CHEMOTHERAPY APPOINTMENT SCHEDULING AND OPERATIONS PLANNING

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CHEMOTHERAPY APPOINTMENT SCHEDULING AND OPERATIONS PLANNING

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Dissertation

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ABSTRACT

In recent times operational planning and scheduling has become extremely important in healthcare delivery systems due to increase in demand and limited supply, even more so in chemotherapy clinics. Cancer is one of the most commonly found diseases in general population today and there are new techniques conceived almost every day to better cure and control this disease. There has been a shift in the responsibilities of care givers with nurses being more involved in care delivery task today than ever before [4]. Studies show that the growth of this resource is not enough to catch up with the demand and hence it is imperative to cut down inefficiencies in cancer clinics by making use of the nursing resource optimally. It has been concluded through various surveys that one of the biggest problems causing delays in care delivery for cancer patients is scheduling appointment at clinics and keeping those appointment times. There is a considerable amount of delay between patients physically being present for their appointments and the actual appointment start times. This research aims to develop a mathematical model to handle the chemotherapy scheduling problem by optimally assigning patients to nurses and reducing the nurse utilization. This problem is uniquely interesting because, unlike other scheduling requirements, cancer patient require variable nursing times, their appointment durations are not fixed and they require various other resources such as chairs/beds, etc. The mathematical model presented in this study is tested at a cancer clinic in a community hospital in northeast Ohio and the results are

discussed in this dissertation. Also, the effect of various different scenarios on the operations of the cancer clinic is tested using a discrete event simulation model.

ACKNOWLEDGEMENTS

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CHAPTER I

BACKGROUND

1.1 Nature of the problem: Can we match the supply to the demand?

Cancer is the second most common cause of deaths in the western world and more than half of the patients diagnosed with cancer are treated with chemotherapy. 80 to 90 % of all the cancer care delivered today is done in an outpatient setting [1]. The demand for oncology services is expected to grow at 48% by 2020 due to aging and growth in population [2]. This is partly because of the expected 81% increase in cancer survival rate. Figure 1 illustrates the projected demand and supply for oncology services [2]. The supply of services provided by the number of oncologists, however, is anticipated to grow at approximately 14% during the same time frame [2]. This unbalances the demand-supply equilibrium. It is likely that we may have 2,550 to 4,080 less oncologists than needed [2]. Figure 2 depicts the exact nature of the problem. There is an increase in overall volume of cancer patients, increase in acuities and treatment complexities but not enough workforce to handle this demand. It is clear from the two previous figures that it is very difficult to meet the projected demand with the projected supply. Some of the solutions suggested to bridge the gap between the projected supply and demand are revising the Medicare and Medicaid policies [11], increasing the number of oncology training slots and increasing the use of other practitioners such as NPs or PAs, PCPs, and

hospice care providers etc. [10]. However, none of these solutions alone can meet the projected shortages.

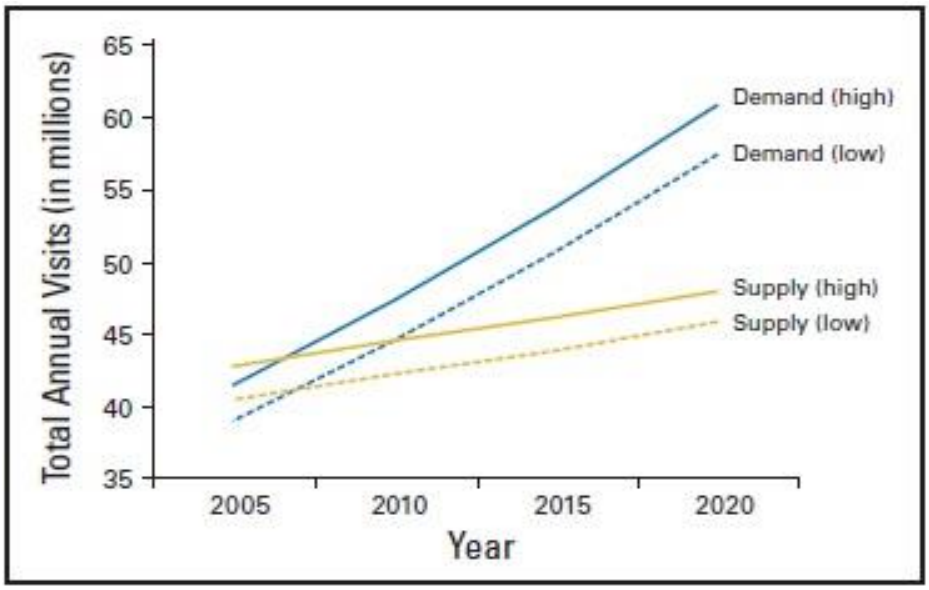

Figure 1: Projected supply and demand for oncology services from 2005 to 2020 [10, 22]

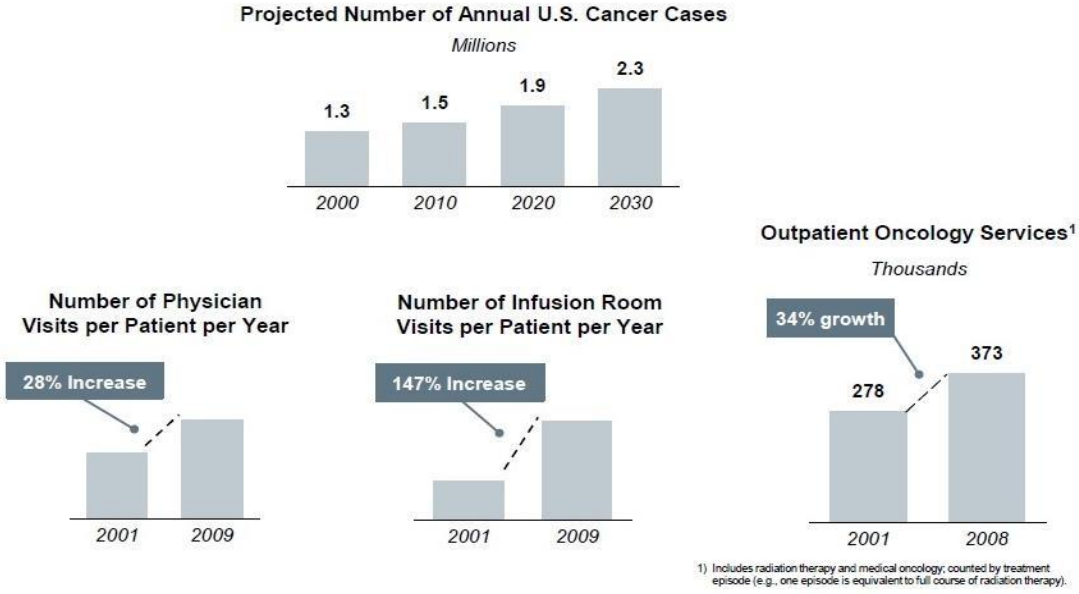

Figure 2: Projected volume increase and unmatched increase in supply of services [13]

Part of the problem is also in the inefficiencies in delivering treatment to patients. Operationally optimizing the way care is delivered can reduce this shortage if not eliminate it. In order to match the demand to the supply without incurring additional costs onto the clinics it is extremely essential to efficiently use available resources without affecting the overall patient care experience and safety. This research objective focuses on scheduling patient appointments such that the overall nursing workload is balanced for each day and available nursing time is used optimally with very little idle time and overtime.

1.2 Introduction to Cancer and Chemotherapy Treatment Plans

Cancer is caused by cells that divide at an unregulated rate resulting in an uncontrolled production of new cells. Cell division of normal cells is tightly controlled by our body but in case of cancerous cells our body fails to regulate this function. Figure 3 compares normal cell division to cell division in cancerous cells. Gradual increase in the number of dividing cells creates a growing mass of tissue called the “tumor” or "neoplasm" [30]. These tumors are referred to as malignant tumors. Cancers can spread throughout the body by two mechanisms: invasion and metastasis. Invasion refers to the migration and penetration of cancer cells into the neighboring tissue and metastasis refers to penetration of cancer cells into the blood stream and migrating to other normal/ healthy parts of the body [30]. There are four stages of cancer: Stage I, II III and IV. Stages III and IV have more cell abnormalities and large number of dividing cells and are less responsive to treatment as compared to stages I and II [30]. There are various ways of treating this disease such as radiation therapy, chemotherapy, surgery, hormonal therapy,

targeted therapy, transplants etc. Chemotherapy is a used to treat many cancers either alone or in combination with other treatments. In chemotherapy, a single chemical drug or a combination of drugs is usually administered through the patient's blood stream.

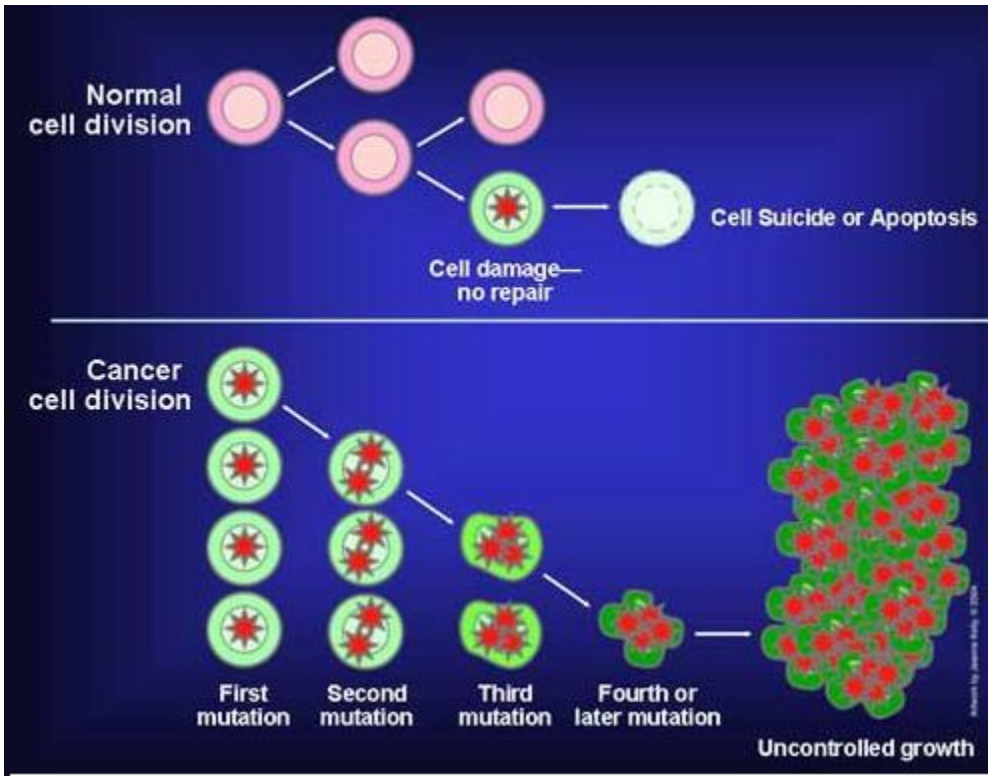

Figure 3: Cause of cancer: unregulated cell growth [30]

Figure 4(a) show the main stages in a cell growth and figure 4(b) shows the stages of tumor growth and its migration. Cells spend most time in the G0 phase which is also called as the "resting" phase. In the G1, S and G2 phase the cell gets ready to divide. The actual cell division happens in the M phase where the cell splits to form two new cells. This process is called as mitosis. Chemotherapy drugs interfere with cell activity in G1,

S, G2 or M phase that reduce or stop the growth of cancerous cells. They never work on the cells that are in the resting phase (G0 phase) [27,28].

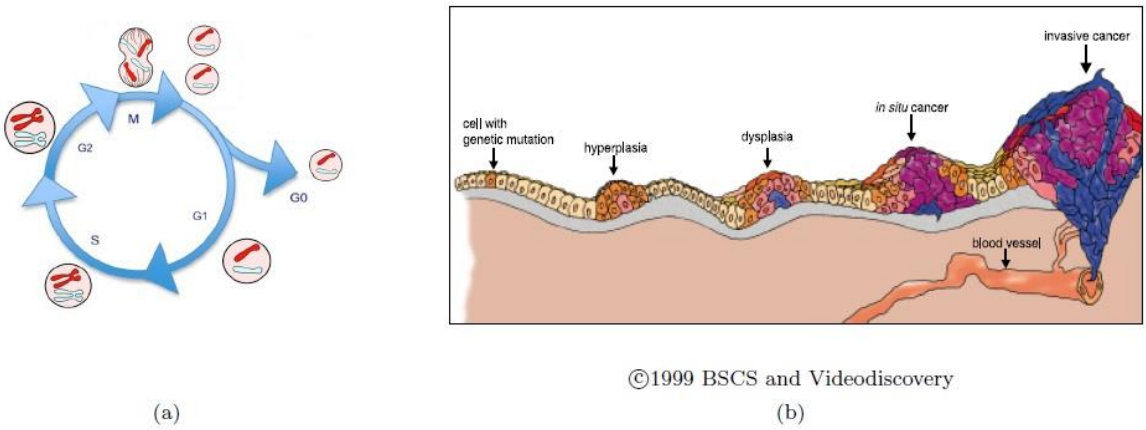

Figure 4 (a): 5 phases of cell division [26, 27], (b) Stages of tumor growth [28]

Chemotherapy drugs are administered in various ways such as by injecting into a body cavity, delivering orally in the form of a pill or topically (applied on the skin) [9]. Chemotherapy is a systemic therapy to control, cure and prevent the growth of cancer in a patient which means that cancer-fighting drugs circulate in the blood to parts of the body where the cancer may have spread and can kill cancers cells at sites away from the original site. Surgery, radiation therapy kill cancer cells in a certain area and are hence considered local treatments. Chemotherapy affects the whole body causing a range of side effects because the drugs spread throughout the body and hence is given it cycles. The time is between chemotherapy cycles is used by the body to rest and recover. Multiple cycles are required for the drug(s) to be effective as chemotherapy only attacks the cells that are dividing and not the cells that are dormant [3,4]. One course of treatment is not a good fit for all the patients and hence the oncologist decides individual treatment

plans based on the type of cancer, stage of the decease, location of the disease and various other factors specific to patients. Each course consists of a number of cycles of chemotherapy that constitute to a complete chemotherapy treatment protocol [5]. The process of delivering drug(s) is called an infusion. An infusion lasts from 15 minutes to 7 hours or longer [9]. Continuous infusion refers to a process where drugs are given slowly over days by attaching a pump to the patient. Depending on the cancer type and the drugs used to fight it, a patient may need daily, weekly or monthly chemotherapy infusions. Figure 5 shows an example of one such chemotherapy treatment plan [6]. In this example a ten week treatment plan is shown with three cycles. Each cycle consists of three chemotherapy sessions. Week 1, 4 and 7 are treatment weeks and the time in between is given for the patient to rest and recuperate. Blood is drawn every week and results from the Laboratory inform the oncologists if the patient is ready for the next cycle or not and if the cancer is responding to the drugs. Drawing blood and testing it is a standard procedure on any oncology clinic. If the patient is too weak then the cycle is either postponed or the drug dosage is reduced/ changed [6].

