed in this table are the unconfirmed assumptions left in the model, many coming from labor standards. Labor standards are defined by hospital administration, and were developed historically to estimate the amount of

employee time associated with each patient on average. This information comes from both past experiences of the time it takes to process patients, as well as any other incidental non-direct patient contact activities such as filing paperwork or scheduling future appointments online. A labor standard includes a direct patient time component and non-direct patient time component; we use only the direct patient time component in our model. We list the process the probability distribution is for, as well as the source of the information and probability distribution. Historical data sources came from several places, as the hospital we study uses multiple data collection applications. Additionally, we provide a list of information used to split patient routing in the cancer center in Table 3.3.

Table 3.2: List of probability distributions and their sources as used in the simulation model (all times in minutes).

Process Type	Location	Probability Distribution	Information Source	Sample SIze
Check-In	Surgical Oncology	4.81	Labor standard	-
Check-In	Hematology Oncology	4.89	Labor standard	-
Check-In	Brain Tumor Center	4.15	Labor standard	-
Check-In	Prostate Center	4.81	Labor standard	-
Check-Out	Surgical Oncology	6.61	Labor standard	-
Check-Out	Hematology Oncology	LOGN(9.33,11.3)	Time Study	50
Check-Out	Brain Tumor Center	5.47	Labor standard	-
Check-Out	Prostate Center	6.61	Labor standard	-
Vitals	All Clinics	5	Assumption	-
Nurse Assessment and Questioning	All Clinics	10	Assumption	-
Nurse Vitals, Assessment, and Questioning	All Clinics	15	Assumption	-
Check-In	OTC	1	Expert Opinion (Receptionist)	-
Pharmacist Processing	Pharmacy	-0.5 + LOGN(5.46,6.74)	Time Study	72
Pharmacy Drug Mixing	Pharmacy	1.5 + ERLA(2.94,2)	Time Study	210
Injection Treatment Length	OTC	TRIA(1, 2.1, 30)	Assumption	-
Drawn to Receive Labs	Central Labs Processing	9.5 + GAMM(12, 1.33)	Historical Data – Patient Tracker	6259
Receive Labs to Verified	Central Labs Processing	19.5 + LOGN(19.5, 35.7)	Historical Data – Patient Tracker	6259
Radiology Processing	Radiology	30 + GAMM(62.2, 1.18)	Historical Data	4184

Table 3.3 – List of routing percentages and their sources as used in the simulation model.

Routing Decision	Location	Percentage	Information Source	Sample Size
% New Patients	Surgical Oncology	22.8	Monthly Performance Report, July 2010	461
% New Patients	Hematology Oncology	13.2	Monthly Performance Report, July 2010	647
% New Patients	Brain Tumor Center	7.3	Monthly Performance Report, July 2010	160
% New Patients	Prostate Center	17.9	Monthly Performance Report, July 2010	161
% Patients to Radiology	Surgical Oncology	27.33	Historical Data - IDX	461
% Patients to Radiology	Hematology Oncology	32.15	Historical Data - IDX	647
% Patients to Radiology	Brain Tumor Center	21.88	Historical Data - IDX	160
% Patients to Radiology	Prostate Center	18.63	Historical Data - IDX	161
% Non-Treat Patients Receiving Labs	Surgical Oncology	33.3	Expert Opinion (Administrative Manager)	-
% Non-Treat Patients Receiving Labs	Hematology Oncology	70.0	Expert Opinion (Administrative Manager)	-
% Late Tray Patients	Surgical Oncology	4.07	Expert Opinion (PSA)	-
% Late Tray Patients	Hematology Oncology	5.96	Expert Opinion (PSA)	-
% Late Tray Patients	Brain Tumor Center	6.45	Expert Opinion (PSA)	-
% Late Tray Patients	Prostate Center	5.49	Expert Opinion (PSA)	-
% Patients to OTC	Surgical Oncology	13.68	Historical Data - IDX	461
% Patients to OTC	Hematology Oncology	30.77	Historical Data - IDX	647
% Patients to OTC	Brain Tumor Center	11.76	Historical Data - IDX	160
% Patients to OTC	Prostate Center	22.66	Historical Data - IDX	161
% Patients with Port	All Clinics	5 + 13*BETA(2.26, 2.46)	Historical Data – Patient Tracker	45
% Labs fine for treatment	OTC	UNIF(80,85)	Expert Opinion (Clinical Operations Director)	-
% Breast DBG Monday	OTC	23.7	Historical Data - ARIA	654
% Breast DBG Tuesday	OTC	29.5	Historical Data - ARIA	845
% Breast DBG Wed.	OTC	39.3	Historical Data - ARIA	644
% Breast DBG Thursday	OTC	25.6	Historical Data - ARIA	844
% Breast DBG Friday	OTC	27.1	Historical Data - ARIA	702
% GIGU DBG Monday	OTC	17.0	Historical Data - ARIA	654
% GIGU DBG Tuesday	OTC	22.2	Historical Data - ARIA	845
% GIGU DBG Wed.	OTC	10.6	Historical Data - ARIA	644
% GIGU DBG Thursday	OTC	25.1	Historical Data - ARIA	844
% GIGU DBG Friday	OTC	13.0	Historical Data - ARIA	702
% HOA DBG Monday	OTC	26.5	Historical Data - ARIA	654
% HOA DBG Tuesday	OTC	29.5	Historical Data - ARIA	845
% HOA DBG Wed.	OTC	16.9	Historical Data - ARIA	644
% HOA DBG Thursday	OTC	25.6	Historical Data - ARIA	844
% HOA DBG Friday	OTC	25.6	Historical Data - ARIA	702
% Lung DBG Monday	OTC	20.3	Historical Data - ARIA	654
% Lung DBG Tuesday	OTC	11.1	Historical Data - ARIA	845
% Lung DBG Wed.	OTC	18.3	Historical Data - ARIA	644
% Lung DBG Thursday	OTC	11.6	Historical Data - ARIA	844
% Lung DBG Friday	OTC	14.0	Historical Data - ARIA	702

In the absence of historical data and time studies, initial estimates were made using constant, uniform, and triangular probability distributions based on expert opinion. However, preliminary validation showed that these initial estimations did not appear to correctly represent processes in the cancer center, as many of the processes tend to be centered on a most common time with long narrow tails reflecting process variability. Therefore, it was decided to use Beta distributions for processes with no data. Expert opinion was solicited for the minimum, most frequent (mode), maximum, and average processing times, which were used to define Beta distributions. The following equations were used to calculate the beta distributions using an excel spreadsheet. We used the asymmetry ratio, *r*, to estimate the shape parameters, α_1 and α_2. The fit was determined to be successful if the use of minimum, maximum, and most likely times yielded a probability distribution with a mean that matched the average processing time as provided by the pilot time study or expert estimation. In a very small number of cases, we had a small sample size of time study data available, but with too few data points to find a reasonable fit for a probability distribution. In such cases we also used Beta distribution estimations. In one case, charge nurse chart check time, using the asymmetry ratio approximation yielded a solution with an expected mean that differed from the time study data mean. In this case, with mean and mode values available, a system of equations was solved to determine the beta distribution parameters using the equations for mean and mode listed below. The final distribution fits are shown in Table 3 below.

General Form of Beta Distribution:

a= minimum value

b= maximum value

m= mode

$r= (b-m)/(m-a)$

$\alpha_1= (4 + 3r + r^2) / (1+ r^2)$

$\alpha_2= (1 + 3r + 4r^2) / (1+ r^2)$

$\mu = (b\alpha_1 + a\alpha_2)/(\alpha_1 + \alpha_2)$

$m= [(\alpha_1 - 1)b + (\alpha_2 -1) a]/[\alpha_1+ \alpha_2 -2]$

Generalized Beta Distribution:

$a + (b-a)BETA(\alpha_1 , \alpha_2)$

Input Distributions for Service Times

The results of the time studies are as follows. Probability distributions for the pharmacy time study were fit as -0.5 + LOGN(5.46,6.74) for pharmacist processing and 1.5 + ERLA(2.94,2) for drug mixing. For the clinic check out time study, an average time of 8.41 minutes was observed, and the following distribution was fit using Arena's Input Analyzer: LOGN(9.33,11.3). For the charge nurse chart check time study an average time of 2.5 minutes for regular chart checks and 29 minutes for prolonged chart checks were observed. There was not enough data to get a good probability distribution fit with software, but the average times were useful in combining with expert opinion to develop a distribution. Figure 3.5 below shows an example of a probability distribution fit based upon a time study, for the drug mixing process. All service times were uploaded into Arena's Input Analyzer, which generated the histogram, goodness of fit, and probability distribution parameters for each potential probability distribution.

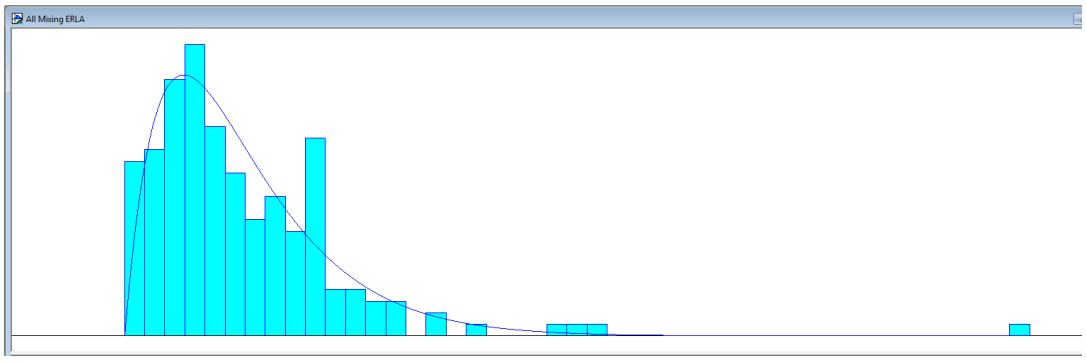

Figure 3.5: An example of an Erlang Probability Distribution Fit for Drug Mixing Process (1.5 + ERLA(2.94,2)).

For the distributions that were estimated without data, experts were interviewed. The results of that effort are shown in Table 3.4, with the expert estimates of minimum, most likely (mode), and maximum time provided, along with the average if a pilot time study was performed. The probability distribution fit is provided in the final column. Beta distributions were used because the nature of the process is that the bulk of the probability mass is concentrated at some lower value near the mode with a long tail representing potential complications associated with certain complex patients. In the case of percent of unfilled orders, a triangular distribution was actually believed to be more consistent with the mean from the pilot time study. Additionally, in cases where we received multiple responses in an expert opinion survey, we averaged the values of each parameter to achieve our input parameters for the model. Asterisks are used in the table to denote process types were not calculated using the asymmetry ratio, but rather by solving a system of equations based on the input of average and mode obtained from time study data.

Table 3.4: Processes analyzed for fitting without data; parameter estimates and distribution fit based on expert opinion (minutes where applicable for time units).

Process Type	Min.	Mode	Max.	Average	Distribution Fit
Blood Draw, Port	15	20	30	20	15 + 15*BETA(2.80, 4.60)
Blood Draw, No Port	3	9	19	10	3 + 16*BETA(3.12, 4.53)
Doc Consult Length New Patient	20	45	75	45	20 + 55*BETA(3.70, 4.25)
Doc Consult Length Return Patient	10	17.5	45	20	10 + 35*BETA(1.97, 4.55)
Time for Doc to Enter Order into Computer	1	2	5	2	1 + 4*BETA(2.20, 4.60)
Charge Nurse Chart Check*	0.5	1	38	2.5	0.5 + 37.5*BETA(1.30, 23.06)
% of Unfilled Orders	82	85	86	-	TRIA(82, 85, 86)
Time for Unfilled Orders to be Called In*	4	16	100	29	4 + 96*BETA(1.48,4.36)
OTC Nurse Chart Check	2	5	17.5	-	2 + 15.5*BETA(1.84, 4.52)
OTC Nurse Set-up Time for Treatments	5	15	30	-	5 + 25*BETA(3.31, 4.46)
HR 1 Infusion Type Treatment Length	15	60	90	-	15 + 75*BETA(4.46, 3.31)
HR 3 Infusion Type Treatment Length	90	80	210	-	90 + 120*BETA(4.60, 2.20)
HR 5 Infusion Type Treatment Length	210	330	480	-	210 + 210*BETA(4.36, 3.52)

* corresponds to a process where probability distribution was fit by taking the average and mode values to solve a system of equations for parameters α_1 and α_2.

Section 3: Model Validation

Initial validation consisted of expert opinion on the prototype simulation model to determine if the results on process times, arrivals, and flow logic appeared reasonable. Experts consulted included the clinical operations director, the assistant vice president and associate chief nursing officer of oncology, a management engineer in oncology, the administrative manager, and healthcare administration staff. Many of the results were found to be reasonable based on past experience; and the results identified as potentially invalid were examined further and fixed. This process involved a number of minor changes to the initial model including re-examining labor standards for check-in and check-out to remove indirect labor time, estimating variability on check-in and check-out service times based on expert opinion, adding a small percentage of patients designated as *late trays* (patients who do not go through the check-out process because they schedule their appointment by phone or e-mail), and interviewing treatment center nurses to construct more accurate and updated probability distributions on length of infusion times in the treatment center.

The examination process entailed an extensive troubleshooting process. We examined each major area of the model and checked the logic to ensure everything was working properly. We used a root-cause analysis approach, with two major areas of focus to cover the entire model: a thorough examination of the upstream portions from the OTC (clinic, labs, radiology) and the assumptions and logic built into the OTC portion of the model. We reviewed all of our assumptions in the model and made changes where appropriate. Finally, we examined all of the processing time inputs estimated with no data and eliminated the constant times and most of the triangular distribution fits to better capture the variability of the processes. We used Beta distributions with parameters based on expert opinion as outlined previously, and checked the associated processing times from the simulation model with experts for validation.

In addition to expert validation, statistical validation was performed. Three main areas were used to statistically validate the model: the arrival distributions, the OTC throughput, and the flow times for the clinic and the OTC. To ensure the model was validated, we calculated 95% confidence intervals on the mean of both the model results and the mean of actual hospital data in each of

these areas. Then, if the confidence intervals for the model and historical data overlapped, we concluded the model parameters appropriately represented the cancer center. Each criterion was examined in an effort to statistically validate the performance of the simulation model.

Flow time validation was performed by validating each specific clinic's flow time, along with the OTC. Data was not available to validate the sum total of clinic and OTC flow time; therefore, we validated flow time for the clinic and OTC separately. Data for clinic flow times was obtained for three of the five clinics; the other two clinics did not have data available. For those clinics, we sought expert opinion to validate the model. Historical data for OTC flow time was unavailable, as there is no official check-out process, and thus, no data collected on when a patient leaves the OTC. Thus, we validated our model in this regard with expert opinion as well.

Animation was also used for the model to aid with the validation and verification process. Animations were created for one of the clinics and for the OTC, and were generally built for very specific processes to troubleshoot behavior deemed inappropriate. For example, the model initially showed very high flow times in one of the clinics. Building an animation helped us see check-out queues build up and notice that some of the service times were much longer than they should have been. Thus, we changed the probability distribution associated with check-out, from a constant labor-standard time of approximately 10 minutes to the lognormal distribution defined in Table 3.2 for the Hematology Oncology check-out. We found the labor standard to include both direct and indirect patient care time, which led us to remove the indirect patient care time from all other labor standards used for model inputs (time constraints prevented us from performing time studies on all such processes). This action of removing indirect care times from the check-in and check-out times significantly improved performance of our model. The animation also helped visualize patient flow through the entire cancer center, and allowed for visualization of some of the bottlenecks and how they interact. For example, we used an animation of the OTC to notice chairs did not fill up during the day as they should, and that the OTC was never fully occupied. Further examination identified outdated and inaccurate data on infusion times; we then estimated a Beta probability distribution that generated appropriate behavior in the model.

Validation Results

Table 3.5 highlights the results of patient arrivals and throughput in the OTC. The results show that the patient arrivals and OTC throughput for each day of the week are validated in the model, as the 95% confidence intervals of the simulation model and the arrival data overlap. Thus, we would fail to reject H_0, the hypothesis that our mean values are the same for the model and data. We have no evidence to conclude the model does not accurately represent the patient arrival process. The data used to validate the model was the same data the model was constructed from.

Clinic

The results for the flow time validation in each of the clinics are contained below in Table 3.6. The results of the validation vary by day of week. For example, the Brain Tumor Center shows statistical validation for every day of the week, although there is significant variability in both the historical and simulation model output. Additionally, the differences in the means for the Brain Tumor Center are significant for lower volume days (note that there were only 3 data points available for Friday Brain Tumor Center appointments). The surgical oncology clinic demonstrates good validation on high volume days (Monday and Wednesday) but poor validation on lower volume days (Tuesday, Thursday, and Friday). For Clinic 1B1C the model overestimates mean flow time on every day. No data was available for Clinics 2L and 2B2C.

The reason why the validation results vary by day and clinic is unclear. Further work needs to be performed in conjunction with the team of experts to fully identify the cause of these differences in the model. Potential causes for these differences include the following. First, there are sources of data entry error in the observed flow time data, such as employees missing a particular time stamp and entering an estimated time several minutes or hours later. Second, there may be some flawed model assumptions about resource capacity and probability distributions processing times. Currently, a static resource capacity is assumed for nurses, exam rooms, and oncologists available in each clinic. It may be more accurate to use a model that includes schedules that differ by day of week with lower volume days having fewer resources.

Table 3.5: Comparison of simulation arrivals with system data for validation.

Monday Arrivals/TH Validation							
	Simulation Model (50 replications)			Historical Data			
Clinic	Mean	LCL	UCL	Mean	LCL	UCL	Sample Size
Surgical Oncology	146.32	143.23	149.41	147.40	130.71	164.09	2211
Hematology Oncology	167.04	163.12	170.96	167.87	159.47	176.26	2518
Brain Tumor Center	46.18	44.03	48.33	46.53	44.06	49.01	698
Prostate Center	36.08	34.27	37.89	36.40	33.19	39.61	546
Thoracic Surgery/Transplant Center	169.56	166.44	172.68	170.87	161.43	180.30	2563
OTC Direct Arrivals, Other Sources	26.76	25.59	27.93	27.40	26.01	28.79	411
OTC Throughput	100.34	97.53	103.15	103.20	98.22	108.18	1548

Tuesday Arrivals/TH Validation							
	Simulation Model (50 replications)			Historical Data			
Clinic	Mean	LCL	UCL	Mean	LCL	UCL	Sample Size
Surgical Oncology	103.92	101.24	106.60	105.24	97.74	112.73	1789
Hematology Oncology	164.7	161.17	168.23	165.00	152.72	177.28	2805
Brain Tumor Center	45.12	43.05	47.19	44.35	41.11	47.59	754
Prostate Center	34.88	33.02	36.74	32.53	28.28	36.78	553
Thoracic Surgery/Transplant Center	196.32	192.51	200.13	194.71	182.15	207.27	3310
OTC Direct Arrivals, Other Sources	28.06	26.62	29.50	27.94	25.04	30.84	475
OTC Throughput	106.1	102.77	109.43	107.94	103.07	112.82	1835

Wednesday Arrivals/TH Validation							
	Simulation Model (50 replications)			Historical Data			
Clinic	Mean	LCL	UCL	Mean	LCL	UCL	Sample Size
Surgical Oncology	146.48	143.46	149.50	146.35	137.31	155.40	2488
Hematology Oncology	164.30	160.83	167.77	164.06	153.57	174.55	2789
Brain Tumor Center	39.30	37.30	41.30	38.94	37.40	40.49	662
Prostate Center	33.32	31.53	35.11	33.76	30.51	37.02	574
Thoracic Surgery/Transplant Center	204.58	200.15	209.01	203.35	192.12	214.58	3457
OTC Direct Arrivals, Other Sources	40.54	38.70	42.38	38.71	35.40	42.01	658
OTC Throughput	115.98	112.96	119.00	117.00	112.70	121.30	1989

Thursday Arrivals/TH Validation							
	Simulation Model (50 replications)			Historical Data			
Clinic	Mean	LCL	UCL	Mean	LCL	UCL	Sample Size
Surgical Oncology	109.28	106.11	112.45	109.33	101.53	117.14	1968
Hematology Oncology	161.7	158.52	164.88	162.28	147.16	177.40	2921
Brain Tumor Center	36.02	34.47	37.57	36.28	33.87	38.69	653
Prostate Center	34.54	32.85	36.23	34.61	30.00	39.22	623
Thoracic Surgery/Transplant Center	154.72	150.91	158.53	155.94	143.97	167.92	2807
OTC Direct Arrivals, Other Sources	43.90	42.12	45.68	43.50	40.26	46.74	783
OTC Throughput	101.86	98.69	105.03	106.56	102.80	110.32	1918

Table 3.5 Continued

Friday Arrivals/TH Validation							
	Simulation Model (50 replications)			Historical Data			
Clinic	Mean	LCL	UCL	Mean	LCL	UCL	Sample Size
Surgical Oncology	121.56	118.89	124.23	119.17	105.64	132.69	2145
Hematology Oncology	99.56	97.15	101.97	97.89	91.15	104.62	1762
Brain Tumor Center	8.26	7.31	9.21	8.44	6.95	9.94	152
Prostate Center	22.3	21.14	23.46	22.44	18.19	26.70	404
Thoracic Surgery/Transplant Center	144.68	140.99	148.37	146.89	136.10	157.67	2644
OTC Direct Arrivals, Other Sources	38.92	37.13	40.71	40.00	36.18	43.82	720
OTC Throughput	92.64	89.99	95.29	94.83	89.61	100.05	1707

Other concerns that could influence validation include missing and inaccurate data collection. The percent of patients for which all time stamps in the process flow were entered is less than 50%, and in many cases, no check-out or check-in time was recorded. Often the first time stamp is actually “worked-in”, which is the time stamp designated for when the patient leaves the waiting room for the first time to have a blood draw. It is possible many employees are using the “worked-in” time stamp as a check-in time stamp as well, or assuming that a separate computer system for finance and billing (an accurate system that our arrival data came from) is sufficient to capture the arrival times. In such cases of incomplete data entry, the total flow time would be calculated using whatever the most recent time stamp recorded was for an end time, and whatever the first time stamp was as a start time, potentially not capturing the entire visit. Even though we did not use flow times of less than 30 minutes in our calculations to guard against this possibility, we might still be using inaccurate data results. Additionally, there are differences in how time stamps are recorded from employee to employee. Thus, further work may be warranted to collect data to better validate the simulation model. Nevertheless, combining the statistical results with the positive results of solicited expert opinion has led to confidence among decision makers involved in the study about the validity of the model.

Table 3.6: Results for flow time values in each of the clinics of the model over each day of the week.

Monday Flow Time Validation							
	Simulation Model			Historical Data (Patient Tracker)			
Clinic	Average	LCL	UCL	Average	LCL	UCL	Sample Size
Surgical Oncology	151.42	146.34	156.50	155.53	151.51	159.55	1727
Hematology Oncology*	145.52	141.25	149.79	128.69	125.48	131.89	1906
Brain Tumor Center	161.48	149.71	173.25	173.98	161.75	186.22	127
Prostate Center	127.14	120.21	134.07	-	-	-	-
Tuesday Flow Time Validation							
	Model			Historical Data (Patient Tracker)			
Clinic	Average	LCL	UCL	Average	LCL	UCL	Sample Size
Surgical Oncology*	113.27	109.86	116.68	138.22	134.81	141.63	1295
Hematology Oncology*	152.19	147.79	156.59	130.72	127.36	134.08	2101
Brain Tumor Center	154.57	145.41	163.73	163.13	150.40	175.86	103
Prostate Center	162.87	152.99	172.75	-	-	-	-
Wednesday Flow Time Validation							
	Model			Historical Data (Patient Tracker)			
Clinic	Average	LCL	UCL	Average	LCL	UCL	Sample Size
Surgical Oncology	151.91	147.07	156.75	160.38	156.71	164.06	1813
Hematology Oncology*	159.53	154.76	164.30	114.90	112.16	117.64	2108
Brain Tumor Center	134.19	126.49	141.89	147.27	132.98	161.56	61
Prostate Center	128.96	122.81	135.11	-	-	-	-
Thursday Flow Time Validation							
	Model			Historical Data (Patient Tracker)			
Clinic	Average	LCL	UCL	Average	LCL	UCL	Sample Size
Surgical Oncology*	116.29	113.70	118.88	130.17	126.71	133.64	1475
Hematology Oncology	145.63	141.22	150.04	142.54	138.98	146.10	2241
Brain Tumor Center*	132.27	124.22	140.32	155.96	147.36	164.56	129
Prostate Center	163.28	154.34	172.22	-	-	-	-
Friday Flow Time Validation							
	Model			Historical Data (Patient Tracker)			
Clinic	Average	LCL	UCL	Average	LCL	UCL	Sample Size
Surgical Oncology*	124.40	120.75	128.05	135.07	131.59	138.56	1593
Hematology Oncology*	114.49	111.94	117.04	99.38	96.14	102.63	1160
Brain Tumor Center	102.12	94.23	110.01	N/A	N/A	N/A	3
Prostate Center	117.28	112.46	122.10	-	-	-	-

*indicates statistically significant difference

Expert opinion has indicated that the clinic model operates as expected. However, we have not statistically validated the clinic portion of the model since we were not able to obtain a suitable validation dataset. In the remainder of this section we discuss validation of the OTC in isolation using observed patient flow times from the simulation model. In Chapter 4, we analyze nurse schedules in the OTC using the model without the clinics. We have time stamps for patient arrivals into the OTC from historical data, and use this data to generate patient arrivals. The non-stationary Poisson arrival stream data for this case can be found in Appendix 2 with the other arrival stream data.

Treatment Center

Table 3.7 below shows the results for flow time for patients in the OTC, and Table 3.8 below shows the results for waiting room times. The results for the waiting room time appear to be a little lower than expected (about 15 minutes lower); however, when it is considered that there are no delays reflected from earlier portions of the cancer center such as waiting for lab results to come in for example (a 13 minute average wait in the full model), these values seem appropriate. These results come from the simulation model with just the OTC. This has a residual effect on flow times being about 15 minutes lower than expected, making flow times to appear slightly low. The flow time results are given in minutes for Injection patients and in hours for all other infusion types. Expert opinion has indicated these flow times to be consistent with observation in practice.

Table 3.7: OTC flow times by treatment type for the OTC-only simulation model.

OTC Flow Time Validation (minutes), OTC only simulation model								
	Injection (minutes)		HR 1 (hours)		HR 3 (hours)		HR 5 (hours)	
Day	95% LCL	95% UCL	95% LCL	95% UCL	95% LCL	95% UCL	95% LCL	95% UCL
Monday	39.88	43.86	1.69	1.75	3.63	3.71	6.13	6.25
Tuesday	43.05	47.79	1.76	1.83	3.69	3.78	6.26	6.39
Wednesday	46.28	52.98	1.79	1.89	3.74	3.87	6.22	6.36
Thursday	47.83	55.35	1.82	1.94	3.78	3.93	6.30	6.44
Friday	44.61	52.01	1.73	1.81	3.68	3.80	6.20	6.32

Table 3.8: OTC waiting room time values.

OTC Waiting Room Time (minutes)			
Day	**Average**	**LCL**	**UCL**
Monday	31.87	30.10	33.64
Tuesday	36.12	34.07	38.17
Wednesday	39.35	36.18	42.52
Thursday	42.00	38.08	45.92
Friday	35.82	33.26	38.38

Section 4: Results

We used the validated simulation model for some initial experiments. We ran the model for 50 replications on a Dell Optiplex 980 PC, Intel® Core™, 2.93 GHz, 8.00GB RAM. We used the preliminary results to identify bottlenecks and potential methods for improving system flow. All results for the clinics come from the whole system cancer center model, and due to the aforementioned challenges with model validation, all results for the OTC come from the simulation model built for only the OTC.

Table 3.9 below contains the results for the simulation run of the whole system cancer center model for the clinics. We only report results for processes with nonzero waiting times. There are several interesting observations. First, there is significant variation from day to day in the mean waiting time for patients. The most significant bottlenecks appear to be phlebotomy in the surgical oncology and hematology oncology clinics, with wait times ranging anywhere from 10-30 minutes, depending on clinic and day of week, and wait for oncologist, which also ranges from 10-30 minutes depending on clinic and day of week. The overall average waiting time at check-in and check-out is fairly small, indicating those processes generally are not bottlenecks; however, at certain times of the day it is possible for those processes to be bottlenecks.

Table 3.10 below shows the results for OTC waiting room time, the time a patient waits after checking in and before being brought back into the OTC for chemotherapy. This time is of particular concern to administrators in the OTC. In light of the discussion from the validation section about the OTC-only model lacking some of the delays associated with lab work and the clinic, the reported waiting room times are approximately 10-15 minutes lower than they would be with the full model. A look at these numbers indicates potential improvement in the OTC in processing patients. Additionally, it is of note that waiting time typically tends to be lower on the tails of the day; in other words, at the beginning and end of the day, the OTC is not stressed and patient waiting times tend to be lower. Wait times during peak hours of the day tend to be much higher than wait times early or late in the day. The maximum waiting room time column in Table 9 indicates the worst case scenario, calculated by averaging the longest wait for each replication. These values indicate significant potential for improvement in the OTC.

Table 3.9: Wait time results in the clinic portion of the model.

Average Waiting Times for Clinic Processes by day of week (50 replications)						
	Monday			Tuesday		
Process	Average	LCL	UCL	Average	LCL	UCL
Phlebotomy Surg. Onc.	27.66	23.10	32.22	11.73	9.07	14.39
Phlebotomy Hem. Onc.	13.70	10.85	16.55	9.37	7.08	11.66
Check In Surg. Onc.	1.21	1.05	1.37	0.36	0.29	0.43
Check In Hem. Onc.	1.40	1.14	1.66	0.88	0.74	1.02
Check In Brain Tumor	2.14	1.70	2.58	1.59	1.33	1.85
Check In Prostate	0.78	0.60	0.96	0.80	0.63	0.97
Check Out Surg. Onc.	0.13	0.10	0.16	0.05	0.03	0.07
Check Out Hem. Onc.	2.41	1.99	2.83	3.74	3.12	4.36
Check Out Brain Tumor	0.54	0.49	0.59	0.58	0.50	0.66
Check Out Prostate	0.32	0.25	0.39	0.32	0.26	0.38
Oncologist Surg. Onc.	23.92	22.83	25.01	13.32	12.27	14.37
Oncologist Hem. Onc.	19.97	19.13	20.81	22.04	21.17	22.91
Oncologist Brain Tumor	25.71	24.32	27.10	25.21	23.63	26.79
Oncologist Prostate	17.18	15.32	19.04	29.57	26.84	32.30
	Wednesday			Thursday		
Process	Average	LCL	UCL	Average	LCL	UCL
Phlebotomy Surg. Onc.	30.04	25.65	34.43	8.49	6.52	10.46
Phlebotomy Hem. Onc.	10.85	8.77	12.93	10.59	8.34	12.84
Check In Surg. Onc.	0.87	0.73	1.01	0.33	0.28	0.38
Check In Hem. Onc.	0.83	0.67	0.99	1.18	0.96	1.40
Check In Brain Tumor	1.54	1.28	1.80	1.61	1.32	1.90
Check In Prostate	0.69	0.54	0.84	1.32	1.08	1.56
Check Out Surg. Onc.	0.24	0.19	0.29	0.05	0.03	0.07
Check Out Hem. Onc.	2.33	1.75	2.91	2.80	2.28	3.32
Check Out Brain Tumor	0.53	0.46	0.60	0.51	0.45	0.57
Check Out Prostate	0.21	0.16	0.26	0.27	0.20	0.34
Oncologist Surg. Onc.	24.49	23.32	25.66	14.91	13.83	15.99
Oncologist Hem. Onc.	24.37	23.48	25.26	20.11	19.12	21.10
Oncologist Brain Tumor	21.87	20.10	23.64	21.99	20.25	23.73
Oncologist Prostate	18.30	15.91	20.69	27.73	25.95	29.51
	Friday					
Process	Average	LCL	UCL			
Phlebotomy Surg. Onc.	14.67	11.13	18.21			
Phlebotomy Hem. Onc.	1.42	1.08	1.76			
Check In Surg. Onc.	0.45	0.38	0.52			
Check In Hem. Onc.	0.51	0.26	0.76			
Check In Brain Tumor	0.41	0.20	0.62			
Check In Prostate	0.61	0.43	0.79			
Check Out Surg. Onc.	0.08	0.03	0.13			
Check Out Hem. Onc.	0.65	0.49	0.81			
Check Out Brain Tumor	0.17	0.10	0.24			
Check Out Prostate	0.15	0.10	0.20			
Oncologist Surg. Onc.	16.99	15.90	18.08			
Oncologist Hem. Onc.	11.23	10.38	12.08			
Oncologist Brain Tumor	9.92	7.65	12.19			
Oncologist Prostate	14.15	11.61	16.69			

Table 3.10: OTC waiting room time results for the OTC-only model.

