Chemotherapy Outpatient Scheduling at the Segal Cancer Center Using Mixed Integer Programming Models

Nathalie Wong Kee Yan

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By: Nathalie Wong Kee Yan

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Signed by the final Examining Committee:

______________________________ Chair

Dr. Gerard J. Gouw

______________________________ Examiner

Dr. Ali Akgunduz

______________________________ Examiner

Dr. Jia Yuan Yu

______________________________ Supervisor

Dr. Ivan Contreras

______________________________ Co-Supervisor

Dr. Nadia F. Bhuiyan

Approved by ______________________________

Chair of Department or Graduate Program Director

_______ 2017

____

Dean of Faculty

Abstract

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Appointment scheduling in an outpatient oncology clinic is a daunting task due to the stochastic and dynamic nature of the appointment requests. Each patient has a different trajectory and varying requirements of appointment length time that differ from one another. It is not possible to predict the amount of time required nor the amount of patients that will be treated in a day. Due to the oncologist's prescribed regimen, there is almost no flexibility to choose an appointment date because of the strict resting period required between treatments to achieve the best curative outcome.

The purpose of this thesis is to demonstrate the benefit of using integer programming to model and to solve some of the challenges faced by the Segal Cancer Center of the Jewish General Hospital in Montreal, Quebec, when designing appointment schedules. We study two scheduling problems.

The *chemotherapy outpatient scheduling problem* determines the allocation of patient appointment to days and the determination of appointment start time on those days for a planning horizon of four weeks. The objectives are to maximize the adherence to protocol, maximize the proper assignment of primary nurses to patients and minimize the completion date of treatments. With this model, the clinic can schedule appointment requests as they arise.

When taking an integrated approach to solve the *oncology clinic multi-stage scheduling problem*, it is possible to coordinate the clinic's departments and determine the start time of each activity required by patients no matter their trajectory through the system. Due to the minimization of patient wait time and the completion time of their visit, there will be a better coordination within the clinic, reduction of staff idle time and a balance of resource utilization. Most importantly, it will ensure the completion of tasks within a single day, eliminating the current two-days scheduling policy of the Segal Cancer Center.

The findings of this thesis will facilitate decision making in healthcare scheduling, improve the service level of oncology clinics and serve as a workforce management tool.

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Chapter 1

Introduction

1.1 Problem Motivation

Cancer affects the lives of many Canadians, being the leading cause of death, at 30% per year [1]. Fortunately, there are three common methods that can have a curative impact or control this disease. There is radiotherapy, surgery and chemotherapy, also known as drug therapy. Chemotherapy is a cancer treatment that requires recurrent infusions of powerful drugs, based on established and recognized chemotherapy regimens. Even though two people can be diagnosed with the same illness, there are distinctions such as the type of cancer, the stage of the cancer, the patient's overall health, the age of the patient and the patient's preference that can influence the regimen and treatment. Considering these factors, an oncologist will determine the drug or combination of drugs, the dosage, the cycle and the frequency of the infusions for each patient based on standardized regimen monographs [2], [3] .

It is important to note the significance of respecting the prescribed regimen as it has a considerable impact on the effectiveness and curative nature of the chemotherapy. It is serious when a patient cannot receive an appointment on their prescribed day. This issue is regrettably common in busy oncology outpatient clinics. The healthcare system in Canada is well established, but is unfortunately accompanied by important flaws that affect the growing and aging population, causing additional stress and wasting the time of patients. Because of this, there is a sense of urgency to improve the quality of service provided to the population.

There is a tight relationship between planning and scheduling, as well as the performance and the cost effectiveness of a system. Operations research is very present in the domains of production scheduling, transportation and logistics as well as the service industries [4]. In recent years, solutions that are developed by using mathematical optimization methods have been introduced in the healthcare industry.

1.2 Objectives

The focus of this thesis is to develop two different mixed-integer linear programming models to solve appointment scheduling issues experienced by the Segal Cancer Center of the Jewish General hospital in Montreal, Quebec, Canada. The task of chemotherapy scheduling is complex due to its uncommon characteristics and differs from other outpatient scheduling problems. The operational challenges found in oncology outpatient clinics are generally present in other parts of the healthcare system as well. Patients are required to visit multiple departments and specialists on the same day and use a large variety of resources specific to their needs. There are multiple patient trajectories and appointments of varying duration that convey sources of uncertainty and unique resource constraints to these two scheduling problems.