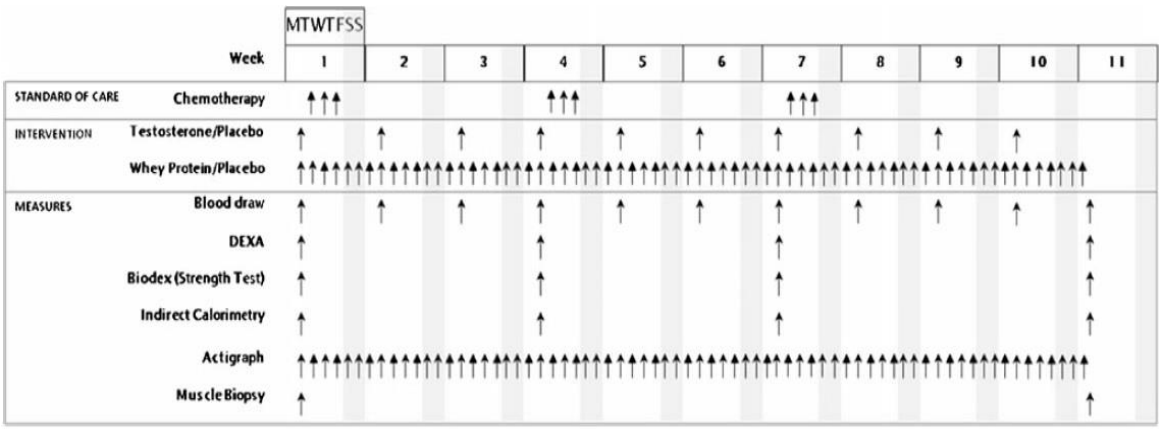

Figure 5: Example of a chemotherapy treatment protocol [6]

It is evident from figure 5 that chemotherapy treatment entails a lot of other interventions and not just the actual drug delivery. It is a complicated process and each patient is unique with specific needs. Nursing time is required during most of these interventions if not all. Balancing the nurses' workload without over or under utilizing them is a challenge at all cancer treatment outpatient clinics. This presents a research opportunity to optimize the scheduling algorithm for cancer patients.

1.3 Significance of this research: Why optimal scheduling is so important?

The oncologist decides the treatment protocol for a patient but the nurse is responsible for administering the drugs. These days, majority of the physician tasks are delegated to the oncology nurses such as patient education, counseling and accessing patient's response to the treatment, providing counseling to patient's family members etc. [4]. A recent survey by the National Academic Press found that a significant amount of nursing time is spent in doing indirect care delivery tasks. The survey concluded that 23% of nursing time per week is spent in filling out patient care–related notes and documentation [7]. Nurses are getting more involved in the management aspects of the clinics and this takes time away from their patients. In a survey conducted by Buerhaus et. al. it was concluded that 80% of all oncology nurses perceived that staffing levels were inadequate. They felt that there is a substantial increase in overtime and double shifts. 52% of the oncology RNs reported working overtime at least once a week [11]. With added responsibility on nurses and shortage of this workforce it is paramount to implement new models of care that will facilitate optimal care delivery by improving efficiencies in outpatient cancer clinics. One of the ways to improve efficiency is by

reducing the delays in the chemotherapy delivery process. Waiting times is one of the biggest outcomes of process delays and is an important quality indicator which affects the level of satisfaction of the patient with the clinic/ hospital [8]. Figure 8 highlights the bottlenecks in chemotherapy treatment. Long waiting times affect patient compliance to treatment regimens and clinical outcomes and also increases frustration not only among patients but also among care providers [8]. Chemotherapy appointments are always scheduled in advance and even though the patients arrive on time for their appointments they are not always treated on time [8]. Appointments are scheduled in an ad-hoc manner or based on patient preference. Scheduling patients optimally during the available clinic hours and maximizing resource utilization to match the demand is one of the ways to give patients a better experience, reduce the overall waiting time and increase process efficiency. All the processes in a chemotherapy clinic are interdependent and hence careful timing is critically important to achieve minimum patient waiting times [13]. If patients are optimally scheduled over the operating hours during the day, a week or even a month then it can significantly reduce the extra costs that might be incurred otherwise in staff overtime expenses or idle time. Figure 7 shows the cost of these wait times by putting a dollar value on these wait times. A scheduling algorithm can help the clinics/ hospitals achieve a better schedule for their patients and also save the additional costs associated with waiting times. This research develops a mathematical model to do just that.

The remainder of this dissertation is organized as follows: Chapter 2 reviews the work of other researches and highlights the uniqueness of my research. Chapter 3 describes the mathematical model used for chemotherapy appointment scheduling. In

Chapter 4 the results generated from the proposed algorithm are compared to the baseline historical data. Chapter 5 concludes the research and enumerates the additions that can be made to the proposed algorithm as part of the future work.

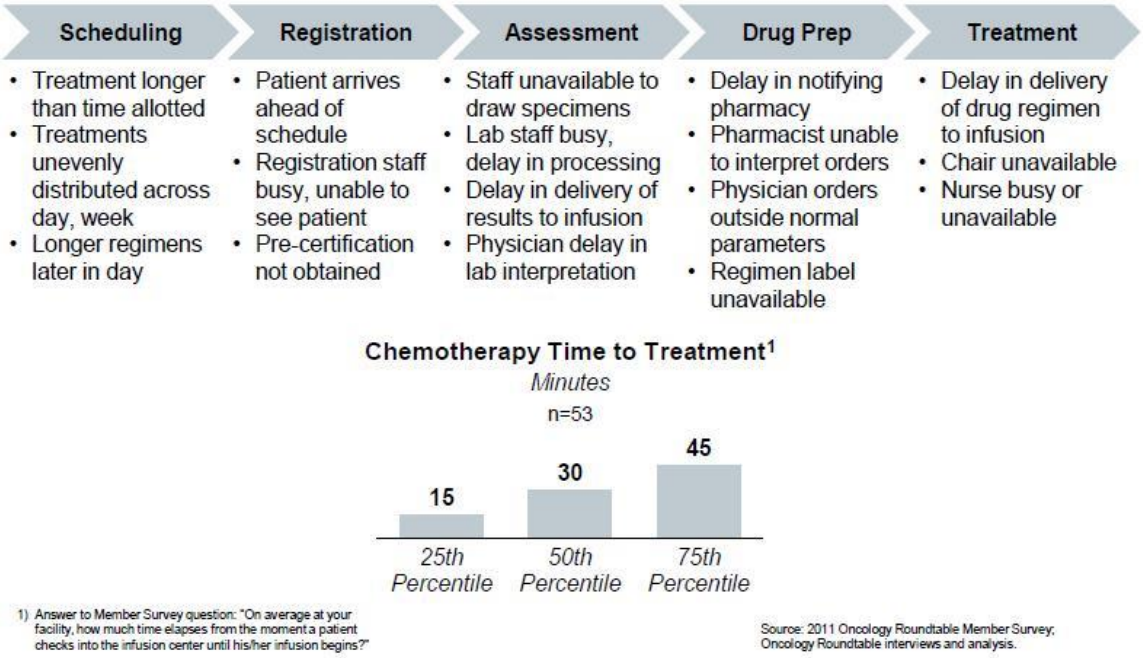

Figure 6: Common bottlenecks in chemotherapy scheduling process [13]

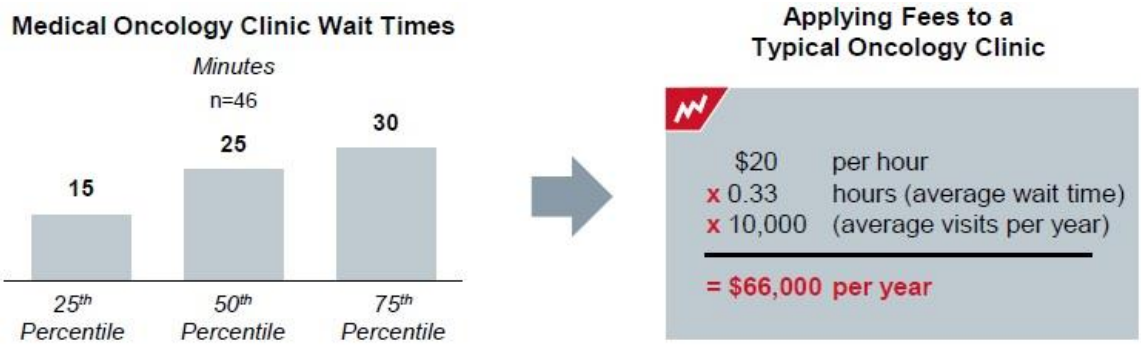

Figure 7: Dollar value for delays in a cancer clinic [13]

CHAPTER II

LITERATURE REVIEW

Extensive research has been done that deals with the clinical aspects of cancer diagnosis and treatment like better drugs, better delivery protocols, drugs that will minimize side effects, techniques to target the tumor better etc. But, to our know knowledge, there is very little research done that impacts the operational aspects of care deliver, specifically the scheduling problem for patients undergoing chemotherapy. Scheduling chemotherapy appointments is especially challenging because of constraints like variability in treatment times, their cyclic nature, the need for variable nursing time during each appointment and requirement of various other resources such as pumps, beds/chairs etc. In the following section a review of the literature is presented and work of researchers in the chemotherapy patient scheduling and resource utilization area is discussed briefly. A description of patient flow in a chemotherapy clinic is presented to understand the steps in the system and the associated bottlenecks.

2.1 Chemotherapy Process

Patients come to the outpatient clinics for their chemotherapy treatments on the appointment times that are always set in advance based on the treatment protocol, physician availability and patient convenience. The patients arrive and they are checked-in by a clerical associate or a secretary. Patient's blood is drawn either by a nurse or a

phlebotomist based on whether the patient has a port inserted under their skin or not. After the blood draw, the patient waits in the waiting area until the laboratory results become available. Sometime the patients get their blood drawn and analyzed at another facility prior to their actual appointment. If this is the case then the blood draw step is not repeated on the appointment day. Based on the results of the blood test, the physician decides if the patient can be infused on the appointment day and if the same drugs can be continued or not. The physician consultation can last from 15 minutes to 30 minutes [9]. If it is decided to continue with the same regime of drugs and if the patient seems to be fit/ ready for the infusion then the patient is sent to the infusion clinic. Sometimes the physician offices and the infusion clinic are available in the same facility. When the patients arrive to the infusion clinic they have to wait till the bed/ chair and the nurse becomes available. When all these resources become available and the pharmacy finishes mixing the patient's drugs then the nurse takes the patient to the infusion room and prepares the patient. This might take about 30 minutes and then the actual infusion starts. The infusion might last from 0.5 hours to 8 hours. This is referred to as the hang time. Figure 8 shows the important steps in the patient pathway in a chemotherapy clinic. Delivery of drugs or infusion is the most important and sometimes a time consuming step in this process. After finishing the session the patient departs to go home and the same cycle repeats before and during the patient's next session. Every cancer clinic follows more or less the same protocol. Patient education is also needed after the actual infusion process and is often overlooked. Dedicated nursing time is required for this education and should be added into the entire appointment duration while scheduling the appointment.

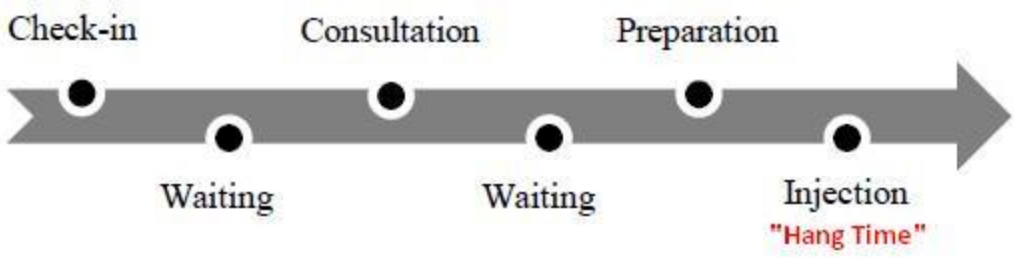

Figure 8: Chemotherapy infusion process at an outpatient cancer clinic [9]

2.2 Previous Work

Appointments are scheduled based on time required for pharmacy, blood draw, physician consultation or a combination of these three components along with the actual infusion time / hang time. Since there are various components in determining appointment durations for scheduling patients at infusion clinics many problems arise which are fixed by the nursing staff as the arise [12]. Researchers have proposed a few patient scheduling algorithms in order to effectively use all the required resources and minimize the associated problems.