OTC Waiting Room Time (minutes)							
Average Waiting Room Time (50 replications)				Maximum Waiting Room Time (50 replications)			
Day	Average	LCL	UCL	Day	Average	LCL	UCL
Monday	31.87	30.10	33.64	Monday	100.83	94.41	107.25
Tuesday	36.12	34.07	38.17	Tuesday	106.77	99.98	113.56
Wednesday	39.35	36.18	42.52	Wednesday	116.91	107.89	125.93
Thursday	42.00	38.08	45.92	Thursday	120.70	109.70	131.70
Friday	35.82	33.26	38.38	Friday	107.19	99.09	115.29

Table 3.11 below shows the patient waiting times for various resources in the OTC. Specifically, we analyze all nurses and chairs in the OTC, the resources with queue time associated with them. The maximum average column lists the average waiting time for the replication with the highest value. These results seem to indicate the chair as being the source of the longest waiting time for patients, with the highest average wait time values (ranging from 3-10 minutes). Additionally, in the worst-case scenario replications, these average waiting times are in excess of 20 minutes. Furthermore, much like the waiting room time results in the prior paragraph, there is little wait time early or late in the day. Thus, the values of waiting time are typically much higher than average during peak times of the day.

Table 3.11 also shows average wait times for nurses, with OTC nurse wait reflecting the overall average wait time for a nurse, with each specific DBG's values provided separately. The wait for charge nurses and OTC nurses can also become bottlenecks at certain times in the day, though these wait time values appear to be fairly low on the average. However, in the worst-case scenario, average wait for a nurse can exceed 20 minutes. More noteworthy is that specific DBGs have patient waiting time for nurses that can range from 10-30 minutes in a worst-case replication, and again, that patient waiting times are higher than the values listed during peak hours of the day. Also, the HOA DBG shows the highest waiting times for nurses, particularly seen by the maximum average waiting time seen across all replications. The HOA DBG appears to be the primary source of bottlenecking for nurses, and thus, hiring an additional HOA nurse would seem to help. Expected volume in the HOA DBG is similar to the Breast DBG, which employees 5 nurses to the HOA group's

4, so future staff additions should be directed to this DBG. The conclusion of nurses and chairs being bottlenecks is also supported by Figure 3.6.

Figure 3.6 illustrates the concept of waiting time being higher in the peak volume hours of the day than on the tails of the day. This diagram is taken from the simulation model, and is from one of the replication runs on the Wednesday model. Thus, it is a sample of some of the behavior exhibited by the model. The graph tracks the number of patients waiting in the waiting room at the OTC for either a chair (red line) or a nurse (blue line). This time is non-value-added time, as the drug has completed mixing and all other pre-processing has taken place before these queue statistics are tracked. Furthermore, the time is tracked in terms of minutes that have passed since the beginning of the simulation run (which began at 7 a.m.). As reference points, 225 minutes corresponds to 10:45 a.m., 300 minutes with 12:00 p.m., and 450 minutes with 2:30 p.m. This graph shows the nature of queue lengths throughout the day for these two specific tasks, with a larger number in queue corresponding to longer waiting time.

Table 3.11: Patient waiting time for different resources in the OTC-only model.

Average Waiting Times for OTC Processes by day of week (50 replications)				
	Monday			
Waiting Type	**Average**	**LCL**	**UCL**	**Max Avg**
Charge Nurse	2.37	1.98	2.76	
Breast Nurse Wait	0.16	0.06	0.26	1.89
GIGU Nurse Wait	0.09	0.02	0.16	1.14
HOA Nurse Wait	4.47	3.37	5.57	16.06
Lung Nurse Wait	0.07	0.02	0.12	0.80
Chair Wait	2.76	1.32	4.20	26.79
OTC Nurse Wait	0.96	0.74	1.18	26.79
	Tuesday			
Waiting Type	**Average**	**LCL**	**UCL**	**Max Avg**
Charge Nurse	2.67	2.15	3.19	
Breast Nurse Wait	0.55	0.31	0.79	3.56
GIGU Nurse Wait	0.16	0.08	0.24	1.32
HOA Nurse Wait	1.46	0.99	1.93	6.71
Lung Nurse Wait	0.04	0.00	0.08	0.71
Chair Wait	7.27	5.48	9.06	22.96
OTC Nurse Wait	0.44	0.34	0.54	1.45
	Wednesday			
Waiting Type	**Average**	**LCL**	**UCL**	**Max Avg**
Charge Nurse	3.13	2.64	3.62	
Breast Nurse Wait	0.36	0.18	0.54	3.10
GIGU Nurse Wait	0.01	0.00	0.02	0.27
HOA Nurse Wait	3.63	2.67	4.59	11.91
Lung Nurse Wait	0.35	0.03	0.67	7.71
Chair Wait	9.98	7.21	12.75	40.92
OTC Nurse Wait	0.87	0.67	1.07	2.40
	Thursday			
Waiting Type	**Average**	**LCL**	**UCL**	**Max Avg**
Charge Nurse	3.93	3.18	4.68	
Breast Nurse Wait	0.57	0.33	0.81	3.29
GIGU Nurse Wait	0.04	0.01	0.07	0.63
HOA Nurse Wait	5.88	4.50	7.26	21.75
Lung Nurse Wait	0.03	0.00	0.08	1.22
Chair Wait	11.21	7.73	14.69	57.29
OTC Nurse Wait	1.30	1.02	1.58	4.45
	Friday			
Waiting Type	**Average**	**LCL**	**UCL**	**Max Avg**
Charge Nurse	2.18	1.87	2.49	
Breast Nurse Wait	0.71	0.42	1.00	4.34
GIGU Nurse Wait	0.00	0.00	0.00	0.00
HOA Nurse Wait	5.95	4.21	7.69	30.50
Lung Nurse Wait	0.37	0.13	0.61	4.21
Chair Wait	5.42	3.15	7.69	30.15
OTC Nurse Wait	1.41	1.06	1.76	6.17

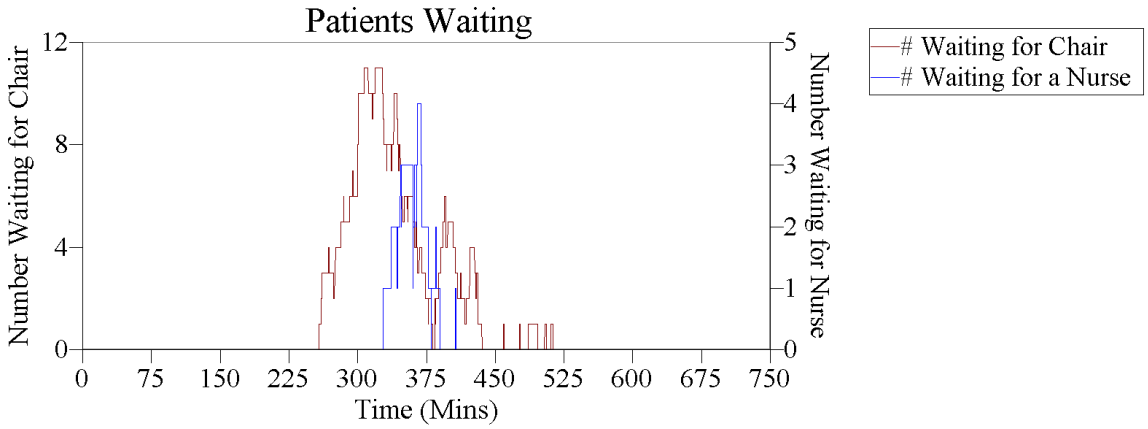

Figure 3.6: Graph from simulation model run showing the number in queue for chairs and nurses in the OTC.

Section 5: Conclusions

In conclusion, a conceptual model was developed and extensive data collection was performed to develop a discrete event simulation model of the cancer center for a large, academic, medical research center. The simulation model contains five different cancer clinics, radiology, processing of lab work in a central labs area, the pharmacy for chemotherapy drugs, and the OTC. This model reflects the trend in health systems engineering to take a systems approach in evaluating hospitals, taking into account the complex interactions of major components within the same hospital and their impact on overall process efficiency.

The model was validated using a mix of expert opinion and feedback from nurses and administrators, and statistical validation. Statistical and expert opinion validation was performed for patient arrivals and OTC throughput, and only expert opinion for clinic and OTC flow time. However, constructing a model with a whole-system approach is both challenging and time-consuming, and our model comes with limitations. We have gone through an extensive process lasting over a year to collect data, make, confirm, and improve modeling assumptions. There are still several unconfirmed assumptions in the model, such as static service times based on labor standards in the clinic, assumptions allotting the number of oncologists and patients to oncologists in the clinics, and estimated processing times. A wider base of expert opinion should be sought in estimating service times such as oncologist visit length, length of vitals recording, and pre-consult assessment. Additionally, behavior of the simulation model in recording and collecting statistics in specific cases of parallel processing (e.g. patient in waiting room while pre-treatment processing takes place) and modeling of the interaction between clinics, radiology, central labs, and the OTC must be examined to ensure the model operates as intended.

Some numerical experiments were performed to identify common bottlenecks and potential opportunities for improving patient flow through the cancer center. In summary, the results indicate chairs, charge nurses, and OTC nurses as the primary sources of patient waiting time in the OTC. Furthermore, HOA DBG nurses appear to be the bottleneck in terms of nurses and due to the significantly higher waiting times associated with this DBG, we recommended hiring an additional nurse for the HOA DBG. Improving each of these bottlenecks has its own set of unique challenges.

For example, to improve the chair bottleneck, there are only two alternatives; spread out patient arrivals more evenly during the day (which is heavily dependent upon coordinating an entire system) or increase the number of chairs through capital investments. Space is limited at many cancer centers. Additionally, we learned that there is a large amount of variability in wait times across the cancer center across days and within the days. Wait times within the day tend to be concentrated during peak volume with tails of the day having less waiting time on average, and day-to-day and even weekday-to-weekday there is much variation as well.

In the remainder of this thesis we discuss operations and resource planning questions. We evaluate alternative OTC nurse scheduling policies to find the best schedule and shift length combinations under different staffing scenarios. We use a combination of simulation-optimization and mixed-integer programming techniques to determine allocation and arrival times for nurses during the day to match the supply of nurses with the uncertain nature of demand as patients flow into the OTC. We also modify the model to reflect a move to a new cancer center to identify potential future bottlenecks.

Chapter 4: Treatment Center Nurse Scheduling

Section 1: Introduction

The OTC is an important part of any cancer center, as it is the location where patients receive the drugs and medication used to treat their cancer. The OTC is a large entity within most cancer centers due to its high levels of patient volume and resource requirements. In a high volume setting, it is commonly a bottleneck in the overall patient flow process. OTCs face many challenges including uncertain daily demand, variation in patient arrivals during the day, and high nurse workload during peak times of the day. As a common bottleneck in the cancer center, the OTC is often associated with high patient waiting times. This leads to congestion which can have repercussions on the quality of care as the number of patients seen by nurses increases. Furthermore, excessive wait time can also cause patient dissatisfaction.

OTCs are dependent on many parts of the cancer center including clinics, labs, and radiology, for patient supply, since most patients make earlier stops in the cancer center on the day of treatment. As the last step in the patient flow process, OTCs are subject to variability induced by upstream services. Thus, it can be difficult to predict patient arrivals into the OTC and plan accordingly, creating difficulty in running an efficient patient flow process.

Another challenge facing OTCs is a highly varying arrival rate across the day. Typically, patient arrivals are low early in the day, increase during the mid to late morning hours, remain at a peak until early to mid afternoon. In the mid to late afternoon, patient volume begins to decrease as patients work their way through the cancer center (Figure 5 in Chapter 2 illustrates this). The highly variable arrival rate is also challenging for planning, as nurse schedules must be planned to cover the entire day, typically based on 8 or 10 hour shifts.

Due to the challenges described above it is important to carefully consider the allocation of resources within the OTC. Preliminary analysis using our simulation model in Chapter 4 revealed two major bottlenecks: chairs and nurses. In this chapter we report on the use of our simulation model to design an OTC nurse schedule to see if a better schedule design could reduce patient waiting time without the need to increase other expensive resources, such as treatment chairs. Furthermore, we considered nurses because there are anticipated shortages in skilled nurse

availability in the coming years and specifically in our cancer center of study. Even when there is budget to hire more nurses, finding and hiring qualified nurses can still be a challenge. Therefore it is likely that improved efficiency in the allocation of nurses will be important in the future. Examining nurse schedules is also a relatively inexpensive way to improve process efficiency within the OTC (compared to additional capital investments), and one of high interest at our cancer center of study.

Our approach to planning nurse schedules is threefold and hierarchical in nature. Figure 4.1 illustrates the three major components to developing a nurse schedule for an OTC. Each component must be considered in developing a schedule. The nurse staffing level is the basis for developing schedules, and drives the allotment of nurses across the month and week. The monthly schedule is a cyclic schedule where nurses rotate off days from week to week. Each schedule a nurse uses for a particular week is called a *track*. Thus, each track contains a different off day for the nurse, and tracks are rotated to provide nurses with long weekends with an equal frequency level for fairness. Nurses are scheduled in tracks with the assumption that shift times will remain the same across the week. Therefore the weekly schedule defines the daily arrival and departure times for each nurse. Daily schedules are subject to constraints such as requiring at least two nurses to open and close and a 30-minute lunch for each nurse.

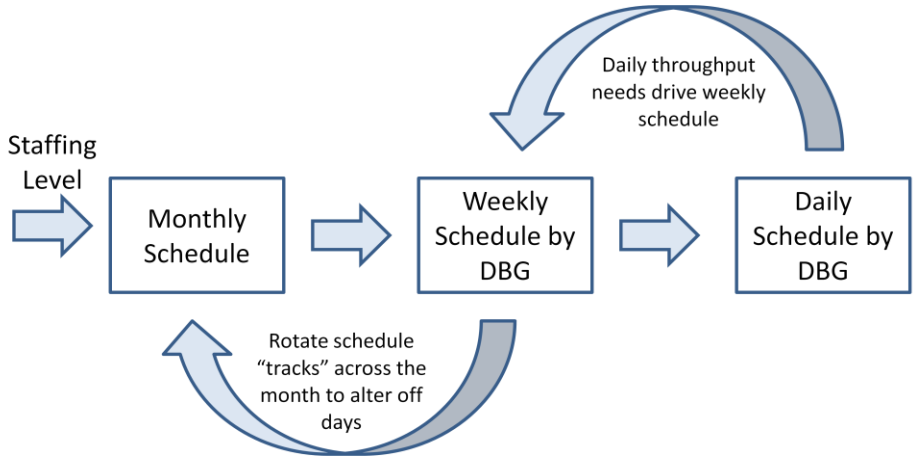

Figure 4.1: Diagram illustrating relationship between major components in OTC nurse scheduling.

Figure 4.1 illustrates the feedback loop across each component of nurse scheduling that helps develop and define a schedule. The daily needs of the OTC in meeting patient demand drive the weekly schedule. OTC throughput defines how many nurses are needed each day of the week, which then turns into a weekly schedule with off days for nurses. Each potential weekly schedule is then used to define the monthly schedule, rotating which off day a nurse has, and the monthly and weekly schedules in turn further influence the optimal daily schedule. Feedback between the monthly/weekly and daily schedules is provided iteratively to arrive at a near optimal nurse schedule.

There are different kinds of nurses within the OTC, each with differing roles. In general, there are *OTC nurses* and *charge nurses*. OTC nurses are the nurses that perform the direct patient care tasks, such as retrieving the patient, briefing the patient, hooking up the IV, monitoring the patient, and discharging the patient. Within the OTC, nurses serve patients of different classifications. These classifications are called *DBGs* (Disease-based groups), and contain patients of similar cancer types. OTC nurses are assigned to a specific DBG and only serve patients within that DBG during the day, with one exception. After 6:30 p.m. when nurses are leaving for the day and staff levels are much lower, the closing nurses will serve patients from any DBG.

Charge nurses are responsible for managing the OTC nurses from the floor as well as fulfilling duties in communicating with oncologists, the pharmacy, and ensuring safety standards are met. One charge nurse always is responsible for initial processing of patient charts, reviewing patient history, and reviewing blood specimen results to ensure patient health is appropriate for the chemotherapy being received. Any additional charge nurses present in the OTC operate as a *float nurse* on the floor; in other words, they move from DBG to DBG starting and monitoring patients as needed.

Nurse shift length and arrival time policies vary by OTC, but some generalities can be found. Shift lengths typically are 8-hours, 10-hours, or 12-hours for full-time nurses. There are various combinations and scheduling practices industry-wide, and additional consideration is given in many cases to hiring part-time nurses. Scheduling and staggering arrival times for nurses across the day also can have bearing on the ability of an OTC to meet patient demand across the day. In general,

nurse start times are staggered to begin the day, reaching a peak staff level somewhere in the early portion of the day, with staggered departure, reflecting patient demand needs that is typically variable across the day. Another challenge in developing a nurse schedule is that 10-hour and 12-hour shift nurses have off-days; thus, the off-days must be carefully selected so as to appropriately plan for expected patient demand.

Any nurse scheduling decisions require careful planning for the OTC, and also for each specific DBG. In order to provide high quality care, there are minimum staff levels for the OTC and for each individual DBG that must be taken into consideration. Generally, the budget for nurses entails the entire OTC, and then administrators must determine the best way to allot nursing resources from DBG to DBG. Additionally, those resources must be allotted at the appropriate time within the day to meet variable daily demand. In the nurse scheduling problem, as we design, develop, and analyze schedules these must all be taken into consideration.

Section 2: Methods

Our goal is to optimize the delivery of oncology services in the OTC by improving the scheduling of OTC nurses. To achieve this overarching goal we approach solving the nurse scheduling in two parts. We use a mixed integer program (MIP) to solve the monthly and weekly planning problem to allocate a predetermined fixed number of nurses across weekly tracks subject to constraints reflecting a minimum number of off days, and minimum allocation levels across DBGs. We use simulation optimization, based on Arena's OptQuest, to determine a near optimal schedule of nurse arrival times during the day based on an ad-hoc schedule development process. The simulation model used did not model the clinics, but the OTC in isolation, due to the validation challenges discussed in the validation section of Chapter 3. Expert opinion was elicited at each stage of the process to account for qualitative and human elements that are not easily modeled.

We analyze monthly, weekly, and daily nurse schedules under several different scenarios of nurse staffing levels to reflect potential levels of staffing the OTC we studied may face in the future. We examine a full-staffed, best case scenario, a most-likely scenario, and a worst case scenario. The best case scenario has 21 nurses (3 charge nurses), the most-likely scenario has 18 nurses (3 charge nurses), and the worst-case scenario has 16 nurses (2 charge nurses). These scenarios allow us to inform decision makers at the cancer center studied as to the best way to schedule and allocate nurses depending upon varying levels of nurse staffing. This is useful as staffing levels change over time due to various reasons such as retirement, relocation, and budget changes. Furthermore, there are currently serious shortages of experienced nurses in the U.S. and other countries indicating a potential shortfall in nurses needed to staff cancer centers.

We also use the MIP to determine the optimal mix of nurse types, while meeting scheduling requirements such as providing long weekends for nurses, and daily scheduling requirements based upon expected patient throughput. We incorporate in our study the potential benefit of part time (PT) nurses. We consider three types of nurses: 10-hour nurses that work 4 days a week for 40 hours in total, 8-hour nurses that work 5 days a week for 40 hours in total, and PT nurses working varying days per week, hours per day, and hours per week. Five possible PT nurse shifts are made available in the MIP, and are shown in Table 4.1. We perform sensitivity analysis with respect to a

constraint on the minimum levels of full-time (FT) nurses, so as to inform a wide possibility of potential scenarios. This is motivated by the potential clinical benefits of having full time nurses present in the clinic since they offer greater continuity of care during the day.

We use the MIP to identify general opportunities to improve nurse scheduling which can then be tested as inputs to the simulation optimization model. We do not use the results of the MIP directly in the simulation optimization model (we leave this for future work). However, the general insights about weekly and monthly scheduling identified using the MIP can be used to define nurse staffing levels for the daily simulation optimization model.

Scheduling Constraints

There are a number of constraints that define feasible schedules for the OTC on a daily, weekly, and monthly basis. OTC daily hours of operation are fixed (e.g. 7:00 a.m. – 8:30 p.m). There must be at least two nurses in the OTC at any point in time it is open; thus, there must be two "openers" and two "closers", where openers begin their shift at 7:30 a.m. and closers end their shift at 8:30 p.m. Also, a minimum level of coverage is required in each DBG during peak hours (e.g. 10:00 a.m. – 6:30 p.m.). In the OTC studied the requirement is that each DBG has a minimum of three nurses scheduled each day. Furthermore, the OTC on the whole must have at least 14 nurses scheduled on Monday through Thursday, and 13 on Friday. Nurse staffing levels typically fluctuate and are not held constant in the high-stress environment of the cancer center. Thus, we choose to model three scenarios of nurse staff levels to provide insight for best scheduling practices under various circumstances of nurse supply. In some cases, the OTC can actually be unable to meet the overall staffing level requirements, and nurses will immediately be sought for hire. We call this situation the "worst-case" scenario. In addition to these DBG constraints there must be two charge nurses overall. Scheduling policy at the OTC studied dictates that each nurse should also have the same schedule each day of the week for continuity, and should work a set number of hours and shifts per week. Finally, each nurse receives a 30 minute lunch break each day, with the constraint that no more than one nurse per DBG can be on lunch at any given point in time.

There are also constraints surrounding the allocation of off days to 10-hour shift nurses. Each 10-hour shift nurse will work 4 of the 5 days in the week, receiving one day off. Each nurse must receive at least one long weekend per month (4-day weekend). Four-day weekends occur when the nurse has Friday off one week, and then Monday off the next week. For PT nurses with off-days, the location of the off-day is not constrained, with the goal to schedule the PT nurse on the busiest days.

Performance Measures

The following performance measures are reported for each scenario examined:

- *Patient Wait Room Time* – the amount of time a patient waits in the waiting room after checking-in until being called back for treatment by an OTC nurse. Activities while waiting include charge nurse chart check, delays for unfilled orders or labs, pharmacy mixing drug, and OTC nurse chart check.
- *Patient Throughput* – The number of patients completing treatment and leaving the OTC per day.
- *Chair Turns* – The sum of patient throughput divided by the total number of chairs.
- *Chair Wait* – The average amount of time a patient spends waiting for a chair following processing by a charge nurse and availability of chemotherapy drug after pharmacy mixing.
- *Nurse Wait* – The average amount of time a patient spends waiting for a nurse to become available. In the simulation model, this time reflects the wait for an OTC nurse chart check after all other processing work and chair seizing is complete.
- *OTC In-Service WIP* – The patients-in-process of the OTC.
- *OTC Waiting Room WIP* – The average number of patients in the waiting.

Monthly and Weekly Schedule Optimization

In the monthly and weekly scheduling MIP experiments, we seek to determine the best way to allocate nurses across the week to meet variable day-to-day demand with a particular focus on constraining the model to allot one 4-day weekend (consecutive Friday and Monday off) for each FT, 10-hour shift nurse. The objective is to minimize total shortage hours in the OTC nurse schedule.

Shortage hours are determined based upon the daily scheduling requirements. Each day has a certain ideal number of nursing hours required to meet patient demand. However, due to constraints on the number of nurses available, these requirements may not be met. The deficit is referred to as nurse shortage.

The total number of nurses is limited by the maximum number of FT nurses that are available as defined by the clinical operations director. In our MIP we allow for 6 possible FT 10-hour shift nurses, 6 possible FT 8-hour shift nurses, and 6 possible PT nurses, or any combination therein for each DBG. Each of these 18 nurses has an associated binary decision variable, with a value of 1 indicating the nurse is selected and zero that the nurse is not selected.

Table 4.1: Different PT nurse shifts considered in the MIP monthly scheduling model.

PT Shift Policy Number	# Shifts / week	Shift Length	Hours / week	# Slots used in MIP
1	5	4-hours	20	2
2	2	10-hours	20	1
3	3	10-hours	30	1
4	3	8-hours	24	1
5	4	8-hours	32	1

Table 4.1 identifies each of the alternative PT nurse shifts. Each potential PT shift type has an associated number of shifts per week, hours worked per day, and hours worked per week. In our study, we incorporate all possible PT nurse shifts into the 6 available slots as defined in Table 4.1. A slot is merely a defined binary variable for a nurse working that particular shift that may or may not be selected by the MIP. As mentioned previously, there are 18 possible nurses/shifts to be chosen from per DBG, with 6 possible PT nurses available for selection. The number of slots column lists the amount of each possible PT shift made available for use. Thus, of the 6 possible PT nurses per DBG, two of them work 5 4-hour days for 20 hours per week, and one works 2 10-hour days for 20 hours per week.

Daily nursing hour requirements were calculated based upon expected patient throughput. First, anticipated throughput per DBG per day was calculated based on historical data as provided in Table 4.2. The row titled “Adjusted” reflects the assumption that off-service patients will be seen in

equal weight by the different DBGs. Thus, the expected throughput for off-service patients is split equally amongst all DBGs. The sum of each DBG's expected throughput and the expected off-service patient throughput per DBG reflects the total expected throughput for the day. This value was then multiplied by the average number of hours required per patient to calculate a desired number of nursing hours to staff. The results of this calculation are found in Table 4.3.

Table 4.2: Expected throughput values and anticipated off-service volume for each DBG.

Total Expected TH by DBG by Day					
DBG	**Monday**	**Tuesday**	**Wednesday**	**Thursday**	**Friday**
Breast	24.46	30.44	40.56	26.42	27.97
HOA	27.35	30.44	17.44	26.32	26.42
GIGU	17.54	22.91	10.94	25.90	13.42
Lung	20.95	11.46	18.89	11.97	14.45
Off-Service	12.90	7.95	15.38	12.59	20.95
Adjusted	3.23	1.99	3.84	3.15	5.24

The average number of nursing hours per day was determined based upon historical arrival data for the OTC. This calculation was made by taking the total number of nursing hours scheduled per month for that time period and dividing by the average monthly throughput in the OTC. Historical data came over a 4-month period from July – October 2010, and the average of each month's throughput was taken to determine a baseline average monthly throughput. In the 21 nurse, or fully-staffed scenario, we would have 18 FTE used for OTC nurses (as 3 FTE would be used for charge nurses). The total number of monthly hours would then be this value multiplied by 40 hours per week, multiplied by the 4 weeks that make up a monthly schedule. The results of the calculation were as follows:

$$2880\ nurse\ hours\ per\ month \div 2250\ patients\ per\ month = 1.28\ nurse\ hours\ per\ patient$$

This average amount of nursing hours per patient measures the average amount of direct care time a nurse would spend with one patient, including briefing activities, hooking up IV, taking down IV, direct care in infusion, and debriefing activities. This number might seem a little higher

than expected, but is inflated by the lower volume early and late in the day and is not necessarily indicative of peak volume times of the day. It was also developed from a large sample size of data, removing some of the possibility of outlier values skewing the results. We tested this result by interviewing the charge nurse and scheduling planner, asking for expert opinion as to the appropriate levels of nurses to staff in each DBG for a day with minimal idle time and patient waiting time. We assumed each nurse to have 10-hours of work for ease of calculation, and the daily requirements matched closely with those calculated. In most cases, the expert opinion values were within 10 hours of the calculated values (generally higher due to the assumption of all 10-hour shifts). The advantage of using throughput values is that the bias towards 10-hour shifts is removed from the model. Finally, we use this value in all three scenarios mentioned earlier; thus, we set the nursing hour requirements based on the ideal scenario with the expectation that shortage hours will increase in the most likely and worst case scenarios.

Table 4.3: Daily nursing hour requirements for each DBG for every day of the week.

Target nursing hours scheduled by DBG by day (d_t)					
DBG	Mon	Tues	Wed	Thurs	Fri
Breast	36	42	57	38	43
HOA	40	42	28	38	41
GIGU	27	32	19	38	24
Lung	31	18	30	20	26

Monthly and weekly scheduling MIP formulation

Following is a description of the mathematical formulation of our model:

Decision Variables:

x_{it} = Nurse *i* scheduled on day *t*. (Binary variable)

y_{ij} = Nurse *i* scheduled long weekend *j.* (Binary variable)

z_i = Nurse *i* selected on the schedule. (Binary variable)

s_t = shortage of nurse hours on day t. (Continuous variable)

o_t = overage of nurse hours on day t. (Continuous variable)

Parameters:

f_i = FTE (Full-Time Employee) value for each nurse i

t = day in the 4-week schedule. (t = 1,2,…,20)

d_t = # of nursing hours required for day t.

N = maximum # nurses for a particular DBG shift type.

n = minimum nurses in each DBG for the day

r = minimum nurse in OTC for the day

M = maximum # FTE (Full-Time Employees) for OTC nurses

F = Desired total # of full-time nurses used

j = index for long weekends

- j = 1 corresponds to 1st weekend of the month
- j = 2 corresponds to 2nd weekend of the month
- j = 3 corresponds to 3rd weekend of the month
- j = 4 corresponds to 4th weekend of the month

i = index for nurses. (i = 1,2,…3N)

- *(i = 1,2,…,N corresponds to a part-time nurse)
- (i = 1,2 corresponds to a 4-hour shift nurse, scenario 1)
- (i = 3 corresponds to a 10-hour shift nurse working 2 shifts, scenario 1)
- (i = 4 corresponds to a 10-hour shift nurse working 3 shifts, scenario 1)
- (i = 5 corresponds to an 8-hour shift nurse working 3 shifts, scenario 1)

- (i = 6 corresponds to an 8-hour shift nurse working 4 shifts, scenario 1)
- ($i = N + 1, N + 2,\ldots,2N$ corresponds to a FT 8-hour shift nurse)
- ($i = 2N + 1, 2N + 2,\ldots,3N$ corresponds to a FT 10-hour shift nurse)

w_i = # days worked for the week for the nurse

- w_i = 2,3,4,or 5 for $i = 1,2,\ldots,N$ (part-time nurses under varying policies)
- w_i = 5 for $i = N + 1, N + 2,\ldots,2N$ (full-time 8-hour shift nurses)
- w_i = 4 for $i = 2N + 1, 2N + 2,\ldots,3N$ (full-time 10-hour shift nurses)

k_i = # of hours available per day for nurse i

- k_i = 4, 8, or 10 for $i = 1,2,\ldots,N$ (part-time nurses)
- k_i = 8 for $i = N + 1, N + 2,\ldots 2N$ (full-time 8-hour shift)
- k_i = 10 for $i = 2N + 1, 2N + 2,\ldots,3N$ (full-time 10-hour shift)

Following is the complete formulation of the monthly and weekly scheduling MIP.

Objective Function:

$$Minimize \sum_{t=1}^{20} s_t$$

s.t.

$$\sum_{i=1}^{3N} z_i f_i \leq M$$ Total FTE Constraint (1)

$$\sum_{i=N+1}^{3N} z_i \geq F$$ Minimum number of FT nurses used (2)

$$\sum_{i=1}^{3N} x_{it} \geq r_t \quad \forall t$$ Minimum nurse requirement for entire OTC (3)

$\sum_{i=1}^{3N} x_{it} \geq n$	$\forall t$	Minimum nurse requirement for each DBG	(4)
$x_{it} \leq z_i$	$\forall i, t$	Nurse *i* selected constraint	(5)
$\sum_{i=1}^{3N} x_{it} k_i + s_t - o_t = d_t$	$\forall t$	Nursing hours per day constraint	(6)
$\sum_{t=1}^{5} x_{it} = w_i z_i$	$\forall i$	Days worked per week 1 constraint	(7)
$\sum_{t=6}^{10} x_{it} = w_i z_i$	$\forall i$	Days worked per week 2 constraint	(8)
$\sum_{t=11}^{15} x_{it} = w_i z_i$	$\forall i$	Days worked per week 3 constraint	(9)
$\sum_{t=16}^{20} x_{it} = w_i z_i$	$\forall i$	Days worked per week 4 constraint	(10)
$x_{i5} + x_{i10} + x_{i15} + x_{i20} = 3z_i$	$i = 2N+1, \ldots, 3N$	FT 10-hour nurse # Fridays worked constraint	(11)
$x_{i1} + x_{i6} + x_{i11} + x_{i16} = 3z_i$	$i = 2N+1, \ldots, 3N$	FT 10-hour nurse # Mondays worked constraint	(12)
$\sum_{j=1}^{4} y_{ij} = z_i$	$i = 2N+1, \ldots, 3N$	4-day weekend constraint for FT 10-hour shift nurses	(13)
$x_{i5} + x_{i6} \leq 2(1 - y_{i1})$	$\forall i$	Long weekend constraint, weekend 1	(14)
$x_{i10} + x_{i11} \leq 2(1 - y_{i2})$	$\forall i$	Long weekend constraint, weekend 2	(15)
$x_{i15} + x_{i16} \leq 2(1 - y_{i3})$	$\forall i$	Long weekend constraint, weekend 3	(16)

$x_{i20} + x_{i1} \leq 2(1 - y_{i4})$	$\forall i$	Long weekend constraint, weekend 4	(17)
$x_{it}, z_i, y_{ij}\ binary$	$\forall i, j, t$	Binary variables constraint	(18)
$s_t, o_t \geq 0$	$\forall t$	Non-negativity constraints	(19)

Each of constraints (4)-(19) is required to be met for each DBG, even though we do not list any variables for DBGs in any of our formulation. It is assumed the same process is used for each DBG. In the case of the objective function, calculation of total FTE used, constraint on the minimum level of FT nurses used, and minimum OTC nurse staff level requirements (all constraints non-DBG-specific; constraints (1)-(3)), we take the sum across all DBGs. Based on the scenarios described above, additional assumptions were made for the maximum staff levels of OTC nurses to be 18 in the 21 nurse scenario (assumed 3 charge nurses), 15 in the 18 nurse scenario (3 charge nurses), and 14 in the 16 nurse scenario (2 charge nurses). Additionally, the parameter for FTE, f_i, is calculated by multiplying the length of the shift worked for that particular nurse, k_i, by the number of days worked by that particular nurse, w_i, and dividing by 40.