1.2.1 Chemotherapy Outpatient Scheduling

The *chemotherapy outpatient scheduling problem* is defined as the allocation of patient appointment to days and the determination of appointment start time on those days. The objectives are to maximize the adherence to protocol, maximize the proper assignment of primary nurses to patients and minimize the completion date of appointments.

To simplify the chemotherapy scheduling process, which is currently done manually by a full-time employee, a multi-objective mixed-integer linear programming model will be used to set appointments over a four-week period. The model will determine the earliest day on which the first appointment can be scheduled, such that the series of additional appointments can follow the sequence of treatment days and rest days prescribed by the oncologist as it is imperative to respect the regimen to obtain the best curative outcome. To the eyes of the clinic, it is very important to respect the assignment of nurses and patients. Unlike a functional care delivery model, the primary care delivery model requires the constant pairing of the patient with its primary care nurse [5]. While keeping these targets in mind, the model also sets the start time of appointments per staff and resource availability. This allows to eliminate scheduling errors such as overbooking and violating hard constraints.

This model can be used every time a new appointment request arises and before the entire demand of the next four weeks is known. This tool can be used such that the appointments that are already confirmed in the schedule do not change of date, but can change of start time on that day. When a patient needs to book an appointment, they are given a date, which is determined by the model. The time of their appointment will not be confirmed until a day or two prior, which is per the preference of the decision maker, the management team of the Segal Cancer Center. Because of the flexibility of the model, any last-minute modifications such as appointment cancelations, postponements or an adjustment to the length of the appointment can easily be done with this optimization model.

1.2.2 Oncology Clinic Multi-Stage Scheduling

The *oncology clinic multi-stage scheduling problem* is defined as the determination of arrival time of each patient to the clinic's registration office, the start time of the oncology consultation (if required), the start time of the drug preparation by the pharmacy (if required) and the start time of chemotherapy appointment (if required). The objectives are to minimize patient wait time and minimize the completion time of their visit at the clinic, no matter their trajectory. There will be a better coordination between departments, reduction of staff idle time and a balance of resource utilization. Most importantly, it will also ensure the completion of tasks within a single day, eliminating the current two-days scheduling policy of the Segal Cancer Center.

Completing chemotherapy procedures in a single visit has been replaced in April of 2014 by a two-day system as it had become infeasible to coordinate in a timely manner all the activities required by their patients. To eliminate exaggerated on-site wait time, the patients are currently requested to complete their blood test and oncologist consultation on the first day, followed by the chemotherapy procedure scheduled on the following day. This solution was considered to eliminate on-site wait time, although it has caused unnecessary off-site wait time and additional stress for patients as they need to organize travel plan for two days instead of one. The proposed scheduling tool, based on a multi-objective mixed-integer linear programming model, will demonstrate that by properly coordinating the clinic's activities, it is possible to accommodate every patient and complete every activity in a single day. No matter the trajectory of the patient and the number of departments they must visit in one day, they are scheduled in a manner that minimizes wait time throughout the system and ensures that they spend the least amount of time possible at the clinic.

1.3 Plan of Thesis

The remainder of this thesis is structured as follows:

Chapter 2 presents the literature review. It showcases recent papers that focus on different aspects of oncology outpatient clinic planning and scheduling. Typical topics include the single-stage scheduling of the oncology department, the pharmacy department or the chemotherapy treatments. Additional papers reflect the necessity to consider the oncology clinic as an integrated system, thus combining two or more departments of the clinic to obtain scheduling solutions.

Chapter 3 elaborates on the background of the chemotherapy outpatient scheduling problem experienced at the Segal Cancer Center of the Jewish General Hospital in Montreal, Quebec. It proposes a multi-objective mixed-integer linear programming model to optimize the adherence to the prescribed regimen, maximize the primary nurse assignment and begin treatments as early as possible. A numerical example and analysis follows to demonstrate the positive impacts in planning and scheduling.