Ahmed, ElMekkawy and Bates used a simulation model to design and evaluate the best schedule for patients and nurses. The model replicated the current state of operations of the clinic under study and various experiments were run with an aim to reduce the patient waiting time. In one of their experiments, they matched the patient arrival pattern to the nursing time availability that yielded the best results. The throughput was increased by 22.5%. They also significantly increased the resource utilization and reduced the average waiting time that was acceptable to the clinic under study. Laboratory testing times and pharmacy times were not included in the patient's overall treatment time. One of the main aims of their study was to design an efficient patient

scheduling template. They modified the existing scheduling template to efficiently assign appointments to patients. Patients were assigned a priority and appointments were given by sorting this list in a descending order. Priorities were estimated based on their "slack time" (slack time = clinic closing time – (arrival time + treatment time) and secondarily based on the longest service time first [14]. Hahn-Goldberg, Carter and Beck suggested a dynamic scheduling template to address the uncertainty in chemotherapy scheduling by combining the proactive and the online optimization model. They created a template based on the day's expected appointments defined as an empirical distribution. This deterministic optimization model was based on historical data. This was considered as an offline optimization model which was based on three stage flexible flow shop model. The objective function of this model was to minimize makespan which was in turn believed to reduce the patient waiting time. The online optimization model was only used when there was a conflict between appointments and the request could not fit the template [15]. Their assumptions include the time taken for drug preparation but not for the laboratory tests [15]. In both the studies discussed so far the nurse to patient ratio or patient acuities is not considered as one of the modeling parameters. Chemotherapy clinics tend to book appointments based on scheduler's/ nurse's experience and patient preferences in a very ad-hoc manner without using much optimization. Often only one resource, nursing availability, is considered while making scheduling decisions instead of all the necessary resources like beds, chairs etc. Chabot and Fox defined acuity and patient classification system to increase throughput and distribute patients through the day thereby balancing the nurses' workload. Before implementing the solution that they proposed, the cancer clinic under study was using a fixed scheduling algorithm. They fixed schedule did not

consider the actual nursing time available per day and the patients were scheduled using a five column grid. A maximum of 10 patients were scheduled per column at 15 minute intervals. The lunch breaks for the nurses were not staggered. They studied the current state of the process and as one of the solutions proposed a 30, 60 and 90 minute acuity level and were based on whether pre-medications were required or not. They also considered that the chair time or the actual hang time is different than the nursing time required for a patient. The acuity levels determines the direct nursing time required for a patient and the hang time or chair time is the time required for the infusion. Patients were assigned to nurses on a daily patient-scheduling log by matching nurses' scheduled hours with patient care time requirements [16]. Due to an unbalance workload nurses often had to skip their lunches or take breaks whenever they could instead of dedicated time to do so. In their model, they dedicated a staggered schedule for lunches thereby giving nurses a much needed break from their work. Their patient classification and acuity system resulted in increasing throughput maintaining the same staffing levels, increased patient satisfaction and better coordination of physician appointments and infusion appointment [16]. Dobish proposed a next-day scheduling model in which laboratory appointments and physician appointments were done one day prior to their treatment and the actual infusion was done on the next day. The patients were categorized in one of five levels of chemotherapy protocol. These five levels were defined by the time required to administer the drugs. The patients with levels assigned to them were then placed on a scheduling template based on available nursing time slots. Pharmacy, responsible for mixing chemotherapy drugs, worked along with the next day scheduling model to prioritize their workload so that chemotherapy drugs were available at the precise appointment time the

following day. This also reduced the pharmacy's workload in preparing drugs for patients whose appointments were cancelled or rescheduled. This reduced the overall patient waiting time for all the resources to become available and improve efficiency for both pharmacy and nursing [17]. Patients who could not be schedule using the next day scheduling technique were identified and not considered as a part of the overall patient mix for this study [17]. Cusack, Jones-Wells and Chisholm [20, 24], Moore and Hastings [19] developed a tool called the Ambulatory Intensity System (AIS)/ Ambulatory Nursing Intensity system with an objective to quantify nursing time requirement for a heterogeneous patient populations with adaptability across different specialty areas in an outpatient setting. After conducting an extensive literature review they formulated a 6-level intensity system that correlated the workload parameters and intensity levels with nursing time requirement. Direct and indirect nursing activities were taken into consideration and all the levels and the activities under that level were clearly defined. Figure 9 shows the definition and description of each level. They also developed a factor of 0.8 Full Time Equivalent (FTE) for nursing time requirement for non-scheduled patients to do activities such as telephone triage, care co-ordination and research team meeting etc. Their system was used to justify the need for hiring additional nurses and adjust the staffing patterns based on intensity trends defined and illustrated by the tool [19]. This tool enabled the nursing managers of the clinics where it was piloted to quantify workload, examine and match the staffing to the workload demand and appropriately allocate resources [20]. Figure 10 shows the Intensity tool and the way it was used to calculate the staffing requirements [24]. West and Shere [23] adopted the tool developed by Cusack, Jones-Wells and Chisholm and modified it to fit their needs

and achieved enhanced patient and staff satisfaction. The terms Ambulatory nursing intensity system, acuity rating system and patient classification system are often used interchangeably in literature but they mean the same. It is a system to quantify nursing time requirement based on the patient care activities which are in turn depend on the patient condition. The more the time required, higher is the acuity. Following the same concept Hawley and Carter developed an acuity rating system by which patients were assigned to one of five levels of acuity based on the "ideal" time required for treatment. Ideal time was defined by the total treatment time and additional time required with the patient/ family members, blood draws, patient education etc. They calculated that a maximum acuity of 22 can be assigned to a single nurse each day. After piloting this system for several months they developed a "Treatment Length Scheduling Template" as a communication tool for team members [18]. Most of the work discussed so far deals with acuity based scheduling and defining efficient scheduling templates for chemotherapy scheduling. Turkcan, Zeng and Lawley suggested acuity based two-stage rolling horizon approach to formulate mathematical models for both the planning and scheduling problems in chemotherapy operations. Planning problem is solved in stage 1 to find the treatment start day (first day of patient's treatment cycle). Acuity levels, treatment days are calculated at this stage and patients are assigned to chairs, nurses and appointment times. Figure 11 shows the planning and scheduling methodology. The goal of stage 1 was to minimize the deviation from patient's optimal treatment plan due to unavailability of nursing time. Integer programming model is used to solve the planning problem with a goal to minimize treatment delays. Each day was divided in to 30 minute time slots. Patient acuity was calculated per slot and nursing time required during each

slot was assigned. Acuity violation was one of the constraints for the model and hence the nursing resource was never over utilized but it was concluded that there were not enough nurses to handle the patient load with their proposed model.

Level	Time	Category	Descriptors
I	0–15 minutes	Integrative care	Psychosocial support
		Coordination of care	Order supplies that patient will pick up
II	16–30 minutes	Infusion/medication administration	Antibiotics
		Specimen collection	Per central venous device or peripheral vein
		Chemotherapy/ biologics	Includes simple cassette change
		Procedure/recovery	Bone marrow aspiration/biopsy; lumbar puncture; paracentesis, thoracentesis; recovery from bronchoscopy, colonoscopy, and endoscopy
		Integrative care	Inpatient admission; may include dressing change, IV placement, nontunneled catheter removal (PICC, SICC, Apheresis), port access, antibiotics, teaching, tube feeding, tracheostomy care, and psychosocial support, consult
III	31–60 minutes	Assessment	Assessment involving consults; health assessments
		Infusion/medication administration	Antibiotics; hydration
		Specimen collection	Includes catheter dressing, catheter removal, and trouble shooting
		Chemotherapy/ biologics	Observe for sensitivity reactions; increased observation parameters per MD orders; includes ambulatory pump cassette changes
		Procedure/recovery	Difficult bone marrow aspiration; complicated lumbar puncture, paracentesis, thoracentesis, or complicated recovery
		Integrative care	Treatments and assessments requiring more supportive nursing interventions
IV	61–120 minutes	Assessment	Fever workup; pain management; complex dressing change such as ulcerations; assessments requiring increased psychosocial support
		Teaching	First injection teaching; chemotherapy/drug teaching associated with symptom management
		Blood/cellular	Stem cell, donor lymphocytes, packed red blood cells, platelets, fresh frozen plasma
		Chemotherapy/ biologics	Multiple chemotherapy agents with premedications
		Procedure/recovery	Increased monitoring for bone marrow aspiration/biopsy, lumbar puncture, thoracentesis, bronchoscopy, colonoscopy, and endoscopy
		Integrative care	Increased need for psychosocial support and coping assistance
V	121–240 minutes	Assessment	Assessment related to disease progression or new therapies; fever workup with multiple site sampling; assessment with multiple symptom management
		Infusion/medication administration	Multiples of antifungals, antibiotics, IV hydration, electrolyte replacement, medications to manage diarrhea or pain
		Serial test/ pharmacokinetics	Protocol specific blood draws
		Blood/cellular	Multiple types of infusions for the same patient; reaction interventions
		Chemotherapy/ biologics	Includes multiple chemotherapy agents requiring hydration and premedications
		Procedure/recovery	Longer recovery required or increased monitoring parameters for bone marrow aspiration/biopsy, lumbar puncture, paracentesis, thoracentesis, recovery from bronchoscopy, colonoscopy, endoscopy
		Integrative care	Increased time required for multiple, complex physical and supportive nursing interventions, including decision-making support, complex psychosocial support and teaching related to disease progression and new therapies
VI	>4 hours	Assessment	Acute physiologic events
		Infusion/medication administration	Patient came in for hydration, then required multiples of antibiotics, blood, antifungals, electrolytes, and medications for pain or diarrhea
		Blood/cellular	Donor lymphocytes; patient requires even longer time for multiple infusions and reaction interventions
		Chemotherapy/ biologics	Chemotherapy with specimens; patient requires longer infusion time; Rituxin, Day 1 chemotherapy including making calendars
		Integrative care	Nursing interventions to help patient/family cope with need for inpatient admission

Figure 9: Ambulatory Intensity System (AIS)/ Ambulatory Nursing Intensity system [19]

		Number of Patient Encounters									
		1	2	3	4	5	6	7	8	9	10
Intensity Levels	**Average Time**	**Staff Requirements**									
I 0-15 min	7.5 min	0.01	0.03	0.04	0.06	0.07	0.09	0.10	0.12	0.13	0.15
II 16-30 min	22 min	0.05	0.09	0.14	0.18	0.23	0.28	0.32	0.37	0.41	0.46
III 31-60 min	45 min	0.09	0.19	0.28	0.38	0.47	0.56	0.66	0.75	0.84	0.94
IV 61-120 min	90 min	0.19	0.38	0.56	0.75	0.94	1.13	1.31	1.50	1.69	1.88
V 121-240 min	180 min	0.38	0.75	1.13	1.50	1.88	2.25	2.63	3.00	3.38	3.75
VI >240 min	360 min	0.75	1.5	2.25	3.00	3.75	4.50	5.25	6.00	6.75	7.50

Intensity Level: Time required to deliver nursing care (direct and indirect)
Average Time: Average nursing time for each Intensity Level
Staff Requirements: RN time required to see a patient at a given intensity level, reflected as a fraction of 480 (minutes in an 8-hour shirt)

Example:
If during a shift seven Level III patients (0.66) and six Level II patients are treated (0.28), nursing hours needed are 0.66 plus 0.28, which equals 0.94 or approximately one RN FTE.

Figure 10: Intensity tool used to calculate staffing requirements [24]

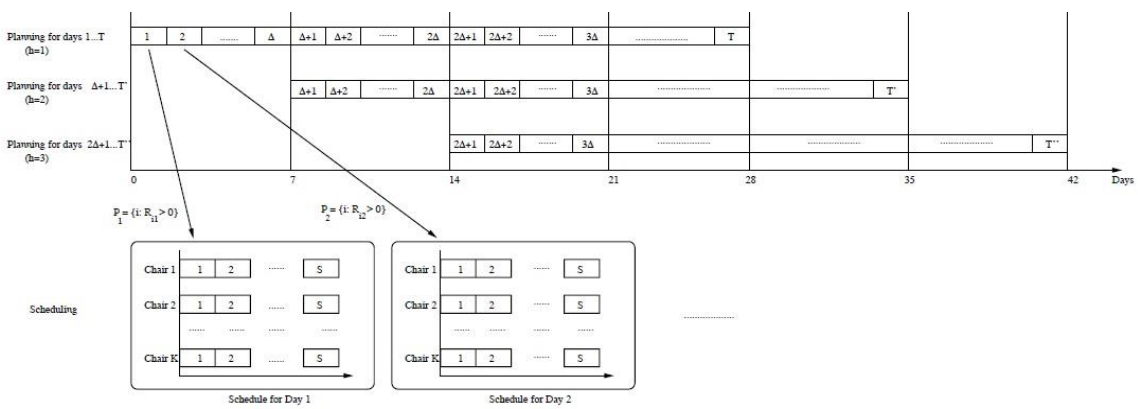

Figure 11: Planning and scheduling methodology [21]

Their model generated a more balanced workload for nurses and smaller treatment delays compared to the current practice (experimentally set up). Stage 2 solved the scheduling problem in which daily schedule for a patient is fixed for the days assigned in stage 1. Two different approaches were sued to solve the scheduling problem: an integer programing models and a heuristic ($ALTT_t$). The $ALTT_t$ is similar to longest

processing time rule, and is used to limit the total acuity level and the number of treatment starts per nurse. A rolling horizon methodology is suggested to solve the planning and scheduling algorithms sequentially to balance the chair and the nurse utilization per slot [21]. Mathematical models have been developed to reduce patient waiting times, improve patient satisfaction and increase business productivity to efficiently manage and schedule resources other than nursing time requirement. There are studies that specifically investigate in better managing bed capacity requirement, scheduling oncology physicians to match the patient demand using mixed integer programming models [9]. Some research is done in efficiently preparing chemotherapy drug doses using minimizing the maximum tardiness of jobs algorithm [25].

Research discussed so far fails to give a comprehensive list of acuity levels for various treatment durations. In addition to that, it is assumed that all the nursing time is required at the beginning of the appointment. The nursing time required during the entire length of each appointment varies and in my research it is defined as the nurse-to-patient ratio. I am not defining an acuity based scheduling model but a weighted mathematical model that assigns patients to nurses based on how far are they into their appointments. The uniqueness of my research lays in the fact that I consider additional nursing time before and after the treatment. Also, different nurse-to-patient ratios are assigned based on their appointment status via a new patient, returning patients or patients with consecutive appointments. All of this is done with a goal to reduce nurse utilization and balance the nurses' workload through the day. This would also result in reduced patient waiting time.

2.3 Research Objectives

The objectives of this research are as follows:

1. Mathematically formulate a scheduling algorithm that optimally schedules patients per day while balancing the nursing workload throughout that day.
2. Test the nurse utilization using the schedule generated by the mathematical model with the current state of the cancer clinic at Parma Community General Hospital.
3. Investigate and quantify operational impact of various real-life scenarios using the schedule generated by the scheduling algorithm at the cancer center by developing a discrete event simulation model.

CHAPTER III

CHEMOTHERAPY APPOINTMENT SCHEDULING PROBLEM FORMULATION

In this chapter a patient scheduling algorithm is presented which allocates variable nursing time to patients based on their appointment types. A mathematical model generates schedule for patients' next appointment and not for the entire course of their treatment. This is done to accommodate any changes in the patient's treatment schedule that might happen over their entire course of treatment. The number of rooms, chairs/ beds etc. is considered a fixed capacity resource. The only resource that can be adjusted based on the demand is the available nursing capacity. Hence this model considers nursing availability as a flexible resource and assigns patients to nurses with a goal of balancing workload for nurses and schedule patients appointments such that their waiting time for their appointments is reduced. Waiting time is defined as the delay between patient arrival/ check-in and actual start of the patient's appointment.

3.1 Model Assumptions and Definitions

We assume that the length of the treatment is known before scheduling the appointment. This is a realistic assumption because the length of the treatment is dependent on the drugs and the clinician would have this information in advance. This information would have to be communicated by the clinician to the scheduler. Another

assumption of this model is that all chemotherapy patients fall in one of the following three categories:

- Category 1 - New patients: Patients that have never undergone chemotherapy before or returning patients who are starting a new course of treatment or a new drug.
- Category 2 - Returning patients: Patients that have competed their first chemotherapy session and are returning for their successive sessions.
- Category 3 - Patients with 2 consecutive appointments on the same day.

The nursing time requirement changes based on which category the patients falls under and hence it is important for the clinician to communicate this information to the scheduler along with the treatment duration.