Daily Schedule Optimization

In the daily schedule optimization experiments, we seek to determine the best way to schedule nurses to minimize the amount of patient waiting time in the OTC. We examine three specific shift policy combinations; all 10-hour shifts, all 8-hour shifts, and a mix of 10-hour and 8-hour shifts (ratio of 10-hour to 8-hour is approximately 2:1). Our goals are to gain insights into the effect different shift policies have on patient waiting time, the importance of setting appropriate arrival schedules for nurses, and the effectiveness of using good rules-of-thumb in developing ad-hoc schedules.

The daily schedule simulation-optimization model is based on evaluating "candidate" schedules which were developed by hand based upon current staffing levels and shift policies. In

the mixed shift policy, the ratio of 10-hour shift to 8-hour shift nurses (2:1) was determined based upon current levels of 10-hour and 8-hour shift employees, as well as weighting current staff opinion on how many would be willing to work 80hour shifts (general preference is for 10-hour shifts). Decision variables in the simulation-optimization model define adjustments to nurse arrival times relative to the candidate schedule, allowing us to compare three shift-length combinations and differing arrival times to draw conclusions on effective ways to reduce patient waiting time. Table 4.4 below illustrates each combination of nurse staff level and shift policy we consider in these experiments.

Table 4.4: Nurse staff level and shift policy combinations for daily schedule optimization.

Scenario	Nurse Staff Level	Shift Policy	Breakdown
1	21	All 10s	21 10-hour
2	21	Mix 10s and 8s	13 10-hour, 8 8-hour
3	21	All 8s	21 8-hour
4	18	All 10s	18 10-hour
5	18	Mix 10s and 8s	12 10-hour, 6 8-hour
6	18	All 8s	18 8-hour
7	16	All 10s	16 10-hour
8	16	Mix 10s and 8s	10 10-hour, 6 8-hour
9	16	All 8s	16 8-hour

Development of a Candidate Daily Schedule

The candidate schedule for each scenario was developed in an ad-hoc manner by working with experts involved in scheduling at the cancer center studied. First, the minimum number of openers and closers were defined. The following opening and closing shift times apply, as defined in Table 4.5:

Table 4.5: Opening and closing shift times for different shift lengths.

Shift Length	Shift-Time	Type of Shift
10-hour	7:30 a.m. – 6:00 p.m.	Opening
10-hour	10:00 a.m. – 8:30 p.m.	Closing
8-hour	7:30 a.m. – 4:00 p.m.	Opening
8-hour	12:00 p.m. – 8:30 p.m.	Closing

After allotting closers and openers, all other shifts were then allotted across DBGs, with the available shifts for 10-hour nurses and 8-hour nurses defined in Table 4.6. The schedule for each DBG was developed one at a time, with shifts chosen to try to spread nursing resources over the day such that the most resource availability is covered across the day prior to 6:30 p.m. 10-hour shift nurses were allotted off-days based upon 1) long weekend constraints, and 2) lowest expected throughput constraints. Table 4.7 illustrates the expected daily throughput by DBG, calculated from data on total OTC throughput by day and percent of patients by DBG per day (sample sizes contained in Tables 3.5, and 3.3, respectively. Nurses were allotted off-days on Fridays and Mondays in an effort to get at least one Friday or Monday off day for each DBG to meet the scheduling criterion. Next, the day of the week with the lowest expected throughput was allotted an off day for nurses for each DBG. All base schedules developed can be found in the Appendix 5.

Table 4.6: Potential shift times for OTC nurses under differing shift lengths.

Shift-Length	Shift-Time
10-hour	8:00 a.m. – 6:30 p.m.
10-hour	9:00 a.m. – 7:30 p.m.
8-hour	8:00 a.m. – 4:30 p.m.
8-hour	9:00 a.m. – 5:30 p.m.
8-hour	10:00 a.m. – 6:30 p.m.

Table 4.7: Expected daily throughput for each DBG in the OTC.

Total Expected TH by DBG by Day					
DBG	**Monday**	**Tuesday**	**Wednesday**	**Thursday**	**Friday**
Breast	24.46	30.44	40.56	26.42	27.97
HOA	27.35	30.44	17.44	26.32	26.42
GIGU	17.54	22.91	10.94	25.90	13.42
Lung	20.95	11.46	18.89	11.97	14.45
Off-Service	12.90	7.95	15.38	12.59	20.95

Daily Schedule Simulation-Optimization Model Formulation

The simulation-optimization model was defined for each day of the week in each base scheduling scenario. In total 45 different optimization models were solved, as each of the nine scenarios defined in Table 4.4 has a model for each day of the week. We used the candidate schedules discussed earlier for each scenario's simulation optimization model. We then ran each of these simulation models to seek to improve the candidate schedule, with improvement being measured as a reduction in patient waiting time. We achieve this by allowing the simulation-optimization model to adjust the start and end times for nurse work schedules in an effort to match the timing of work schedules with patient demand better.

Each day of the week varies in patient needs and volume, potentially leading to different solutions and allocations. Decision variables are binary, and determine the start time which may vary by 30 or 60 minutes before or after those defined by the candidate schedule. None of the shifts can start earlier than 7:30 a.m. or end later than 8:30 p.m. Thus, an 8:00 a.m. start will only be allowed to move forward by 30 minutes and not 60 minutes. For this phase of the study we used the simulation model for the OTC alone, with patient arrivals generated based upon historical data recording the actual time of check-in for patients in the OTC. The objective function is expected patient waiting.

The empirical formulation for our model is provided below. Decision variable a_{ij} is a binary variable that represents whether nurse *i* is working shift *j*; this variable will have a value of 1 if the nurse is on-shift. Each nurse *i* will have a series of shifts *j* associated with it, each representing a potential shift time for that nurse and numbering *n* in total. Each nurse has *j* shifts that correspond to an altered work-schedule for that nurse, with start and end-times adjusted in half-hour increments for each *j*. This will allow the simulation-optimization model to adjust the shift time fo the nurse. Variables *k* and *l* are also binary, with *k* corresponding to an opening shift and *l* to a closing shift; a value of 1 indicates the shift is chosen.

Minimize E[Patient Waiting Time]

s.t.

$$\sum_{j=1}^{n} a_{ij} = 1 \qquad \forall i\ on-shift$$

$$\sum_{j=1}^{n} a_{ij} = 0 \qquad \forall i\ off-shift$$

$$\sum_{j=1}^{n} a_{ij} k_i \geq 2 \qquad \forall j$$

$$\sum_{j=1}^{n} a_{ij} l_i \geq 2 \qquad \forall j$$

$$a_{ij}, k_i, l_i\ binary \qquad \forall i, j$$

A small example is provided to illustrate the model. Suppose that the HOA DBG will have the following schedule on a given day, shown in Table 4.8:

Table 4.8: Sample schedule of nurses for the HOA DBG.

Nurse #	Nurse DBG	Monday
1	HOA	off
2	HOA	7:30-6:00
3	HOA	10:00-6:30
4	HOA	10:00-8:30

The decision variables are defined as follows:

- a_{1j} : binary decision variable that equals 1 if HOA nurse 1 is on-shift and 0 otherwise (in this case, 0).
- a_{2j}: binary decision variable that equals 1 if HOA nurse 2 is on-shift and 0 otherwise; the base shift time is 7:30-6:00 and will not be changed since it is an opening shift.

- a_{3j}: binary decision variable that equals 1 if HOA nurse 3 is on-shift and 0 otherwise; the base shift is 10:00-6:30 and can be moved earlier or later by as much as an hour; all associated variables (e.g. a_{32}) listed below are also binary variables.
    - a_{32} : 30-minute earlier shift time (9:30 a.m. - 6:00 p.m.)
    - a_{33} : 60-minute earlier shift time (9:00 a.m. - 5:30 p.m.)
    - a_{34} : 30-minute later shift time (10:30 a.m. - 7:00 p.m.)
    - a_{35} : 60-minute later shift time (11:00 a.m. - 7:30 p.m.)
- a_{4j}: binary decision variable that equals 1 if HOA nurse 4 is on-shift and 0 otherwise; the base shift is 10:00-8:30 and will not be changed since it is a closing shift

The following example shows how the constraints are used to force the optimizer to choose only one shift for each nurse and to ensure nurse 1 is off-shift. The sum of all shifts for nurse 1 must equal zero, forcing that nurse to be off-shift. Nurse 3 is free to work any of the available schedules, as any choice is a feasible time frame. Nurse 2 works an opening shift and nurse 4 a closing shift, so we force those values to be 1 when the nurse is on-shift and do not allow them to be adjusted. We do this to ensure the integrity of our minimum number of openers and closers constraint is met. Thus, when we developed the candidate schedule, we manually enforced the constraint and uphold it in the formulation of the simulation-optimization model.

- $a_{11} + a_{12} + a_{13} + a_{14} + a_{15} = 0$
- $a_{21} = 1$
- $a_{31} + a_{32} + a_{33} + a_{34} + a_{35} = 1$
- $a_{41} = 1$

The capacity schedule in Arena is defined as follows in Table 19 with lunch time considerations included (parentheses added to group each nurse's variables together). The first column indicates the time slot, and the second column contains the value for the total number of resource units available in that time slot, depending upon the selection of schedules by the optimizer. The aforementioned constraints restrict the selection of nurse 1 (off-shift) and the selection of nurse 3 to be one of the available 5 shifts. Furthermore, nurses 2 and 4 are required to

be selected (opener and closer). Thus, from 7:30-8:00, the nurse capacity would be 1 for the HOA DBG as

$$a_{11} + a_{21} = 0 + 1 = 1.$$

If a_{32} is the shift time selected for nurse 3, then the capacity from 11:00-11:30 would be 3, as

$$a_{11} + a_{22} + a_{31} + a_{32} + a_{33} + a_{34} + a_{35} + a_{41} = 0 + 1 + 0 + 1 + 0 + 0 + 0 + 1 = 3.$$

The constraints defined in the optimizer surrounding the total summation of each nurse variable set off-shifts and restrict the number of working shifts selected to one per nurse. When entered into the simulation model, each of the capacity values representing the units of nurse on-shift are in turn multiplied by a nurse factor (value of 6) so that 6 units of nurse are used per nurse in the simulation model. This allows the limitations in starting patients to 4 patients per nurse as described in Chapter 3, Section 2 in the "Scheduling of Resources" section. This does not affect the formulation of the simulation-optimization, as all variables must still sum to equal one or zero depending on the nurse, but rather is only used in defining the schedule to the simulation model such that the logic for nurses in the OTC will work appropriately. Thus, in our example, every row in Table 4.9 would be multiplied by 6 when entered into the simulation model.

Table 4.9: Sample capacity schedule for each time block of the day for an HOA DBG nurse schedule.

Time	HOA Nurse Capacity
7:00-7:30	0
7:30-8:00	$a_{11} + a_{21}$
8:00-8:30	$a_{11} + a_{21}$
8:30-9:00	$a_{11} + a_{21}$
9:00-9:30	$a_{11} + a_{21} + a_{33}$
9:30-10:00	$a_{11} + a_{21} + a_{32} + a_{33}$
10:00-10:30	$a_{11} + a_{21} + a_{31} + a_{32} + a_{33} + a_{41}$
10:30-11:00	$a_{11} + a_{21} + a_{31} + a_{32} + a_{33} + a_{34} + a_{41}$
11:00-11:30	$a_{11} + a_{21} + a_{31} + a_{32} + a_{33} + a_{34} + a_{35} + a_{41}$
11:30-12:00	$a_{11} + a_{21} + a_{31} + a_{32} + a_{33} + a_{34} + a_{35} + a_{41}$
12:00-12:30	$a_{21} + a_{31} + a_{32} + a_{33} + a_{34} + a_{35} + a_{41}$
12:30-1:00	$a_{11} + a_{31} + a_{32} + a_{33} + a_{34} + a_{35} + a_{41}$
1:00-1:30	$a_{11} + a_{21} + a_{41}$
1:30-2:00	$a_{11} + a_{21} + a_{31} + a_{32} + a_{33} + a_{34} + a_{35}$
2:00-2:30	$a_{11} + a_{21} + a_{31} + a_{32} + a_{33} + a_{34} + a_{35} + a_{41}$
2:30-3:00	$a_{11} + a_{21} + a_{31} + a_{32} + a_{33} + a_{34} + a_{35} + a_{41}$
3:00-3:30	$a_{11} + a_{21} + a_{31} + a_{32} + a_{33} + a_{34} + a_{35} + a_{41}$
3:30-4:00	$a_{11} + a_{21} + a_{31} + a_{32} + a_{33} + a_{34} + a_{35} + a_{41}$
4:00-4:30	$a_{11} + a_{21} + a_{31} + a_{32} + a_{33} + a_{34} + a_{35} + a_{41}$
4:30-5:00	$a_{11} + a_{21} + a_{31} + a_{32} + a_{33} + a_{34} + a_{35} + a_{41}$
5:00-5:30	$a_{11} + a_{21} + a_{31} + a_{32} + a_{33} + a_{34} + a_{35} + a_{41}$
5:30-6:00	$a_{11} + a_{21} + a_{31} + a_{32} + a_{34} + a_{35} + a_{41}$
6:00-6:30	$a_{31} + a_{34} + a_{35} + a_{41}$
6:30-7:00	$a_{34} + a_{35} + a_{41}$
7:00-7:30	$a_{35} + a_{41}$
7:30-8:00	a_{41}
8:00-8:30	a_{41}

Section 3: Results

We used our MIP model to analyze the monthly and weekly nurse scheduling problem to gain insights into the optimal allocation of nurses and nurse shift length policies subject to scheduling constraints on variable daily demand. We used a simulation-optimization model to analyze the daily scheduling problem to find optimal work schedules under various shift length policies, where optimal is defined as the smallest patient waiting room time.

Monthly and Weekly Scheduling Optimization: MIP Results

We ran all experiments for the MIP monthly and weekly scheduling problem on an HP notebook, Dual-Core Processor, 1.30 GHz, 4.00 GB RAM using Microsoft Excel. We used the solver add-on Premium Solver Platform to perform all runs. This program used the branch and bound method to determine an optimal solution, and we set the integer tolerance level for solutions to be 0.1%. Additionally, we set computation time to a maximum of 1-hour.

Table 4.10: MIP results for the optimal allotment of nurses, 21 FTE scenario.

21 Nurse Staffing Level; 18 OTC nurses, 3 charge nurses					
Min. # FT Nurses	**# FT 10s**	**# FT 8s**	**# PT Nurses**	**Shortage (Hours)**	**Lower Bound (Hours)**
None	6	1	18	18	0
9	7	5	10	17	0
10	6	5	12	11	0
11	7	4	12	26	0
12	7	5	10	17	0
13	9	4	9	18	0
14	12	2	7	88	0
15	9	6	4	90	0
16	12	4	4	65	0
17	11	6	2	57	20
18	9	9	0	85	66

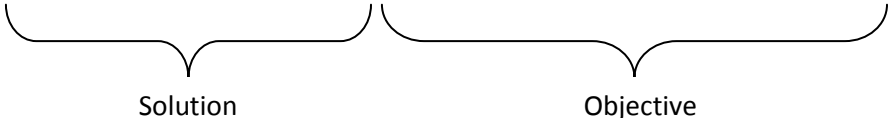

Table 4.10 shows results for the MIP based on a maximum 1-hour run-time for the 21 nurse scenario under various constraint levels on the minimum level of FT nurses. The columns bracketed under solution indicate the number of FT nurses used for both 10-hour and 8-hour shifts, as well as the number of PT nurses used in the optimal solution found after 1 hour. The last two columns provide upper and lower bounds obtained on the optimal solution. The shortage hours column contains the value of the objective function (shortage hours) at the time the MIP finished running. The lower bound column is the best bound Premium Solver Pro obtained.

The results suggest two main conclusions; first, that using part-time nurses could significantly reduce total shortage hours. Second, that as the number of PT nurses used increases, diminishing returns or no improvement at all is seen in reducing shortage hours. Regarding the latter conclusion, the results seem to indicate that there is some optimal point of FT nurse staff level that maximizes the number of FT nurses (to improve continuity of care) while still minimizing shortage hours. Similar tables can be found in Appendix 6 for the 18 and 16 nurse scenarios.

Figure 4.2 further illustrates the two conclusions described in the previous paragraph. The y-axis tracks the number of shortage hours for the particular MIP run, and the x-axis tracks the constraint on the minimum level of FT nurses, with the far right indicating all FT nurses and the far left no constraint on FT nurses. As the reader travels from right to left along the red line, more PT nurses are being added. The red line tracks the shortage hours in the 1-hour run length case, and shows that the presence of PT nurses improves the schedule (more PT nurses scheduled as graph is read from right to left). This solution is the upper bound and while not completely smooth or easy to see, the addition of PT nurses has an immediate improvement in shortage hours, with diminishing returns as time goes on. The numbers for the lower bound in Table 4.10 support this conclusion as well, with no further improvement in shortage hours seen as fewer than 16 FT nurses are present (more PT nurses added). Thus, in the 21 nurse scenario, 16 or 17 FT nurses appears to be the best solution, with the remainder of the nurses PT nurses.

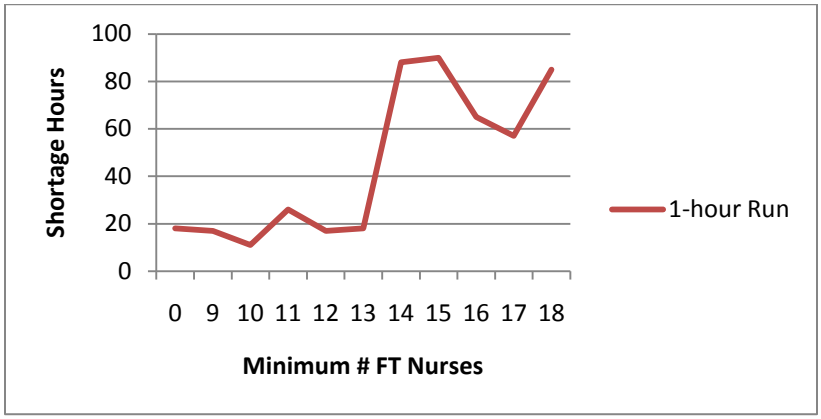

Figure 4.2: Best objective function values (shortage hours) for MIP runs, 21 nurses.

Similar graphs are available for the 18 nurse and 16 nurse scenarios and are provided in Figures 4.3 and 4.4, respectively. These graphs show the same behaviors and conclusions as in the 21 nurse scenario, with the exception that in both cases, it appears to be optimal to be a little further away from full staffed with FT nurses. It is much easier to see the trend of more PT nurses improving shortage hours with diminishing returns in these graphs than the graph for the 21 nurse scenario. Further collaboration with the team of experts at our hospital of study will be required to decide the optimal point as well, as the diminishing returns in adding PT nurses is more gradual in these cases. However, it appears that 11 FT nurses is the point at which no further objective function improvement is made in both cases.

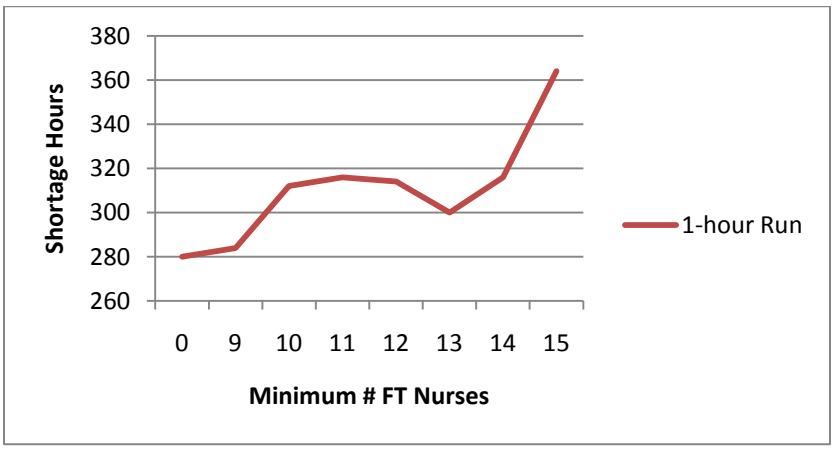

Figure 4.3: Best objective function values (shortage hours) for MIP runs, 18 nurses.

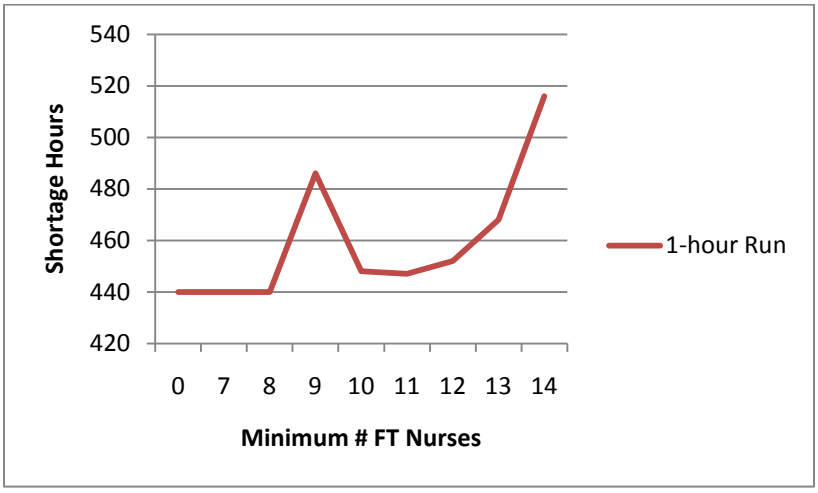

Figure 4.4: Best objective function values (shortage hours) for MIP runs, 16 nurses.

We additionally tracked the number of each PT shift selected in each scenario. Our model is constrained in that each type of PT shift is only allowed to be selected once (twice in the case of the 4-hour shift) for each DBG. Thus, it is difficult to do a complete analysis on how to schedule PT shifts. There are no distinct trends noticed in the selection of PT nurse shifts, with the exception that as fewer and fewer PT nurses can be chosen, the 5 4-hour shift and 2 10-hour shift options seem to be chosen more frequently. However, further work needs to be done to confirm or make any further conclusions on the selection of PT nurse shifts. All results for the breakdown of PT nurse shifts selected can be found in Appendix 6.

Daily Schedule Optimization: Simulation-Optimization Results

All simulation-optimization runs were conducted on a Dell Optiplex 980 PC Intel® Core™, 2.93 GHz, 4.00GB RAM PC using the optimizer OptQuest and our simulation model built in Arena. OptQuest uses a combination of Tabu Search and other heuristics to reach the optimal solution (Kelton et al., 2007). The stopping time criterion was set to stop the simulation-optimization after 1000 iterations in order to limit the computation time. This number was chosen after observing a few simulation-optimization runs when objective function improvements had not been made for several hundred simulation runs. We set the tolerance of equally defined schedules to be 0.1

minutes (difference in waiting time), and allowed the optimizer to vary simulation model replications from 10 to 100, under the constraint that confidence interval widths were within 10% of the mean. Simulation run times were approximately 2-4 hours.

Table 4.11 contains the results of the simulation-optimization runs in the 21 nurse scenario. The "original" column shows the average waiting room time for the ad-hoc schedules developed by hand, and the "optimal" column shows the (near optimal) average waiting room time based on the best solution OptQuest found after 1000 iterations. HW represents the half-width of the confidence interval. The results for the 18 nurse and 16 nurse scenarios can be found in Appendix 6.

The results suggest a few general conclusions. First, the ad-hoc scheduling process seems to work well in generating good solutions, as most of the schedules are statistically the same in terms of patient waiting time relative to the optimal schedules. However, in some cases, the ad-hoc schedule development process does not provide the best solution; in such cases, the simulation-optimization model was useful in improving the schedule. Second, while the average patient waiting times are lower in the mix of 10-hour and 8-hour shifts and all 8-hour shift scenarios, there are far more instances in which going from original schedule to optimized schedule is statistically significant than changing shift combinations in every scenario of nurses. This is an indication that the largest driver in reducing patient waiting time is the timing of the nurse work schedule more so than the combination of shift lengths used. The reason for the behavior is possibly due to the fact that the majority of patient waiting for nurses takes place in the center portions of the day and not at the beginning or end of the day. Thus, if nurse schedules can be aligned such that the most overlap of nurses available takes place when patient demand is greatest, it is possible to achieve good schedules under multiple shift combinations.

In particular, the addition of shift starts on the half-hour helped, as the optimizer chose an 8:30 a.m. – 7:00 p.m. shift for 10-hour shift nurses quite often. The 8:00a.m. – 6:30 p.m. and 9:00a.m. – 7:30 p.m. shifts were not removed completely, but the optimizer adjusted many of them to 8:30a.m. – 7:00p.m. Thus, we recommend future inclusion of 8:30a.m. – 7:00 p.m. nurse work schedules by changing some of the 8:00a.m. – 6:30 p.m. and 9:00 a.m. – 7:30 p.m. shifts. All final schedules chosen by the optimizer can be found in Appendix 6; there are 5 possible schedules for

each scenario as the simulation-optimization run for each day of the week yielded a different solution.

Another general conclusion is that as nurse staff becomes more of a bottleneck, there is more benefit from using the optimizer. As the nurse staff level is reduced across scenarios, the number of days and shift policies where the optimizer had a statistically significant improvement on the candidate schedules increases. Additionally, as nurses become more of a scarce resource, benefits are seen in using shorter shift lengths (mixed and all 8-hour shift scenario) as the nurses are able to be more concentrated on high demand times. However, the impact of changing shift combination is still significantly less than the impact of adjusting work schedule times.

Table 4.11: Results of 21 nurse simulation-optimization comparing original and optimal schedules.

Average OTC Wait Room Time					
		Orig		Opt	
		Avg	HW	Avg	HW
Monday	All 10s	32.28	2.78	29.02	2.32
	13 10s	29.63	2.18	27.36	1.31
	All 8s	29.33	2.29	27.69	1.84
Tues	All 10s	34.44	3.41	29.43	1.88
	13 10s	32.11	3.18	29.66	2.74
	All 8s	38.48	3.24	27.73	1.45
Wed	All 10s	38.06	3.96	35.79	3.52
	13 10s	34.66	3.33	33.31	3.30
	All 8s	36.06	4.02	33.47	3.33
Thurs	All 10s	38.18	3.93	32.73	3.16
	13 10s	36.55	3.75	30.32	2.16
	All 8s	35.17	3.65	28.86	2.78
Fri	All 10s	32.81	3.16	26.95	1.63
	13 10s	30.75	2.97	25.88	1.58
	All 8s	32.07	3.20	25.75	1.27

The improvement in average waiting time is limited. However, the benefits are disproportionately allocated to patients seen during peak hours. The results of the maximum waiting room times are found in Appendix 6, and typically average about 90 minutes. Improvements in waiting room time at peak volumes can improve by as much as 25 minutes in some cases.

Section 4: Conclusions

In conclusion, we explored several methods for determining an optimal nurse schedule and the monthly, weekly, and daily level. We developed a MIP for optimizing the selection of nurse types (10 hour, 8 hour, and part time nurses) for monthly and weekly schedules. We also explored the use of ad-hoc schedule design for daily nurse arrival schedules based on expert opinion and compared these results to those of a simulation-optimization model.

Results based on the MIP identified merits of using PT nurses, as well as useful insights about the diminishing returns on shortage hours as more PT nurses are used. FT nurses seem to be used to spread nurse supply across the week, while PT nurses are used to schedule nurse supply on high demand days, allowing the highly variable day-to-day demand to be met effectively. In a number of instances of the MIP could not be solved to optimality within one hour of computation time. Therefore there may be benefits to exploring MIP methods to improve the computation time, or test other solvers capable of solving large scale MIPs.

The use of the simulation-optimization model had mixed results in improving the nurse scheduling. The ad-hoc scheduling process often worked well in generating good schedules, but in some cases the simulation-optimization model helped make statistically significant improvements with impact of as much as 25 minutes in waiting room times at peak volume. Furthermore, the scarcer nursing resources are, the more of an impact the optimizer had in generating optimal solutions. Additional improvements were seen in some cases by using a mix of 10-hour and 8-hour shifts and all 8-hour shifts, although changing shift start times for nurses (improvement seen going from candidate to optimizer schedule) had the greatest impact. One limitation of the simulation-optimization model is that it is very computationally intensive and it does not identify a provable optimal solution or bounds on the optimality gap (e.g. such as for the MIP model). It is possible that longer run times or enhancements to the simulation optimization methods could lead to better daily nurse schedules, but at the price of many hours of computation. Furthermore, each day of the week yielded a different optimal schedule, creating difficulties in implementing specific schedules. Thus, we focus on general recommendations, such as the inclusion of an 8:30 a.m. – 7:00 p.m. shift.

Opportunities for future work on nurse scheduling include more directly coordinating the use of the MIP and simulation-optimization models to interact iteratively in a heuristic fashion in which the simulation optimization model provides feedback to the MIP, and the MIP provides the information on the shift types to use for FT and PT nurses in a candidate schedule. Additionally, the MIP could be developed further and set up for use as an ongoing scheduling tool in the OTC. Inputs would be expected patient throughput volumes by DBG, current nurse staffing levels and shift times, and the output would be the allotment of shifts across days to determine which nurses receive off-days when. The MIP could also be set up such that the user could explore different scenarios of hiring new nurses, with the MIP informing the best type of nurse to hire and where to schedule the nurse.

Chapter 5: Future Resource Planning

Section 1: Introduction

Predicting future resource shortages and potential bottlenecks is an important part of planning for a new cancer center. By nature, the cancer center and the OTC are variable and dynamic; over time, they change. As plans for future expansion take place, it is very important to make well-informed planning decisions such that process patient access to care is optimized. As mentioned in Chapter 1, process efficiency is one way to optimize patient access to care, with benefits of increasing patient throughput and revenue, and reduced congestion and patient waiting time. Due to the dynamic nature of cancer centers, it does not follow that already gained process efficiencies translate or that bottlenecks remain the same. In this chapter we evaluate a hypothetical new cancer center, and provide the results of numerical experiments to help inform the capacity planning process. In Chapter 3 we identified two common bottlenecks in the OTC to be nurses and chairs, and now use our simulation model to run two simple experiments that analyze bottlenecks in the OTC as hypothetical changes are made for the new cancer center.

In Chapter 4, we examined the nurse bottleneck identified in the OTC, but did not consider the chair bottleneck. In this chapter, we return to the chair bottleneck identified in Chapter 3 and look at increasing chair capacity to address it. In this first set of experiments we evaluate bottlenecks in the current cancer center with respect to a varying number of chairs. We analyze the behavior of the OTC to determine how many chairs must be added in the current state for chairs to no longer be a bottleneck. In the case of the hypothetical new cancer center, we are then able to use these results to predict whether the increased chair capacity proposed in the new cancer center is sufficient to remove the chair bottleneck that already exists.

Next, we report the results of a second set of experiments in which the number of patient arrivals increases from the current level in the hypothetical new cancer center. This set of experiments is used to inform potential bottlenecks in the hypothetical new cancer center as expected patient demand steadily increases. We update our model to use the planned increase in the number of chairs in order to inform current proposed plans for the hypothetical new cancer center. The purpose of these experiments is twofold. First, we seek to analyze the extent to which nurses are a bottleneck with the proposed chair capacity increase in the hypothetical new cancer

center (which would start with the current level of patient arrivals). Second, we seek to analyze the bottlenecks in the OTC under specific anticipated scenarios of future patient volume increases.