Chapter 4 describes the current two-day scheduling policy of the Segal Cancer Center. It showcases the challenges of scheduling in an integrated manner this oncology outpatient clinic. With the suggested mixed-integer linear programming model, it is possible to eliminate off-site wait time and reduce on-site wait time of patients. A numerical example demonstrates the capacity of the clinic to schedule patient's activities in a single day.

Chapter 5 describes the deficiencies and difficulties experienced by the pharmacy. Through an analysis and compilation of data found on Endovault, the software used by the Jewish General Hospital to manage health records [6], it was possible to conclude what caused most of the delays and suggest a solution to be implemented between the oncologists and pharmacists.

Chapter 6 is the conclusion, it elaborates on some of the highlights, possible directions for future work and summarizes the main contributions in the field of healthcare scheduling.

Chapter 2

Literature Review

The goal of this chapter is to outline the work that has been done in the field of outpatient scheduling, more precisely chemotherapy outpatient scheduling. Eliminating the option of overnight care can greatly cut costs in term of staff remuneration and management. The concept of outpatient scheduling is very common healthcare: dentists, optometrists, dermatologists and many other specialists schedule appointments such that they can be completed before the closing time of the clinic. In these areas of expertise, time is not a critical issue as it does not deal with emergencies. This mindset is completely different in the fields of radiotherapy scheduling, operation room scheduling, emergency care scheduling and even chemotherapy scheduling as the health of people in need for these services can often worsen in very little time.

In an outpatient setting such as an oncology clinic, it is essential to create schedules that are efficient as the life of many patients rely on its services. Depending on the objective of the clinic's management, different performance measures can be targeted. These may include and are not only limited to the reduction of the makespan of the clinic, the reduction of patient wait time, the reduction of staff and resource idle time and the reduction of staff overtime. It is also possible that a clinic might want to find a way to properly distribute and balance the workload of its nurses, or even optimize the patient's adherence to a treatment plan. The following papers expand on subjects relevant to the chemotherapy outpatient scheduling problem.

2.1 Single Stage Scheduling

For a large portion of the literature, the main objective is the optimization of a single-stage process leading to the completion of chemotherapy. Either to determine the optimal scheduling of oncologists to consult patients, the scheduling of drug preparation in the pharmacy, the scheduling of nurses to supervise patients during their treatment or the scheduling of chairs to accommodate patients during their chemotherapy infusions.

2.1.1 Oncology Appointment Scheduling

The oncologist is the healthcare specialist that will diagnose and monitor a patient with cancer. They will evaluate which treatment and protocol to administer according to the specific needs of this person. The knowledge and recommendation of these specialists is necessary in an oncology outpatient clinic and they play an integral role in chemotherapy.

Santibanez et al. [7] used simulation to model a chemotherapy outpatient clinic in British Columbia. The objective was to reduce patient wait time and improve the utilization of the clinic's resources such as examination rooms for the single-stage of oncology consultation. Through the analysis of many factors, it was determined that multiple aspects of the clinic had to be modified before having a significant impact on patient wait time.

Mazier et al. [8] develop an integer linear program to address physician planning in an oncology clinic. They integrate an interesting concept that allows a patient to be consulted by an intern if the primary oncologist of the patient is not present or already busy. When testing this idea, they could better balance the workload of the staff and increase the performance of the clinic by seeing more patients.

2.1.2 Pharmacy Production Scheduling

Pharmacists and pharmacy technicians in an oncology outpatient clinic play an important role in chemotherapy treatment. The pharmacist validates the prescription suggested by the oncologist in terms of dosage and proportion with the blood test result and passes the instruction to the pharmacy technician for the preparation of it.

With the concern of reducing patient wait time, an optimized pharmaceutical laboratory will be able to work more efficiently and increase production of chemotherapy drugs. Mazier et al. [9] paid attention to both the offline scheduling method and the online scheduling method. The use of a linear programming model allowed to minimize the maximum tardiness of prescription preparation in a day in the offline setting. To apply this concept to an online scenario, the output of this linear programming model is used in a greedy algorithm. This has the consequence of increasing productivity and overall service to the patient by reducing their wait time.