Chabot and Fox [16] proposed an acuity based scheduling algorithm in which they assume that all the nursing time is required at the beginning of the appointment. The time required to monitor the patient during their appointment, however small, is not accounted for. The nursing time requirement during the appointment may not be as intense as it is at the beginning of the appointment but must be accounted for. Turkcan, Zeng and Lawley [21] propose an algorithm in which patients are assigned to a nurse based on their acuities during each slot in a day. This accounts for the nursing time requirement during the treatment. They assume that a nurse can start only one patient treatment per slot but not such assumption is made for ending appointments.

In this research each day is divided into 15 minute time slots. We assume standard working hours for the clinic in a day (8 am to 4.30 pm) which translates to 34 slots per day. Half an hour is set aside for nurses to take lunch breaks and the breaks are

staggered. Nursing time availability is calculated per slot per day. For example: if we have 3 nurses starting their shifts at 8 am then from 8 am to 8.15 am the total available nursing time would be 3 (if there are no patients scheduled for that day). Similarly if one of the nurses takes her lunch break at 11.30 am then the total nursing time available between 11.30am and 12pm would be 2. Patients are scheduled as the requests for appointments are generated. Patient-to-nurse ratio is assigned to each patient per slot. The ratio changes based on how far along are they in their appointment. The patient-to-nurse ratio changes throughout the appointment because nurses need to perform different tasks at different time. The demand for nursing time is not constant throughout the appointment. It is heavier at the beginning and end and lighter in the middle. We have divided each appointment into three distinct sections: the start, the middle (actual hang time) and the end. We assume that the actual appointment length does not include the start and the end time. Start and the end times are added to the appointment duration based on the patient category. Start and end times are used by the nurses for patient education and getting the patient ready for infusion. Thus, the actual duration for which the model assigns nurses to patients is:

Actual appointment duration = Start time + length of the appointment + End time

The nursing time requirement and the actual appointment duration for all three patient categories are as follows:

- Category 1: New patients: For a new patient an hour is required to start the appointment hence the start time in 1 hour. The nurse to patient ratio during this time

is 1. The actual appointment length varies is between 1 and 8 hours. The nurse to patient ratio during this time is 0.1. Half hour is required to end the appointment and nurse to patient ratio during this time is 1 again. Figure 12 shows an example of these calculations for a four hour long appointment. Four hour appointment translates to a 5 and half hours or 22 slots with variable nursing time required during each of the 22 slots. The nurse-to-patient ration during the first four slots and the last two slots is 1. The nurse-to-patient ratio for all the slots in between is 0.1.

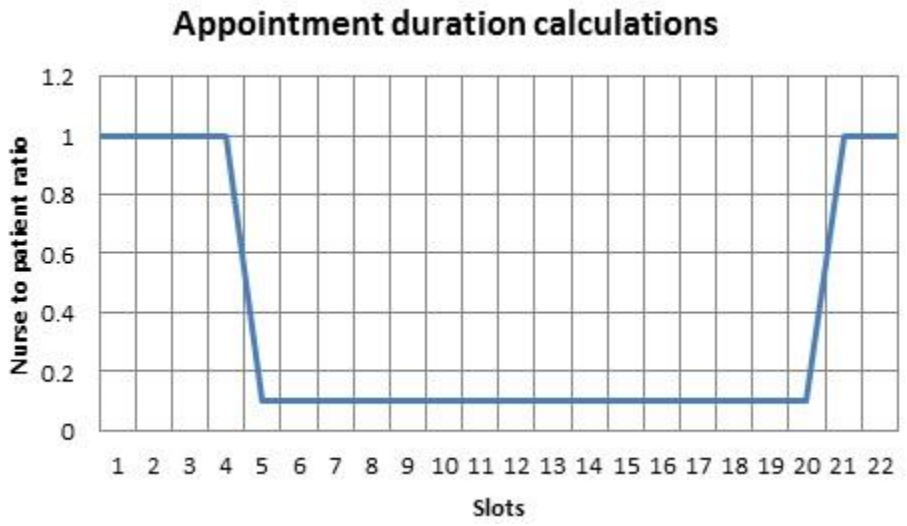

Figure 12: Nurse-to-patient ratio for patient category = 'NEW'

- Category 2: Returning patients: For returning patient half an hour is required to start the appointment hence the start time in half hour. The nurse to patient ratio during this time is 1. The actual appointment length varies between 1 and 8 hours. The nurse to patient ratio during this time is 0.1. Fifteen minutes are required to end the appointment and nurse to patient ratio during this time is 1 again. Figure 13 shows an example of these calculations for a four hour long appointment. A four hour appointment is translated to a 4 hours 45 minutes, or 19 slots with variable nursing

time required during each of the 19 slots. The nurse-to-patient ratio during first two slots and last slot is 1. The nurse-to-patient ratio for all the slots in between is 0.1.

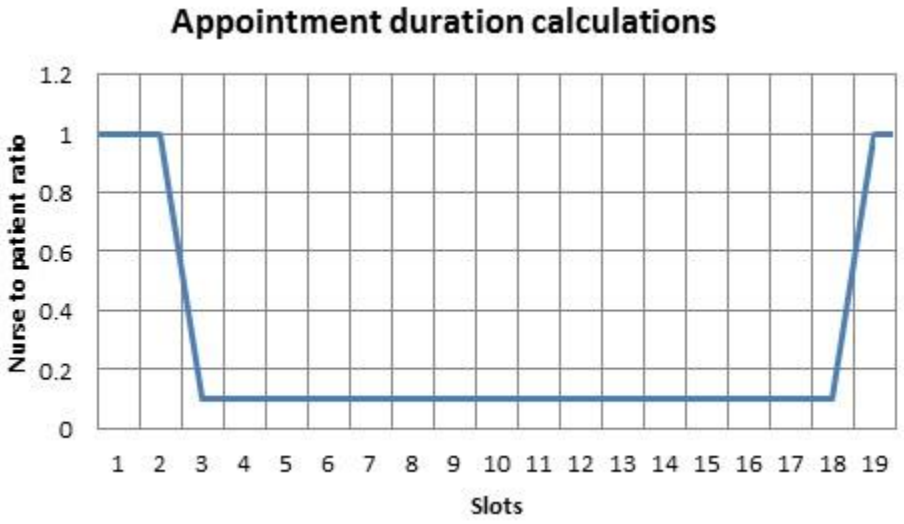

Figure 13: Nurse-to-patient ratio for patient category = 'RETURNING'

- Category 3: Patients with 2 consecutive appointments: For patients for 2 consecutive appointments, half an hour is required to start their first appointment hence the start time in half hour. The nurse to patient ratio during this time is 1. The actual appointment length is calculated by adding both appointment durations. The nurse to patient ratio during this time is 0.1. There is no dedicated end time between the two appointments. Fifteen minutes are required to end the second appointment and nurse to patient ratio during this time is 1 again. Figure 14 shows an example of these calculations for two, two hour long appointments. Thus a patient with two consecutive two hour long appointments can be considered as a patient with one four hour long appointment for a returning patient. The nurse-to-patient ration during first two slots and last slot is 1. The nurse-to-patient ratio for all the slots in between is 0.1.

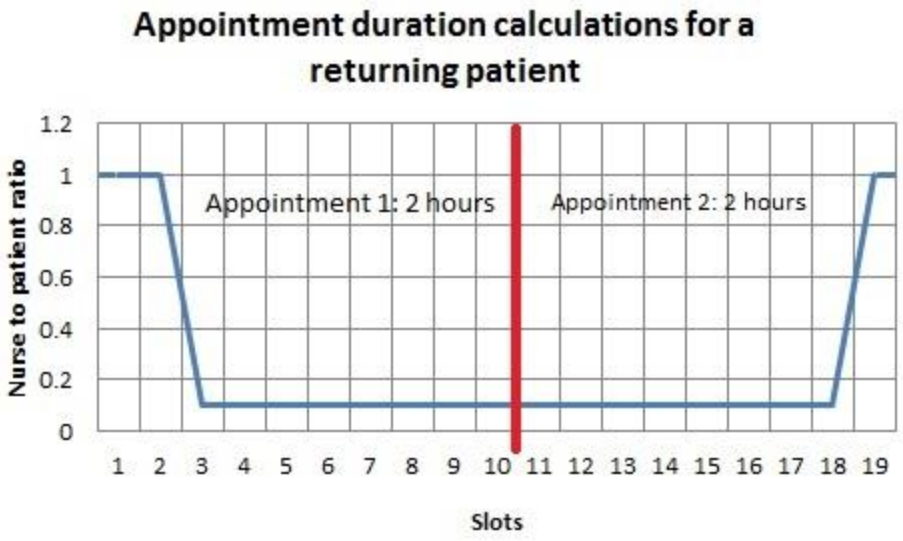

Figure 14: Nurse-to-patient ratio for patient category = 'PATIENTS WITH 2 CONSECUTIVE APPOINTMENTS'

The pharmacy times and the laboratory times are not included in this model. However, the chapter IV of this thesis addresses that. Another assumption for this model is that if we are scheduling the first patient of the day then start time of the first appointment is always assigned to the slot between 8am to 8.15am (1st slot). These nurse-to-patient ratios and the assumptions are based on extensive field and literature research. Interviews of direct care givers, ancillary staff and the facility manager were conducted at a facility (discussed in detail in chapter IV: case study) to formulate these measures.

3.2 Mathematical Model

The following section describes the mathematical model developed to optimally schedule patients daily while balancing the nursing workload for that day. It is an

iterative algorithm that generates the best 'start time' for patient appointments by considering the scheduling volume and available nursing time for a particular day.

3.2.1: Model Variables

Following variables would be used throughout this research. All the variables are initialized in the first step.

s = Number of slots (fixed) = 36

p = Number of patients

t = Patient type (new, returning)

U_i= Nurse Utilization per slot (i = 1, 2… s)

$A1_i$ = Number of nurses available per slot at beginning of the day (i = 1, 2… s)

$A2_i$ = Number of nurses available per slot after scheduling patients (i = 1, 2… s)

w_{ip}= Patient to nurse ratio per slot per patient (i = 1, 2… s ; p = 1, 2… p)

b_i = Slot number (i = 1, 2… s)

d_p = Appointment duration in terms of number of slots per patients (p = 1, 2… p)

3.2.2 Objective function

The objective of this algorithm is to balance the nurses' workload and distribute work throughout the day by optimally assigning patient appointments. To achieve this, the algorithm assigns patients per slot while checking for nurse availability in that slot. Just the average nursing time required or a count of patients in a slot is not a good measure because the nursing time requirement per slot is different based on the patient category and the stage of the infusion (start, end or middle). The objective function is to keep the nurse utilization U_i per slot (nurse utilization per slot after scheduling patients)

as close to the nurse availability in that slot as possible. There would be some time slots in which the nurses would be underutilized because of various nurse-to-patient ratios that the algorithm assigns for each patient. But underutilization doesn't mean idle time because the nurses can use this time for non-direct patient care activities. There are situations in which a patient needs to be scheduled on a particular day in which the nurses' schedule is already full. On such days, there is also a possibility that the nurses would be overutilized in some slots. But as long as the overall nurse utilization at the end of the day is close to the nurse availability at the beginning of the day, the nurses would be utilized optimally.

For each patient schedule,

$$U_i \sim A1_i \qquad (i = 1 \ldots s)$$

This algorithm assumes that the nurse that starts the appointment has to finish the entire start stage and the nurse that starts to end the appointment has to finish the entire end stage. The middle stage is not nurse specific. Any available nurse can check on the patients during the middle stage.

3.2.3 Model Algorithm

It is a four step algorithm in which step one is 'Initialization'. This step is done only once per day before scheduling any patients for that day. For all the subsequent patients the algorithm follows only steps 2, 3 and 4 iteratively and recursively. At the beginning of the day, when the schedule for the day in question is wide open, the nurse utilization per slot is zero and nurse availability per slot is calculated as follows:

Step 1: Initialization

A1 = total number of nurses available to work on that day

$A1_i = A1_i$ (i = 3…16 and 23 … 34)

$A1_i = A1_i - 1$ (i = 1, 2, 17 … 22)

$A1_i = A1_i - 2$ (i = 35, 36)

Between slots 17 and 22 the nurse availability reduces by 1 because of staggered lunch breaks of half hour. Nurse availability is reduced by 1 in slots 1 and 2 and by 2 in slots 35 and 36 because for staggered shifts. Figure 15 shows this step in an excel worksheet.

Slots	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
Time	8:00	8:15	8:30	8:45	9:00	9:15	9:30	9:45	10:00	10:15	10:30	10:45	11:00	11:15	11:30	11:45	12:00	12:15
A1	2	2	3	3	3	3	3	3	3	3	3	3	3	3	3	3	2	2
A2	2	2	3	3	3	3	3	3	3	3	3	3	3	3	3	3	2	2
U	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Slots	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36
Time	12:30	12:45	13:00	13:15	13:30	13:45	14:00	14:15	14:30	14:45	15:00	15:15	15:30	15:45	16:00	16:15	16:30	16:45
A1	2	2	2	2	3	3	3	3	3	3	3	3	3	3	3	3	1	1
A2	2	2	2	2	3	3	3	3	3	3	3	3	3	3	3	3	1	1
U	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Figure 15: Step 1, Initialization, of the proposed scheduling algorithm

Step 2: Calculating the 1st slot for starting the appointment

Before calculating the appointment start time the duration of the appointment is converted from hours to number of slots.

For patient category = ‘new’ or ‘returning’

d = appointment duration (in hours) * 4

For patient category = ‘patient with 2 consecutive appointments’

d = (1st appointment duration + 2nd appointment duration) (in hours) * 4

Step 2 also calculates the number of available nurses after scheduling patients. At the beginning of the day, when there are no patients scheduled for that day (p=0), $A2_i$ is equal to $A1_i$. The slot number is also calculated in this step in which the start stage of the patient's appointment can start. It is an iterative step and it starts by sorting $A2_i$ in a descending order. The slot with is highest $A2_i$ value is selected and assigned as the starting time of the appointment start stage. Three constraints have to be satisfied before fixing this slot as the appointment starting time. The first constraint is that the appointment should end before the clinic's closing time. In other words, the total number of slots required for the entire appointment should be less than or equal to the slots available from the first slot selected. The second constraint is to check for nurse availability in the start and the end phase of the appointment. To start the appointment we need 2 or 4 continuous slots based on patient category (new or returning) in which the nurse availability ($A2_i$) is greater than 1. The third constraint is to have 1 or 2 continuous slots to start the end stage of the appointment based on patient category (new or returning) in which the nurse availability is greater than 1. If any one of these constraints is violated then the slot with next highest $A2_i$ value is selected for assignment and this process continues until all the constraints are satisfied.