Section 2: Methods

In this chapter we use the same model OTC model as in Chapter 4. We vary model inputs including the number of chairs and the patient arrival process.

Sensitivity Analysis on Number of Chairs

The current OTC has 38 chairs, with both chairs and nurses being bottlenecks. In our experiments, we perform a sensitivity analysis on how increasing the number of chairs impacts the bottlenecks in the OTC. We began with the current number of chairs (38), and increased the number of chairs in increments of 4, up to 72 chairs (approximate capacity of new cancer center). As we reached the point at which chairs ceased to be bottlenecks, we conducted further experiments with finer granularity, using smaller increments to the number of chairs. Table 5.1 summarizes the model instances that were considered for each day of the week, and data fields with a range of numbers listed indicate chair levels that had the same output statistics in terms of patient waiting time:

Table 5.1: Different numbers of chairs used to test bottlenecking in the OTC for each day.

Monday	Tuesday	Wednesday	Thursday	Friday
38	38	38	38	38
42	46	42	46	46
46	50	46	54	54
48	54	50	60	58
50	56	54	64	60
51	57	56	66	61
52	58-72	57-72	67	62-73
54-72	N/A	N/A	68-72	N/A

Sensitivity Analysis on Number of Patient Arrivals

The second set of experiments assumes the number of chairs is fixed at 73 to reflect the proposed increase in chair capacity at the hypothetical new cancer center. We assume that in the new cancer facility, the arrival rate will follow the same pattern, just scaled-up to reflect the expected increase in patient volume. All other inputs are the same.

We look at three scenarios of patient volume in the hypothetical new cancer center; the current volume level, a 6% increase, and a 12% increase in total average demand, based on anticipated growth in patient demand. We report results for average patient waiting time for the waiting room, chairs, and nurses.

Section 3: Results

All simulation runs in both sets of experiments used 50 replications, using Arena version 11, and a Dell Optiplex 980, Intel® Core™, 2.93 GHz, 8.00GB RAM PC.

Sensitivity Analysis on Number of Chairs

The results for sensitivity analysis to the number of chairs vary by day. In this section we provide results for a specific day, Thursday, chosen because the highest patient waiting times for chairs was seen on Thursday. The complete sets of results for all days, Monday through Friday, are provided in Appendix 7.

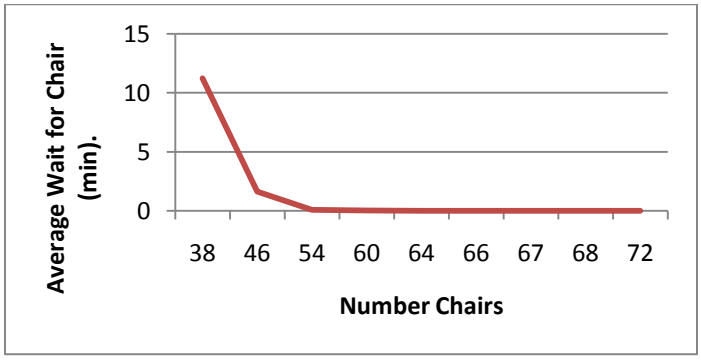

Figure 5.1: Patient wait times for chairs with respect to the number of chairs on Thursday.

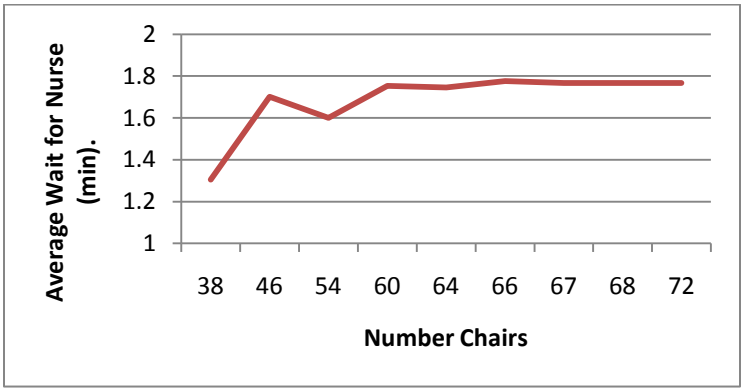

Figure 5.2: Patient wait times for nurses with respect to the numbers of chairs on Thursday.

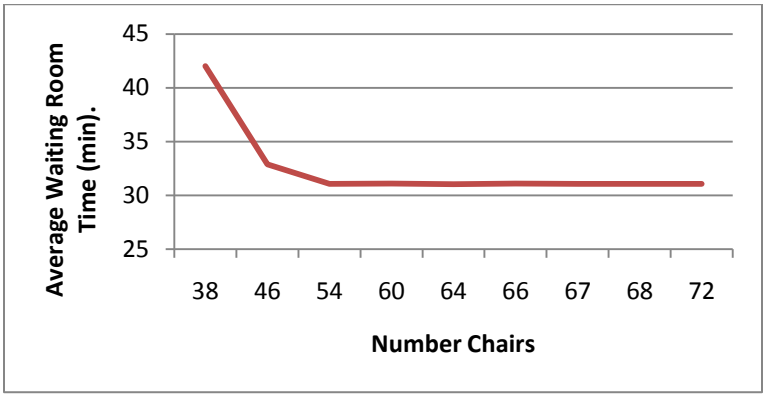

Figure 5.3: Patient waiting room time with respect to the number of chairs on Thursday.

Figure 5.1 shows the chair wait times for Thursday, indicating that chairs are generally not a source of wait beyond 54 chairs. As expected, as the number of chairs increases, the waiting time for chairs decreases. Additionally, Figure 5.2 illustrates the effect of increasing the number of chairs has on patient waiting time for nurses. As expected, as chairs are removed as a bottleneck, nurses become the bottleneck. Figure 5.3 illustrates the improvement in waiting room time for patients as the number of chairs is increased. Each of the graphs in Figures 5.1-5.3 exhibit similar characteristics. As the number of chairs increases, the value of each respective waiting time changes with diminishing returns, tending to level off at 54 chairs.

Table 5.2 provides results for when chairs cease to be bottlenecks for each day of the week. Thus, if the new OTC had these numbers of chairs, the anticipated waiting time for a chair to become available would be near zero. The third column indicates the point at which average wait is virtually zero, but still exists. Furthermore, under the same conditions of patient volume, arrival times, and service times, the proposed chair capacity of 73 for the new cancer center will not be a bottleneck, with an expected waiting time of 0.

Table 5.2: Results for the numbers of chairs at which each day has no chair wait.

Day of the Week	# of Chairs for no wait	# of Chairs for minimal wait
Monday	52	48
Tuesday	58	54
Wednesday	57	54
Thursday	66	54
Friday	62	46

Sensitivity Analysis for Patient Arrivals

Table 5.3 shows the results of the second set of experiments. The results are presented for Wednesday, as Wednesday is the highest volume day in the OTC. We provide a summary of patient waiting times under the current OTC model, the new OTC model, and the different increases of patients (assuming arrivals are proportionate to existing scenario). The full results can be found in Appendix 8.

Table 5.3 shows the results from the second experiment for the current cancer center, the hypothetical new cancer center with equal patient volume, and scenarios of a 6% and 12% increase in patient volume. These results provide several insights into the nature of bottlenecks and patient waiting time in the new cancer center. First, moving from the current cancer center to the new cancer center with the same number of patient arrivals leads to a reduction in overall patient waiting time, as well a change in bottleneck. Chairs cease to be a bottleneck with increased capacity, and nurses become the primary bottleneck as evidenced by an increase in average waiting time. Second, as patient volume increases over time, in the absence of other changes, the average waiting for a nurse increases while the average waiting time for a chair remains at 0. Thus, the nurse remains the primary bottleneck corresponding to the increase in overall waiting time. This shows that the more patient demand grows (as is expected), the more of a bottleneck nurses become. Appendix 8 contains a full list of statistics and confidence intervals for these experiments.

Table 5.3: Results for Increasing Patient Arrivals on Wednesday in the new OTC.

Metric	Current	New	6% Increase	12% Increase
Number Treated	114.28	116.38	124.50	130.56
Waiting Room Time	39.35	30.53	32.23	34.17
Average Time Waiting for Chair	9.98	0.00	0.00	0.00
Average Time Waiting for Nurse	0.87	2.15	2.87	3.36

Section 4: Conclusions

In conclusion, two sets of experiments were run to help predict and manage the future OTC setting. From the first experiment, we identified the number of chairs required to remove chairs as a bottleneck. Looking at the results across all days of the week it appears that an expansion of 16 chairs from 38 to 54 in total would remove chairs as being the primary bottleneck in the OTC. Thus, the new OTC chair capacity of 73 is ample to remove chairs as a bottleneck. In the second set of experiments we found that not only is the chair bottleneck removed when the number of chairs is increased to 73, but nurses become the primary bottleneck. Furthermore, the more patient volume increases, the longer patient waiting times in the waiting room and for the nurse becomes. Meanwhile, even with a 12% increase in patient volume, the chair still is not a bottleneck. This analysis led to the identification of OTC nurses as the primary bottleneck in the immediate future, and the conclusion that more nurses need to be hired to staff the new cancer center. This need may become more exaggerated as patient volumes continue to increase beyond the 12% increase level.

Chapter 6: Conclusions & Future Research

Section 1: Introduction

In this chapter, we begin by summarizing the work we did and highlighting key findings and conclusions from this study. Next, we describe some of the tangible benefits of the work. We then discuss limitations of the study. Finally, we discuss opportunities to further improve our work and extend it into the future.

Section 2: Key Findings, Recommendations, and Conclusions

Constructing a validated simulation model is time consuming due to the complexity of cancer center operations and the large number of data sources needed to develop a validated model. There were many challenges in accessing the data needed to build the model and data came from a variety of sources including historical data, the results of time studies, and expert opinion. We found that using expert opinion to estimate probability distributions was an effective way to handle these challenges in accessing data. Although patient arrivals are scheduled to the cancer center we found that generating patient arrivals based upon mean arrivals during discrete parts of the day, using historical data, to fit a non-stationary Poisson arrival process was an effective way to model patient arrivals. Much of the data collected for this project will be useful for other process improvement projects in the future. Furthermore, the simulation model will be useful for answering questions related to resource planning beyond the scope of this thesis.

The simulation model was used to identify bottlenecks and assess patient flow for a particular cancer center. Our model revealed bottlenecks for phlebotomy and oncologist consultation in the clinics. Patient wait times for phlebotomists in the clinics varied by clinic and day of week, but ranged anywhere from 10-30 minutes on average. Patient wait times in the examination room waiting for the oncologist varied by clinic and day of week as well, also ranging anywhere from 10-30 minutes on average. The model indicates a large amount of variability in waiting times by clinic and day, which is consistent with what we expect and confirmed as the case by expert opinion.

Bottlenecks were also identified in the OTC. Patient wait times in the OTC were largest for chairs, with an average wait time of 2-10 minutes, but more significantly, a maximum average wait time ranging from 25-40 minutes at peak times during the day. Additionally, patient wait times for OTC nurses ranged from 1-2 minutes on average; however, specific DBGs have maximum average wait times as high as 30 minutes at peak times during the day. In particular, most of the higher waiting times for nurses were centralized in the HOA DBG, ranging from 5-30 minutes for the maximum average waiting time across all replications. Thus, we recommend the hiring of an

additional HOA DBG nurse to bring the HOA nurse staff level from 4 to 5, given that expected volume for HOA DBG patients is similar to breast DBG patients and the breast DBG has 5 nurses.

This study revealed a large amount of variability in wait times across the cancer center across days and within the days. Wait times within the day tend to be concentrated during peak times of 10:00 a.m. – 3:00 p.m. with tails of the day having less waiting time on average. Wait times also vary significantly from day-to-day with Wednesday and Thursday having the highest patient waiting room times. This results from Wednesday having the most patient volume, and Thursday having moderate patient volume combined with more off-days and a lower nurse staff level.

We formulated an MIP to analyze monthly and weekly nurse schedules, subject to scheduling constraints. We used the MIP to perform sensitivity analysis on the number of FT and PT nurses. Our analysis shows that FT nurses are useful for covering supply needs across the day, whereas PT nurses are useful for meeting the variable day-to-day peak demand. PT nurses provide the capability to target increase nurse availability at peak times during the day. Thus, PT nurses are very helpful in reducing shortage hours in a nurse schedule. Furthermore, we found that adding PT nurses has diminishing returns in reducing shortage hours; thus, we conclude it only takes a small number of PT nurses to make a significant impact in reducing shortage hours. Taking one or two FT nurses and replacing with equivalent levels of PT nurses can achieve this. Additionally, given the expected increase in patient demand and increased waiting time for nurses, this can also be achieved with future hires.

We analyzed daily scheduling using a simulation-optimization model. We developed candidate schedules in an ad-hoc manner with the help of experts to begin the optimization and compared those schedules to those generated by the simulation optimization model. Our results show that the ad-hoc approach of scheduling each DBG independently and then scheduling the OTC collectively, with allotment of off-days to lower expected volume days for each DBG, can generate a good schedule in many cases. However, simulation optimization can significantly improve daily schedules in some cases. The simulation-optimization model indicated changing arrival and departure times of nurse schedules has the most impact on patient waiting time. In particular, the addition of shift starts on the half-hour helped, as the optimizer chose an 8:30 a.m. – 7:00 p.m. shift

for 10-hour shift nurses quite often. Thus, we recommend changing some of the 8:00a.m. – 6:30 p.m. and 9:00 a.m. – 7:30 p.m. shifts to 8:30 a.m. – 7:00 p.m. Using a combination of 10-hour and 8-hour shifts as opposed to exclusively 10-hour or exclusively 8-hour shifts can have an impact on average patient waiting time as well, though we see mixed results as to whether or not this improves patient waiting time in our experiments. Our results indicate that the lower nurse staff levels are, the more of a bottleneck they become, and the larger the improvement in using optimization methods to improve candidate schedules.

We also used our model to explore future resource capacity planning for a new cancer center, forecasting future bottlenecks and OTC performance in several scenarios to inform the planning process for administrators. We began by increasing the number of chairs to determine how much expansion is needed such that chairs are no longer a bottleneck. The results of the model showed that an expansion of chair capacity by 16 from 38 to 54 chairs removed most of the waiting time for chairs in the OTC. Thus, the proposed increase in chair levels to 73 in the new cancer center sufficiently meets the demand needs. Additionally, we translated our model to have a chair capacity equivalent to that of a new cancer center, and performed an analysis on patient waiting time under scenarios of patient volume increases. We identified nurses as the primary bottleneck in the new cancer center, and also showed that expected waiting time for a chair goes to zero under current patient throughput levels and a 6% or 12% increase in throughput. We also found that expected patient waiting time for nurses and in the waiting room increases as patient volume increases. Thus, more nursing staff will be needed for the cancer center to operate at full capacity.

Section 3: Additional Project Benefits

This study has had a number of benefits for the cancer center studied, including information learned in the development process, identification of bottlenecks, recommendations for improving patient flow, time study data, and useful tools for future use. The simulation model development process was beneficial in quantifying each specific process in the cancer center from the perspective of value added versus non-value added patient waiting time and provider service time. Mean and variance for processing times such as check out in the clinics, pharmacy drug mixing times, charge nurse chart check times, infusion lengths, and OTC nurse patient briefing were analyzed to identify significant sources of uncertainty and variation in the patient flow process. Additionally, patient waiting times in various portions of the cancer center were quantified, useful information to administrators as they make decisions as to the best way to improve the cancer center. Furthermore, a byproduct of creating the simulation model was the provision of data analysis surrounding the arrival processes and punctuality of patients, as well as patient volume trends. All of the graphs generated in Chapter 2 of the thesis about time-varying arrival rates across the day, OTC patient volume trends, and patient punctuality was information gleaned as a result of this project.

As part of this project several time studies were performed, providing valuable information to cancer center staff to improve the management of operations. We conducted time studies for check-out in one of the clinics, pharmacist processing and drug mixing in the pharmacy, and charge nurse chart checks in the OTC. This data was useful in providing information for more informed decisions, and the pharmacy time study data was specifically needed by the pharmacy manager in making future planning decisions. The data for check-out in one of the clinics was used to verify existing labor standards (with the considerations for non-patient contact time removed) that needed to be updated. Additionally, the process of collecting data helped enforce the benefits and merits of collecting different kinds of data than has previously been collected (related to service times with a patient focus rather than just for the purposes of labor standards). This encourages analysis not just for the total labor standard, but also in terms of required labor based on patient contact times.

Additionally, an automated time study data collection and reporting application was built to facilitate the collection and reporting of data. This application is user-friendly and contains several user-interfaces that allow the user to select a specific process to record data for, enter in time stamps surrounding start and end times of a particular service, and enter the information into a table stored in the database. Then, the user can select a reporting screen the provides summary statistics such as average, standard deviation, median, maximum, and minimum as well as a histogram showing the variation in service times.

Finally, a long term benefit of the project is that the models we have developed can be used in the future to answer questions about policy changes, planning and capacity investment decisions, and staff hiring and scheduling. The models can serve as a valuable resource to support a continuous effort to improve patient access and efficient delivery of oncology services.

Section 4: Limitations

Constructing a model with a whole-system approach for a large and complex system such as a cancer center is both challenging and time-consuming. While expert opinion has indicated that the model appears to be well validated, statistical validation had some shortcomings due to availability of suitable observational data on flow times for comparison to model inputs. There are a number of unconfirmed assumptions in the model, such as static service times based on labor standards in the clinic, assumptions allotting the number of oncologists and patients to oncologists in the clinics, and estimated processing times. Additionally, the data used to populate the model is over a four month period of time, and may not reflect seasonality in cancer center operations. Future work can entail obtaining a larger data set to construct the model from and verifying that seasonality does not play a significant role in cancer center operations. A continued effort to validate these assumptions through observation and interviewing of cancer center staff is recommended.

Section 5: Future Work

There are many opportunities for future work resulting from this project. The current simulation model can be used to guide design decisions for the new cancer center including nurse hiring, measuring the effect of new capacity investments, and evaluating the potential gains from changes to cancer center policies. Specifically, future work can address the bottlenecks already identified in the clinics of phlebotomy and oncologist wait, either in increasing staff levels, adjusting work schedules, or managing patient arrival flow. In the case of phlebotomy, individual clinics will no longer perform their own blood draws in the new cancer center. Thus, a scenario examining the impact of one centralized blood draw area can be done in the new cancer center model. Additionally, experiments can be performed to evaluate the benefits of policy changes such as pooling exam rooms to estimate the effects of these changes on patient waiting and cancer center efficiency.

Future work could involve informing hiring decisions in the new cancer center setting in response to the identification of nurses as the primary bottleneck. Other opportunities include the integration of the simulation-optimization model and MIP model to develop monthly, weekly, and daily schedules. Developing specific candidate schedules from the results of the MIP could greatly reduce the number of experiments required in the simulation-optimizer, and thus, the total computation time. Furthermore, the MIP can be developed and used as a scheduling tool in the OTC on a month-to-month basis, to better match nurse supply and patient demand. It can also be used to inform hiring decisions to determine the types of nurses that will have the greatest impact on patient waiting time and process efficiency.

There are a number of opportunities to use the simulation model to study policy changes that may lead to substantial improvements in patient access and provider efficiency. For example, experiments can be performed to examine the impact of smoothing out the patient arrivals during the day (see Figure 5 for an example of the non-uniform arrivals during the day). This could be achieved in a number of ways. One possibility is to implement a “two-day” model for returning patients that may be able to have their consult and labs prior to their day of treatment. Alternatively, a “fast-track” policy could be evaluated. Such a scenario would use a mid-level

provider in the OTC that checks some chemotherapy patients, depending on patient need. In such a case, designated patients would not travel to one of the cancer clinics but instead arrive directly into the OTC, and visit the mid-level provider for pre-chemotherapy consult. Thus, less patients would arrive into the cancer clinics, and analysis can be done on how many new patients to replace the return patients no longer using the cancer clinic (new patients take longer than return patients, so this would not be a 1:1 ratio).

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APPENDICES

APPENDIX 1: PUNCTUALITY

This appendix contains pie charts showing punctuality by different clinics within the cancer center. The following figures are included:

- Figure A1.1: Punctuality for Surgical Oncology Clinic.
- Figure A1.2: Punctuality for Hematology Oncology Clinic.
- Figure A1.3: Punctuality for Brain Tumor Center.
- Figure A1.4: Punctuality for Prostate Center.

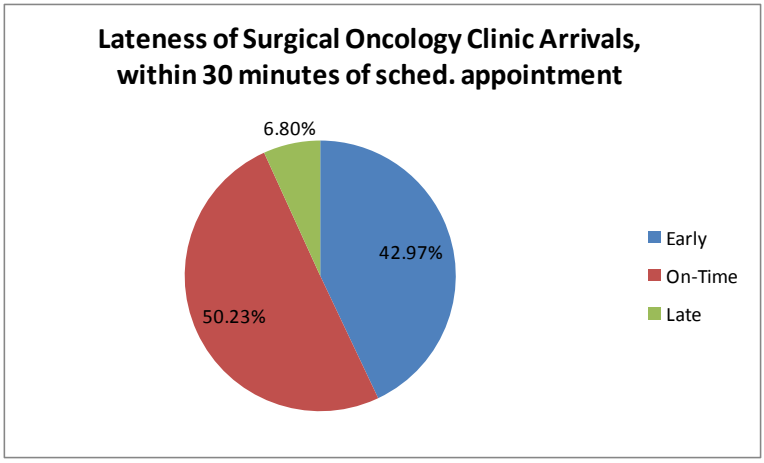

Figure A1.1: Punctuality for Surgical Oncology Clinic.

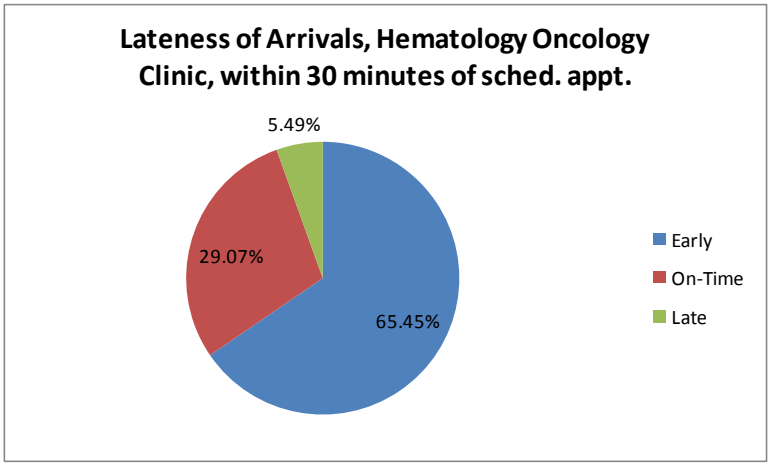

Figure A1.2: Punctuality for Hematology Oncology Clinic.

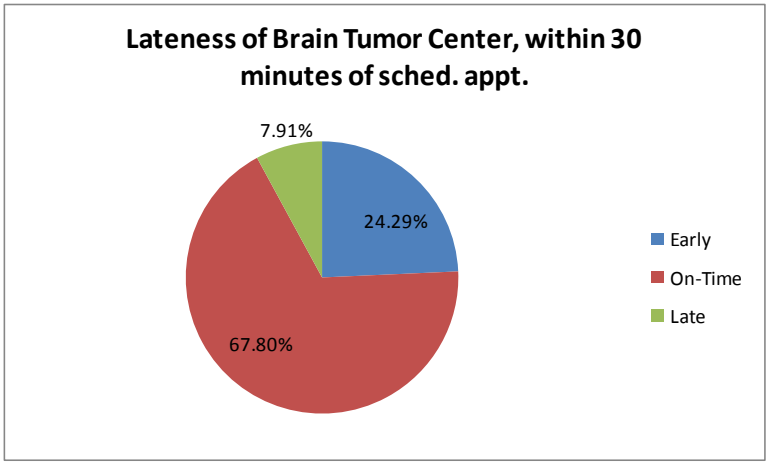

Figure A1.3: Punctuality for Brain Tumor Center.

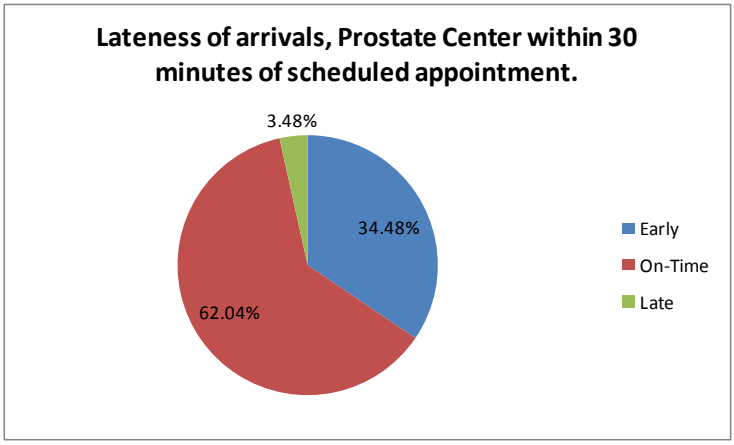

Figure A1.4: Punctuality for Prostate Center.

APPENDIX 2: PATIENT ARRIVALS

This appendix contains all tables for patient arrival volume and throughput levels by time of day for each of the clinics, as well as the overall arrivals into the OTC. These graphs contain expected daily throughput for the entire clinic, as well as by each time period of the day. The following tables are provided:

- Table A2.1: Patient arrival and volume information for the surgical oncology clinic.
- Table A2.2: Patient arrival and volume information for the hematology oncology clinic.
- Table A2.3: Patient arrival and volume information for the brain tumor center.
- Table A2.4: Patient arrival and volume information for the prostate center.
- Table A2.5: Patient arrival and volume information, direct OTC arrivals.
- Table A2.6: Patient arrival and volume information for all OTC arrivals regardless of clinic.

Table A2.1: Patient arrival and volume information for the surgical oncology clinic.

Surgical Ocology Patient Volume and Arrival Rates by Time of Day and Day of Week												
# Mondays	15	E[Total TH]	147.4	# Tuesdays	17	E[Total TH]	105.2353	# Wednesdays	17	E[Total TH]	146.3529	
half-hour counts		E[TH]/Day	TH/Hour	half-hour counts		E[TH]/Day	TH/Hour	half-hour counts		E[TH]/Day	TH/Hour	
7-7:30	119	7.93	15.87	7-7:30	97	12.59	12.59	7-7:30	85	5.00	10.00	
7:30-8	114	7.60	15.20	7:30-8	117	6.88	13.76	7:30-8	99	5.82	11.65	
8-8:30	181	12.07	24.13	8-8:30	119	7.00	14.00	8-8:30	173	10.18	20.35	
8:30-9:00	221	14.73	29.47	8:30-9:00	158	9.29	18.59	8:30-9:00	230	13.53	27.06	
9:00-9:30	225	15.00	30.00	9:00-9:30	166	9.76	19.53	9:00-9:30	227	13.35	26.71	
9:30-10:00	220	14.67	29.33	9:30-10:00	142	8.35	16.71	9:30-10:00	221	13.00	26.00	
10:00-10:30	212	14.13	28.27	10:00-10:30	144	8.47	16.94	10:00-10:30	196	11.53	23.06	
10:30-11:00	170	11.33	22.67	10:30-11:00	148	8.71	17.41	10:30-11:00	206	12.12	24.24	
11:00-11:30	142	9.47	18.93	11:00-11:30	106	6.24	12.47	11:00-11:30	142	8.35	16.71	
11:30-12:00	103	6.87	13.73	11:30-12:00	86	5.06	10.12	11:30-12:00	120	7.06	14.12	
12:00-12:30	95	6.33	12.67	12:00-12:30	71	4.18	8.35	12:00-12:30	103	6.06	12.12	
12:30-1:00	92	6.13	12.27	12:30-1:00	90	5.29	10.59	12:30-1:00	115	6.76	13.53	
1:00-1:30	81	5.40	10.80	1:00-1:30	83	4.88	9.76	1:00-1:30	121	7.12	14.24	
1:30-2:00	78	5.20	10.40	1:30-2:00	75	4.41	8.82	1:30-2:00	108	6.35	12.71	
2:00-2:30	58	3.87	7.73	2:00-2:30	75	4.41	8.82	2:00-2:30	108	6.35	12.71	
2:30-3:00	36	2.40	4.80	2:30-3:00	61	3.59	7.18	2:30-3:00	101	5.94	11.88	
3:00-3:30	31	2.07	4.13	3:00-3:30	35	2.06	4.12	3:00-3:30	72	4.24	8.47	
3:30-4:00	17	1.13	2.27	3:30-4:00	7	0.41	0.82	3:30-4:00	40	2.35	4.71	
4:00-4:30	11	0.73	1.47	4:00-4:30	4	0.24	0.47	4:00-4:30	15	0.88	1.76	
4:30-5:00	2	0.13	0.27	4:30-5:00	5	0.29	0.29	4:30-5:00	3	0.18	0.35	
5:00-5:30	2	0.13	0.27	5:00-5:30	0	0.00	0.00	5:00-5:30	2	0.12	0.24	
# Thursdays	18	E[Total TH]	109.3333	# Fridays	18	E[Total TH]	119.1667					
half-hour counts		E[TH]/Day	TH/Hour	half-hour counts		E[TH]/Day	TH/Hour					
7-7:30	55	3.06	6.11	7-7:30	69	3.83	7.67					
7:30-8	111	6.17	12.33	7:30-8	120	6.67	13.33					
8-8:30	136	7.56	15.11	8-8:30	156	8.67	17.33					
8:30-9:00	148	8.22	16.44	8:30-9:00	198	11.00	22.00					
9:00-9:30	195	10.83	21.67	9:00-9:30	169	9.39	18.78					
9:30-10:00	186	10.33	20.67	9:30-10:00	175	9.72	19.44					
10:00-10:30	175	9.72	19.44	10:00-10:30	171	9.50	19.00					
10:30-11:00	162	9.00	18.00	10:30-11:00	155	8.61	17.22					
11:00-11:30	126	7.00	14.00	11:00-11:30	144	8.00	16.00					
11:30-12:00	75	4.17	8.33	11:30-12:00	110	6.11	12.22					
12:00-12:30	77	4.28	8.56	12:00-12:30	99	5.50	11.00					
12:30-1:00	96	5.33	10.67	12:30-1:00	112	6.22	12.44					
1:00-1:30	79	4.39	8.78	1:00-1:30	115	6.39	12.78					
1:30-2:00	99	5.50	11.00	1:30-2:00	92	5.11	10.22					
2:00-2:30	70	3.89	7.78	2:00-2:30	79	4.39	8.78					
2:30-3:00	71	3.94	7.89	2:30-3:00	79	4.39	8.78					
3:00-3:30	51	2.83	5.67	3:00-3:30	57	3.17	6.33					
3:30-4:00	30	1.67	3.33	3:30-4:00	35	1.94	3.89					
4:00-4:30	19	1.06	2.11	4:00-4:30	6	0.33	0.67					
4:30-5:00	4	0.22	0.44	4:30-5:00	3	0.17	0.33					
5:00-5:30	2	0.11	0.22	5:00-5:30	1	0.06	0.11					

Table A2.2: Patient arrival and volume information for the hematology oncology clinic.