2.1.3 Nurse Assignment Scheduling

The nurse assignment problem is frequently assessed in research. Oncology clinics may respect two different nursing care models when scheduling chemotherapy appointments. If patients are scheduled without considering the nurse that will be assigned to them during their next treatment, then it is based off the functional care delivery model. On the contrary, if it is necessary to assign a patient for their current and any subsequent appointments with the same nurse, this clinic operates by the primary care delivery model.

Liang and Turkan [5] compare these two care delivery models. With the use of multi-objective optimization techniques, they facilitate patient scheduling and nurse assignment. With their method, it is possible to obtain the optimal schedule of a single day in the clinic. Every patient is evaluated and given an acuity level. With this information, is it possible to determine the start time of each treatment while respecting the nurse's skills and workload.

In Turckan et al. [10], the objectives of maximizing treatment adherence and minimizing patient wait time while taking into account the resources of the clinic, are met with a two-stage integer programming model. Their first mathematical model determines the treatment day to complete the prescribed protocol in full, which extends the planning horizon to 81 weeks. This information then serves as an input to the second model, which confirms the appointment time while once again respecting acuity level of patients in a functional delivery care setting. Patient appointment scheduling is very intricate. For example, some patient may only have transportation at specific times of the day. Start time constraint linked to same day oncology appointment is also something to consider. An extension of the daily appointment scheduling shown by Turckan et al. [10] is done by [11] and considers patient's preference and the coordination with oncologist appointment.

The use of a discrete-event simulation is a method frequently used to determine a system's bottleneck. Woodall et al. [12] observed that the Duke Cancer Institute suffered from poor nurse scheduling during chemotherapy treatments. To optimize the weekly and monthly scheduling of nurses, a mixed-integer program was developed. This contributed to an improved flow of patients within the oncology clinic. Yokouchi et al. [13] also employed simulation to observe the impact of changing patient arrival rates and adding or removing nurses at different parts of the day to minimize patient wait time and maximize the number of patients treated in a day.

Template scheduling is a method that can be used to schedule a single day [14], or multiple days, as done by Condotta et al. [15]. A set of artificial patients with common treatment regimen is generated and used to obtain a template that specifies the date, the time, and the nurse assignment for a given planning horizon. As patients arrive, they are given a series of appointments that coordinate with their regimen. With the objective of minimizing patient wait time and balancing nurse workload, the filled template is re-optimized with an integer linear program.

With the objective of maximizing adherence to protocol, Alvarado et al. [16] used mean-risk stochastic integer programming model to schedule the chemotherapy appointment of patients. They consider the acuity level of patients, the availability of nurses and the length of infusions.

2.1.4 Chair Assignment Scheduling

Due to the layout and dimension of an oncology outpatient clinic, the amount of chairs and beds available are considered a limiting resource as they can only serve one patient at a time. Because of this, the idle time of this valuable equipment must be minimized.

Limitations set by the nursing or oncology staff should not be the only thing to consider when scheduling appointments. Sevinc et al. [17] propose a negative-feedback scheduling algorithm to limit the chair load and even it out through the day. The second stage of their method is to implement two heuristics based on the multiple knapsack problem to determine the proper assignment of patients to chairs.

The following paper also focused on balancing the chair load of an oncology outpatient clinic. Sadki et al. [18] consider the working period of the oncologists and the day of chemotherapy prescribed to patients. A mixed-integer program is used to even out the chair capacity required each week instead of a single day. It proved to reduce patient wait time and provide managerial insights for the organization and utilization of chairs and beds.

2.2 Multi-Stage Scheduling

In multi-stage scheduling, some attention is paid to obligations that can affect the start time of chemotherapy infusions. The hematology clinic, the oncologists, the pharmacy and the treatment station depend on one another and have their own resource limitations. If delays occur within any of these areas, it affects the performance of the rest of the clinic. It is then relevant to consider upstream events to coordinate the start time of chemotherapy treatments. The scheduling problem of an outpatient healthcare clinic is rarely studied in an integrated approach.

Instead of considering a single aspect of chemotherapy outpatient scheduling, Hahn-Goldberg [14] integrated the pharmacy to determine the start time for drug preparation and treatment administration. With historical data from the clinic and the use of constraint programming techniques, they generate templates to schedule appointments. For each day, a template with availabilities of different lengths is created and gets filled as requests arrive. Whenever an appointment does not fit the template, using their method of dynamic template scheduling, a new template is regenerated such that it can be accommodated. A shifting algorithm is also presented to make room for medical emergencies and walk-ins.