$b = \text{first max}\ (A2_i) \quad s.\ t$	$(i = 1 \ldots\ldots s)$
$s\text{-}b \geq d + 6$	for t = 'new'
$s\text{-}b \geq d + 3$	for t = 'returning'
$A2_b, A2_{b+1}, A2_{b+2}, A2_{b+3}, A2_{b+d+5}, A2_{b+d+6} >= 1$	for t = 'new'
$A2_b, A2_{b+1}, A2_{b+d+3} >= 1$	for t = 'returning'

Step 3: Assigning weights per slot for a patient appointment

Step 3 of the algorithm assigns the appropriate nurse-to-patient ratios in slots for each patient. This can also be referred to as the 'weight' of the appointment per slot. The weight for the start and end stage is 1 which means that the nurse has to dedicate 100% of her time to that patient in the start and end stage. The nurse-to-patient ratio in the middle stage is 0.1. This means that the nurse has a minute and a half per 15 minutes to check back on the patients getting their chemotherapy infusion.

$w_{s1} = 1$	(s1 = b, b+1, b+2, b+3)	for t = 'new'
	(s1 = b, b+1)	for t = 'returning'
$w_{s2} = 1$	(s2 = b+d+5, b+d+6)	for t = 'new'
	(s2 = b+d+3)	for t = 'returning'
$w_{s3} = 0.1$	(s3 = b+4, b+5, ….. b+d+4)	for t = 'new'
	(s3 = b+2, b+3, ….. b+d+2)	for t = 'returning'

Step 4: Calculate the nurse utilization after scheduling a patient

Step 4 calculates the nurse utilization after assigning patients to a daily schedule. Utilization per slot (U_i) is obtained by adding the weights in that slot for all the scheduled appointments. If the U_i greater than $A1_i$ in that slot then it means that that the nurses are overutilized in that slot whereas if U_i is less than $A1_i$ the nurses are underutilized. Nurses' availability per slot after scheduling patients ($A2_i$) is also calculated by subtracting U_i from the $A1_i$ in that slot.

$$U_i = \sum_{j=1}^{p} w_{ji} \qquad (i = 1 \ldots s)$$

$$A2_i = A1_i - U_i \qquad (i = 1 \ldots s)$$

Figure 16 shows an example of three patients with appointment durations as 4 hours, 5 hours and 2 hours in that order. It is a recursive algorithm because steps 2, 3 and 4 are repeated before scheduling each patient.

Slot numbers				1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
A1				2	2	3	3	3	3	3	3	3	3	3	3	3	3	3	3	2	2
A2				2.0	2.0	2.0	2.0	1.9	1.9	2.8	2.8	2.8	2.8	2.8	2.8	2.8	2.8	2.8	2.8	1.8	1.8
U = ∑wji				0.0	0.0	1.0	1.0	1.1	1.1	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2
Pt. Name	Appt Date	Appt Dur	Slot (b)	8.00	8.25	8.50	8.75	9.00	9.25	9.50	9.75	10.00	10.25	10.50	10.75	11.00	11.25	11.50	11.75	12.00	12.25
Patient1	5/5/11	4	3			1.0	1.0	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
Patient2	5/5/11	5	5					1.0	1.0	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
Patient3	5/5/11	2	23																		

Slot numbers				19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36
A1				2	2	2	2	3	3	3	3	3	3	3	3	3	3	3	3	1	1
A2				1.8	1.8	0.9	1.9	1.9	1.9	2.8	2.8	1.9	2.9	2.9	2.9	2.9	2.9	2.0	3.0	1.0	1.0
U = ∑wji				0.2	0.2	1.1	0.1	1.1	1.1	0.2	0.2	1.1	0.1	0.1	0.1	0.1	0.1	1.0	0.0	0.0	0.0
Pt. Name	Appt Date	Appt Dur	Slot (b)	12.50	12.75	13.00	13.25	13.50	13.75	14.00	14.25	14.50	14.75	15.00	15.25	15.50	15.75	16.00	16.25	16.50	16.75
Patient1	5/5/11	4	3	0.1	0.1	1.0															
Patient2	5/5/11	5	5	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	1.0									
Patient3	5/5/11	2	23					1.0	1.0	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	1.0			

Figure 16: Steps 3 and 4 for the proposed scheduling algorithm

CHAPTER IV

RESULTS

This thesis deals with chemotherapy appointment scheduling and operational planning. The scheduling part is done using the proposed mathematical model. A case study is also presented in this section in which the mathematical model is tested in a real clinical environment. The planning part of this thesis is done using a discrete event simulation modeling (DESM) approach. A model is developed and various what if scenarios are tested to understand their effect in the performance of the Cancer center under study.

4.1 Excel-VBA template

The proposed mathematical model is converted into a full-fledged scheduling tool using MS Excel and VBA. MS Excel was selected as a template for scheduling because Excel is a tool that is widely used in the healthcare industry. That makes it a little intimidating for process owners and managers to use it and is simple to understand. Excel is the front end of the tool. The modeling logic is developed using VBA scripts. Thus VBA becomes the backend of this tool. Data such as patient name, appointment date, appointment duration and appointment status (new, returning patient) is entered by the clerical associate/ secretary on the excel worksheet. This data is given to her by the oncology nurse by filing out a scheduling template for each patient at the end of their

appointment or physician visit. It is an automated process and once the data is entered in the Excel sheet, the VBA script running at the background generates an appointment time for the patient. The front end is shown in figure 17.

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W
1	Nurse availability at beginning of day (A1)					2.0	2.0	3.0	3.0	3.0	3.0	3.0	3.0	3.0	3.0	3.0	3.0	3.0	3.0	3.0	3.0	2.0	2.0
2	Calculate	Nurse Availability (A2)				2.0	2.0	2.0	2.0	1.9	1.9	2.8	2.8	2.8	2.8	2.8	2.8	2.8	2.8	2.8	2.8	1.8	1.8
3	Results	Nurse Utilization (U)				0.0	0.0	1.0	1.0	1.1	1.1	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2
4	Name	Appt Date	Appt Dur	Status	Slot	8.00	8.25	8.50	8.75	9.00	9.25	9.50	9.75	10.00	10.25	10.50	10.75	11.00	11.25	11.50	11.75	12.00	12.25
5	Patient 1	5/5/11	4		3			1.0	1.0	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
6	Patient 2	5/5/11	5		5					1.0	1.0	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
7	Patient 3	5/5/11	2		23																		

8	X	Y	Z	AA	AB	AC	AD	AE	AF	AG	AH	AI	AJ	AK	AL	AM	AN	AO
	2.0	2.0	2.0	2.0	3.0	3.0	3.0	3.0	3.0	3.0	3.0	3.0	3.0	3.0	3.0	3.0	1.0	1.0
	1.8	1.8	0.9	1.9	1.9	1.9	2.8	2.8	1.9	2.9	2.9	2.9	2.9	2.9	2.0	3.0	1.0	1.0
	0.2	0.2	1.1	0.1	1.1	1.1	0.2	0.2	1.1	0.1	0.1	0.1	0.1	0.1	1.0	0.0	0.0	0.0
	12.50	12.75	13.00	13.25	13.50	13.75	14.00	14.25	14.50	14.75	15.00	15.25	15.50	15.75	16.00	16.25	16.50	16.75
	0.1	0.1	1.0															
	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	1.0									
					1.0	1.0	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	1.0			

Figure 17: Front end of MS Excel-VBA tool

4.2 Case Study

The schedule generated using the proposed scheduling algorithm was compared to the historical schedule followed at a Parma Community General Hospital's (PCGH) Cancer Center. PCGH is a community hospital in northeast Ohio offering a full range of treatments for cancer patients, including medical oncology/ chemotherapy and radiation oncology. Currently, for medical chemotherapy, the Cancer Center does not use any scheduling algorithm and most of the scheduling is done as per patient preference. The schedulers use rules to schedule patient's next appointment but they don't have an

automated algorithm to generate appointment time based on the nursing workload for that day. They usually schedule longer appointments earlier in the day and try not to schedule any appointment after 2.30 pm. These rules may or may not be followed and hence nurses are often over or under worked using the current method for scheduling appointments. Various appointment types at the cancer center are shown in table 1. Only the first five types of appointments are scheduled ahead of time. Paracentesis, Hydration, Injection – Chemo, IVAD Flush, Bone Marrow and Platelets are not considered as pre-scheduled appointments. They are treated as same day appointments because some of them take only 15 minutes and those appointments do not require an oncology nurse to overlook their administration. Cancer center at Parma Community General Hospital (PCGH) has 3 full time nurses and 13 patient rooms. They have 2 full time clerical associates/ secretaries to schedule chemotherapy appointments. The cancer center is open from 8am to 5pm, Monday through Friday.

Table 1: Duration in hours for all chemotherapy treatments performed at PCGH

Appointment Type	**Duration (hours)**
Blood Transfusion	4,8
Chemo Drug Change	2,3,4,5,6
Chemo New Patient	1,2,3,4,5,6
Chemo Subsequent	1,2,3,4,5,6
Non-Chemo IV Infusion	1,2,3,4,5,6
Paracentesis	1.5
Hydration	2.5
Injection - Chemo	15 mins
IVAD Flush	15 mins
Bone Marrow	2
Platelets	2

Historical scheduling data was collected from the cancer center's database for over three months (1st June 2011 to 31st August 2011) consisting of 65 work days. The workload for the nurses was assigned just like the excel model for the appointment start times that were given out by the schedulers to actual patients (start, middle and end time with the appropriate nurse-to-patient ratios). The nurses' shifts were staggered to accommodate the opening and closing time of the cancer center. Two nurses were assigned the 8 am to 4.30 pm shift whereas the third nurse was assigned the 8.30 am to 5 pm shift. Each nurse had a dedicated lunch time of half hour where the nurse availability was made zero. The mathematical model was developed using MS Excel and a VBA script. A total of 913 patients were compared over the entire study period with an average of 14 patients per day. The objective function was overridden for some days when the patient volume was high. This was necessary since we were comparing the already scheduled patients and we could not change the way they were scheduled in the past. Figure 18 shows the comparison of average nurse utilization per time slot (U_i) after scheduling all the patients using the proposed algorithm with the historical data (baseline). The graph also shows nurses availability at the beginning of the day in the respective time slots (red line). If the nurse utilization goes over the red line it means that more work is assigned to the nurses than they can handle and hence they are overutilized. If the nurse utilization is below the red line it means that the nurses are underutilized. The graph for the baseline data goes over the red line during lunch hours for almost 5 slots (1 hour 15 minutes) and also after hours whereas it goes over the red line only for 1 slot (15 minutes) for the proposed algorithm. The graph also shows that using the proposed scheduling algorithm the cancer center closes at 5 pm every day whereas the baseline

graph shows that the nurses had to work over time to accommodate the patient demand. The cancer center sometimes closed at 7 pm due to improper scheduling. Nurses require free time towards the end of the day, especially after 2.30 pm to prepare for the next day. The results show that the proposed scheduling algorithm allows this extra nursing time towards the end of the day. Figure 19 compares the percentage of slots in which the nurses are underutilized and overutilized over the entire duration of study. Overutilization can have an adverse effect on patient safety and must be avoided. Underutilization is acceptable because the nurses can use their downtime to do indirect patient care activities such as phone triaging, paperwork etc. The proposed scheduling algorithm increases underutilized nursing time by 24% and reduces the overutilization by the same amount.

The objective function is to balance the nursing workload throughout the day and more importantly to reduce the overutilization. A simple count of over and underutilized nursing slots is not a good measure to conclude that the proposed scheduling algorithm performs better than the baseline. It is also important to quantitatively understand the amount of overutilization and underutilization. Variance was calculated for nurse utilization for each of the 65 days between 8 am to 5 pm. The equality of variance for the proposed algorithm was statistically compared to the baseline using the F-test at a significance level of 0.05 ($\alpha = 0.05$).

The null and the alternate hypothesis are as follows:

H_0: $\sigma_{\text{proposed algorithm}}^2 = \sigma_{\text{baseline}}^2$

H_1: $\sigma_{\text{proposed algorithm}}^2 \neq \sigma_{\text{baseline}}^2$

F-test shows that the variance of the proposed algorithm as compared to the baseline is statistically different (p-value < 0.0001) and hence we reject the null hypothesis.

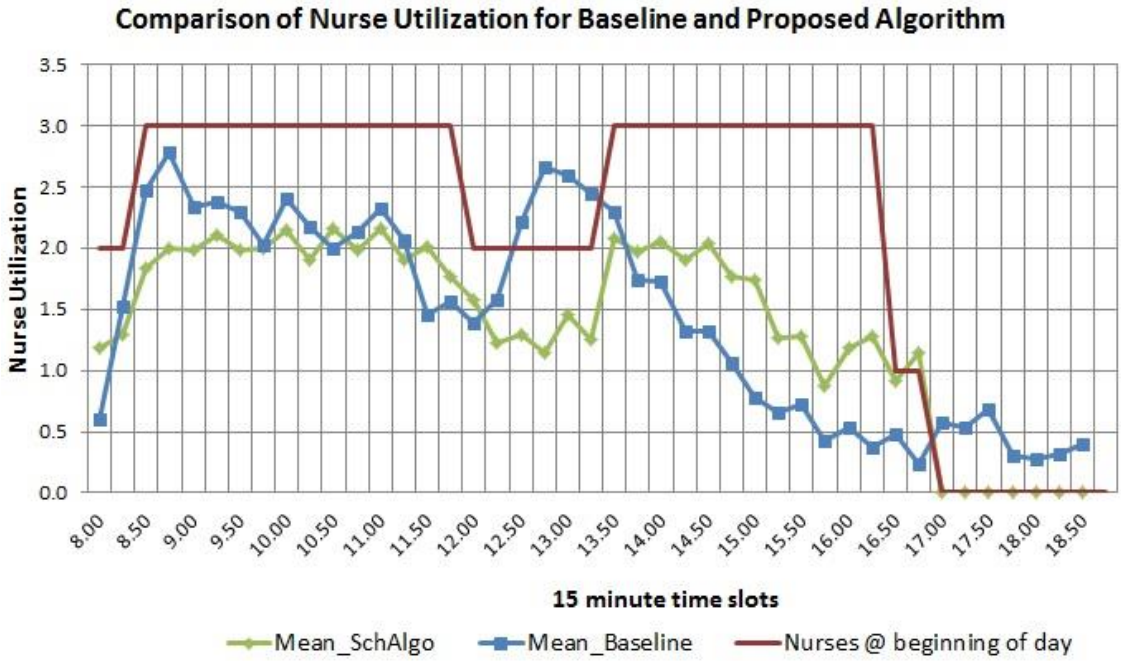

Figure 18: Comparison of mean nurse utilization per time slot for the proposed algorithm and the baseline data over the entire data collection period

Figure 20 shows the comparison of standard deviation in nurse utilization for the proposed algorithm with the baseline data. The lower the standard deviation the closer are the data points to the mean. In this case the mean nurse utilization per day for both the data sets is the same (indicated by the blue line). The standard deviation for the proposed algorithm (indicated by the red line) is lower than the standard deviation for the baseline data (indicated by the green line). This means that the nursing workload is more balanced throughout the day and closer to the average nurse utilization for the proposed algorithm as compared to the baseline data.