Hematology Ocology Patient Volume and Arrival Rates by Time of Day and Day of Week			
# Mondays	15	E[Total TH]	167.8667
half-hour counts		E[TH]/Day	TH/Hour
7-7:30	260	17.33	34.67
7:30-8	206	13.73	27.47
8-8:30	215	14.33	28.67
8:30-9:00	220	14.67	29.33
9:00-9:30	239	15.93	31.87
9:30-10:00	195	13.00	26.00
10:00-10:30	182	12.13	24.27
10:30-11:00	169	11.27	22.53
11:00-11:30	106	7.07	14.13
11:30-12:00	113	7.53	15.07
12:00-12:30	123	8.20	16.40
12:30-1:00	108	7.20	14.40
1:00-1:30	106	7.07	14.13
1:30-2:00	73	4.87	9.73
2:00-2:30	77	5.13	10.27
2:30-3:00	52	3.47	6.93
3:00-3:30	31	2.07	4.13
3:30-4:00	18	1.20	2.40
4:00-4:30	14	0.93	1.87
4:30-5:00	7	0.47	0.93
5:00-5:30	4	0.27	0.53

# Tuesdays	17	E[Total TH]	165
half-hour counts		E[TH]/Day	TH/Hour
7-7:30	273	16.06	32.12
7:30-8	209	12.29	24.59
8-8:30	195	11.47	22.94
8:30-9:00	238	14.00	28.00
9:00-9:30	201	11.82	23.65
9:30-10:00	247	14.53	29.06
10:00-10:30	229	13.47	26.94
10:30-11:00	215	12.65	25.29
11:00-11:30	119	7.00	14.00
11:30-12:00	131	7.71	15.41
12:00-12:30	108	6.35	12.71
12:30-1:00	149	8.76	17.53
1:00-1:30	130	7.65	15.29
1:30-2:00	108	6.35	12.71
2:00-2:30	89	5.24	10.47
2:30-3:00	58	3.41	6.82
3:00-3:30	48	2.82	5.65
3:30-4:00	39	2.29	4.59
4:00-4:30	12	0.71	1.41
4:30-5:00	2	0.12	0.24
5:00-5:30	5	0.29	0.59

# Wednesdays	17	E[Total TH]	164.0588
half-hour counts		E[TH]/Day	TH/Hour
7-7:30	172	10.12	20.24
7:30-8	180	10.59	21.18
8-8:30	213	12.53	25.06
8:30-9:00	290	17.06	34.12
9:00-9:30	300	17.65	35.29
9:30-10:00	263	15.47	30.94
10:00-10:30	268	15.76	31.53
10:30-11:00	218	12.82	25.65
11:00-11:30	186	10.94	21.88
11:30-12:00	109	6.41	12.82
12:00-12:30	130	7.65	15.29
12:30-1:00	123	7.24	14.47
1:00-1:30	93	5.47	10.94
1:30-2:00	75	4.41	8.82
2:00-2:30	67	3.94	7.88
2:30-3:00	52	3.06	6.12
3:00-3:30	25	1.47	2.94
3:30-4:00	6	0.35	0.71
4:00-4:30	10	0.59	1.18
4:30-5:00	8	0.47	0.94
5:00-5:30	1	0.06	0.12

# Thursdays	18	E[Total TH]	162.2778
half-hour counts		E[TH]/Day	TH/Hour
7-7:30	271	15.06	30.11
7:30-8	255	14.17	28.33
8-8:30	275	15.28	30.56
8:30-9:00	283	15.72	31.44
9:00-9:30	251	13.94	27.89
9:30-10:00	243	13.50	27.00
10:00-10:30	190	10.56	21.11
10:30-11:00	174	9.67	19.33
11:00-11:30	136	7.56	15.11
11:30-12:00	118	6.56	13.11
12:00-12:30	122	6.78	13.56
12:30-1:00	128	7.11	14.22
1:00-1:30	110	6.11	12.22
1:30-2:00	114	6.33	12.67
2:00-2:30	83	4.61	9.22
2:30-3:00	76	4.22	8.44
3:00-3:30	49	2.72	5.44
3:30-4:00	24	1.33	2.67
4:00-4:30	13	0.72	1.44
4:30-5:00	5	0.28	0.56
5:00-5:30	1	0.06	0.11

# Fridays	18	E[Total TH]	97.8889
half-hour counts		E[TH]/Day	TH/Hour
7-7:30	113	6.28	12.56
7:30-8	107	5.94	11.89
8-8:30	121	6.72	13.44
8:30-9:00	136	7.56	15.11
9:00-9:30	197	10.94	21.89
9:30-10:00	215	11.94	23.89
10:00-10:30	173	9.61	19.22
10:30-11:00	148	8.22	16.44
11:00-11:30	122	6.78	13.56
11:30-12:00	77	4.28	8.56
12:00-12:30	75	4.17	8.33
12:30-1:00	71	3.94	7.89
1:00-1:30	61	3.39	6.78
1:30-2:00	49	2.72	5.44
2:00-2:30	26	1.44	2.89
2:30-3:00	23	1.28	2.56
3:00-3:30	14	0.78	1.56
3:30-4:00	15	0.83	1.67
4:00-4:30	9	0.50	1.00
4:30-5:00	4	0.22	0.44
5:00-5:30	6	0.33	0.67

Table A2.3: Patient arrival and volume information for the brain tumor center.

Brain Tumor Center Patient Volume and Arrival Rates by Time of Day and Day of Week												
# Mondays	15	E[Total TH]	46.53333	# Tuesdays	17	E[Total TH]	44.35294	# Wednesdays	17	E[Total TH]	38.94118	
half-hour counts		E[TH]/Day	TH/Hour	half-hour counts		E[TH]/Day	TH/Hour	half-hour counts		E[TH]/Day	TH/Hour	
7-7:30	0	0.00	0.00	7-7:30	0	0.00	0.00	7-7:30	0	0.00	0.00	
7:30-8	60	4.00	8.00	7:30-8	66	3.88	7.76	7:30-8	56	3.29	6.59	
8-8:30	80	5.33	10.67	8-8:30	80	4.71	9.41	8-8:30	62	3.65	7.29	
8:30-9:00	69	4.60	9.20	8:30-9:00	50	2.94	5.88	8:30-9:00	53	3.12	6.24	
9:00-9:30	74	4.93	9.87	9:00-9:30	54	3.18	6.35	9:00-9:30	70	4.12	8.24	
9:30-10:00	59	3.93	7.87	9:30-10:00	61	3.59	7.18	9:30-10:00	37	2.18	4.35	
10:00-10:30	36	2.40	4.80	10:00-10:30	40	2.35	4.71	10:00-10:30	32	1.88	3.76	
10:30-11:00	38	2.53	5.07	10:30-11:00	50	2.94	5.88	10:30-11:00	46	2.71	5.41	
11:00-11:30	53	3.53	7.07	11:00-11:30	43	2.53	5.06	11:00-11:30	33	1.94	3.88	
11:30-12:00	42	2.80	5.60	11:30-12:00	49	2.88	5.76	11:30-12:00	62	3.65	7.29	
12:00-12:30	48	3.20	6.40	12:00-12:30	68	4.00	8.00	12:00-12:30	63	3.71	7.41	
12:30-1:00	46	3.07	6.13	12:30-1:00	54	3.18	6.35	12:30-1:00	39	2.29	4.59	
1:00-1:30	25	1.67	3.33	1:00-1:30	32	1.88	3.76	1:00-1:30	24	1.41	2.82	
1:30-2:00	21	1.40	2.80	1:30-2:00	29	1.71	3.41	1:30-2:00	37	2.18	4.35	
2:00-2:30	20	1.33	2.67	2:00-2:30	29	1.71	3.41	2:00-2:30	14	0.82	1.65	
2:30-3:00	17	1.13	2.27	2:30-3:00	30	1.76	3.53	2:30-3:00	19	1.12	2.24	
3:00-3:30	9	0.60	1.20	3:00-3:30	11	0.65	1.29	3:00-3:30	9	0.53	1.06	
3:30-4:00	0	0.00	0.00	3:30-4:00	4	0.24	0.47	3:30-4:00	3	0.18	0.35	
4:00-4:30	0	0.00	0.00	4:00-4:30	3	0.18	0.35	4:00-4:30	3	0.18	0.35	
4:30-5:00	1	0.07	0.13	4:30-5:00	1	0.06	0.12	4:30-5:00	0	0.00	0.00	
5:00-5:30	0	0.00	0.00	5:00-5:30	0	0.00	0.00	5:00-5:30	0	0.00	0.00	
# Thursdays	18	E[Total TH]	36.27778	# Fridays	18	E[Total TH]	8.444444					
half-hour counts		E[TH]/Day	TH/Hour	half-hour counts		E[TH]/Day	TH/Hour					
7-7:30	2	0.11	0.22	7-7:30	1	0.06	0.11					
7:30-8	79	4.39	8.78	7:30-8	23	1.28	2.56					
8-8:30	97	5.39	10.78	8-8:30	23	1.28	2.56					
8:30-9:00	50	2.78	5.56	8:30-9:00	17	0.94	1.89					
9:00-9:30	69	3.83	7.67	9:00-9:30	22	1.22	2.44					
9:30-10:00	67	3.72	7.44	9:30-10:00	17	0.94	1.89					
10:00-10:30	33	1.83	3.67	10:00-10:30	13	0.72	1.44					
10:30-11:00	33	1.83	3.67	10:30-11:00	9	0.50	1.00					
11:00-11:30	37	2.06	4.11	11:00-11:30	8	0.44	0.89					
11:30-12:00	51	2.83	5.67	11:30-12:00	6	0.33	0.67					
12:00-12:30	43	2.39	4.78	12:00-12:30	7	0.39	0.78					
12:30-1:00	31	1.72	3.44	12:30-1:00	2	0.11	0.22					
1:00-1:30	8	0.44	0.89	1:00-1:30	1	0.06	0.11					
1:30-2:00	25	1.39	2.78	1:30-2:00	0	0.00	0.00					
2:00-2:30	9	0.50	1.00	2:00-2:30	0	0.00	0.00					
2:30-3:00	10	0.56	1.11	2:30-3:00	0	0.00	0.00					
3:00-3:30	7	0.39	0.78	3:00-3:30	2	0.11	0.22					
3:30-4:00	1	0.06	0.11	3:30-4:00	0	0.00	0.00					
4:00-4:30	1	0.06	0.11	4:00-4:30	0	0.00	0.00					
4:30-5:00	0	0.00	0.00	4:30-5:00	1	0.06	0.11					
5:00-5:30	0	0.00	0.00	5:00-5:30	0	0.00	0.00					

Table A2.4: Patient arrival and volume information for the prostate center.

Prostate Center Patient Volume and Arrival Rates by Time of Day and Day of Week												
# Mondays	15	E[Total TH]	36.4	# Tuesdays	17	E[Total TH]	32.52941	# Wednesdays	17	E[Total TH]	33.76471
half-hour counts		E[TH]/Day	TH/Hour	half-hour counts		E[TH]/Day	TH/Hour	half-hour counts		E[TH]/Day	TH/Hour
7-7:30	0	0.00	0.00	7-7:30	0	0.00	0.00	7-7:30	0	0.00	0.00
7:30-8	29	1.93	3.87	7:30-8	24	1.41	2.82	7:30-8	26	1.53	3.06
8-8:30	38	2.53	5.07	8-8:30	41	2.41	4.82	8-8:30	40	2.35	4.71
8:30-9:00	23	1.53	3.07	8:30-9:00	51	3.00	6.00	8:30-9:00	46	2.71	5.41
9:00-9:30	27	1.80	3.60	9:00-9:30	42	2.47	4.94	9:00-9:30	34	2.00	4.00
9:30-10:00	41	2.73	5.47	9:30-10:00	49	2.88	5.76	9:30-10:00	38	2.24	4.47
10:00-10:30	33	2.20	4.40	10:00-10:30	48	2.82	5.65	10:00-10:30	46	2.71	5.41
10:30-11:00	30	2.00	4.00	10:30-11:00	44	2.59	5.18	10:30-11:00	40	2.35	4.71
11:00-11:30	36	2.40	4.80	11:00-11:30	27	1.59	3.18	11:00-11:30	30	1.76	3.53
11:30-12:00	37	2.47	4.93	11:30-12:00	8	0.47	0.94	11:30-12:00	28	1.65	3.29
12:00-12:30	35	2.33	4.67	12:00-12:30	14	0.82	1.65	12:00-12:30	21	1.24	2.47
12:30-1:00	38	2.53	5.07	12:30-1:00	42	2.47	4.94	12:30-1:00	23	1.35	2.71
1:00-1:30	39	2.60	5.20	1:00-1:30	44	2.59	5.18	1:00-1:30	43	2.53	5.06
1:30-2:00	34	2.27	4.53	1:30-2:00	35	2.06	4.12	1:30-2:00	42	2.47	4.94
2:00-2:30	25	1.67	3.33	2:00-2:30	18	1.06	2.12	2:00-2:30	39	2.29	4.59
2:30-3:00	33	2.20	4.40	2:30-3:00	22	1.29	2.59	2:30-3:00	30	1.76	3.53
3:00-3:30	27	1.80	3.60	3:00-3:30	20	1.18	2.35	3:00-3:30	28	1.65	3.29
3:30-4:00	16	1.07	2.13	3:30-4:00	12	0.71	1.41	3:30-4:00	14	0.82	1.65
4:00-4:30	5	0.33	0.67	4:00-4:30	11	0.65	1.29	4:00-4:30	5	0.29	0.59
4:30-5:00	0	0.00	0.00	4:30-5:00	1	0.06	0.12	4:30-5:00	1	0.06	0.12
5:00-5:30	0	0.00	0.00	5:00-5:30	0	0.00	0.00	5:00-5:30	0	0.00	0.00

# Thursdays	18	E[Total TH]	34.61111	# Fridays	18	E[Total TH]	22.44444
half-hour counts		E[TH]/Day	TH/Hour	half-hour counts		E[TH]/Day	TH/Hour
7-7:30	0	0.00	0.00	7-7:30	0	0.00	0.00
7:30-8	50	2.78	5.56	7:30-8	23	1.28	2.56
8-8:30	56	3.11	6.22	8-8:30	41	2.28	4.56
8:30-9:00	46	2.56	5.11	8:30-9:00	32	1.78	3.56
9:00-9:30	44	2.44	4.89	9:00-9:30	26	1.44	2.89
9:30-10:00	58	3.22	6.44	9:30-10:00	37	2.06	4.11
10:00-10:30	67	3.72	7.44	10:00-10:30	30	1.67	3.33
10:30-11:00	79	4.39	8.78	10:30-11:00	12	0.67	1.33
11:00-11:30	65	3.61	7.22	11:00-11:30	13	0.72	1.44
11:30-12:00	23	1.28	2.56	11:30-12:00	8	0.44	0.89
12:00-12:30	11	0.61	1.22	12:00-12:30	14	0.78	1.56
12:30-1:00	31	1.72	3.44	12:30-1:00	27	1.50	3.00
1:00-1:30	20	1.11	2.22	1:00-1:30	33	1.83	3.67
1:30-2:00	15	0.83	1.67	1:30-2:00	34	1.89	3.78
2:00-2:30	22	1.22	2.44	2:00-2:30	25	1.39	2.78
2:30-3:00	13	0.72	1.44	2:30-3:00	24	1.33	2.67
3:00-3:30	12	0.67	1.33	3:00-3:30	14	0.78	1.56
3:30-4:00	7	0.39	0.78	3:30-4:00	9	0.50	1.00
4:00-4:30	4	0.22	0.44	4:00-4:30	1	0.06	0.11
4:30-5:00	0	0.00	0.00	4:30-5:00	1	0.06	0.11
5:00-5:30	0	0.00	0.00	5:00-5:30	0	0.00	0.00

Table A2.5: Patient arrival and volume information, direct OTC arrivals.

Direct OTC Arrival Patient Volume and Arrival Rates by Time of Day and Day of Week												
# Mondays	15	E[Total TH]	27.4	# Tuesdays	17	E[Total TH]	27.94118	# Wednesdays	17	E[Total TH]	38.70588	
half-hour counts		E[TH]/Day	TH/Hour	half-hour counts		E[TH]/Day	TH/Hour	half-hour counts		E[TH]/Day	TH/Hour	
7-7:30	17	1.13	2.27	7-7:30	14	0.82	1.65	7-7:30	17	1.00	2.00	
7:30-8	36	2.40	4.80	7:30-8	42	2.47	4.94	7:30-8	50	2.94	5.88	
8-8:30	69	4.60	9.20	8-8:30	57	3.35	6.71	8-8:30	61	3.59	7.18	
8:30-9:00	46	3.07	6.13	8:30-9:00	54	3.18	6.35	8:30-9:00	84	4.94	9.88	
9:00-9:30	52	3.47	6.93	9:00-9:30	48	2.82	5.65	9:00-9:30	97	5.71	11.41	
9:30-10:00	31	2.07	4.13	9:30-10:00	41	2.41	4.82	9:30-10:00	52	3.06	6.12	
10:00-10:30	31	2.07	4.13	10:00-10:30	36	2.12	4.24	10:00-10:30	39	2.29	4.59	
10:30-11:00	29	1.93	3.87	10:30-11:00	34	2.00	4.00	10:30-11:00	36	2.12	4.24	
11:00-11:30	13	0.87	1.73	11:00-11:30	24	1.41	2.82	11:00-11:30	32	1.88	3.76	
11:30-12:00	11	0.73	1.47	11:30-12:00	17	1.00	2.00	11:30-12:00	40	2.35	4.71	
12:00-12:30	11	0.73	1.47	12:00-12:30	10	0.59	1.18	12:00-12:30	19	1.12	2.24	
12:30-1:00	14	0.93	1.87	12:30-1:00	20	1.18	2.35	12:30-1:00	28	1.65	3.29	
1:00-1:30	13	0.87	1.73	1:00-1:30	23	1.35	2.71	1:00-1:30	24	1.41	2.82	
1:30-2:00	7	0.47	0.93	1:30-2:00	16	0.94	1.88	1:30-2:00	21	1.24	2.47	
2:00-2:30	7	0.47	0.93	2:00-2:30	6	0.35	0.71	2:00-2:30	10	0.59	1.18	
2:30-3:00	3	0.20	0.40	2:30-3:00	5	0.29	0.59	2:30-3:00	13	0.76	1.53	
3:00-3:30	3	0.20	0.40	3:00-3:30	10	0.59	1.18	3:00-3:30	16	0.94	1.88	
3:30-4:00	5	0.33	0.67	3:30-4:00	9	0.53	1.06	3:30-4:00	1	0.06	0.12	
4:00-4:30	2	0.13	0.27	4:00-4:30	5	0.29	0.59	4:00-4:30	6	0.35	0.71	
4:30-5:00	6	0.40	0.80	4:30-5:00	2	0.12	0.24	4:30-5:00	8	0.47	0.94	
5:00-5:30	5	0.33	0.67	5:00-5:30	2	0.12	0.24	5:00-5:30	4	0.24	0.47	
# Thursdays	18	E[Total TH]	43.5	Total # Fridays	18	E[Total TH]	40					
half-hour counts		E[TH]/Day	TH/Hour	half-hour counts		E[TH]/Day	TH/Hour					
7-7:30	17	0.94	1.89	7-7:30	12	0.67	1.33					
7:30-8	78	4.33	8.67	7:30-8	76	4.22	8.44					
8-8:30	95	5.28	10.56	8-8:30	82	4.56	9.11					
8:30-9:00	86	4.78	9.56	8:30-9:00	76	4.22	8.44					
9:00-9:30	99	5.50	11.00	9:00-9:30	84	4.67	9.33					
9:30-10:00	63	3.50	7.00	9:30-10:00	57	3.17	6.33					
10:00-10:30	59	3.28	6.56	10:00-10:30	61	3.39	6.78					
10:30-11:00	34	1.89	3.78	10:30-11:00	41	2.28	4.56					
11:00-11:30	40	2.22	4.44	11:00-11:30	36	2.00	4.00					
11:30-12:00	36	2.00	4.00	11:30-12:00	42	2.33	4.67					
12:00-12:30	33	1.83	3.67	12:00-12:30	26	1.44	2.89					
12:30-1:00	28	1.56	3.11	12:30-1:00	28	1.56	3.11					
1:00-1:30	25	1.39	2.78	1:00-1:30	18	1.00	2.00					
1:30-2:00	17	0.94	1.89	1:30-2:00	10	0.56	1.11					
2:00-2:30	20	1.11	2.22	2:00-2:30	14	0.78	1.56					
2:30-3:00	12	0.67	1.33	2:30-3:00	12	0.67	1.33					
3:00-3:30	8	0.44	0.89	3:00-3:30	14	0.78	1.56					
3:30-4:00	8	0.44	0.89	3:30-4:00	8	0.44	0.89					
4:00-4:30	6	0.33	0.67	4:00-4:30	12	0.67	1.33					
4:30-5:00	10	0.56	1.11	4:30-5:00	6	0.33	0.67					
5:00-5:30	9	0.50	1.00	5:00-5:30	5	0.28	0.56					

Table A2.6: Patient arrival and volume information for all OTC arrivals regardless of clinic.

OTC Volume and Arrival Rates by Time of Day and Day of Week, Regardless of Clinic

# Mondays	15	E[Total TH]	103.2
half-hour	counts	E[TH]/Day	TH/Hour
7-7:30	19	1.27	2.53
7:30-8	46	3.07	6.13
8-8:30	92	6.13	12.27
8:30-9:00	95	6.33	12.67
9:00-9:30	143	9.53	19.07
9:30-10:00	130	8.67	17.33
10:00-10:30	119	7.93	15.87
10:30-11:00	100	6.67	13.33
11:00-11:30	101	6.73	13.47
11:30-12:00	83	5.53	11.07
12:00-12:30	84	5.60	11.20
12:30-1:00	106	7.07	14.13
1:00-1:30	88	5.87	11.73
1:30-2:00	64	4.27	8.53
2:00-2:30	56	3.73	7.47
2:30-3:00	54	3.60	7.20
3:00-3:30	41	2.73	5.47
3:30-4:00	40	2.67	5.33
4:00-4:30	34	2.27	4.53
4:30-5:00	27	1.80	3.60
5:00-5:30	18	1.20	2.40
5:30-6:00	8	0.53	1.07

# Tuesdays	17	E[Total TH]	107.9
half-hour	counts	E[TH]/Day	TH/Hour
7-7:30	16	0.94	1.88
7:30-8	60	3.53	7.06
8-8:30	90	5.29	10.59
8:30-9:00	128	7.53	15.06
9:00-9:30	164	9.65	19.29
9:30-10:00	156	9.18	18.35
10:00-10:30	138	8.12	16.24
10:30-11:00	145	8.53	17.06
11:00-11:30	141	8.29	16.59
11:30-12:00	114	6.71	13.41
12:00-12:30	98	5.76	11.53
12:30-1:00	118	6.94	13.88
1:00-1:30	104	6.12	12.24
1:30-2:00	86	5.06	10.12
2:00-2:30	67	3.94	7.88
2:30-3:00	54	3.18	6.35
3:00-3:30	49	2.88	5.76
3:30-4:00	40	2.35	4.71
4:00-4:30	37	2.18	4.35
4:30-5:00	15	0.88	1.76
5:00-5:30	7	0.41	0.82
5:30-6:00	8	0.47	0.94

# Wednesdays	17	E[Total TH]	117
half-hour	counts	E[TH]/Day	TH/Hour
7-7:30	24	1.41	2.82
7:30-8	61	3.59	7.18
8-8:30	80	4.71	9.41
8:30-9:00	125	7.35	14.71
9:00-9:30	173	10.18	20.35
9:30-10:00	156	9.18	18.35
10:00-10:30	153	9.00	18.00
10:30-11:00	145	8.53	17.06
11:00-11:30	147	8.65	17.29
11:30-12:00	142	8.35	16.71
12:00-12:30	107	6.29	12.59
12:30-1:00	119	7.00	14.00
1:00-1:30	106	6.24	12.47
1:30-2:00	102	6.00	12.00
2:00-2:30	69	4.06	8.12
2:30-3:00	63	3.71	7.41
3:00-3:30	60	3.53	7.06
3:30-4:00	54	3.18	6.35
4:00-4:30	35	2.06	4.12
4:30-5:00	38	2.24	4.47
5:00-5:30	21	1.24	2.47
5:30-6:00	9	0.53	1.06

# Thursdays	18	E[Total TH]	106.6
half-hour	counts	E[TH]/Day	TH/Hour
7-7:30	19	1.06	2.11
7:30-8	89	4.94	9.89
8-8:30	131	7.28	14.56
8:30-9:00	146	8.11	16.22
9:00-9:30	192	10.67	21.33
9:30-10:00	191	10.61	21.22
10:00-10:30	164	9.11	18.22
10:30-11:00	138	7.67	15.33
11:00-11:30	125	6.94	13.89
11:30-12:00	112	6.22	12.44
12:00-12:30	110	6.11	12.22
12:30-1:00	115	6.39	12.78
1:00-1:30	87	4.83	9.67
1:30-2:00	58	3.22	6.44
2:00-2:30	49	2.72	5.44
2:30-3:00	56	3.11	6.22
3:00-3:30	39	2.17	4.33
3:30-4:00	30	1.67	3.33
4:00-4:30	27	1.50	3.00
4:30-5:00	21	1.17	2.33
5:00-5:30	14	0.78	1.56
5:30-6:00	5	0.28	0.56

# Fridays	18	E[Total TH]	94.8
half-hour	counts	E[TH]/Day	TH/Hour
7-7:30	19	1.06	2.11
7:30-8	89	4.94	9.89
8-8:30	115	6.39	12.78
8:30-9:00	129	7.17	14.33
9:00-9:30	151	8.39	16.78
9:30-10:00	131	7.28	14.56
10:00-10:30	131	7.28	14.56
10:30-11:00	141	7.83	15.67
11:00-11:30	137	7.61	15.22
11:30-12:00	133	7.39	14.78
12:00-12:30	106	5.89	11.78
12:30-1:00	102	5.67	11.33
1:00-1:30	80	4.44	8.89
1:30-2:00	47	2.61	5.22
2:00-2:30	44	2.44	4.89
2:30-3:00	34	1.89	3.78
3:00-3:30	36	2.00	4.00
3:30-4:00	30	1.67	3.33
4:00-4:30	24	1.33	2.67
4:30-5:00	15	0.83	1.67
5:00-5:30	10	0.56	1.11
5:30-6:00	3	0.17	0.33

APPENDIX 3: PROBABILITY DISTRIBUTIONS

This appendix contains information showing the probability distributions fit in the model where data existed, and also lists other probability distributions used throughout the simulation model. The first section entails the distribution fits from data, using the following figures:

- Figure A3.1: % Clinic Patients with Port Draws.
- Figure A3.2: Drawn to Receive Labs Time (Lab Processing).
- Figure A3.3: Lab Received to Verified (Lab Processing).
- Figure A3.4: Pharmacist Processing Time.
- Figure A3.5: Technician Mix Drug (Pharmacy).
- Figure A3.6: Radiology Processing Time.
- Figure A3.7: Check-out Hematology Oncology.

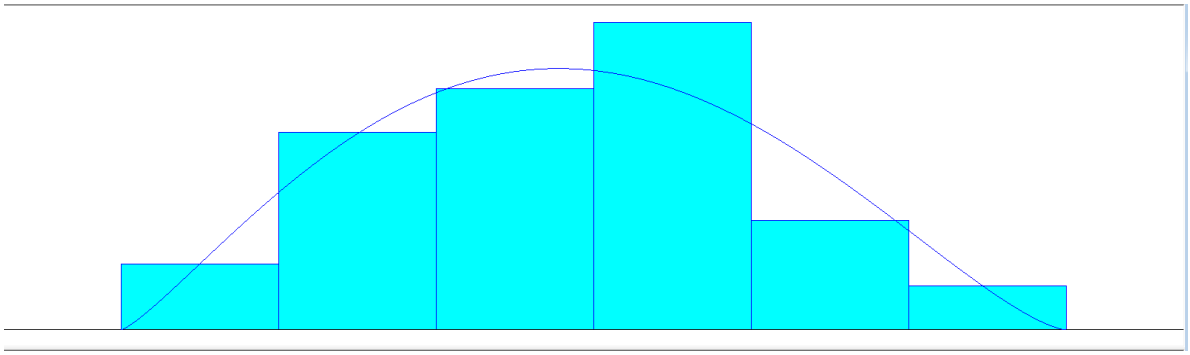

Figure A3.1: % Clinic Patients with Port Draws: 5 + 13*BETA(2.26, 2.46); sqaure error = 0.007541.

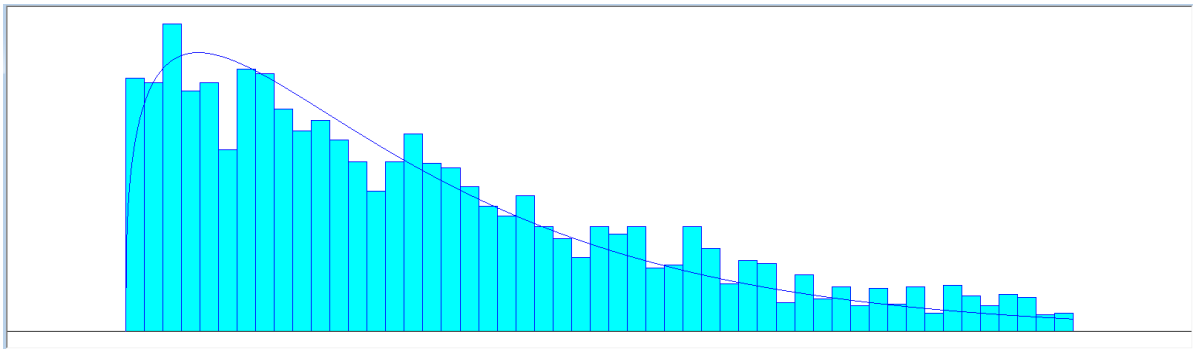

Figure A3.2: Drawn to Receive Labs Time (Lab Processing): 9.5 + GAMM(12, 1.33); square error = 0.000954.

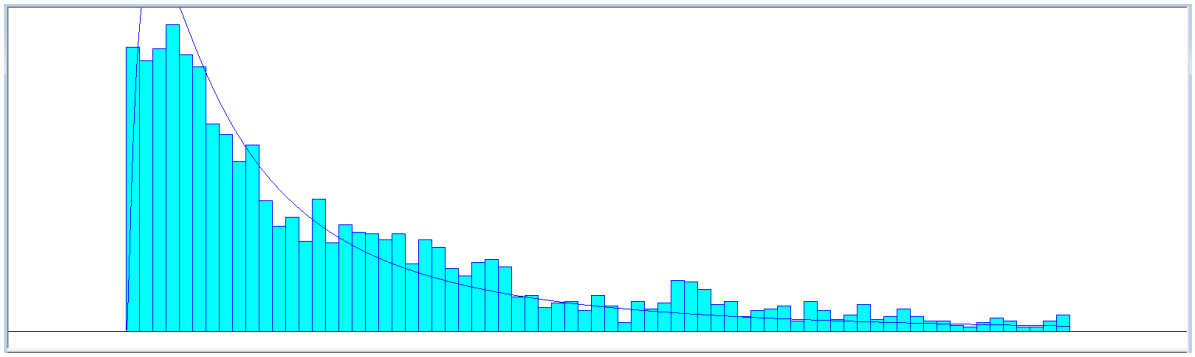

Figure A3.3: Lab Received to Verified (Lab Processing): 19.5 + LOGN(19.5, 35.7); square error = 0.001898.

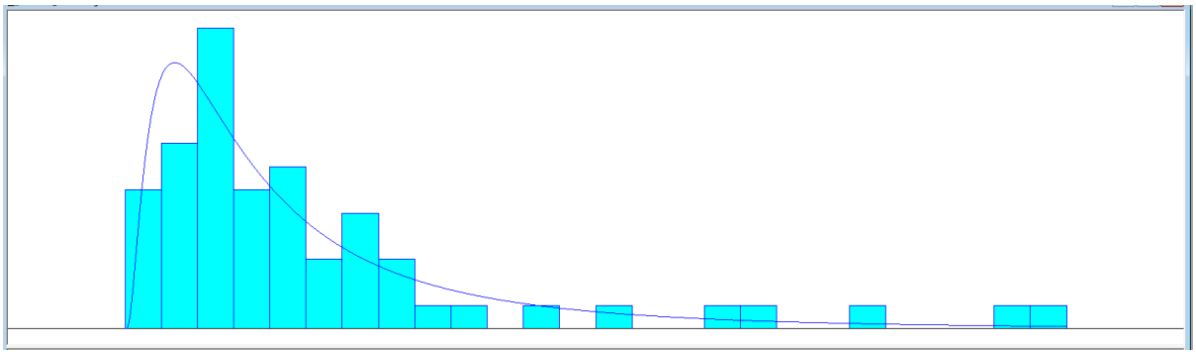

Figure A3.4: Pharmacist Processing Time: -0.5 + LOGN(5.46, 6.74); square error: 0.010918.

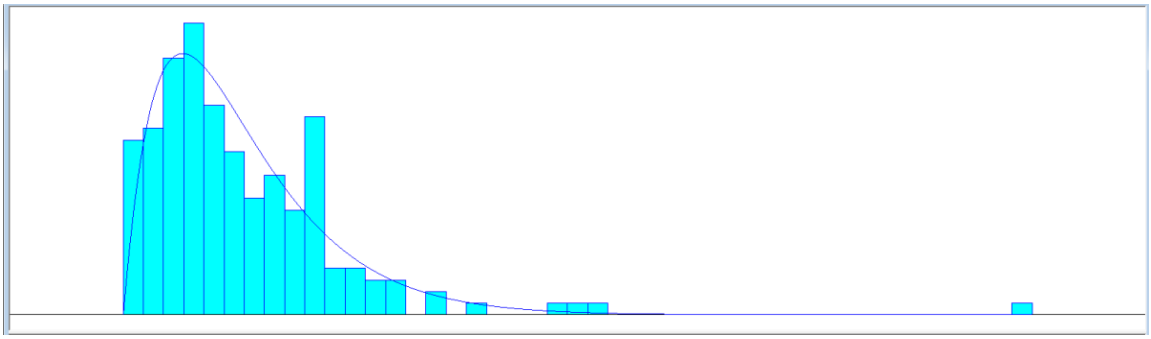

Figure A3.5: Technician Mix Drug (Pharmacy): 1.5 + ERLA(2.94, 2); square error = 0.006274.