Both optimization and simulation techniques are used by Liang et al. [19] to enhance the flow of chemotherapy patients. With the help of a mathematical program, different types of patients are distributed through time slots to evenly distribute the workload of healthcare specialists such as the oncologists and the nurses. After multiple runs, these optimal schedules served to establish a probability matrix that predicts the possibility of scheduling different patient types to different time slots. With this information, it is possible to book appointments in an online setting, as the appointment requests arrive and before they are all known.

In Sadki et al. [20], the chemotherapy outpatient scheduling problem is proven to be NP-hard. Through this article, they mention the importance of scheduling the oncology and the chemotherapy appointments simultaneously, in an integrated manner. By solving this multi-stage problem, which is done with a mixed-integer program that minimizes patient wait time and makespan of the clinic, they are able to establish the start time of the consultation, the drug preparation and the infusion while respecting limitations set by the number of oncologists and chairs in the system. It is assumed that a pharmacist and a nurse is always available to prepare a drug or set up a patient. There are no limitations set for these two stages.

Ahmed et al. [21] were able to generate a template with the use of simulation to determine the proper arrival rate of patients and improve the performance of the oncology clinic. They focused on the objectives of increasing patient throughput and reducing patient wait time.

Similarly to the Segal Cancer Center, Dobish et al. [22] suggested a two-day treatment scheduling process. This signifies a visit to the oncologist on the first day and the chemotherapy treatment on the following day. This method serves to reduce the wait time of patients in oncology clinics and furthermore allow flexibility in the organization and planning of each patient's next day appointment. This proposition converts the online problem into its offline counterpart by creating a one-day leeway. Although they faced a lot of resistance from patients when implementing this change, the results were satisfactory. Achieving the objective of reducing on site wait time was successful. It also had a beneficial impact on the efficiency of the pharmacy department and nurse's coordination for treatment.

2.3 Summary

This chapter gave an overview of the literature relevant to the chemotherapy outpatient scheduling problem. Through these papers, some similarities stand out and are summarized as follows:

The proper assignment of nurses and patients is a recurring topic. The patient's acuity level is considered in [5], [10] and [16]. By recognizing there is a level of difficulty associated with each patient and treatment, it is understandable that these papers aim to balance the workload of every nurse. The concept of primary care delivery model is not explored very often and is only done in [5]. Otherwise, the functional care delivery model is commonly used in, [5], [15], [16] and [20], to model the chemotherapy treatment process.

Simulation is an exceptional and versatile tool that can be used to model different types of scenarios. This practical method was useful in many papers, [7], [12],[13], [19] and [21], allowing them to recreate an oncology clinic and analyze it. It allowed to find bottlenecks, evaluate the impact of modifying certain characteristics, generate templates for scheduling or evaluate the performance of a mathematical program.

In most oncology outpatient clinics, patients perform a blood test, consult with their oncologist and complete their chemotherapy treatment in a single day. This scheduling ideology reduces unnecessary travelling and reduces transportation costs for the patient. To improve this process and prevent the extension of scheduling appointments over two days, [19], [20] find ways to improve the efficiency of the clinic and reduce patient wait time.

In the event that exaggerated wait time and overly crowded waiting area becomes unmanageable, some clinics must stretch a patient's single visit over two days, inducing off-site wait time. It is often met with a lot of resistance [23], but proves to be advantageous to coordinate the drug preparation and chemotherapy treatment [22].

The oncologist prescribes a regimen of multiple treatments that must be completed in accordance to the protocol. The papers [10] and [16] consider this important aspect that impacts the curative nature of a regimen. Therefore, chemotherapy scheduling does not only consist of optimizing a single day, [5] , [11], [13], [14], [16], [19], [20], [21], but could be extended to optimizing a longer planning horizon [10], [12], [15], to fit multiple appointments of a single patient.