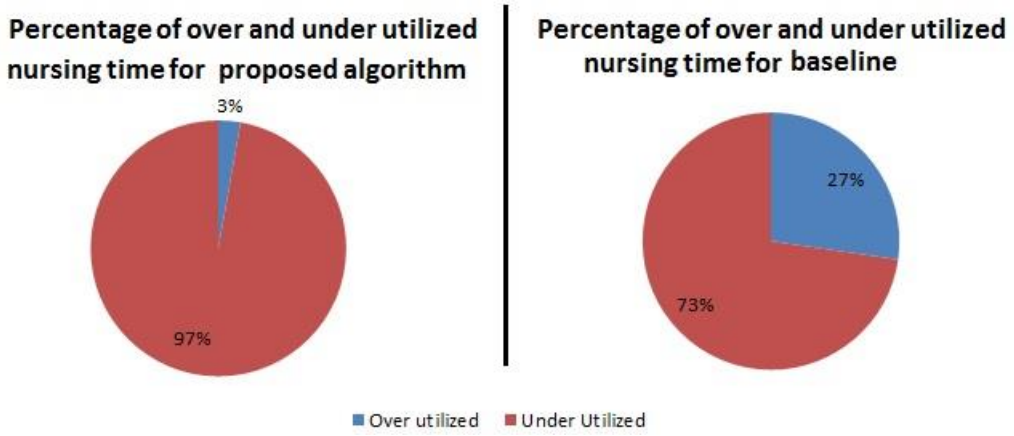

Figure 19: Pie chart for nurse utilization over the entire time of study

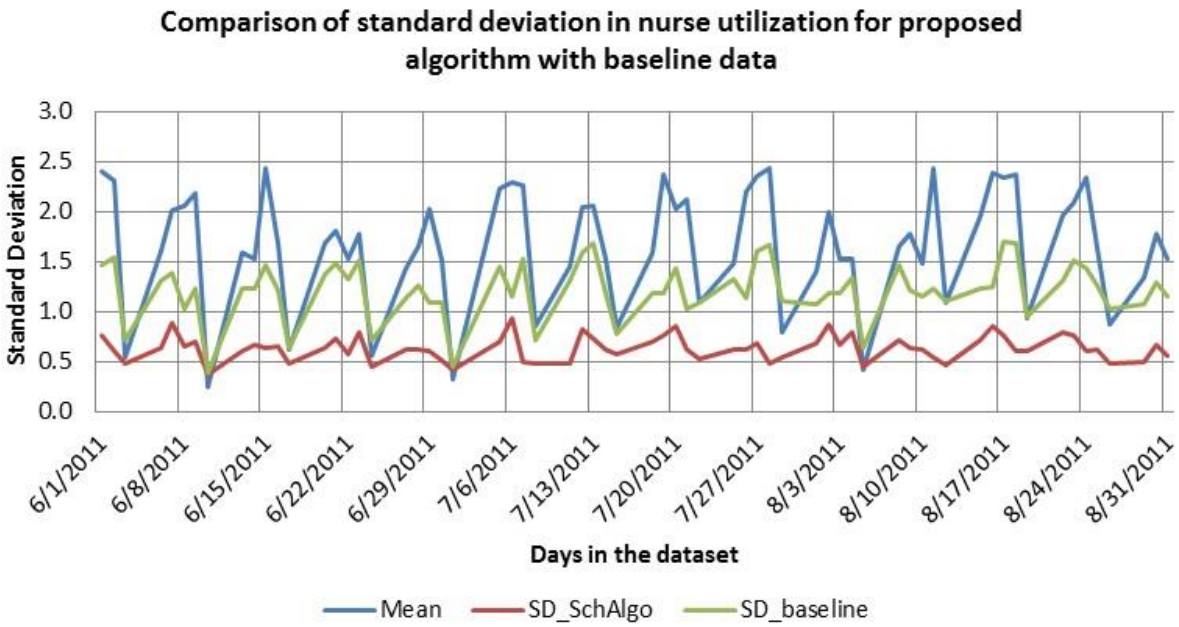

Figure 20: Comparison of standard deviations in nurse utilization

4.3 Discrete Event Simulation Model (DESM)

The output of the mathematical model/ scheduling algorithm are appointment times for each patient and these times are generated such that the nursing time is

optimally used throughout each day. However, there are other operational variations that need to be considered to draw conclusions about the overall performance of a cancer center. In the past, researchers have used various other techniques in the healthcare systems to draw conclusions from data such as computer models, excel spreadsheet analysis, state transition technique: Markov model, Monte-Carlo simulation etc. but discrete event simulation model (DESM) has been proposed as a better choice [31, 32]. Queuing theory has been one of the most dominant analytical tools is studying patient flow in healthcare systems [34]. One of the biggest disadvantages of using queuing theory is qualitative and quantitative approximations and the need to understand complicated mathematical models which makes it inaccessible to the managers [35]. Sometimes it is impossible to build equations that these techniques demand because of the sheer complexity of the process under study. Excel analysis can be used to predict operational requirements and is extremely simple to use. But most of the calculations in excel are done using average value of parameters rather than probability distributions as is the case with DESM. There is tremendous value of animation and visualization provided by DESM which can assist the health care organizations in exploring variations in the process [33]. The inputs applied to these models can be given in the form of distributions rather than just averages which take into consideration the variations of these inputs. DESM enables us to run what-if scenarios which can be used as a decision making tool.

A DSEM was developed to mimic the actual system which assisted us in visualizing and evaluating the performance of the system under different scenarios. In order to develop this model, the current state of the patient flow at the Cancer Center was

observed and understood. Patient appointments were be generated using the proposed scheduling algorithm described in chapter 3. The simulation model was developed using Simio software. The model had to replicate the major patient pathways as shown in chapter 2, figure 8. Three basic Simio standard library objects were used to develop the model logic: source, servers, their associated queues and entities. Source objects were used to create entities at a specified rate, by a specified arrival pattern, on the firing of an event [37]. Specifically, the firing event was rows in a table which mentioned the appointment's date and time for each patient. Source can be considered analogous to the entrance of the Cancer Center. Entities are the elements of the system which are being simulated and can be individually identified and processed [36]. Entities represented patients and had their own distinct intelligent behavior. They were also used to simulate nurses and are referred to as worker objects in the Simio library. Model entity states were used to define specific patient types and respective processing times. Servers are capacitated resource with associated input, output and processing buffers where entities can queue up based on the modeling logic [37]. Server objects were used to model the chemotherapy chairs. These objects processed entities based on processing time defined as a start, end and middle times for each appointment. The output queues associated with the server objects were used to model the patient waiting for their treatment. A set of 3 servers represented 1 chair. So a total of 39 servers are used to represent 13 patient chairs. 2 extra chairs are modeled using 6 servers if the patient demand is high. There were dedicated servers for the start, end and the middle phases of each of the appointments. They were connected to each other by connectors. Connectors were used because we wanted a zero length connect between various phases without any time delays. No

‘warm-up’ period was added before processing patients because the model simulates the day-to-day operations of the center. Work Schedule tables were used to assign work schedules to each registrar and greeter as shown in Figure 21. Work schedules were used to assign and remove capacity to resources based on their shifts. The nurses picked the patients up from the waiting area and escorted them to the treatment areas. This was modeled using paths and not connectors because travel time needed to be considered. Add-on process triggers were used to apply added process steps to various resources, for example seizing and releasing a resource when the object is on or off shift respectively, etc. This enabled us to customize their behavior so as to fit our process logic. The nurse-to-patient ratio during the actual appointment length is 0.1. If the day is divided into 15 minute time slits then a ratio of 0.1 means that the nurse only has to spend 1.5 minutes per time slot with the patient. This is achieved using the third add on process shown in figure 22. A timer event is used to trigger an event once every 15 minutes. The timer does not fire an event if the second server in each group of three servers has a resource state as 0 (server is idle). As soon as the entity enters this server for processing (the server capacity changes), the time starts to fire at a time interval of 15 minutes. Tally element was referenced in the tally step to extend the model logic in add on processes. In this model tallies or statistics were generated when an entity entered and exited the node to calculate the key performance indicators (KPIs) which were not calculated by default by the model. An experiment was designed so that the entire dataset of 65 days was run with 10 replications making it a total of 650 days.

Three KPIs were considered for the study:

1. Average and Maximum Nurse Utilization during scheduled shifts.
2. Average and Maximum overtime for nurses.
3. Average and Maximum patient waiting time before start of treatment.

These KPIs are shown in tables 2, 3, 4, and 5.

Nurse1

Work Periods

Start Time	Duration	End Time	Value	Cost Multiplier	Description
8:00 AM	4 hours	12:00 PM	1	1	
12:30 PM	4 hours	4:30 PM	1	1	

Nurse2

Work Periods

Start Time	Duration	End Time	Value	Cost Multiplier	Description
8:00 AM	4.5 hours	12:30 PM	1	1	
1:00 PM	3.5 hours	4:30 PM	1	1	

Nurse3

Work Periods

Start Time	Duration	End Time	Value	Cost Multiplier	Description
8:30 AM	4.5 hours	1:00 PM	1	1	
1:30 PM	3.5 hours	5:00 PM	1	1	

Figure 21: Work tables to assign and remove nursing capacity

Figure 23 shows the histogram of patient waiting times for the entire dataset. Figures 24, 25 and 26 show the box plots to show the variation in nurse1, nurse 2 and nurse 3's utilization.

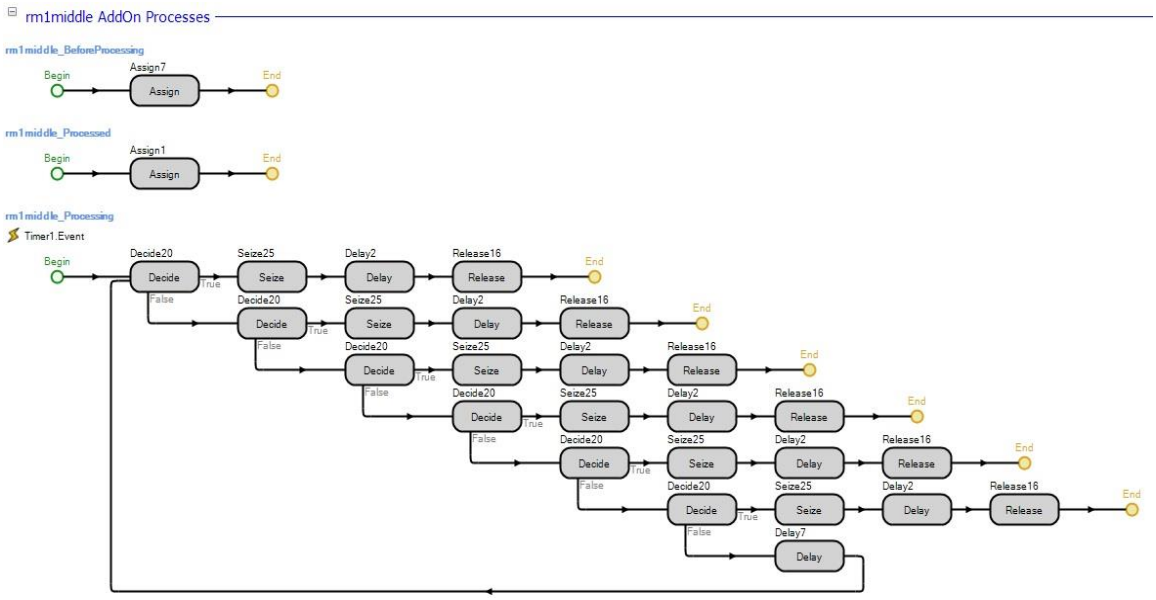

Figure 22: Add-on process triggers

Table 2: Patient waiting time

KPIs	Values
Average Patient waiting time	1.26 minutes
Maximum Patient waiting time	21.88 minutes
Standard deviation	± 2.297

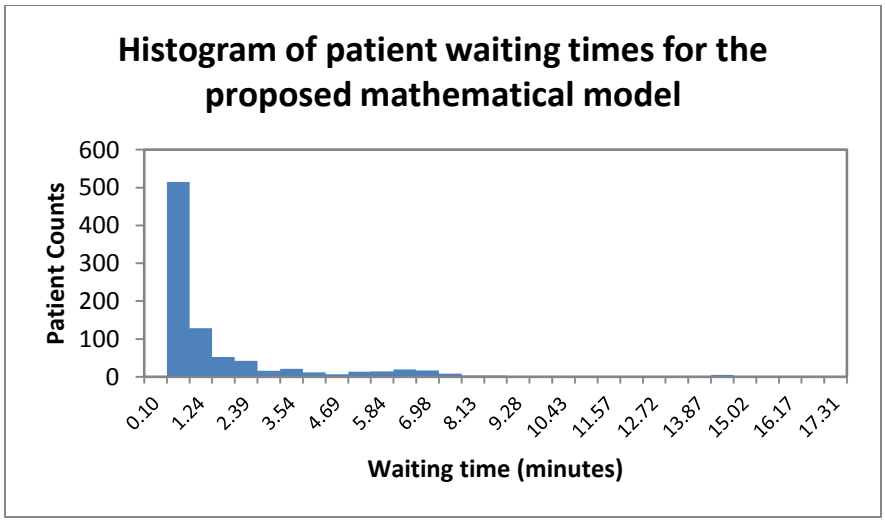

Figure 23: Histogram of patient waiting times

Table 3: Utilization for Nurse 1 in shift 8 am to 4.30 pm

KPIs for Nurse 1 (8 am to 4.30 pm)	Values
Average Nurse Utilization during scheduled shifts	54.31 %
Maximum Nurse Utilization during scheduled shifts	97.33 %
Average overtime	11.7 minutes
Maximum overtime	67.5 minutes
Standard Deviation	± 7.206

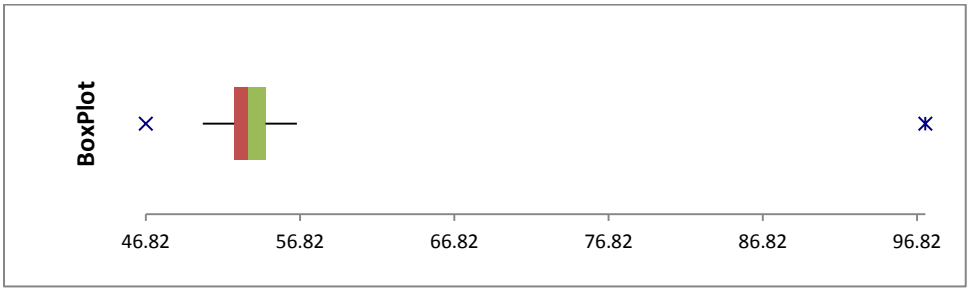

Figure 24: Box plot showing the median, 1st and 3rd percentile for Nurse 1 utilization