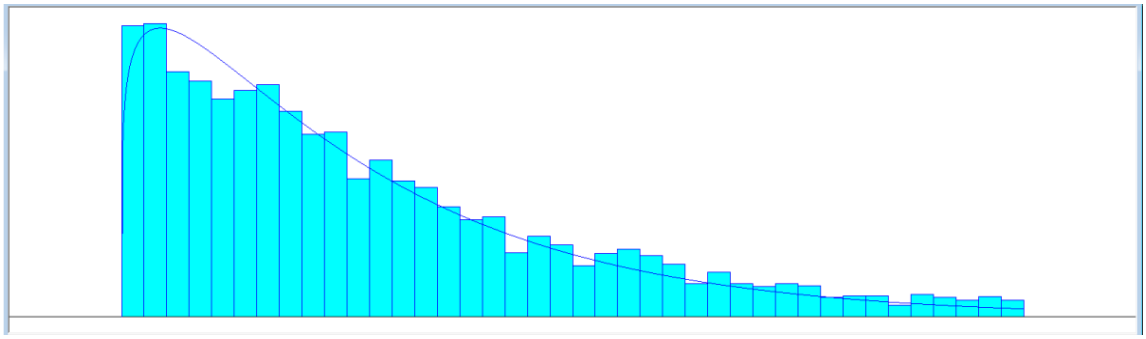

Figure A3.6: Radiology Processing Time: 30 + GAMM(62.2, 1.18); square error = 0.000569.

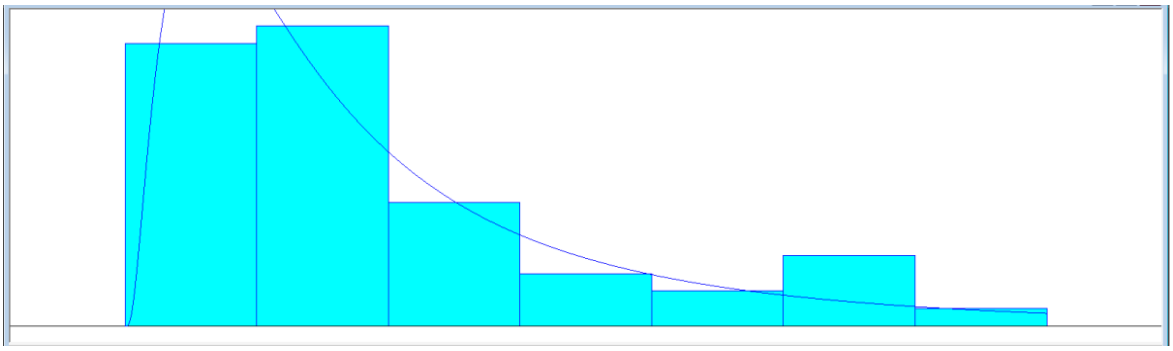

Figure A3.7: Check-out Hematology Oncology: LOGN(9.33, 11.3); square error = 0.007150.

The second section of this Appendix entails the definition of different other modeling inputs, in this case the length of time a treatment is scheduled in the OTC. This distribution follows a random variable discrete 5-point distribution as follows:

Table A3.1: Random variable describing the allotment of scheduled infusion length as a discrete 5-point distribution.

Time Block	% Injection	% HR 1 Treats	% HR 3 Treats	% HR 5 Treats
Before 9:30	14.9	27.7	38.3	19.1
9:30 a.m. – 11:30 a.m.	16.0	24.0	52.0	8.0
11:30 a.m. – 1:30 p.m.	13.8	17.2	51.7	17.3
1:30 p.m. – 3:30 p.m.	12.5	21.9	65.6	0.0
After 3:30 p.m.	20.0	80.0	0.0	0.0

APPENDIX 4: OTC SCHEDULES

This appendix lists all the different schedules for each of the different resources used in the simulation model for the base model. Adjustments to specific nurse's schedules from the nurse scheduling chapter can be found in Appendix 5. First, the nurse schedules reflecting the current cancer center are provided in Table A4.1.

Table A4.1: Nurse schedules in the OTC in the base case representing the current OTC.

Nurse #	Nurse DBG	Monday	Tuesday	Wednesday	Thursday	Friday	Total Hrs	Lunch
1	Breast	8:00-4:30	8:00-4:30	8:00-4:30	8:00-4:30	8:00-4:30	40	12:00-12:30
2	Breast	8:00-6:30	8:00-6:30	8:00-6:30	8:00-6:30	off	40	12:30-1:00
3	Breast	off	9:00-5:30	9:00-5:30	9:00-5:30	9:00-5:30	40	1:00-1:30
4	Breast	9:00-7:30	off	9:00-7:30	9:00-7:30	9:00-7:30	40	1:30-2:00
5	Breast	10:00-8:30	10:00-8:30	10:00-8:30	off	10:00-8:30	40	2:00-2:30
1	HOA	7:30-6:00	7:30-6:00	off	7:30-6:00	7:30-6:00	40	12:00-12:30
2	HOA	7:30-6:00	7:30-6:00	7:30-6:00	off	7:30-6:00	40	12:30-1:00
3	HOA	10:00-8:30	10:00-8:30	10:00-8:30	10:00-8:30	off	40	1:00-1:30
4	HOA	off	10:00-8:30	10:00-8:30	10:00-8:30	10:00-8:30	40	1:30-2:00
1	Lung	8:00-6:30	8:00-6:30	8:00-6:30	8:00-6:30	off	40	12:00-12:30
2	Lung	8:00-6:30	off	8:00-6:30	8:00-6:30	8:00-6:30	40	12:30-1:00
3	Lung	9:00-5:30	9:00-5:30	9:00-5:30	9:00-5:30	9:00-5:30	40	1:00-1:30
4	Lung	9:00-7:30	9:00-7:30	off	9:00-7:30	9:00-7:30	40	1:30-2:00
1	GI/GU	off	off	7:00-7:30	7:00-7:30	7:00-7:30	40	12:00-12:30
2	GI/GU	8:00-6:30	8:00-6:30	off	8:00-6:30	8:00-6:30	40	12:30-1:00
3	GI/GU	9:00-5:30	9:00-5:30	9:00-5:30	9:00-5:30	9:00-5:30	40	1:00-1:30
4	GI/GU	10:00-8:30	10:00-8:30	10:00-8:30	10:00-8:30	off	40	1:30-2:00
1	Charge	off	off	7:00-7:30	7:00-7:30	7:00-7:30	40	12:00-12:30
2	Charge	7:00-7:30	7:00-7:30	7:00-7:30	off	off	40	12:30-1:00
3	Charge	7:00-5:30	7:00-5:30	off	7:00-5:30	7:00-5:30	40	1:00-1:30
	Total Nurses	15	18	19	17	15		

The second section lists a series of *capacity* schedules. These schedules reflect the number of employees available to serve a patient throughout the day. Durations are the length of time in half-hours that the listed capacity (staffing level) of employees is available. This is how the schedules were entered into Arena, and are displayed this way as individual employees do not necessarily remain in the same area all day and may move to other locations. Thus, we provide the schedule from the perspective of the number of employees available throughout the day as follows:

- Table A4.2: Capacity schedules for phlebotomists in all clinics
- Table A4.3: Capacity schedules for PSA's (receptionists) for each of the clinics, designated as check-in, check-out, or float.
- Table A4.4: Capacity schedules for OTC receptionists
- Table A4.5: Capacity schedules for pharmacists and pharmacy technicians (mixing drugs)

Table A4.2: Phlebotomist Capacity Schedules.

Clinic	Staffing Level (Capacity)	Duration (Half-hours)
Surgical Oncology	1	4
	2	8
	1	2
	0	13
Hematology Oncology	2	1
	3	1
	4	16
	3	1
	2	1
	1	6
	0	1

Table A4.3: PSA Capacity Schedules (Check-in and Check-out for Clinics).

Clinic	Type of PSA	Staffing Level (Capacity)	Duration (Half-hours)
Surgical Oncology	Check-In	2	3
		3	1
		2	13
		0	10
Surgical Oncology	Check-Out	0	1
		1	1
		2	2
		3	1
		4	13
		3	1
		2	1
		1	2
		0	5
Surgical Oncology	Float	0	4
		1	17
		0	6
Hematology Oncology	Check-In	3	17
		2	2
		1	1
		0	7
Hematology Oncology	Check-Out	0	2
		1	2
		2	1
		3	12
		2	4
		1	1
		0	5
Hematology Oncology	Float	0	3
		1	14
		0	10
Brain Tumor Center	One-Station – All tasks	0	1
		1	17
		0	9
Prostate Center	One-Station – All tasks	0	3
		1	5
		2	29
		1	5
		0	12

Table A4.4: Capacity schedules for OTC receptionists.

Staffing Level (Capacity)	Duration (Half-hours)
0	1
2	1
3	16
1	5
0	4

Table A4.5: Capacity schedules in the pharmacy.

Type of Resource	Staffing Level (Capacity)	Duration (Half-hours)
Pharmacist	0	1
	3	7
	2	6
	3	9
	0	4
Pharmacy Technician	0	1
	5	9
	4	6
	5	7
	0	4

The final section of this appendix contains information on static staffing levels as assumed throughout the day. Table A4.6 lists the different resources used in the cancer center for which schedules have not been made available or used in the simulation model. Provided is the assumed staffing level across the entire day.

Table A4.6: List of all resources in the simulation model with fixed capacity levels.

Resource	Location	Capacity Level Assumed
Room	Surgical Oncology Clinic	27
Room	Hematology Oncology Clinic	30
Room	Brain Tumor Center	6
Room	Prostate Center	6
Nurse	Surgical Oncology Clinic	9
Nurse	Hematology Oncology Clinic	10
Nurse	Brain Tumor Center	2
Nurse	Prostate Center	2
Oncologist	Surgical Oncology Clinic	9
Oncologist	Hematology Oncology Clinic	10
Oncologist	Brain Tumor Center	2
Oncologist	Prostate Center	2
Vitals Specialist	Surgical Oncology Clinic	2
Vitals Specialist	Hematology Oncology Clinic	2
Vitals Specialist	Brain Tumor Center	1
Vitals Specialist	Prostate Center	1
Chair	OTC	27
Bed	OTC	11

APPENDIX 5: CANDIDATE NURSE SCHEDULES

This appendix contains the candidate schedules used in the daily scheduling simulation-optimization model. There are schedules for three different shift policies under three different staffing level scenarios as follows:

- Table A5.1: All 10-hour shift candidate schedule – 21 total nurses.
- Table A5.2: Mix of 10-hour and 8-hour shift candidate schedule – 21 total nurses.
- Table A5.3: All 8-hour shift candidate schedule – 21 total nurses.
- Table A5.4: All 10-hour shift candidate schedule – 18 total nurses.
- Table A5.5: Mix of 10-hour and 8-hour shift candidate schedule – 18 total nurses.
- Table A5.6: All 8-hour shift candidate schedule – 18 total nurses.
- Table A5.7: All 10-hour shift candidate schedule – 16 total nurses.
- Table A5.8: Mix of 10-hour and 8-hour shift candidate schedule – 16 total nurses.
- Table A5.9: All 8-hour shift candidate schedule – 16 total nurses.

Table A5.1: All 10-hour shift candidate schedule – 21 total nurses.

Nurse #	Nurse DBG	Monday	Tuesday	Wednesday	Thursday	Friday	Total Hrs	Lunch
1	Breast	8:00 - 6:30	8:00 - 6:30	8:00 - 6:30	8:00 - 6:30	off	40	12:00-12:30
2	Breast	8:00 - 6:30	8:00 - 6:30	8:00 - 6:30	off	8:00 - 6:30	40	12:30-1:00
3	Breast	off	9:00-7:30	9:00-7:30	9:00-7:30	9:00-7:30	40	1:00-1:30
4	Breast	10:00-8:30	10:00-8:30	10:00-8:30	10:00-8:30	off	40	1:30-2:00
5	Breast	off	10:00-8:30	10:00-8:30	10:00-8:30	10:00-8:30	40	2:00-2:30
1	HOA	7:30-6:00	7:30-6:00	7:30-6:00	off	7:30-6:00	40	12:00-12:30
2	HOA	7:30-6:00	7:30-6:00	off	7:30-6:00	7:30-6:00	40	12:30-1:00
3	HOA	8:00-6:30	8:00-6:30	8:00-6:30	8:00-6:30	off	40	1:00-1:30
4	HOA	off	8:00-6:30	8:00-6:30	8:00-6:30	8:00-6:30	40	1:30-2:00
5	HOA	10:00-8:30	off	10:00-8:30	10:00-8:30	10:00-8:30	40	2:00-2:30
1	Lung	7:30-6:00	7:30-6:00	7:30-6:00	off	7:30-6:00	40	12:00-12:30
2	Lung	off	8:00-6:30	8:00-6:30	8:00-6:30	8:00-6:30	40	12:30-1:00
3	Lung	8:00-6:30	8:00-6:30	8:00-6:30	8:00-6:30	off	40	1:00-1:30
4	Lung	9:00-7:30	off	9:00-7:30	9:00-7:30	9:00-7:30	40	1:30-2:00
1	GI/GU	8:00-6:30	8:00-6:30	off	8:00-6:30	8:00-6:30	40	12:00-12:30
2	GI/GU	8:00-6:30	off	8:00-6:30	8:00-6:30	8:00-6:30	40	12:30-1:00
3	GI/GU	off	9:00-7:30	9:00-7:30	9:00-7:30	9:00-7:30	40	1:00-1:30
4	GI/GU	9:00-7:30	9:00-7:30	9:00-7:30	9:00-7:30	off	40	1:30-2:00
1	Charge	7:30-6:00	7:30-6:00	7:30-6:00	off	7:30-6:00	40	12:00-12:30
2	Charge	7:30-6:00	7:30-6:00	7:30-6:00	7:30-6:00	off	40	12:30-1:00
3	Charge	off	7:30-6:00	7:30-6:00	7:30-6:00	7:30-6:00	40	1:00-1:30
	Total Nurses	15	18	19	17	15		

Table A5.2: Mix of 10-hour and 8-hour shift candidate schedule – 21 total nurses.

Nurse #	Nurse DBG	Monday	Tuesday	Wednesday	Thursday	Friday	Total Hrs	
1	Breast	8:00-4:30	8:00-4:30	8:00-4:30	8:00-4:30	8:00-4:30	40	12:00-12:30
2	Breast	8:00-6:30	8:00-6:30	8:00-6:30	off	8:00-6:30	40	12:30-1:00
3	Breast	9:00-5:30	9:00-5:30	9:00-5:30	9:00-5:30	9:00-5:30	40	1:00-1:30
4	Breast	10:00-8:30	10:00-8:30	10:00-8:30	10:00-8:30	off	40	1:30-2:00
5	Breast	off	10:00-8:30	10:00-8:30	10:00-8:30	10:00-8:30	40	2:00-2:30
1	HOA	off	7:30-6:00	7:30-6:00	7:30-6:00	7:30-6:00	40	12:00-12:30
2	HOA	7:30-6:00	7:30-6:00	7:30-6:00	7:30-6:00	off	40	12:30-1:00
3	HOA	8:00-6:30	8:00-6:30	off	8:00-6:30	8:00-6:30	40	1:00-1:30
4	HOA	10:00-6:30	10:00-6:30	10:00-6:30	10:00-6:30	10:00-6:30	40	1:30-2:00
5	HOA	10:00-8:30	10:00-8:30	10:00-8:30	off	10:00-8:30	40	2:00-2:30
1	Lung	7:30-6:00	off	7:30-6:00	7:30-6:00	7:30-6:00	40	12:00-12:30
2	Lung	8:00-4:30	8:00-4:30	8:00-4:30	8:00-4:30	8:00-4:30	40	12:30-1:00
3	Lung	9:00-7:30	9:00-7:30	9:00-7:30	off	9:00-7:30	40	1:00-1:30
4	Lung	10:00-6:30	10:00-6:30	10:00-6:30	10:00-6:30	10:00-6:30	40	1:30-2:00
1	GI/GU	8:00-4:30	8:00-4:30	8:00-4:30	8:00-4:30	8:00-4:30	40	12:00-12:30
2	GI/GU	8:00-6:30	8:00-6:30	8:00-6:30	8:00-6:30	off	40	12:30-1:00
3	GI/GU	9:00-7:30	9:00-7:30	off	9:00-7:30	9:00-7:30	40	1:00-1:30
4	GI/GU	10:00-6:30	10:00-6:30	10:00-6:30	10:00-6:30	10:00-6:30	40	1:30-2:00
1	Charge	8:00-4:30	8:00-4:30	8:00-4:30	8:00-4:30	8:00-4:30	40	12:00-12:30
2	Charge	7:30-6:00	7:30-6:00	7:30-6:00	7:30-6:00	off	40	12:30-1:00
3	Charge	off	7:30-6:00	7:30-6:00	7:30-6:00	7:30-6:00	40	1:00-1:30
	Total Nurses	18	20	19	18	17		

Table A5.3: All 8-hour shift candidate schedule – 21 total nurses.

Nurse #	Nurse DBG	Monday	Tuesday	Wednesday	Thursday	Friday	Total Hrs	
1	Breast	8:00-4:30	8:00-4:30	8:00-4:30	8:00-4:30	8:00-4:30	40	12:00-12:30
2	Breast	8:00-4:30	8:00-4:30	8:00-4:30	8:00-4:30	8:00-4:30	40	12:30-1:00
3	Breast	9:00-5:30	9:00-5:30	9:00-5:30	9:00-5:30	9:00-5:30	40	1:00-1:30
4	Breast	10:00-6:30	10:00-6:30	10:00-6:30	10:00-6:30	10:00-6:30	40	1:30-2:00
5	Breast	12:00-8:30	12:00-8:30	12:00-8:30	12:00-8:30	12:00-8:30	40	2:00-2:30
1	HOA	7:30-4:00	7:30-4:00	7:30-4:00	7:30-4:00	7:30-4:00	40	12:00-12:30
2	HOA	7:30-4:00	7:30-4:00	7:30-4:00	7:30-4:00	7:30-4:00	40	12:30-1:00
3	HOA	9:00-5:30	9:00-5:30	9:00-5:30	9:00-5:30	9:00-5:30	40	1:00-1:30
4	HOA	10:00-6:30	10:00-6:30	10:00-6:30	10:00-6:30	10:00-6:30	40	1:30-2:00
5	HOA	12:00-8:30	12:00-8:30	12:00-8:30	12:00-8:30	12:00-8:30	40	2:00-2:30
1	Lung	7:30-4:00	7:30-4:00	7:30-4:00	7:30-4:00	7:30-4:00	40	12:00-12:30
2	Lung	8:00-4:30	8:00-4:30	8:00-4:30	8:00-4:30	8:00-4:30	40	12:30-1:00
3	Lung	10:00-6:30	10:00-6:30	10:00-6:30	10:00-6:30	10:00-6:30	40	1:00-1:30
4	Lung	10:00-6:30	10:00-6:30	10:00-6:30	10:00-6:30	10:00-6:30	40	1:30-2:00
1	GI/GU	8:00-4:30	8:00-4:30	8:00-4:30	8:00-4:30	8:00-4:30	40	12:00-12:30
2	GI/GU	8:00-4:30	8:00-4:30	8:00-4:30	8:00-4:30	8:00-4:30	40	12:30-1:00
3	GI/GU	10:00-6:30	10:00-6:30	10:00-6:30	10:00-6:30	10:00-6:30	40	1:00-1:30
4	GI/GU	10:00-6:30	10:00-6:30	10:00-6:30	10:00-6:30	10:00-6:30	40	1:30-2:00
1	Charge	8:00-4:30	8:00-4:30	8:00-4:30	8:00-4:30	8:00-4:30	40	11:30-12:00
2	Charge	7:30-4:00	7:30-4:00	7:30-4:00	7:30-4:00	7:30-4:00	40	12:00-12:30
3	Charge	10:00-6:30	10:00-6:30	10:00-6:30	10:00-6:30	10:00-6:30	40	12:30-1:00
	Total Nurses	21	21	21	21	21		

Table A5.4: All 10-hour shift candidate schedule – 18 total nurses.

Nurse #	Nurse DBG	Monday	Tuesday	Wednesday	Thursday	Friday	Total Hrs	Lunch
1	Breast	8:00 - 6:30	off	8:00 - 6:30	8:00 - 6:30	8:00 - 6:30	40	12:00-12:30
2	Breast	8:00 - 6:30	8:00 - 6:30	8:00 - 6:30	off	8:00 - 6:30	40	12:30-1:00
3	Breast	10:00-8:30	10:00-8:30	10:00-8:30	10:00-8:30	off	40	1:00-1:30
4	Breast	off	10:00-8:30	10:00-8:30	10:00-8:30	10:00-8:30	40	1:30-2:00
1	HOA	7:30-6:00	7:30-6:00	7:30-6:00	off	7:30-6:00	40	12:00-12:30
2	HOA	7:30-6:00	7:30-6:00	off	7:30-6:00	7:30-6:00	40	12:30-1:00
3	HOA	off	9:00-7:30	9:00-7:30	9:00-7:30	9:00-7:30	40	1:00-1:30
4	HOA	10:00-8:30	10:00-8:30	10:00-8:30	10:00-8:30	off	40	1:30-2:00
1	Lung	7:30-6:00	7:30-6:00	7:30-6:00	7:30-6:00	off	40	12:00-12:30
2	Lung	8:00-6:30	8:00-6:30	off	8:00-6:30	8:00-6:30	40	12:30-1:00
3	Lung	8:00-6:30	8:00-6:30	8:00-6:30	off	8:00-6:30	40	1:00-1:30
4	Lung	9:00-7:30	off	9:00-7:30	9:00-7:30	9:00-7:30	40	1:30-2:00
1	GI/GU	8:00-6:30	8:00-6:30	off	8:00-6:30	8:00-6:30	40	12:00-12:30
2	GI/GU	off	8:00-6:30	8:00-6:30	8:00-6:30	8:00-6:30	40	12:30-1:00
3	GI/GU	9:00-7:30	9:00-7:30	9:00-7:30	9:00-7:30	off	40	1:00-1:30
1	Charge	7:30-6:00	off	7:30-6:00	7:30-6:00	7:30-6:00	40	12:00-12:30
2	Charge	7:30-6:00	7:30-6:00	7:30-6:00	7:30-6:00	off	40	12:30-1:00
3	Charge	off	7:30-6:00	7:30-6:00	7:30-6:00	7:30-6:00	40	1:00-1:30
	Total Nurses	14	15	15	15	13		

Table A5.5: Mix of 10-hour and 8-hour shift candidate schedule – 18 total nurses.

Nurse #	Nurse DBG	Monday	Tuesday	Wednesday	Thursday	Friday	Total Hrs	Lunch
1	Breast	8:00-4:30	8:00-4:30	8:00-4:30	8:00-4:30	8:00-4:30	40	12:00-12:30
2	Breast	8:00 - 6:30	8:00 - 6:30	8:00 - 6:30	off	8:00 - 6:30	40	12:30-1:00
3	Breast	10:00-8:30	10:00-8:30	10:00-8:30	10:00-8:30	off	40	1:00-1:30
4	Breast	off	10:00-8:30	10:00-8:30	10:00-8:30	10:00-8:30	40	1:30-2:00
1	HOA	off	7:30-6:00	7:30-6:00	7:30-6:00	7:30-6:00	40	12:00-12:30
2	HOA	7:30-6:00	7:30-6:00	off	7:30-6:00	7:30-6:00	40	12:30-1:00
3	HOA	10:00-6:30	10:00-6:30	10:00-6:30	10:00-6:30	10:00-6:30	40	1:00-1:30
4	HOA	10:00-8:30	10:00-8:30	10:00-8:30	off	10:00-8:30	40	1:30-2:00
1	Lung	7:30-6:00	7:30-6:00	7:30-6:00	7:30-6:00	off	40	12:00-12:30
2	Lung	8:00-6:30	8:00-6:30	8:00-6:30	off	8:00-6:30	40	12:30-1:00
3	Lung	9:00-5:30	9:00-5:30	9:00-5:30	9:00-5:30	9:00-5:30	40	1:00-1:30
4	Lung	9:00-7:30	off	9:00-7:30	9:00-7:30	9:00-7:30	40	1:30-2:00
1	GI/GU	8:00-4:30	8:00-4:30	8:00-4:30	8:00-4:30	8:00-4:30	40	12:00-12:30
2	GI/GU	9:00-5:30	9:00-5:30	9:00-5:30	9:00-5:30	9:00-5:30	40	12:30-1:00
3	GI/GU	9:00-7:30	9:00-7:30	9:00-7:30	9:00-7:30	off	40	1:00-1:30
1	Charge	8:00-4:30	8:00-4:30	8:00-4:30	8:00-4:30	8:00-4:30	40	12:00-12:30
2	Charge	7:30-6:00	7:30-6:00	7:30-6:00	7:30-6:00	off	40	12:30-1:00
3	Charge	off	7:30-6:00	7:30-6:00	7:30-6:00	7:30-6:00	40	1:00-1:30
	Total Nurses	15	17	17	15	14		

Table A5.6: All 8-hour shift candidate schedule – 18 total nurses.

Nurse #	Nurse DBG	Monday	Tuesday	Wednesday	Thursday	Friday	Total Hrs	Lunch
1	Breast	8:00-4:30	8:00-4:30	8:00-4:30	8:00-4:30	8:00-4:30	40	12:00-12:30
2	Breast	9:00-5:30	9:00-5:30	9:00-5:30	9:00-5:30	9:00-5:30	40	12:30-1:00
3	Breast	10:00-6:30	10:00-6:30	10:00-6:30	10:00-6:30	10:00-6:30	40	1:00-1:30
4	Breast	12:00-8:30	12:00-8:30	12:00-8:30	12:00-8:30	12:00-8:30	40	1:30-2:00
1	HOA	7:30-4:00	7:30-4:00	7:30-4:00	7:30-4:00	7:30-4:00	40	12:00-12:30
2	HOA	9:00-5:30	9:00-5:30	9:00-5:30	9:00-5:30	9:00-5:30	40	12:30-1:00
3	HOA	10:00-6:30	10:00-6:30	10:00-6:30	10:00-6:30	10:00-6:30	40	1:00-1:30
4	HOA	12:00-8:30	12:00-8:30	12:00-8:30	12:00-8:30	12:00-8:30	40	1:30-2:00
1	Lung	7:30-4:00	7:30-4:00	7:30-4:00	7:30-4:00	7:30-4:00	40	12:00-12:30
2	Lung	8:00-4:30	8:00-4:30	8:00-4:30	8:00-4:30	8:00-4:30	40	12:30-1:00
3	Lung	9:00-5:30	9:00-5:30	9:00-5:30	9:00-5:30	9:00-5:30	40	1:00-1:30
4	Lung	10:00-6:30	10:00-6:30	10:00-6:30	10:00-6:30	10:00-6:30	40	1:30-2:00
1	GI/GU	8:00-4:30	8:00-4:30	8:00-4:30	8:00-4:30	8:00-4:30	40	12:00-12:30
2	GI/GU	9:00-5:30	9:00-5:30	9:00-5:30	9:00-5:30	9:00-5:30	40	12:30-1:00
3	GI/GU	10:00-6:30	10:00-6:30	10:00-6:30	10:00-6:30	10:00-6:30	40	1:00-1:30
1	Charge	8:00-4:30	8:00-4:30	8:00-4:30	8:00-4:30	8:00-4:30	40	12:00-12:30
2	Charge	7:30-4:00	7:30-4:00	7:30-4:00	7:30-4:00	7:30-4:00	40	12:30-1:00
3	Charge	10:00-6:30	10:00-6:30	10:00-6:30	10:00-6:30	10:00-6:30	40	1:00-1:30
	Total Nurses	18	18	18	18	18		

Table A5.7: All 10-hour shift candidate schedule – 16 total nurses.

Nurse #	Nurse DBG	Monday	Tuesday	Wednesday	Thursday	Friday	Total Hrs	Lunch
1	Breast	8:00 - 6:30	off	8:00 - 6:30	8:00 - 6:30	8:00 - 6:30	40	12:00-12:30
2	Breast	8:00 - 6:30	8:00 - 6:30	8:00 - 6:30	off	8:00 - 6:30	40	12:30-1:00
3	Breast	10:00-8:30	10:00-8:30	10:00-8:30	10:00-8:30	off	40	1:00-1:30
4	Breast	off	10:00-8:30	10:00-8:30	10:00-8:30	10:00-8:30	40	1:30-2:00
1	HOA	7:30-6:00	7:30-6:00	7:30-6:00	off	7:30-6:00	40	12:00-12:30
2	HOA	8:00-6:30	8:00-6:30	off	8:00-6:30	8:00-6:30	40	12:30-1:00
3	HOA	off	8:00-6:30	8:00-6:30	8:00-6:30	8:00-6:30	40	1:00-1:30
4	HOA	10:00-8:30	10:00-8:30	10:00-8:30	10:00-8:30	off	40	1:30-2:00
1	Lung	7:30-6:00	7:30-6:00	7:30-6:00	7:30-6:00	off	40	12:00-12:30
2	Lung	8:00-6:30	8:00-6:30	8:00-6:30	off	8:00-6:30	40	12:30-1:00
3	Lung	9:00-7:30	off	9:00-7:30	9:00-7:30	9:00-7:30	40	1:00-1:30
1	GI/GU	7:30-6:00	7:30-6:00	off	7:30-6:00	7:30-6:00	40	12:00-12:30
2	GI/GU	off	8:00-6:30	8:00-6:30	8:00-6:30	8:00-6:30	40	12:30-1:00
3	GI/GU	9:00-7:30	9:00-7:30	9:00-7:30	9:00-7:30	off	40	1:00-1:30
1	Charge	7:30-6:00	7:30-6:00	7:30-6:00	off	7:30-6:00	40	12:00-12:30
2	Charge	off	7:30-6:00	7:30-6:00	7:30-6:00	7:30-6:00	40	12:30-1:00
	Total Nurses	12	14	14	12	12		

Table A5.8: Mix of 10-hour and 8-hour shift candidate schedule – 16 total nurses.

Nurse #	Nurse DBG	Monday	Tuesday	Wednesday	Thursday	Friday	Total Hrs	Lunch
1	Breast	8:00-4:30	8:00-4:30	8:00-4:30	8:00-4:30	8:00-4:30	40	12:00-12:30
2	Breast	9:00-5:30	9:00-5:30	9:00-5:30	9:00-5:30	9:00-5:30	40	12:30-1:00
3	Breast	10:00-8:30	10:00-8:30	10:00-8:30	10:00-8:30	off	40	1:00-1:30
4	Breast	off	10:00-8:30	10:00-8:30	10:00-8:30	10:00-8:30	40	1:30-2:00
1	HOA	7:30-6:00	7:30-6:00	7:30-6:00	off	7:30-6:00	40	12:00-12:30
2	HOA	8:00-6:30	8:00-6:30	off	8:00-6:30	8:00-6:30	40	12:30-1:00
3	HOA	9:00-5:30	9:00-5:30	9:00-5:30	9:00-5:30	9:00-5:30	40	1:00-1:30
4	HOA	10:00-8:30	10:00-8:30	10:00-8:30	10:00-8:30	off	40	1:30-2:00
1	Lung	7:30-6:00	7:30-6:00	7:30-6:00	7:30-6:00	off	40	12:00-12:30
2	Lung	8:00-6:30	off	8:00-6:30	8:00-6:30	8:00-6:30	40	12:30-1:00
3	Lung	10:00-6:30	10:00-6:30	10:00-6:30	10:00-6:30	10:00-6:30	40	1:00-1:30
1	GI/GU	7:30-6:00	7:30-6:00	off	7:30-6:00	7:30-6:00	40	12:00-12:30
2	GI/GU	8:00-4:30	8:00-4:30	8:00-4:30	8:00-4:30	8:00-4:30	40	12:30-1:00
3	GI/GU	10:00-6:30	10:00-6:30	10:00-6:30	10:00-6:30	10:00-6:30	40	1:00-1:30
1	Charge	7:30-6:00	7:30-6:00	7:30-6:00	off	7:30-6:00	40	12:00-12:30
2	Charge	off	7:30-6:00	7:30-6:00	7:30-6:00	7:30-6:00	40	12:30-1:00
	Total Nurses	14	15	14	14	13		

Table A5.9: All 8-hour shift candidate schedule – 16 total nurses.