Another important characteristic of chemotherapy outpatient scheduling is the ability to work in an online setting [14], [15], [19], [9] which is more realistic as appointment requests arrive randomly and need to be scheduled before the entire set of demand is known. In some cases, observations made by solving an offline problem [5], [10], [11], [12], [16], [20], [22], [9] can provide insightful information to formulate heuristics or rules to help manage new appointment requests.

Chapter 3

Chemotherapy Outpatient Scheduling Problem

The first part of this thesis pays attention to a single-stage environment, the scheduling of patients for their multiple chemotherapy treatment, without considering the possible implications of previous activities required on that same day. On a daily basis, new patients must be added to a schedule that is already filled with existing appointments. Since the amount of chair time required for infusion is not the same for everyone, it is normally very difficult to determine when to schedule a treatment without affecting the current and future demand.

This chapter develops a scheduling tool that will facilitate the task of scheduling staff and patients such that both parties are satisfied. This mixed-integer linear programming model will help the Segal Cancer Center determine appointment dates and treatment start time while respecting resource's requirements. As an extension to the idea of [15], the model will set the treatment date, the start time of infusion and additionally consider the assignment of patients to their primary nurse. As a result, this model can be used to confirm the date of the appointment immediately, whereas the time will be validated a day or two prior to their visit.

3.1 Problem Definition

The chemotherapy outpatient scheduling problem aims to optimize three objectives. The first one is to maximize the adherence to treatment protocol. The second objective is to maximize the assignment of patients to their primary nurse and the last one is to minimize the completion time. With these targets in mind, the model will determine the appointment start time and date by respecting resource's restrictions.

The determination of the proper chemotherapy treatment is crucial and varies widely among patients. Every regimen is very different from one another. As an example, the FCM, eriBUlin and BEVA regimens are compared and summarized in **Table 3.1**. The comprehensive list and complete monograph for these drugs are established by Cancer Care Ontario and can be found on their website [3].

Table 3.1: Example of Regimen with Protocol

FCM Regimen	**Protocol**
Drug Regimen	fludarabine Days 1 to 3 cyclophosphamide Days 1 to 3 mitoXANTRONE Day 1 only
Cycle Frequency	Repeat every 28 days, for usually a of total 6 cycles unless disease progression or unacceptable toxicity occurs
eriBUlin Regimen	**Protocol**
Drug Regimen	Day 1 and Day 8
Cycle Frequency	Every 3 weeks
BEVA Regimen	**Protocol**
Drug Regimen	bevacizumab, can be given every 2 weeks or every 3 weeks according to oncology recommendation
Cycle Frequency	First infusion 1.5 hours, 2nd infusion 1 hour, subsequent infusions 30 minutes

As it can be observed, some treatments require consecutive appointments such as the FCM regimen with infusions on day one, day two and day three, followed by 25 days of rest. Some treatments such as the eriBUlin drug require a single infusion on day one and day eight, followed by a resting period. Other treatments like the BEVA regimen can be bi-weekly infusions or after three weeks, depending on the oncologist's recommendation. Furthermore, the length of the drug infusion may differ from a session to another as it can be seen with the BEVA regimen that requires a first infusion of 1.5 hours, a second infusion of one hour and any subsequent infusions only last 30 minutes. As if these variants were not plentiful, frequent follow ups with the oncologist may engender modifications since side-effects or poor health improvements need to be dealt with.

Considering these observations, the head nurse of the Segal Cancer Center recommends to schedule no more than three appointments per patient as they often get cancelled, modified or postponed. This is unlike, [10] who extend their planning horizon to fit every single appointment listed in the protocol which can extend the planning horizon up to 81 weeks unnecessarily. For example, even though the FCM regimen must be repeated every 28 days for a total of six cycles, there is a very high chance of receiving treatment modifications after the third appointment. Therefore immediately scheduling all 18 appointments would be unproductive as oncologist consultations will commonly cause treatment amendments. Because of this, the set of appointments K only represents three appointments.

The parameters used in this model are summarized in **Table 3.2**. After a diagnosis is made by the oncologist, each patient $i \in I$ is prescribed a set of appointments $k \in K$. It is a personalized regimen which specifies the treatment days and resting period R_{ik} required between each infusion. They also decide the drug or combination of drugs to be administered and the chair time L_{ik} of a series of chemotherapy treatments. With this information on hand, each patient is required to book their appointments with the chemotherapy clinic. A subset of appointments $K' \subseteq K$ is distinguished and includes the series of recommended appointments except the last appointment.