Table 4: Utilization for Nurse 2 in shift 8 am to 4.30 pm

KPIs for Nurse 2 (8 am to 4.30 pm)	Values
Average Nurse Utilization during scheduled shifts	47.85 %
Maximum Nurse Utilization during scheduled shifts	94.14 %
Average overtime	4.05 minutes
Maximum overtime	22.32 minutes
Standard Deviation	± 7.085

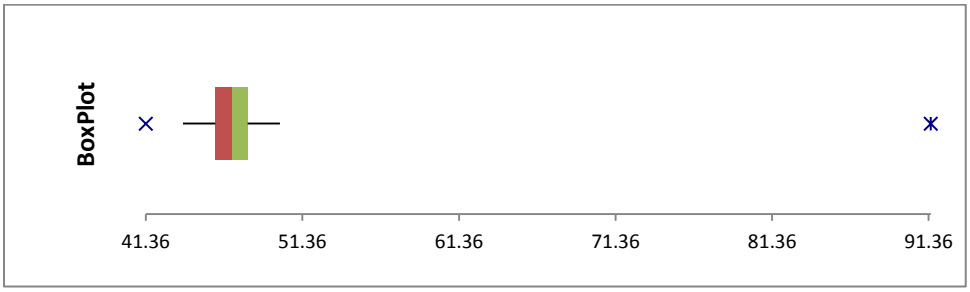

Figure 25: Box plot showing the median, 1st and 3rd percentile for Nurse 2 utilization

Table 5: Utilization for Nurse 3 in shift 8.30 am to 5 pm

KPIs for Nurse 3 (8.30 am to 5 pm)	Values
Average Nurse Utilization during scheduled shifts	43.21 %
Maximum Nurse Utilization during scheduled shifts	99.32 %
Average overtime	5.76 minutes
Maximum overtime	15.24 minutes
Standard Deviation	± 9.105

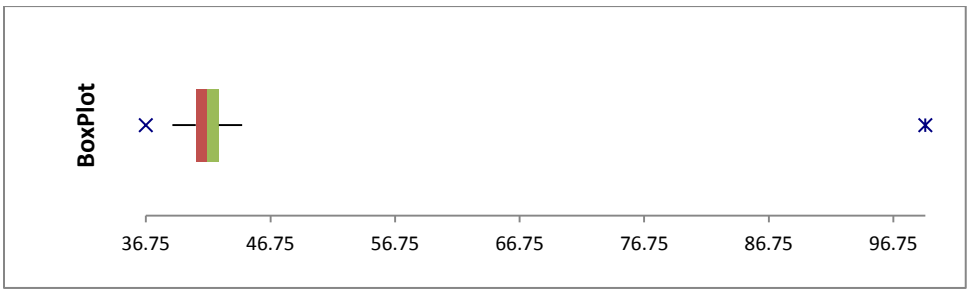

Figure 26: Box plot showing the median, 1st and 3rd percentile for Nurse 3 utilization

The results generated using this scenario are comparable to the results generated using the excel tool. I order to verify the model it was ran, one day at a time, and visually observed the patients entering and leaving the center to make sure that the start, middle and end phases are in accordance to the excel tool. The average nurse utilization for all 3 nurses throughout the entire dataset using the excel tool is 62% where as it is 48% using the simulation model. If the 3 nurses are busy with 3 patients and a fourth patient requests a check in during their middle phase then this request is ignored since the nurses are busy with start, end or middle phases for other patients. After 15 minutes the request can be resent and if the nurses are free they will respond to this request. The utilization is lower in the simulation model because the simulation model represents the real life operation of the cancer center more closely than the excel tool.

CHAPTER V

DISCUSSIONS AND CONCLUSION

Scheduling chemotherapy patients is a tricky problem due to different treatment duration and variable workload requirements. Chemotherapy scheduling has received a lot of attention lately in the operations research field because of the huge cost associated with the resources involved and the nature of the treatment. Achieving an optimal schedule for oncology clinics is not just important from a patient satisfaction perspective but also from a patient safety and clinical outcomes perspective. The nursing workload should be balanced throughout the day so that each patient receives the right level of care at the right time. Currently most of the scheduling is done in an ad-hoc manner or based on patient preference. Clinics also use scheduling template or rule based scheduling methods but there is no standardized and automated algorithm to do the same. There is tremendous shortage in nurses and physicians that provide chemotherapy treatments so it has become necessary to use all the available resources wisely and efficiently. According to the ONS survey nurses reported that their clinics followed one of the following there types of care deliver/ staffing models [12]:

1. Functional model: 40% of the nurses responded that their clinic followed the functional model in which nurses are assigned as needed to a random group of patients based on the patient volume for that day.

2. Primary care: 39% of the nurses responded that their clinic followed the primary care model in which nurses are assigned to the same patients in a specific group during each visit.
3. Medical model: 20% nurses responded that their clinic followed the medical model in which nurses assist the physician as needed and carry out nursing aspects of clinical care.

According to the survey the number of chemotherapy treatments administered per day by a nurse also varied considerably: 16% administered fewer than 5 treatments per day, 29% administered 5–10 treatments, 30% administered 10–15 treatments, 10% administered 15–20 treatments, and 13% administered more than 20 treatments [12]. One of the reasons for this variation is the different care delivery models that the clinics currently follow and lack of a standard, well defined, mathematical way of developing a daily schedule. This research attempts to a structured, efficient way of scheduling chemotherapy appointments.

Another constraint in chemotherapy scheduling is that a patient receiving chemotherapy may have two or more appointments in a day, the actual infusion, laboratory draws, physician appointment and fast track appointment (for port patients). All these appointments have to happen in a specific order: first the lab draws, fast track treatment followed by the physician appointment if any and finally the actual infusion. Inefficiencies at any one stage can cause significant delays in the following appointment(s). Wait times cause patient dissatisfaction and may compromise patient safety especially when nurses are working after hours.

This research attempts to develop a mathematical model to assign appointment times to patients by taking into account the available nursing time for a particular day. It adds start and end times to the actual appointment length and assigns variable nurse-to-patient ratios in the three phases to achieve optimal scheduling. The mathematical model is incorporated in an Excel based tool for ease of use by the scheduler in the clinics. By a click of a button the excel sheet assigns patients to a daily schedule. The algorithm tells the scheduler when the nurses would be over utilized on any given day by generating a pop-up alert. This alert can be over ridden depending on the patient volume and necessity for scheduling that volume on a particular day. The list of patients that are scheduled before the pop-up alert appears is the schedule throughput with optimal nurse utilization. After that if the patients are schedule for that day then it would result in nurses being over utilized. Conversely this mathematical model can also be used to determine the correct staffing levels for a clinic. For example, consider a smaller practice with just 10 patients needing to be scheduled for a day and 1.5 nurses. Figure 27 shows the results for this scenario. 10 patients were randomly selected from the 1st day of the data set. The available nurses were reduced to 1.5 FTE from 3. The staffing was staggered with the full time nurse working from 8 am to 5pm and the part time nurse working from 10am to 2pm. Only 4 patients could be scheduled without over utilizing the nurses. The KPIs for small practice are given in Tables 6, 7 and 8. Due to the nature of this algorithm, the size of the clinic is not a limit factor that impacts the schedule optimization. It was evident from the results that 1.5 FTE is not enough to handle the patient load of 10. It will be risky to over utilize nurses in this scenario because of patients' safety concerns. Similarly this algorithm can also be used to determine optimal staffing levels for a larger practice.

In the initialization step we can start with unlimited nurses and schedule patients for that day. Based on the utilization curve for that day the clinics can adjust their staffing levels. To test the effectiveness of this algorithm it is compared to the historical schedule obtained from Parma Community general Hospital's (PCGH) Cancer Center. Results clearly show that the nursing workload is more balanced throughout the day with less variability and overutilization using the proposed algorithm as compared to the current practice at the Cancer center.

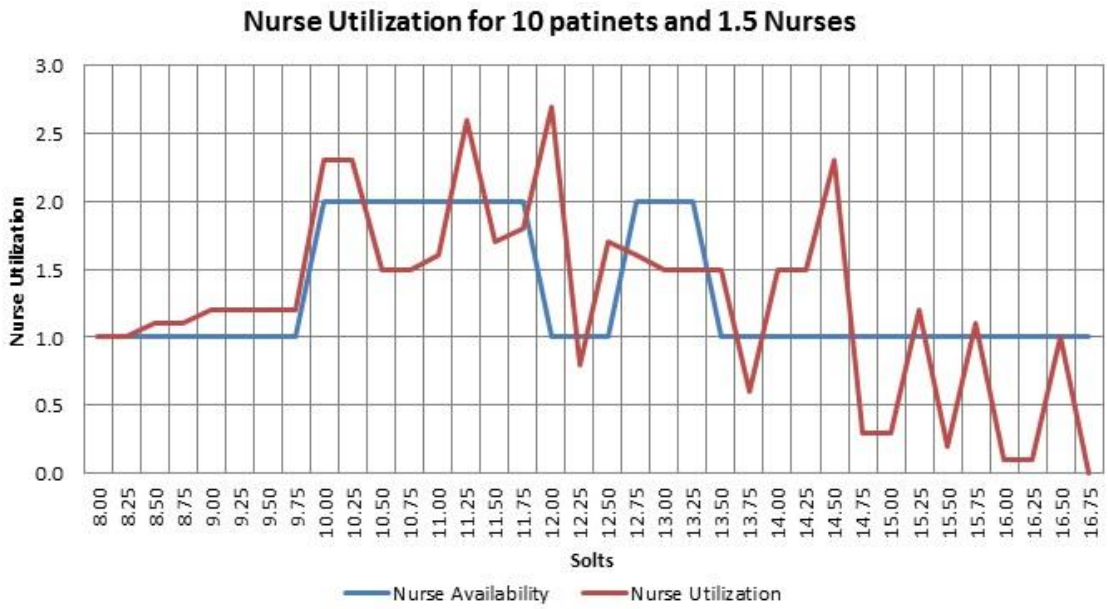

Figure 27: Results when algorithm used for a smaller practice

Table 6: Smaller practice: Patient waiting time

KPIs	Values
Average Patient waiting time	3.03 minutes
Maximum Patient waiting time	29.11 minutes

Table 7: Smaller practice: Utilization for Nurse 1 in shift 8 am to 5.00 pm

KPIs for Nurse 1 (8 am to 4.30 pm)	**Values**
Average Nurse Utilization during scheduled shifts	27.02%
Maximum Nurse Utilization during scheduled shifts	54.05 %
Average overtime & Maximum Overtime	0 minutes

Table 8: Smaller practice: Utilization for Nurse 2 in shift 10 am to 2 pm

KPIs for Nurse 2 (8 am to 4.30 pm)	**Values**
Average Nurse Utilization during scheduled shifts	25.08 %
Maximum Nurse Utilization during scheduled shifts	50.74 %
Average overtime	27 minutes
Maximum overtime	55 minutes

Queuing theory can be used to solve this problem but various assumptions have to be made to develop a queuing model which might be irrational especially in chemotherapy scheduling problem. Queuing models are often used to manage staffing and resource allocation problems to reduce / eliminate delay by taking customer demand into account. Queuing theory assumes that the behavior of entities standing in the queue is deterministic. In chemotherapy scheduling problem the entities in question are human beings and it is almost impossible to predict their behavior. Queuing theory also assumes that the unlimited queue size and unlimited waiting space for the entities in the queue. This assumption does not hold well in infusion clinics their waiting area capacity is limited. Reneging is a phenomenon used in queuing model where if entities wait in the queue for too long then they decide to forgo the service and leave the queue [40]. This is an unreal assumption for a chemotherapy clinic. Queuing theory assumes that the entity arrival rate follows a Poisson distribution. We cannot assume this for chemotherapy patients especially now where most care is delivered in an outpatient setting and patients

are balancing their work/ personal life and treatments. Patients might prefer morning or late evening for their appointments there by making the arrival rate variable during the day. The patient arrival rate during the weekdays could be significantly different than weekends and might not follow a Poisson distribution [38]. It also assumes that the mean arrival rate is less than the mean service rate. In chemotherapy clinics, since the demand is exponentially increasing, there are extensive wait times because the mean service rate is almost always less than the mean arrival rate. Queuing theory largely relies on the steady-state condition which means that the system does not change anymore. It is very difficult to achieve a steady state in chemotherapy clinics due to the nature to the treatments. In chemotherapy clinics it is very common for patients to have more than one appointment a day. Application of queuing theory in such situations becomes even more complex because it becomes a multi-channel queuing problem. The patients may have to join another queue after their first appointment in which departure of one channel queue becomes the arrival of the other channel queue. Developing equations for all the requirements mentioned above would make the queuing problem extremely difficult to formulate and analyze and even then uncertainty will remain [39]. Healthcare systems have just recently begun to manage their practices based on data so it is important to get the managers' buy-in before making any modifications to the already existing practice. On way this can be achieved is by the immense power of visualization (2D and 3D) that simulation modeling renders. It is easier to explain mathematical models, in this case a chemotherapy patient scheduling algorithm, using simulation models with underlying mathematical formulae due to its unparalleled front end. A simulation model was also developed to depict the current situation and understand the resource utilization, service

level provided and the patient waiting times in comparison to the available nurses. Simulation model developed for this research takes into account the variation in the underlying assumptions for the mathematical model. This is done to make the model as close to reality as possible. The time needed at the beginning and end of the appointment and the nurse to patient ratios is dependent on the severity of the patient's condition. Some patients might need the entire start and end phase where as some might not. The following section summarizes the effects of changing parameters such as nurse-to-patient ratios and start and end times on patient waiting time and resource utilization.

5.1 Scenario1: Effects of changing the nurse to patient ratios

The nurse-to-patient during the start and the end phases of the appointment is 1:1. That cannot be changed because the nurse has hook and unhook the patient to the IV injection during these phases. The only nurse-to-patient ratio that can be changes is in the middle phase or the actual appointment length. Based on the field research and observations the maximum patients that a nurse can take care of in one hour is 30 there by making the nurse to patient ratio as 0.033. The minimum number of patients that a nurse can take care of in one hour is 4 there by making the nurse-to-patient ratio as 0.25. In the simulation model the nurse-to-patient ratio was changed from 0.1 to a triangular distribution with maximum= 0.25, minimum = 0.033 and mode = 0.1. The effect of this change on the KPIs is given in tables 9, 10, 11, and 12.