Nurse #	Nurse DBG	Monday	Tuesday	Wednesday	Thursday	Friday	Total Hrs	Lunch
1	Breast	8:00-4:30	8:00-4:30	8:00-4:30	8:00-4:30	8:00-4:30	40	12:00-12:30
2	Breast	8:00-4:30	8:00-4:30	8:00-4:30	8:00-4:30	8:00-4:30	40	12:30-1:00
3	Breast	9:00-5:30	9:00-5:30	9:00-5:30	9:00-5:30	9:00-5:30	40	1:00-1:30
4	Breast	12:00-8:30	12:00-8:30	12:00-8:30	12:00-8:30	12:00-8:30	40	1:30-2:00
1	HOA	7:30-4:00	7:30-4:00	7:30-4:00	7:30-4:00	7:30-4:00	40	12:00-12:30
2	HOA	9:00-5:30	9:00-5:30	9:00-5:30	9:00-5:30	9:00-5:30	40	12:30-1:00
3	HOA	9:00-5:30	9:00-5:30	9:00-5:30	9:00-5:30	9:00-5:30	40	1:00-1:30
4	HOA	12:00-8:30	12:00-8:30	12:00-8:30	12:00-8:30	12:00-8:30	40	1:30-2:00
1	Lung	7:30-4:00	7:30-4:00	7:30-4:00	7:30-4:00	7:30-4:00	40	12:00-12:30
2	Lung	9:00-5:30	9:00-5:30	9:00-5:30	9:00-5:30	9:00-5:30	40	12:30-1:00
3	Lung	10:00-6:30	10:00-6:30	10:00-6:30	10:00-6:30	10:00-6:30	40	1:00-1:30
1	GI/GU	8:00-4:30	8:00-4:30	8:00-4:30	8:00-4:30	8:00-4:30	40	12:00-12:30
2	GI/GU	8:00-4:30	8:00-4:30	8:00-4:30	8:00-4:30	8:00-4:30	40	12:30-1:00
3	GI/GU	10:00-6:30	10:00-6:30	10:00-6:30	10:00-6:30	10:00-6:30	40	1:00-1:30
1	Charge	7:30-4:00	7:30-4:00	7:30-4:00	7:30-4:00	7:30-4:00	40	12:00-12:30
2	Charge	10:00-6:30	10:00-6:30	10:00-6:30	10:00-6:30	10:00-6:30	40	12:30-1:00
	Total Nurses	15	15	15	15	15		

APPENDIX 6: NURSE SCHEDULE RESULTS

Tables on results of MIP runs for the 18 nurse and 16 nurse scenarios are available, showing the combinations of nurses used and objective values:

- Table A6.1: Results from MIP for 18 nurse staffing level scenario.
- Table A6.2: Results from MIP for 18 nurse staffing level scenario.

Table A6.1: Results from MIP for 18 nurse staffing level scenario.

18 Nurse Staffing Level; 15 OTC nurses, 3 charge nurses					
Min. # FT Nurses	**# FT 10s**	**# FT 8s**	**# PT Nurses**	**Shortage (Hours)**	**Lower Bound (Hours)**
None	6	2	12	280	280
9	6	3	10	284	280
10	9	1	9	312	280
11	9	2	7	316	280
12	7	5	5	314	285
13	7	6	4	300	295
14	7	7	2	316	311
15	4	11	0	364	344
	Solution			Objective	

Table A6.2: Results from MIP for 16 nurse staffing level scenario.

16 Nurse Staffing Level; 14 OTC nurses, 2 charge nurses					
Min. # FT Nurses	**# FT 10s**	**# FT 8s**	**# PT Nurses**	**Shortage (Hours)**	**Lower Bound (Hours)**
None	4	2	13	440	440
7	5	2	12	440	440
8	4	6	7	440	440
9	6	3	8	486	440
10	4	6	7	448	440
11	5	6	6	447	440
12	7	5	4	452	443
13	3	10	12	468	463
14	0	14	0	516	500
	Solution			Objective	

Tables on selection of PT nurses in the monthly and daily MIP scheduling problem:

- Table A6.3: PT nurse selection, 21 nurse scenario.
- Table A6.4: PT nurse selection, 18 nurse scenario.
- Table A6.5: PT nurse selection, 16 nurse scenario.

Table A6.3: PT nurse selection, 21 nurse scenario.

Part-Time Nurse Set-Up					
nurse, *i*	**1**	**2**	**3**	**4**	**5**
Hours / Week	4	10	10	8	8
# shifts / week	5	2	3	3	4
# Part-Time Nurses Selected by Type					
FT Constraint	**PT Type 1**	**PT Type 2**	**PT Type 3**	**PT Type 4**	**PT Type 5**
None	6	3	3	3	3
9	3	2	4	3	2
10	4	3	2	2	1
11	3	3	1	4	1
12	2	3	2	2	1
13	3	3	1	2	0
14	1	3	1	2	0
15	1	0	2	0	1
16	2	2	0	0	0
17	0	2	0	0	0
18	0	0	0	0	0
Total	**25**	**24**	**16**	**18**	**9**

Table A6.4: PT nurse selection, 18 nurse scenario.

Part-Time Nurse Set-Up					
nurse, *i*	**1**	**2**	**3**	**4**	**5**
Hours / Shift	4	10	10	8	8
# shifts / week	5	2	3	3	4
# Part-Time Nurses Selected by Type					
FT Constraint	**PT Type 1**	**PT Type 2**	**PT Type 3**	**PT Type 4**	**PT Type 5**
None	5	2	2	2	1
9	3	2	2	2	1
10	4	2	0	2	1
11	4	0	1	2	0
12	2	0	0	2	1
13	2	2	0	0	0
14	1	1	0	0	0
15	0	0	0	0	0
Total	**21**	**9**	**5**	**10**	**4**

Table A6.5: PT nurse selection, 16 nurse scenario.

Part-Time Nurse Set-Up					
nurse, *i*	**1**	**2**	**3**	**4**	**5**
Hours / Shift	4	10	10	8	8
# shifts / week	5	2	3	3	4
# Part-Time Nurses Selected by Type					
FT Constraint	**PT Type 1**	**PT Type 2**	**PT Type 3**	**PT Type 4**	**PT Type 5**
None	5	2	2	1	3
7	6	1	2	2	1
8	4	1	2	0	0
9	3	2	1	0	2
10	4	0	0	2	1
11	3	3	0	0	0
12	3	1	0	0	0
13	2	0	0	0	0
14	0	0	0	0	0
Total	**30**	**10**	**7**	**5**	**7**

Original vs. Optimizer Waiting Room Times

Tables on waiting room time with the daily scheduling simulation-optimization model.

- Table A6.6: Maximum wait room time comparison, original vs. optimizer, 21 nurses.
- Table A6.7: Average and maximum wait room time comparison, original vs. optimizer, 18 nurses.
- Table A6.8: Average and maximum wait room time comparison, original vs. optimizer, 16 nurses.

Table A6.6: Maximum wait room time comparison, original vs. optimizer, 21 nurses.

Max OTC Wait Room Time					
		Orig		Opt	
		Avg	HW	Avg	HW
Monday	All 10s	93.4721	15.16	85.832	10.3
	13 10s	85.7829	7.5	77.6832	8.27
	All 8s	91.2303	9.58	82.3061	12.39
Tues	All 10s	103.87	11.82	109.57	33.02
	13 10s	93.3672	11.05	91.9743	15.21
	All 8s	93.9763	11.59	76.8631	7.94
Wed	All 10s	110.63	10.78	106.86	13.96
	13 10s	100.33	9.65	94.7979	10.3
	All 8s	109.32	8.29	96.2533	7.98
Thurs	All 10s	108.28	11.5	92.5072	11.06
	13 10s	104.23	9.08	91.0785	6.89
	All 8s	102.01	10.68	82.1915	11.11
Fri	All 10s	97.7236	11.94	94.5137	32.99
	13 10s	93.086	9.45	76.6021	5.73
	All 8s	97.9572	14.92	71.3615	5.01

Table A6.7: Average and maximum wait room time comparison, original vs. optimizer, 18 nurses.

		Average OTC Wait Room Time				Max OTC Wait Room Time			
		Orig		Opt		Orig		Opt	
		Avg	HW	Avg	HW	Avg	HW	Avg	HW
Monday	All 10s	30.94	2.99	28.83	1.50	87.57	9.58	82.34	12.73
	13 10s	30.92	3.02	29.18	1.94	91.43	7.82	87.16	8.97
	All 8s	29.94	1.55	27.08	1.86	104.01	33.16	78.76	6.73
Tues	All 10s	35.82	3.57	32.17	3.19	111.07	14.94	98.39	15.41
	13 10s	33.01	3.28	29.96	2.57	105.39	14.60	95.35	14.16
	All 8s	37.87	3.89	28.77	2.08	102.49	10.54	85.71	10.40
Wed	All 10s	41.28	4.22	37.25	3.73	113.29	11.43	110.51	12.14
	13 10s	38.92	4.01	35.32	3.53	109.88	10.04	98.93	10.16
	All 8s	41.24	4.26	31.50	3.09	117.40	12.51	88.72	4.93
Thurs	All 10s	44.38	4.57	36.88	3.69	128.82	11.95	117.77	14.63
	13 10s	39.06	3.91	32.34	2.09	117.63	10.37	102.84	10.24
	All 8s	39.40	3.88	29.88	2.85	113.31	12.89	93.52	14.80
Fri	All 10s	36.77	3.51	28.05	1.54	122.20	16.32	97.65	13.43
	13 10s	34.91	3.39	27.63	1.83	107.74	13.19	83.42	14.43
	All 8s	29.82	2.97	26.42	1.17	89.22	10.07	77.01	4.59

Table A6.8: Average and maximum wait room time comparison, original vs. optimizer, 16 nurses.

		OTC Wait Room Time				Max OTC Wait Room Time			
		Orig		Opt		Orig		Opt	
		Avg	HW	Avg	HW	Avg	HW	Avg	HW
Monday	All 10s	36.36	3.64	31.97	2.09	117.98	13.97	89.20	9.98
	13 10s	32.75	3.23	28.02	1.65	100.35	10.82	86.99	9.66
	All 8s	31.22	2.96	27.69	1.05	90.54	8.94	83.70	6.68
Tues	All 10s	38.74	3.88	32.93	2.19	111.20	11.73	103.63	6.19
	13 10s	39.37	4.04	30.02	1.75	110.18	9.66	96.38	9.04
	All 8s	37.75	3.77	29.94	2.45	101.13	8.42	93.97	18.30
Wed	All 10s	42.80	4.26	38.01	3.75	116.90	13.36	108.36	14.73
	13 10s	46.70	4.79	35.10	2.94	125.87	10.85	108.32	11.86
	All 8s	42.39	4.41	33.19	3.16	120.80	12.92	95.48	10.76
Thurs	All 10s	51.19	5.24	37.42	3.70	142.34	11.81	119.09	23.22
	13 10s	44.30	4.48	35.53	1.97	131.95	12.86	104.74	10.24
	All 8s	42.35	4.38	31.40	2.72	122.82	11.94	88.85	10.51
Fri	All 10s	34.41	3.34	31.14	1.85	105.33	9.15	102.89	13.00
	13 10s	38.82	3.86	30.23	2.22	124.51	14.36	94.86	15.20
	All 8s	38.12	3.82	27.50	1.79	104.54	9.94	80.77	14.37

Tables on results of daily schedules chosen by the Optimizer:

- Table A6.9: All 10-hour shift optimizer schedule, 21 nurse scenario.
- Table A6.10: Mix of 10-hour and 8-hour shift optimizer schedule, 21 nurse scenario.
- Table A6.11: All 8-hour shift optimizer schedule, 21 nurse scenario.
- Table A6.12: All 10-hour shift optimizer schedule, 18 nurse scenario.
- Table A6.13: Mix of 10-hour and 8-hour shift optimizer schedule, 18 nurse scenario.
- Table A6.14: All 8-hour shift optimizer schedule, 18 nurse scenario.
- Table A6.15: All 10-hour shift optimizer schedule, 16 nurse scenario.
- Table A6.16: Mix of 10-hour and 8-hour shift optimizer schedule, 16 nurse scenario.
- Table A6.17: All 8-hour shift optimizer schedule, 16 nurse scenario.

Table A6.9: All 10-hour shift optimizer schedule, 21 nurse scenario.

Nurse #	Nurse DBG	Monday	Tuesday	Wednesday	Thursday	Friday
1	Breast	9:00-7:30	8:00-6:30	8:30-7:00	8:00-6:30	off
2	Breast	9:00-7:30	9:00-7:30	8:00-6:30	off	7:30-6:00
3	Breast	off	8:00-6:30	9:30-8:00	8:30-7:00	8:00-6:30
4	Breast	10:00-8:30	10:00-8:30	10:00-8:30	10:00-8:30	off
5	Breast	off	10:00-8:30	10:00-8:30	10:00-8:30	10:00-8:30
1	HOA	7:30-6:00	7:30-6:00	7:30-6:00	off	7:30-6:00
2	HOA	7:30-6:00	7:30-6:00	off	7:30-6:00	7:30-6:00
3	HOA	8:30-7:00	8:30-7:00	9:00-7:30	7:30-6:00	off
4	HOA	off	7:30-6:00	7:30-6:00	7:30-6:00	9:00-7:30
5	HOA	10:00-8:30	off	10:00-8:30	10:00-8:30	10:00-8:30
1	Lung	7:30-6:00	7:30-6:00	7:30-6:00	off	7:30-6:00
2	Lung	off	8:30-7:00	7:30-6:00	8:00-6:30	9:00-7:30
3	Lung	9:00-7:30	7:30-6:00	9:00-7:30	7:30-6:00	off
4	Lung	8:00-6:30	off	9:00-7:30	8:30-7:00	9:30-8:00
1	GI/GU	7:30-6:00	7:30-6:00	off	8:30-7:00	7:30-6:00
2	GI/GU	7:30-6:00	off	9:00-7:30	8:30-7:00	8:00-6:30
3	GI/GU	off	9:30-8:00	9:30-8:00	9:30-8:00	9:30-8:00
4	GI/GU	9:30-8:00	9:30-8:00	9:30-8:00	9:30-8:00	off
1	Charge	7:30-6:00	7:30-6:00	7:30-6:00	off	7:30-6:00
2	Charge	7:30-6:00	7:30-6:00	7:30-6:00	7:30-6:00	off
3	Charge	off	7:30-6:00	7:30-6:00	7:30-6:00	7:30-6:00

Table A6.10: Mix of 10-hour and 8-hour shift optimizer schedule, 21 nurse scenario.

Nurse #	Nurse DBG	Monday	Tuesday	Wednesday	Thursday	Friday
1	Breast	8:30-5:00	9:00-5:30	9:00-5:30	7:30-4:00	7:30-4:00
2	Breast	8:00-6:30	8:00-6:30	7:30-6:00	off	8:30-7:00
3	Breast	8:30-5:00	9:00-5:30	9:00-5:30	8:30-5:00	8:00-4:30
4	Breast	10:00-8:30	10:00-8:30	10:00-8:30	10:00-8:30	off
5	Breast	off	10:00-8:30	10:00-8:30	10:00-8:30	10:00-8:30
1	HOA	off	7:30-6:00	7:30-6:00	7:30-6:00	7:30-6:00
2	HOA	7:30-6:00	7:30-6:00	7:30-6:00	7:30-6:00	off
3	HOA	8:30-7:00	9:00-7:30	off	8:00-6:30	8:30-7:00
4	HOA	9:30-6:00	9:30-6:00	10:00-6:30	10:30-7:00	11:00-7:30
5	HOA	10:00-8:30	10:00-8:30	10:00-8:30	off	10:00-8:30
1	Lung	7:30-6:00	off	7:30-6:00	7:30-6:00	7:30-6:00
2	Lung	9:00-5:30	8:30-5:00	8:30-5:00	7:30-4:00	9:00-5:30
3	Lung	9:00-7:30	8:30-7:00	9:00-7:30	off	9:30-8:00
4	Lung	9:30-6:00	10:30-7:00	10:30-7:00	10:30-7:00	10:00-6:30
1	GI/GU	8:30-5:00	8:30-5:00	8:30-5:00	7:30-4:00	9:00-5:30
2	GI/GU	8:30-7:00	8:00-6:30	8:00-6:30	7:30-6:00	off
3	GI/GU	8:30-7:00	8:00-6:30	off	8:00-6:30	8:00-6:30
4	GI/GU	11:00-7:30	10:00-6:30	10:30-7:00	10:00-6:30	10:30-7:00
1	Charge	8:00-4:30	8:00-4:30	8:00-4:30	8:00-4:30	8:00-4:30
2	Charge	7:30-6:00	7:30-6:00	7:30-6:00	7:30-6:00	off
3	Charge	off	7:30-6:00	7:30-6:00	7:30-6:00	7:30-6:00

Table A6.11: All 8-hour shift optimizer schedule, 21 nurse scenario.

Nurse #	Nurse DBG	Monday	Tuesday	Wednesday	Thursday	Friday
1	Breast	9:00-5:30	9:00-5:30	8:30-5:00	8:00-4:30	7:30-4:00
2	Breast	7:30-4:00	8:00-4:30	7:30-4:00	8:30-5:00	8:00-4:30
3	Breast	9:00-5:30	9:00-5:30	8:00-4:30	10:00-6:30	9:00-5:30
4	Breast	11:00-7:30	11:00-7:30	10:00-6:30	10:00-6:30	10:30-7:00
5	Breast	12:00-8:30	12:00-8:30	12:00-8:30	12:00-8:30	12:00-8:30
1	HOA	7:30-4:00	7:30-4:00	7:30-4:00	7:30-4:00	7:30-4:00
2	HOA	7:30-4:00	7:30-4:00	7:30-4:00	7:30-4:00	7:30-4:00
3	HOA	8:00-4:30	9:30-6:00	8:30-5:00	8:30-5:00	8:00-4:30
4	HOA	11:00-7:30	11:00-7:30	10:00-6:30	9:00-5:30	10:30-7:00
5	HOA	12:00-8:30	12:00-8:30	12:00-8:30	12:00-8:30	12:00-8:30
1	Lung	7:30-4:00	7:30-4:00	7:30-4:00	7:30-4:00	7:30-4:00
2	Lung	9:00-5:30	9:00-5:30	7:30-4:00	7:30-4:00	8:30-5:00
3	Lung	10:30-7:00	10:30-7:00	9:00-5:30	10:30-7:00	10:00-6:30
4	Lung	10:30-7:00	11:00-7:30	11:00-7:30	10:30-7:00	9:00-5:30
1	GI/GU	9:00-5:30	8:00-4:30	7:30-4:00	8:30-5:00	8:30-5:00
2	GI/GU	7:30-4:00	8:00-4:30	9:00-5:30	9:00-5:30	8:00-4:30
3	GI/GU	10:00-6:30	9:30-6:00	9:00-5:30	9:30-6:00	10:30-7:00
4	GI/GU	11:00-7:30	10:00-6:30	11:00-7:30	9:00-5:30	9:30-6:00
1	Charge	8:00-4:30	7:30-6:00	8:00-4:30	8:00-4:30	8:00-4:30
2	Charge	7:30-4:00	7:30-6:00	7:30-4:00	7:30-4:00	7:30-4:00
3	Charge	10:00-6:30	7:30-6:00	10:00-6:30	10:00-6:30	10:00-6:30

Table A6.12: All 10-hour shift optimizer schedule, 18 nurse scenario.

Nurse #	Nurse DBG	Monday	Tuesday	Wednesday	Thursday	Friday
1	Breast	8:00-6:30	off	9:00-7:30	8:30-7:00	7:30-6:00
2	Breast	9:00-7:30	8:30-7:00	9:00-7:30	off	8:00-6:30
3	Breast	10:00-8:30	10:00-8:30	10:00-8:30	10:00-8:30	off
4	Breast	off	10:00-8:30	10:00-8:30	10:00-8:30	10:00-8:30
1	HOA	7:30-6:00	7:30-6:00	7:30-6:00	off	7:30-6:00
2	HOA	7:30-6:00	7:30-6:00	off	7:30-6:00	7:30-6:00
3	HOA	off	8:30-7:00	9:30-8:00	8:30-7:00	9:30-8:00
4	HOA	10:00-8:30	10:00-8:30	10:00-8:30	10:00-8:30	off
1	Lung	7:30-6:00	7:30-6:00	7:30-6:00	7:30-6:00	off
2	Lung	8:30-7:00	8:00-6:30	off	7:30-6:00	8:30-7:00
3	Lung	8:30-7:00	8:30-7:00	9:00-7:30	off	7:30-6:00
4	Lung	9:00-7:30	off	9:30-8:00	9:30-8:00	8:30-7:00
1	GI/GU	9:00-7:30	9:00-7:30	off	7:30-6:00	7:30-6:00
2	GI/GU	off	8:30-7:00	8:30-7:00	7:30-6:00	8:30-7:00
3	GI/GU	9:30-8:00	8:30-7:00	8:00-6:30	8:00-6:30	off
1	Charge	7:30-6:00	off	7:30-6:00	7:30-6:00	7:30-6:00
2	Charge	7:30-6:00	7:30-6:00	7:30-6:00	7:30-6:00	off
3	Charge	off	7:30-6:00	7:30-6:00	7:30-6:00	7:30-6:00

Table A6.13: Mix of 10-hour and 8-hour shift optimizer schedule, 18 nurse scenario.

Nurse #	Nurse DBG	Monday	Tuesday	Wednesday	Thursday	Friday
1	Breast	9:00-5:30	9:00-5:30	9:00-5:30	8:30-5:00	8:00-4:30
2	Breast	7:30-6:00	9:00-7:30	8:00-6:30	off	7:30-6:00
3	Breast	10:00-8:30	10:00-8:30	10:00-8:30	10:00-8:30	off
4	Breast	off	10:00-8:30	10:00-8:30	10:00-8:30	10:00-8:30
1	HOA	off	7:30-6:00	7:30-6:00	7:30-6:00	7:30-6:00
2	HOA	7:30-6:00	7:30-6:00	off	7:30-6:00	7:30-6:00
3	HOA	10:00-6:30	10:00-6:30	11:00-7:30	10:00-6:30	9:30-6:00
4	HOA	10:00-8:30	10:00-8:30	10:00-8:30	off	10:00-8:30
1	Lung	7:30-6:00	7:30-6:00	7:30-6:00	7:30-6:00	off
2	Lung	8:30-7:00	7:30-6:00	8:00-6:30	off	7:30-6:00
3	Lung	9:30-6:00	8:30-5:00	8:00-4:30	10:00-6:30	8:30-5:00
4	Lung	9:30-8:00	off	9:30-8:00	9:30-8:00	9:30-8:00
1	GI/GU	8:00-4:30	8:00-4:30	7:30-4:00	8:00-4:30	7:30-4:00
2	GI/GU	9:00-5:30	9:30-6:00	8:30-5:00	10:00-6:30	8:30-5:00
3	GI/GU	9:00-7:30	8:30-7:00	8:30-7:00	8:00-6:30	off
1	Charge	8:00-4:30	8:00-4:30	8:00-4:30	8:00-4:30	8:00-4:30
2	Charge	7:30-6:00	7:30-6:00	7:30-6:00	7:30-6:00	off
3	Charge	off	7:30-6:00	7:30-6:00	7:30-6:00	7:30-6:00

Table A6.14: All 8-hour shift optimizer schedule, 18 nurse scenario.

Nurse #	Nurse DBG	Monday	Tuesday	Wednesday	Thursday	Friday
1	Breast	8:00-4:30	9:00-5:30	8:00-4:30	7:30-4:00	7:30-4:00
2	Breast	9:00-5:30	9:30-6:00	8:00-4:30	8:00-4:30	9:30-6:00
3	Breast	11:00-7:30	10:30-7:00	9:00-5:30	10:30-7:00	10:00-6:30
4	Breast	12:00-8:30	12:00-8:30	12:00-8:30	12:00-8:30	12:00-8:30
1	HOA	7:30-4:00	7:30-4:00	7:30-4:00	7:30-4:00	7:30-4:00
2	HOA	9:30-6:00	8:00-4:30	9:30-6:00	8:00-4:30	8:00-4:30
3	HOA	9:30-6:00	10:30-7:00	10:30-7:00	9:30-6:00	11:00-7:30
4	HOA	12:00-8:30	12:00-8:30	12:00-8:30	12:00-8:30	12:00-8:30
1	Lung	7:30-4:00	7:30-4:00	7:30-4:00	7:30-4:00	7:30-4:00
2	Lung	8:30-5:00	7:30-4:00	9:00-5:30	9:00-5:30	7:30-4:00
3	Lung	9:30-6:00	9:00-5:30	9:30-6:00	10:00-6:30	9:30-6:00
4	Lung	10:00-6:30	11:00-7:30	9:30-6:00	9:00-5:30	10:00-6:30
1	GI/GU	8:00-4:30	9:00-5:30	8:00-4:30	8:30-5:00	7:30-4:00
2	GI/GU	8:30-5:00	8:00-4:30	8:00-4:30	9:30-6:00	10:00-6:30
3	GI/GU	9:30-6:00	9:00-5:30	9:30-6:00	9:00-5:30	9:00-5:30
1	Charge	8:00-4:30	8:00-4:30	8:00-4:30	8:00-4:30	8:00-4:30
2	Charge	7:30-4:00	7:30-4:00	7:30-4:00	7:30-4:00	7:30-4:00
3	Charge	10:00-6:30	10:00-6:30	10:00-6:30	10:00-6:30	10:00-6:30

Table A6.15: All 10-hour shift optimizer schedule, 16 nurse scenario.

Nurse #	Nurse DBG	Monday	Tuesday	Wednesday	Thursday	Friday
1	Breast	7:30-6:00	off	8:00-6:30	7:30-6:00	7:30-6:00
2	Breast	9:00-7:30	9:00-7:30	9:00-7:30	off	7:30-6:00
3	Breast	10:00-8:30	10:00-8:30	10:00-8:30	10:00-8:30	off
4	Breast	off	10:00-8:30	10:00-8:30	10:00-8:30	10:00-8:30
1	HOA	7:30-6:00	7:30-6:00	7:30-6:00	off	7:30-6:00
2	HOA	7:30-6:00	9:00-7:30	off	8:00-6:30	9:00-7:30
3	HOA	off	8:30-7:00	8:00-6:30	9:00-7:30	9:00-7:30
4	HOA	10:00-8:30	10:00-8:30	10:00-8:30	10:00-8:30	off
1	Lung	7:30-6:00	7:30-6:00	7:30-6:00	7:30-6:00	off
2	Lung	7:30-6:00	9:00-7:30	7:30-6:00	off	8:30-7:00
3	Lung	9:30-8:00	off	9:30-8:00	9:00-7:30	8:00-6:30
1	GI/GU	7:30-6:00	7:30-6:00	off	7:30-6:00	7:30-6:00
2	GI/GU	off	8:00-6:30	8:30-7:00	8:30-7:00	8:30-7:00
3	GI/GU	8:30-7:00	9:00-7:30	8:30-7:00	8:30-7:00	off
1	Charge	7:30-6:00	7:30-6:00	7:30-6:00	off	7:30-6:00
2	Charge	off	7:30-6:00	7:30-6:00	7:30-6:00	7:30-6:00

Table A6.16: Mix of 10-hour and 8-hour shift optimizer schedule, 16 nurse scenario.

Nurse #	Nurse DBG	Monday	Tuesday	Wednesday	Thursday	Friday
1	Breast	7:30-4:00	7:30-4:00	9:00-5:30	8:00-4:30	7:30-4:00
2	Breast	9:00-5:30	9:30-6:00	9:30-6:00	10:00-6:30	8:00-4:30
3	Breast	10:00-8:30	10:00-8:30	10:00-8:30	10:00-8:30	off
4	Breast	off	10:00-8:30	10:00-8:30	10:00-8:30	10:00-8:30
1	HOA	7:30-6:00	7:30-6:00	7:30-6:00	off	7:30-6:00
2	HOA	8:30-7:00	9:00-7:30	off	8:00-6:30	7:30-6:00
3	HOA	9:00-5:30	9:30-6:00	8:30-5:00	9:00-5:30	9:30-6:00
4	HOA	10:00-8:30	10:00-8:30	10:00-8:30	10:00-8:30	off
1	Lung	7:30-6:00	7:30-6:00	7:30-6:00	7:30-6:00	off
2	Lung	8:00-6:30	off	8:30-7:00	8:30-7:00	9:00-7:30
3	Lung	9:00-5:30	9:30-6:00	9:30-6:00	10:00-6:30	9:00-5:30
1	GI/GU	7:30-4:00	7:30-4:00	off	7:30-4:00	7:30-4:00
2	GI/GU	8:30-5:00	8:00-4:30	9:00-5:30	8:00-4:30	7:30-4:00
3	GI/GU	10:30-7:00	10:00-6:30	11:00-7:30	10:00-6:30	10:30-7:00
1	Charge	7:30-6:00	7:30-6:00	7:30-6:00	off	7:30-6:00
2	Charge	off	7:30-6:00	7:30-6:00	7:30-6:00	7:30-6:00

Table A6.17: All 8-hour shift optimizer schedule, 16 nurse scenario.

Nurse #	Nurse DBG	Monday	Tuesday	Wednesday	Thursday	Friday
1	Breast	9:00-5:30	8:00-4:30	7:30-4:00	9:00-5:30	7:30-4:00
2	Breast	7:30-4:00	7:30-4:00	9:00-5:30	8:00-4:30	7:30-4:00
3	Breast	10:00-6:30	8:30-5:00	9:00-5:30	8:00-4:30	8:30-5:00
4	Breast	12:00-8:30	12:00-8:30	12:00-8:30	12:00-8:30	12:00-8:30
1	HOA	7:30-4:00	7:30-4:00	7:30-4:00	7:30-4:00	7:30-4:00
2	HOA	8:30-5:00	9:00-5:30	10:00-6:30	9:30-6:00	8:30-5:00
3	HOA	9:30-6:00	8:00-4:30	10:00-6:30	8:30-5:00	8:30-5:00
4	HOA	12:00-8:30	12:00-8:30	12:00-8:30	12:00-8:30	12:00-8:30
1	Lung	7:30-4:00	7:30-4:00	7:30-4:00	7:30-4:00	7:30-4:00
2	Lung	8:30-5:00	8:00-4:30	8:30-5:00	8:30-5:00	7:30-4:00
3	Lung	9:00-5:30	9:00-5:30	9:30-6:00	10:00-6:30	9:30-6:00
1	GI/GU	7:30-4:00	8:30-5:00	9:00-5:30	9:00-5:30	8:00-4:30
2	GI/GU	8:30-5:00	7:30-4:00	7:30-4:00	7:30-4:00	9:00-5:30
3	GI/GU	10:30-7:00	9:00-5:30	9:30-6:00	10:30-7:00	9:30-6:00
1	Charge	7:30-4:00	7:30-4:00	7:30-4:00	7:30-4:00	7:30-4:00
2	Charge	10:00-6:30	10:00-6:30	10:00-6:30	10:00-6:30	10:00-6:30

APPENDIX 7: CHAIR INCREASE EXPERIMENTS

Tables on results from experiments with OTC increasing the number of chairs to determine the point at which chairs no longer become a bottleneck, where the maximum average column indicates the maximum of the average wait times across all replications:

- Table A7.1: Results for different wait times as numbers of chairs change on Monday.
- Table A7.2: Results for different wait times as numbers of chairs change on Tuesday.
- Table A7.3: Results for different wait times as numbers of chairs change on Wednesday.
- Table A7.4: Results for different wait times as numbers of chairs change on Thursday.
- Table A7.5: Results for different wait times as numbers of chairs change on Friday.

Table A7.1: Results for different wait times as numbers of chairs change on Monday.

38 Chairs	Avg	HW	Max Avg
OTC Wait Room Time	31.8672	1.77	
ChairWait	2.7630	1.44	26.7910
Avg Max OTC Wait	100.83	6.42	
NurseWait	0.9563	0.22	3.2129
42 Chairs	Avg	HW	Max Avg
OTC Wait Room Time	30.1621	1.25	
ChairWait	1.2959	1.06	23.7550
Avg Max OTC Wait	97.2592	6.75	
NurseWait	1.1294	0.22	2.9320
46 Chairs	Avg	HW	Max Avg
OTC Wait Room Time	29.3006	0.69	
ChairWait	0.2212	0.3	5.8314
Avg Max OTC Wait	93.8955	5.79	
NurseWait	1.0641	0.23	3.9358
48 Chairs	Avg	HW	Max Avg
OTC Wait Room Time	29.0744	0.62	
ChairWait	0.03324	0.05	0.8740
Avg Max OTC Wait	94.2367	5.9	
NurseWait	1.1099	0.23	3.9358
50 Chairs	Avg	HW	Max Avg
OTC Wait Room Time	29.1343	0.63	
ChairWait	0.02369	0.05	1.1470
Avg Max OTC Wait	93.8780	5.87	
NurseWait	1.0973	0.23	3.9358
51 Chairs	Avg	HW	Max Avg
OTC Wait Room Time	29.1028	0.62	
ChairWait	0.003981	0.01	0.1811
Avg Max OTC Wait	93.8049	5.9	
NurseWait	1.1103	0.23	3.9358
52 Chairs	Avg	HW	Max Avg
OTC Wait Room Time	29.0824	0.62	
ChairWait	0.00	0	0.00
Avg Max OTC Wait	94.0166	5.94	
NurseWait	1.1005	0.23	3.9358
54 Chairs-72 Chairs	Avg	HW	Max Avg
OTC Wait Room Time	29.0824	0.62	
ChairWait	0.00	0	0.00
Avg Max OTC Wait	94.0166	5.94	
NurseWait	1.1005	0.23	3.9358

Table A7.2: Results for different wait times as numbers of chairs change on Tuesday.

38 Chairs	Avg	HW	Max Avg
OTC Wait Room Time	36.1241	2.05	
ChairWait	7.2704	1.79	22.9593
Avg Max OTC Wait	106.77	6.79	
NurseWait	0.4412	0.1	1.4521
46 Chairs	Avg	HW	Max Avg
OTC Wait Room Time	30.2817	1.04	
ChairWait	0.8186	0.63	13.0098
Avg Max OTC Wait	90.19	5.03	
NurseWait	0.9207	0.23	3.2684
50 Chairs	Avg	HW	Max Avg
OTC Wait Room Time	29.8229	0.95	
ChairWait	0.2067	0.18	3.3344
Avg Max OTC Wait	89.48	5.13	
NurseWait	1.0439	0.29	4.1167
54 Chairs	Avg	HW	Max Avg
OTC Wait Room Time	29.5717	0.84	
ChairWait	0.0139	0.02	0.4171
Avg Max OTC Wait	88.48	5.01	
NurseWait	1.0402	0.27	3.5881
56 Chairs	Avg	HW	Max Avg
OTC Wait Room Time	29.6094	0.85	
ChairWait	0.0035	0.01	0.1055
Avg Max OTC Wait	89.00	5.18	
NurseWait	1.0428	0.28	4.3040
57 Chairs	Avg	HW	Max Avg
OTC Wait Room Time	29.5748	0.85	
ChairWait	0.0008	0	0.0389
Avg Max OTC Wait	88.86	5.18	
NurseWait	1.0420	0.28	4.3040
58 Chairs-72 Chairs	Avg	HW	Max Avg
OTC Wait Room Time	29.5848	0.85	
ChairWait	0.0000	0	0.0000
Avg Max OTC Wait	88.86	5.18	
NurseWait	1.0535	0.28	4.3040

Table A7.3: Results for different wait times as numbers of chairs change on Wednesday.

38 Chairs	Avg	HW	Max Avg
OTC Wait Room Time	39.3491	3.17	
ChairWait	9.9812	2.77	40.9186
Avg Max OTC Wait	116.91	9.02	
NurseWait	0.8695	0.2	2.4044
42 Chairs	Avg	HW	Max Avg
OTC Wait Room Time	34.0474	2.11	
ChairWait	4.5931	1.66	21.3171
Avg Max OTC Wait	104.03	7.2	
NurseWait	1.0634	0.23	3.8933
46 Chairs	Avg	HW	Max Avg
OTC Wait Room Time	31.5090	1.36	
ChairWait	1.7891	0.9	15.3174
Avg Max OTC Wait	102.16	6.12	
NurseWait	1.4838	0.28	3.9778
50 Chairs	Avg	HW	Max Avg
OTC Wait Room Time	30.3920	1.07	
ChairWait	0.5264	0.42	9.4890
Avg Max OTC Wait	102.16	8.12	
NurseWait	1.7229	0.38	6.7605
54 Chairs	Avg	HW	Max Avg
OTC Wait Room Time	30.0157	0.88	
ChairWait	0.0080	0.01	0.2261
Avg Max OTC Wait	97.66	5.79	
NurseWait	1.8033	0.41	7.2336
56 Chairs	Avg	HW	Max Avg
OTC Wait Room Time	30.0890	0.87	
ChairWait	0.0003	0	0.0154
Avg Max OTC Wait	98.99	5.98	
NurseWait	1.8880	0.43	7.2336
57 Chairs	Avg	HW	Max Avg
OTC Wait Room Time	30.0780	0.86	
ChairWait	0.0000	0	0.0000
Avg Max OTC Wait	98.86	5.79	
NurseWait	1.8731	0.43	7.2336
58 Chairs	Avg	HW	Max Avg
OTC Wait Room Time	30.0780	0.86	
ChairWait	0.0000	0	0.0000
Avg Max OTC Wait	98.86	5.79	
NurseWait	1.8731	0.43	7.2336

Table A7.4: Results for different wait times as numbers of chairs change on Thursday.

38 Chairs	Avg	HW	Max Avg
OTC Wait Room Time	42.0034	3.92	
ChairWait	11.2129	3.48	57.2878
Avg Max OTC Wait	120.70	11	
NurseWait	1.3048	0.28	4.4467
46 Chairs	Avg	HW	Max Avg
OTC Wait Room Time	32.8833	1.68	
ChairWait	1.6248	0.95	15.3829
Avg Max OTC Wait	99.05	5.87	
NurseWait	1.7004	0.36	6.2105
54 Chairs	Avg	HW	Max Avg
OTC Wait Room Time	31.0838	0.99	
ChairWait	0.1046	0.14	3.2656
Avg Max OTC Wait	93.81	4.98	
NurseWait	1.6005	0.3	4.1309
60 Chairs	Avg	HW	Max Avg
OTC Wait Room Time	31.1086	1	
ChairWait	0.0268	0.05	1.3396
Avg Max OTC Wait	94.53	5.2	
NurseWait	1.7530	0.37	5.4819
64 Chairs	Avg	HW	Max Avg
OTC Wait Room Time	31.0456	0.97	
ChairWait	0.0055	0.01	0.2758
Avg Max OTC Wait	94.45	5.18	
NurseWait	1.7447	0.36	5.4819
66 Chairs	Avg	HW	Max Avg
OTC Wait Room Time	31.0932	0.99	
ChairWait	0.0009	0	0.0441
Avg Max OTC Wait	94.46	5.18	
NurseWait	1.7762	0.39	6.5318
67 Chairs	Avg	HW	Max Avg
OTC Wait Room Time	31.0734	0.98	
ChairWait	0.0000	0	0.0000
Avg Max OTC Wait	94.43	5.17	
NurseWait	1.7671	0.38	6.0765
68 Chairs-72 chairs	Avg	HW	Max Avg
OTC Wait Room Time	31.0734	0.98	
ChairWait	0.0000	0	0.0000
Avg Max OTC Wait	94.43	5.17	

Table A7.5: Results for different wait times as numbers of chairs change on Friday.

38 Chairs	Avg	HW	Max Avg
OTC Wait Room Time	35.8165	2.56	
ChairWait	5.4204	2.27	30.1495
Avg Max OTC Wait	107.19	8.1	
NurseWait	1.4057	0.35	6.1710
46 Chairs	Avg	HW	Max Avg
OTC Wait Room Time	31.3766	1.28	
ChairWait	0.4454	0.44	8.8841
Avg Max OTC Wait	94.26	6.02	
NurseWait	1.6624	0.39	8.1326
54 Chairs	Avg	HW	Max Avg
OTC Wait Room Time	31.3451	1.15	
ChairWait	0.0500	0.1	2.4285
Avg Max OTC Wait	95.15	6.25	
NurseWait	1.8100	0.47	9.2047
58 Chairs	Avg	HW	Max Avg
OTC Wait Room Time	31.3433	1.14	
ChairWait	0.0041	0.01	0.2053
Avg Max OTC Wait	95.08	6.22	
NurseWait	1.8379	0.48	8.4690
60 Chairs	Avg	HW	Max Avg
OTC Wait Room Time	31.3121	1.11	
ChairWait	0.0009	0	0.0461
Avg Max OTC Wait	95.14	6.27	
NurseWait	1.8173	0.46	8.4690
61 Chairs	Avg	HW	Max Avg
OTC Wait Room Time	31.3769	1.17	
ChairWait	0.0001	0	0.0028
Avg Max OTC Wait	95.37	6.47	
NurseWait	1.8342	0.48	8.4690
62 Chairs-72 Chairs	Avg	HW	Max Avg
OTC Wait Room Time	31.3354	1.13	
ChairWait	0.0000	0	0.0000
Avg Max OTC Wait	95.09	6.22	
NurseWait	1.8391	0.48	8.4690

Graph results for different wait times in the OTC experiments increasing the number of chairs.

- Figure A7.1: Patient wait for chairs graph, Monday
- Figure A7.2: Patient wait for nurses graph, Monday
- Figure A7.3: Patient waiting room time, Monday
- Figure A7.4: Patient wait for chairs graph, Tuesday
- Figure A7.5: Patient wait for nurses graph, Tuesday
- Figure A7.6: Patient waiting room time, Tuesday
- Figure A7.7: Patient wait for chairs graph, Wednesday
- Figure A7.8: Patient wait for nurses graph, Wednesday
- Figure A7.9: Patient waiting room time, Wednesday
- Figure A7.10: Patient wait for chairs graph, Friday
- Figure A7.11: Patient wait for nurses graph, Friday
- Figure A7.12: Patient waiting room time, Friday

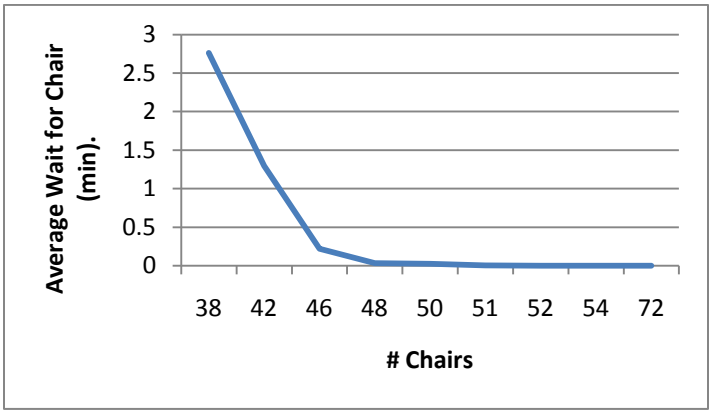

Figure A7.1: Patient wait for chairs graph, Monday.

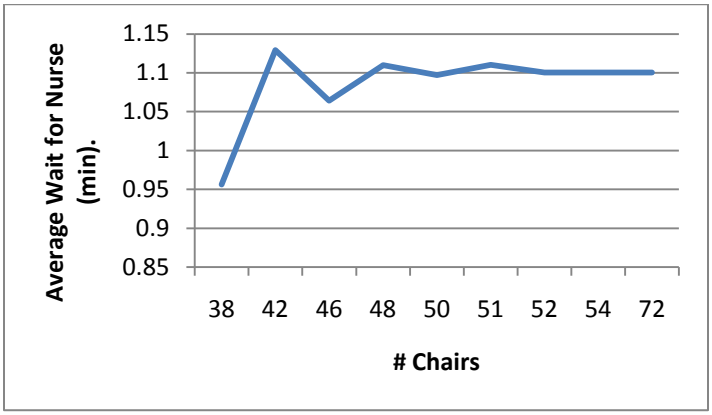

Figure A7.2: Patient wait for nurses graph, Monday.

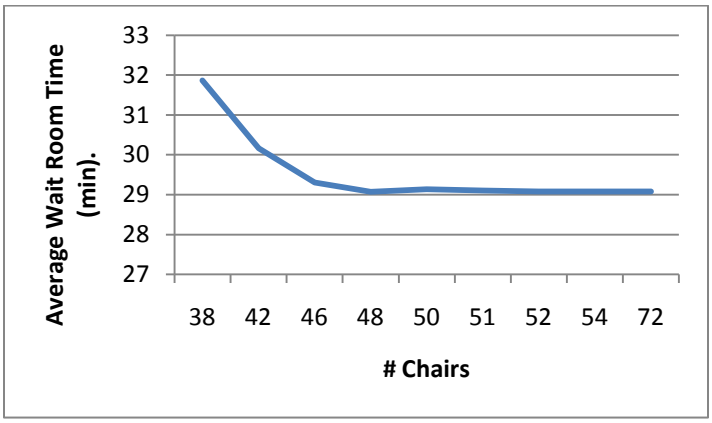

Figure A7.3: Patient waiting room time, Monday.

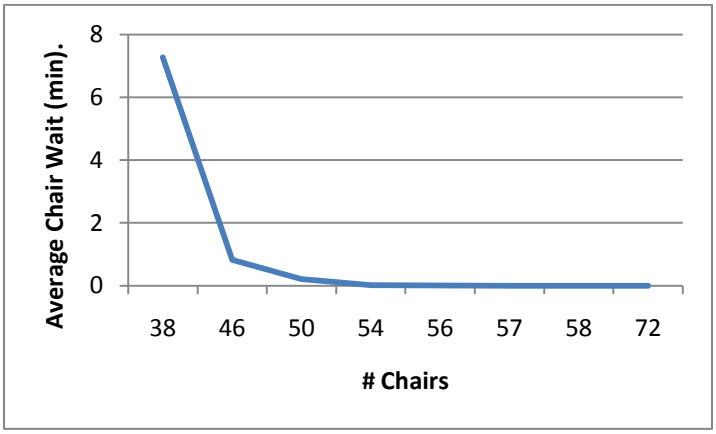

Figure A7.4: Patient wait for chairs graph, Tuesday.

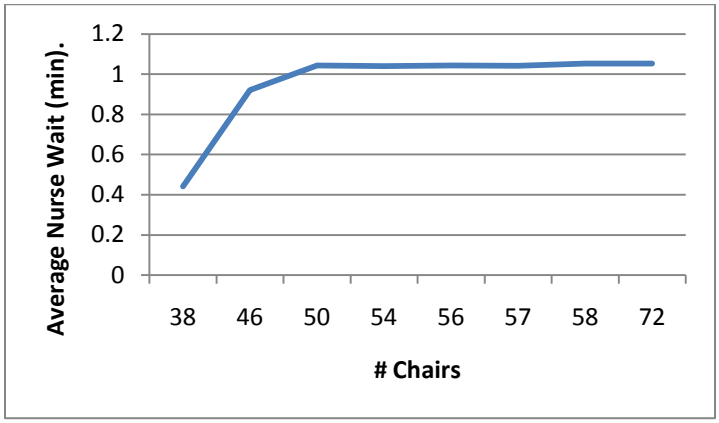

Figure A7.5: Patient wait for nurses graph, Tuesday.

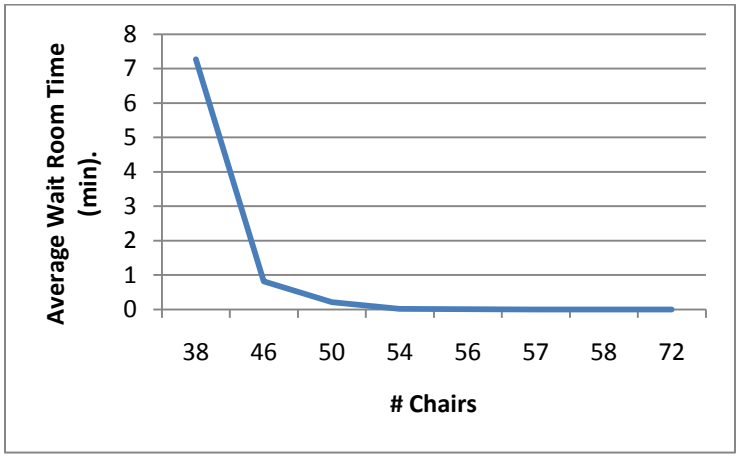

Figure A7.6: Patient waiting room time, Tuesday.

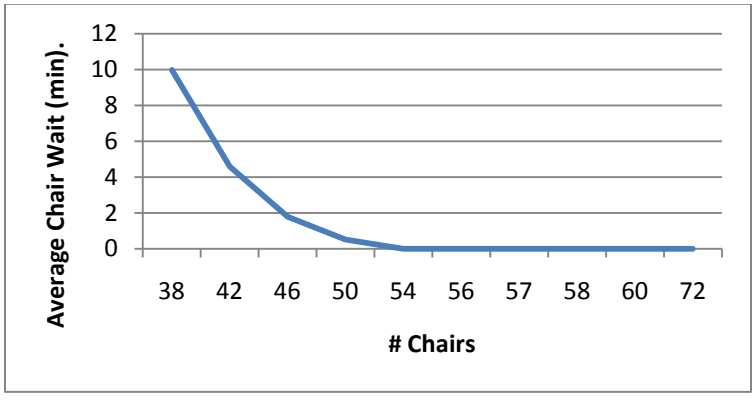

Figure A7.7: Patient wait for chairs graph, Wednesday.

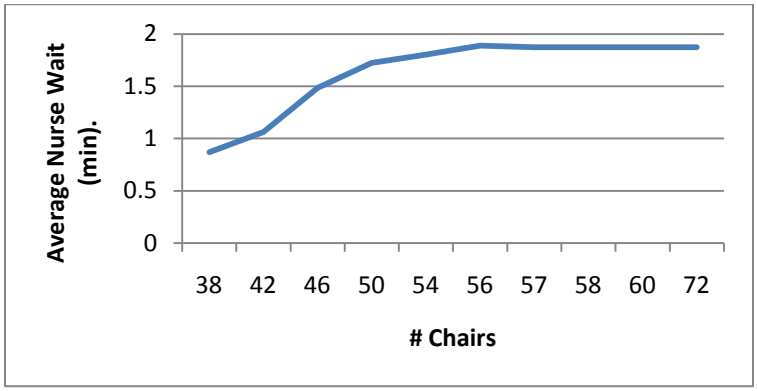

Figure A7.8: Patient wait for nurses graph, Wednesday.

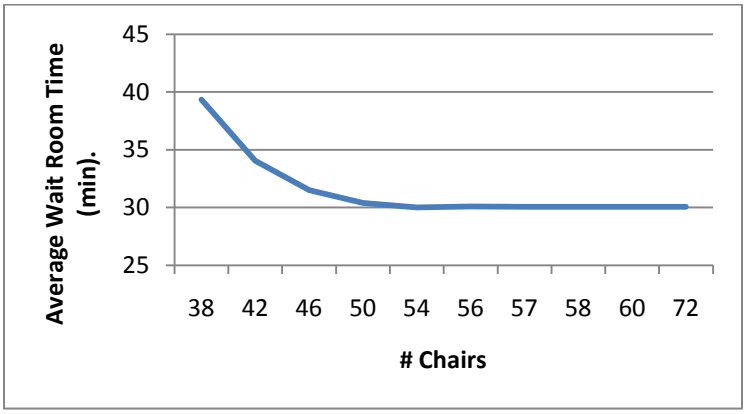

Figure A7.9: Patient waiting room time, Wednesday.

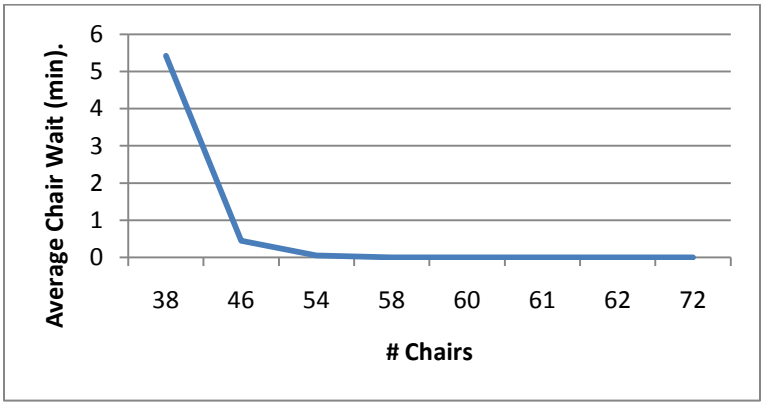

Figure A7.10: Patient wait for chairs graph, Friday.

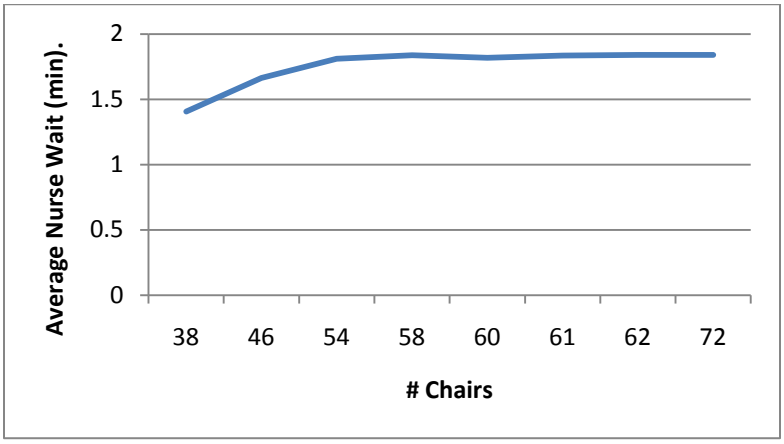

Figure A7.11: Patient wait for nurses graph, Friday.

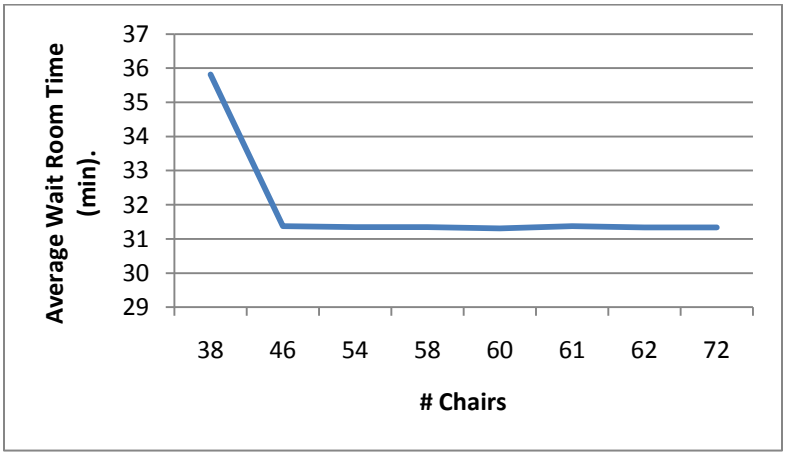

Figure A7.12: Patient waiting room time, Friday.

APPENDIX 8: PATIENT ARRIVAL INCREASE EXPERIMENTS

This appendix includes results from the experiments using the model for the future OTC to increase patient arrivals and predict the behavior of the bottlenecks. The following tables are included:

- Table A8.1: Monday results for the new-OTC model with patient volume increases.
- Table A8.2: Tuesday results for the new-OTC model with patient volume increases.
- Table A8.3: Wednesday results for the new-OTC model with patient volume increases.
- Table A8.4: Thursday results for the new-OTC model with patient volume increases.
- Table A8.5: Friday results for the new-OTC model with patient volume increases.

Table A8.1: Monday results for the new-OTC model with patient volume increases.

	Current		New		6% Increase		12% Increase	
	AVG	HW	AVG	HW	AVG	HW	AVG	HW
Enter Data into ARIA.Queue	2.37	0.39	2.46	0.40	2.54	0.35	2.78	0.46
Match patient with completed mixed drug.Queue	6.58	0.19	6.58	0.21	6.64	0.26	6.62	0.22
Mix Drug.Queue	0.10	0.03	0.10	0.03	0.12	0.05	0.14	0.04
Nurse Chart Check Breast.Queue	0.16	0.10	0.42	0.33	0.38	0.22	1.03	0.86
Nurse Chart Check GIGU.Queue	0.09	0.07	0.51	0.22	1.01	0.77	1.54	0.85
Nurse Chart Check HOA.Queue	4.47	1.10	4.72	1.06	7.89	2.42	7.25	1.70
Nurse Chart Check Lung.Queue	0.07	0.05	0.54	0.56	0.61	0.32	0.90	0.48
Patient Check In OTC.Queue	0.22	0.06	0.21	0.05	0.22	0.06	0.22	0.05
Pharmacy Processing.Queue	0.86	0.24	0.89	0.25	1.15	0.44	1.10	0.27
OTC Wait Room Time	31.87	1.77	29.50	0.71	30.74	0.94	30.90	0.81
OTC Monday Throughput	104.14	3.02	104.12	2.98	108.46	2.51	115.84	3.00
OTC InService WIP	19.35	0.60	19.59	0.61	20.43	0.67	21.87	0.69
OTC Waiting WIP	3.13	0.28	2.75	0.12	2.90	0.12	3.11	0.14
Chair Turns	2.74	0.08	1.43	0.04	1.49	0.03	1.59	0.04
ChairWait	2.76	1.44	0.00	0.00	0.00	0.00	0.00	0.00
Max OTC Wait Time	100.83	6.42	95.44	6.12	100.97	7.57	101.34	5.81
NurseWait	0.96	0.22	1.24	0.23	1.98	0.51	2.14	0.41

Table A8.2: Tuesday results for the new-OTC model with patient volume increases.

	Current		New		6% Increase		12% Increase	
	AVG	HW	AVG	HW	AVG	HW	AVG	HW
Enter Data into ARIA.Queue	2.67	0.52	2.63	0.46	3.43	0.62	4.26	1.11
Match patient with completed mixed drug.Queue	6.53	0.25	6.54	0.22	6.78	0.17	6.69	0.29
Mix Drug.Queue	0.12	0.05	0.14	0.05	0.14	0.05	0.24	0.07
Nurse Chart Check Breast.Queue	0.55	0.24	1.66	1.00	2.43	1.11	2.88	1.63
Nurse Chart Check GIGU.Queue	0.16	0.08	2.95	1.12	3.99	1.48	6.19	2.04
Nurse Chart Check HOA.Queue	1.46	0.47	3.18	1.10	5.14	1.68	3.47	0.93
Nurse Chart Check Lung.Queue	0.04	0.04	0.60	0.39	0.52	0.43	0.69	0.47
Patient Check In OTC.Queue	0.17	0.05	0.16	0.05	0.16	0.05	0.16	0.05
Pharmacy Processing.Queue	1.21	0.41	1.30	0.42	1.70	0.48	1.53	0.29
OTC Wait Room Time	36.12	2.05	30.17	0.87	32.51	1.17	32.57	1.37
OTC Tuesday Throughput	107.98	2.67	108.74	3.27	115.26	3.41	120.02	3.44
OTC InService WIP	20.56	0.62	20.91	0.74	22.11	0.83	22.97	0.82
OTC Waiting WIP	3.91	0.33	2.87	0.11	3.22	0.17	3.35	0.19
Chair Turns	2.84	0.07	1.49	0.04	1.58	0.05	1.64	0.05
ChairWait	7.27	1.79	0.00	0.00	0.00	0.00	0.00	0.00
Max OTC Wait Time	106.77	6.79	94.92	6.27	103.68	7.65	101.49	7.77
NurseWait	0.44	0.10	1.68	0.39	2.42	0.50	2.65	0.57

Table A8.3: Wednesday results for the new-OTC model with patient volume increases.

	Current		New		6% Increase		12% Increase	
	Avg	HW	Avg	HW	Avg	HW	Avg	HW
Enter Data into ARIA.Queue	3.13	0.49	2.85	0.50	3.74	0.63	3.94	0.70
Match patient with completed mixed drug.Queue	6.43	0.16	6.57	0.25	6.66	0.20	7.15	0.58
Mix Drug.Queue	0.17	0.05	0.18	0.06	0.21	0.05	0.36	0.12
Nurse Chart Check Breast.Queue	0.36	0.18	1.94	0.91	3.10	1.16	4.57	1.43
Nurse Chart Check GIGU.Queue	0.01	0.01	0.29	0.25	0.99	0.58	0.49	0.28
Nurse Chart Check HOA.Queue	3.63	0.96	5.01	1.28	5.92	1.64	6.64	1.87
Nurse Chart Check Lung.Queue	0.35	0.32	3.54	1.24	4.35	1.24	5.13	1.53
Patient Check In OTC.Queue	0.22	0.05	0.22	0.06	0.21	0.05	0.21	0.05
Pharmacy Processing.Queue	1.13	0.27	1.62	0.57	1.74	0.55	2.93	1.31
OTC Wait Room Time	39.35	3.17	30.53	0.95	32.23	1.08	34.17	1.60
OTC Wednesday Throughput	114.28	2.67	116.38	3.11	124.50	3.64	130.56	2.56
OTC InService WIP	21.44	0.63	22.04	0.77	23.66	0.80	24.83	0.71
OTC Waiting WIP	4.60	0.53	3.12	0.16	3.47	0.18	3.81	0.23
Chair Turns	3.01	0.07	1.59	0.04	1.71	0.05	1.79	0.04
ChairWait	9.98	2.77	0.00	0.00	0.00	0.00	0.00	0.00
Max OTC Wait	116.91	9.02	95.41	4.41	101.60	5.31	111.36	13.02
NurseWait	0.87	0.20	2.15	0.44	2.87	0.54	3.36	0.66

Table A8.4: Thursday results for the new-OTC model with patient volume increases.

	Current		New		6% Increase		12% Increase	
	Avg	HW	Avg	HW	Avg	HW	Avg	HW
Enter Data into ARIA.Queue	3.93	0.75	2.20	0.31	2.54	0.32	3.34	0.71
Match patient with completed mixed drug.Queue	6.62	0.25	6.71	0.20	6.52	0.26	6.70	0.22
Mix Drug.Queue	0.15	0.05	0.09	0.04	0.12	0.04	0.14	0.05
Nurse Chart Check Breast.Queue	0.57	0.24	0.23	0.15	0.94	0.49	1.63	1.19
Nurse Chart Check GIGU.Queue	0.04	0.03	0.31	0.21	0.48	0.26	0.61	0.43
Nurse Chart Check HOA.Queue	5.88	1.38	6.00	1.51	5.67	1.46	10.42	2.64
Nurse Chart Check Lung.Queue	0.03	0.05	0.03	0.04	0.03	0.04	0.12	0.10
Patient Check In OTC.Queue	0.18	0.05	0.22	0.06	0.22	0.05	0.22	0.05
Pharmacy Processing.Queue	1.12	0.34	1.19	0.37	1.21	0.43	1.37	0.31
OTC Wait Room Time	42.00	3.92	29.93	0.81	29.79	0.80	32.14	1.22
OTC Thursday Throughput	107.14	3.16	103.12	2.84	107.84	3.33	116.86	3.27
OTC InService WIP	20.75	0.75	19.26	0.70	20.33	0.77	22.27	0.77
OTC Waiting WIP	4.60	0.64	2.76	0.12	2.86	0.14	3.20	0.17
Chair Turns	2.82	0.08	1.41	0.04	1.48	0.05	1.60	0.04
ChairWait	11.21	3.48	0.00	0.00	0.00	0.00	0.00	0.00
Max OTC Wait Time	120.70	11.00	94.05	5.82	92.80	5.49	105.75	7.27
NurseWait	1.30	0.28	1.31	0.31	1.42	0.29	2.56	0.57

Table A8.5: Friday results for the new-OTC model with patient volume increases.

	Current		New		6% Increase		12% Increase	
	Avg	HW	Avg	HW	Avg	HW	Avg	HW
Enter Data into ARIA.Queue	2.18	0.31	2.11	0.28	2.51	0.54	3.65	0.86
Match patient with completed mixed drug.Queue	6.83	0.31	6.98	0.29	6.90	0.32	6.83	0.38
Mix Drug.Queue	0.10	0.03	0.12	0.04	0.08	0.02	0.18	0.07
Nurse Chart Check Breast.Queue	0.71	0.29	1.62	0.72	1.68	0.60	3.96	1.36
Nurse Chart Check GIGU.Queue	0.00	0.00	0.43	0.29	0.94	0.57	1.71	1.01
Nurse Chart Check HOA.Queue	5.95	1.74	10.40	2.71	10.75	2.22	14.85	2.94
Nurse Chart Check Lung.Queue	0.37	0.24	2.08	0.86	3.26	1.07	5.06	1.31
Patient Check In OTC.Queue	0.20	0.05	0.20	0.05	0.20	0.06	0.19	0.05
Pharmacy Processing.Queue	1.70	0.61	1.99	0.67	1.49	0.54	1.85	0.76
OTC Wait Room Time	35.82	2.56	32.49	1.37	32.64	1.20	35.47	1.55
OTC Friday Throughput	97.00	3.27	96.50	3.22	100.58	3.07	109.60	3.30
OTC InService WIP	18.85	0.77	18.98	0.88	19.97	0.78	22.46	0.78
OTC Waiting WIP	3.36	0.39	2.68	0.15	2.75	0.16	3.06	0.18
Chair Turns	2.55	0.09	1.32	0.04	1.38	0.04	1.50	0.05
ChairWait	5.42	2.27	0.00	0.00	0.00	0.00	0.00	0.00
Max OTC Wait Time	107.19	8.10	103.14	7.03	105.42	6.73	116.23	7.06
NurseWait	1.41	0.35	2.91	0.70	3.33	0.60	5.12	0.72