Table 9: Scenario1: Patient waiting time

KPIs	Values
Average Patient waiting time	1.74 minutes
Maximum Patient waiting time	31.37 minutes

Table 10: Scenario1: Utilization for Nurse 1 in shift 8 am to 4.30 pm

KPIs for Nurse 1 (8 am to 4.30 pm)	Values
Average Nurse Utilization during scheduled shifts	57.28 %
Maximum Nurse Utilization during scheduled shifts	100 %
Average overtime	15.30 minutes
Maximum overtime	89.1 minutes

Table 11: Scenario1: Utilization for Nurse 2 in shift 8 am to 4.30 pm

KPIs for Nurse 2 (8 am to 4.30 pm)	Values
Average Nurse Utilization during scheduled shifts	51.28 %
Maximum Nurse Utilization during scheduled shifts	99.73 %
Average overtime	7.38 minutes
Maximum overtime	63 minutes

Table 12: Scenario1: Utilization for Nurse 3 in shift 8.30 am to 5 pm

KPIs for Nurse 3 (8.30 am to 5 pm)	Values
Average Nurse Utilization during scheduled shifts	47.62 %
Maximum Nurse Utilization during scheduled shifts	100 %
Average overtime	2.28 minutes
Maximum overtime	37.20 minutes

The average and maximum nurse utilization merely increases by 7% and 3% respectively as compared to results in section 4.3. The average and maximum overtime increases by 11% and 32% respectively as compared to results in section 4.3 if the nurse-to-patient ratios are changed. It also increases the average and maximum patient waiting time by 38% and 43% respectively as compared to results in section 4.3. But it does not

support the idea of hiring a part time resource to handle the overtime workload. The minimum number of patients that a nurse can handle in one hour in this scenario is 4 but if a difficult case/ patient presents itself that requires more nursing time then the nurse utilization and subsequently the overtime will increase. More study is required to quantify the possibility and the frequency of such a situation.

5.2 Scenario 2: Effects of changing the start and end times

For the preliminary study, the start and end times for returning patients was 30 minutes and 15 minutes respectively. The start and the end times for new patients was 1 hour and 30 minutes respectively. Based on the field research and observations, the start time for returning patients was changed to a triangular distribution with minimum= 10 minutes, maximum= 30 minutes and mode = 20 minutes. The end time for returning patients was changed to a triangular distribution with minimum= 10 minutes, maximum= 30 minutes and mode = 15 minutes. The start time for new patients was changed to a triangular distribution with minimum= 30 minutes, maximum= 1 hour and mode = 45 minutes. Similarly the end time for new patients was changed to a triangular distribution with minimum= 10 minutes, maximum= 30 minutes and mode = 15 minutes. The nurse-to-patient ratios were kept similar to the preliminary study. In the start and the end phase the nurse-to-patient ratio was 1 and in the middle phase it was 0.1. The effect of changing the duration of start and end phases on the KPIs is given in tables 13, 14, 15 and 16.

Table 13: Scenario2: Patient waiting time

KPIs	**Values**
Average Patient waiting time	0.74 minutes
Maximum Patient waiting time	17.65 minutes

Table 14: Scenario2: Utilization for Nurse 1 in shift 8 am to 4.30 pm

KPIs for Nurse 1 (8 am to 4.30 pm)	**Values**
Average Nurse Utilization during scheduled shifts	52.91 %
Maximum Nurse Utilization during scheduled shifts	95.25 %
Average overtime	8.1 minutes
Maximum overtime	63.54 minutes

Table 15: Scenario2: Utilization for Nurse 2 in shift 8 am to 4.30 pm

KPIs for Nurse 2 (8 am to 4.30 pm)	**Values**
Average Nurse Utilization during scheduled shifts	42.76 %
Maximum Nurse Utilization during scheduled shifts	87.38 %
Average overtime	3.15 minutes
Maximum overtime	31.5 minutes

Table 16: Scenario2: Utilization for Nurse 3 in shift 8.30 am to 5 pm

KPIs for Nurse 3 (8.30 am to 5 pm)	**Values**
Average Nurse Utilization during scheduled shifts	34.28 %
Maximum Nurse Utilization during scheduled shifts	81.52 %
Average overtime	0.22 minutes
Maximum overtime	4.2 minutes

The average and maximum nurse utilization reduces by 11% and 9% respectively as compared to results in section 4.3. The average and maximum overtime reduces by 49% and 30% respectively as compared to results in section 4.3 if the start and end times are changed. It also reduces the average and maximum patient waiting time by 44% and 19% respectively as compared to results in section 4.3.

5.3 Scenario 3: Scenarios 1 & 2 combined

This scenario combines scenario 1 and scenario 2 where the both the nurse-to-patient ratios and duration of start and end times are changed as mentioned in section 5.1

and 5.2. The effect of changing both these parameters on the KPIs is given in tables 17, 18, 19, and 20.

Table 17: Scenario3: Patient waiting time

KPIs	Values
Average Patient waiting time	1.28 minutes
Maximum Patient waiting time	20.05 minutes
Standard deviation	± 2.21

Table 18: Scenario3: Utilization for Nurse 1 in shift 8 am to 4.30 pm

KPIs for Nurse 1 (8 am to 4.30 pm)	Values
Average Nurse Utilization during scheduled shifts	55.14 %
Maximum Nurse Utilization during scheduled shifts	100 %
Average overtime	10.08 minutes
Maximum overtime	86.40 minutes
Standard deviation	± 7.122

Table 19: Scenario3: Utilization for Nurse 2 in shift 8 am to 4.30 pm

KPIs for Nurse 2 (8 am to 4.30 pm)	Values
Average Nurse Utilization during scheduled shifts	46.61 %
Maximum Nurse Utilization during scheduled shifts	92.84 %
Average overtime	4.14 minutes
Maximum overtime	29.43 minutes
Standard deviation	± 8.769

Table 20: Scenario3: Utilization for Nurse 3 in shift 8.30 am to 5 pm

KPIs for Nurse 3 (8.30 am to 5 pm)	Values
Average Nurse Utilization during scheduled shifts	40.40 %
Maximum Nurse Utilization during scheduled shifts	92.10 %
Average overtime	0.13 minutes
Maximum overtime	13.2 minutes
Standard deviation	± 9.290

Variation in nurse-to-patient ratios and start and end times resembles more closely to the reality instead of fixed values. Even with this variability the average nurse utilization is 47% and average overtime is 5 minutes. The average and maximum patient waiting time is similar to results in section 4.3.

DESM represents operational reality more closely that a mathematical model because of it added randomness. The results obtained from this DESM are similar with the results obtained from the mathematical model. It also gives us the hours of overtime for each nurse if the appointment times generated by the proposed algorithm are followed. Sensitivity analysis was also done by changing the slot times from 15 minutes to 1 hour in the DESM. The results showed that there is no effect of this change on the nurse utilization. The results were same as shown in section 4.3.

CHAPTER VI

FUTURE WORK

This research is a preliminary step in achieving better scheduling for chemotherapy patients. This study was undertaken to develop a mathematical model that assigns appointment start times to patients such that the nursing workload is balanced throughout the day. In the baseline scenario/ current state it was noticed that the patients are not evenly distributed throughout the week. More patients are seen Monday through Thursday and the patient volume is very low on Fridays. Figure 28 shows the comparison of nurse utilization from Monday to Friday for the proposed scheduling algorithm. The proposed scheduling algorithm can be extended to distribute the patients more equally throughout the week so that the nurses' are not overworked on any particular day of the week. Instead of generating just the appointment times the proposed algorithm can be extended to generate the most optimal appointment dates as well. This can be done by looking at the entire week or an entire month as scheduling horizon instead of a single day. Chemotherapy patients have repeating cycles of appointments and extending our scheduling horizon to weeks or months in the future would let the patients have the same appointment times for all their appointments. Being able to keep the same appointment times for all their appointments is a huge patient satisfier because the patients can plan and improve the quality their life even with this deadly disease.

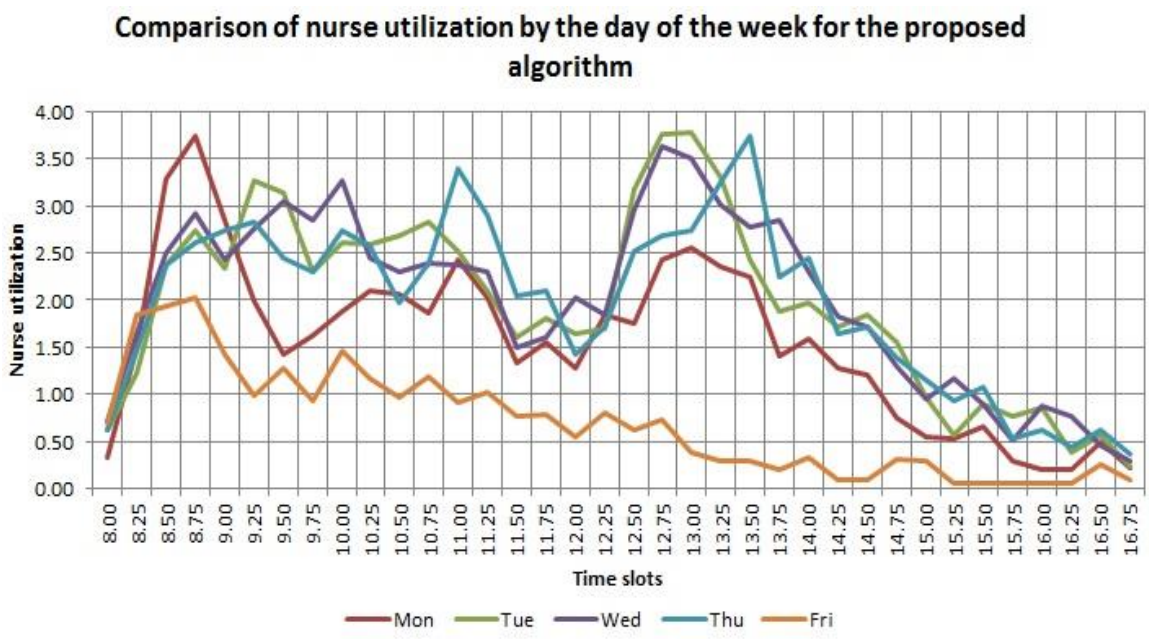

Figure 28: Comparison of nurse utilization by weekdays

It should also be noted that currently the algorithm is dependent on the order in which the patients are scheduled each day. Figure 29 shows the order in which patients are scheduled for the 1st day in our dataset. The blue line on the graph shows the nursing availability at the beginning of the day (same for both scenarios). The red line represents the order in which the patients were scheduled during the study. The green line represents a random order in which patients were scheduled for the same day. The order in which patients present themselves for their appointments are not in our control. Even though scheduling order does have an effect on the results of the algorithm a probabilistic model can be developed to complement the already existing algorithm there by eliminating the dependence of patient order for scheduling.

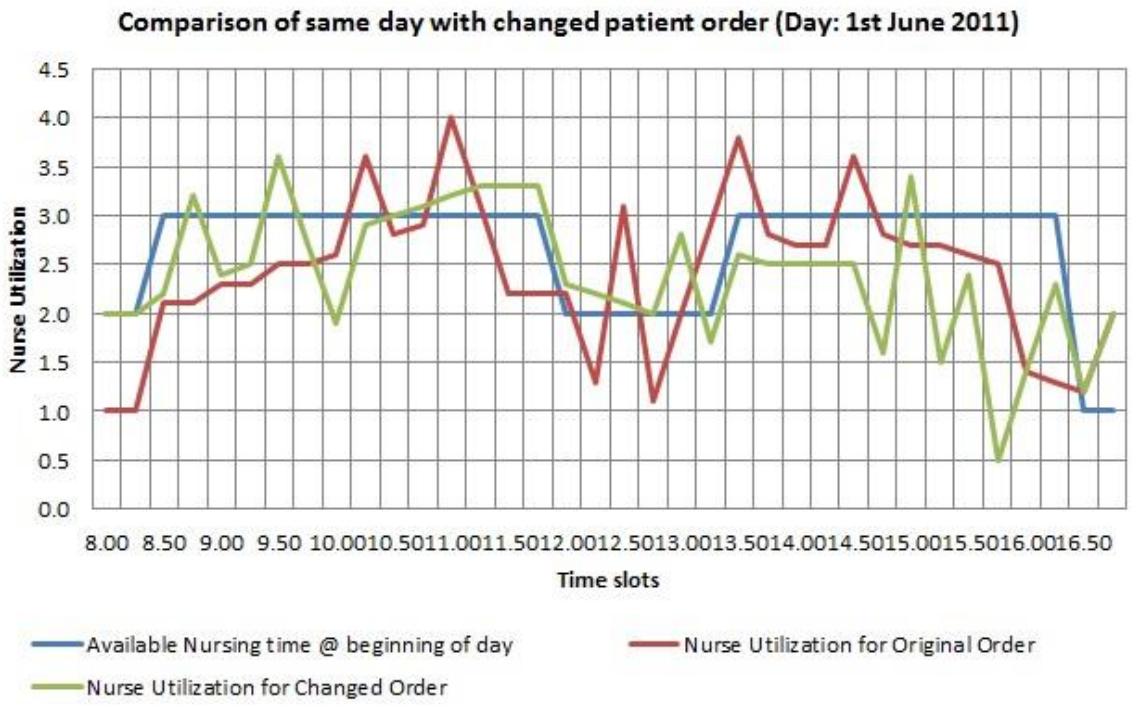

Figure 29: Effect of changing the patient order on the scheduling algorithm

Many add-ons can be added to this model to cover more variables and to make it more flexible and ready to use at Cancer Clinics. The model described above generates only appointment time for a patient. That appointment time might not be feasible for the patient so this model can be extended to generate three appointment times so that the patient gets an option for his treatment times. This can be done by extending the Step 2 of the model. In addition to calculation the first best slot time the model can calculate the second and the third best time to generate three possible options for appointment start times.

This model can also be extended to take schedule efficiently for all the different appointment types that occur at cancer clinics. Apart from infusions patients may have to have a laboratory appointment or an appointment with their physician or a fast track

appointment to get their ports flushed. Patients may have any combinations of these appointments on the day of their infusion. Different resources such as a phlebotomists, physicians, nurse practitioners etc. are required during non-infusion appointments. This model can be extended to optimally assign patients to a daily schedule with two or more appointments a day by taking into consideration the resources available by using the same logic as described in section 3.2. Pharmacy mixing times are also not a part of this research. Pharmacists typically mix drugs after the patients' laboratory tests are resulted and the patients have confirmed their drug mix with their physician. Some clinics may have their patients get their laboratory tests and physician appointments done a day prior to their infusion appointments [17]. If the patients opt to do their laboratory tests and physician appointments on the same day as their infusion then there is an inevitable delay that gets added in between successive appointments. The wait times in between appointment can also be added to the proposed model to make it more efficient. The model can be extended to incorporate these two scenarios so that the patients get a better estimate of the amount of time they would have to be at the clinic under both scenarios. All these variable factors can bed considers as a part of future development to make the proposed algorithm more robust.

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