Table 3.2: Parameters and Decision Variables of the Chemotherapy Outpatient Scheduling Model

	PARAMETERS
I	Set of patients who need to receive chemotherapy.
D	Set of days, planning horizon of the problem.
K	Set of appointments.
K'	Subset of appointments that does not include the last appointment of the set K, $K' \subseteq K$
T	Set of time slots.
N	Set of nurses.
I_n	Set of patients that belong to primary nurse $n \in N$.
W	Set of days the clinic is closed.
S	Subset of patients that may only start treatment as of 10:00 a.m., $S \subseteq I$.
R_{ik}	Amount of resting days patient $i \in I$ needs before appointment $k \in K$.
L_{ik}	Amount of time slots needed for the chemotherapy appointment $k \in K$ of patient $i \in I$.
B_{id}	Boolean data: 1, the nurse of patient $i \in I$ is available on day $d \in D$. 0, otherwise.
M_t	Maximum of newly admitted patients per time slot $t \in T$.
A_t	Amount of nurses available per time slot $t \in T$.
m_n	Maximum of patients per nurse $n \in N$ in a day.
m_d	Maximum of patients in a day $d \in D$.
m_i	Maximum of days patient $i \in I$ is delayed.
c	Amount of chairs available in a day.
	DECISION VARIABLES
X_{ikd}	1, if patient $i \in I$ is scheduled for appointment $k \in K$ on day $d \in D$, 0 otherwise.
Z_{ikdt}	1, if patient $i \in I$ is scheduled for appointment $k \in K$ on day $d \in D$ at time $t \in T$, 0 otherwise.
Q_i	The total amount of days the set of appointment K of patient $i \in I$ is delayed.
Y_i	Amount of appointments for which patient $i \in I$ is not scheduled with his/her primary care nurse.
C_i	Amount of days required to complete all appointments of patient $i \in I$.

The Segal Cancer Center is open from 7:30 a.m. to 6:00 p.m. although chemotherapy treatments only begin at 8:00 a.m. and are scheduled such that they can be completed by 5:00 p.m. This allows patients to register and complete necessary blood tests before their 8:00 a.m. appointment. The last hour of operation from 5:00 p.m. to 6:00 p.m. is left vacant on purpose, such that any delays that may have accumulated during the day may be caught up. Time is represented by time slots $t \in T$ of 30 minutes, where $t = 1$ represents the time slot 8:00 a.m. to 8:30 a.m., and $t = 20$ represents the time slot 5:30 p.m. to 6:00 p.m.

The treatment area is divided into two stations. The first station is composed of sixteen chairs and two rooms with beds. Whereas the second station contains fourteen chairs and three rooms with beds. This represents the possibility of accommodating up to 35 patients simultaneously, represented by the parameter c. It is assumed that chairs and beds represent the same resource although it would be interesting to view them separately as suggested by Hahn-Goldberg [14]. Considering that the layout of the two stations differ by the number of chairs and beds. This would add some complications to the model due to the assignment of nurses to these stations as they may not be in two places at once. Thus, it is assumed as though all the chairs, beds, and staff are all in a single and same location. The concept of having two stations is not considered.

Table 3.3: Amount of Nurses Available per Time slot $t \in T$, per Station and in Total: A_t

Time	Time slot t	Station 1	Station 2	**Total:** A_t
8:00 a.m. to 8:30 a.m.	1	2	2	**4**
8:30 a.m. to 9:00 a.m.	2	2	2	**4**
9:00 a.m. to 9:30 a.m.	3	3	3	**6**
9:30 a.m. to 10:00 a.m.	4	3	3	**6**
10:00 a.m. to 10:30 a.m.	5	4	4	**8**
10:30 a.m. to 11:00 a.m.	6	4	4	**8**
11:00 a.m. to 11:30 a.m.	7	4	4	**8**
11:30 a.m. to 12:00 p.m.	8	3	3	**6**
12:00 p.m. to 12:30 p.m.	9	3	3	**6**
12:30 p.m. to 1:00 p.m.	10	2	2	**4**
1:00 p.m. to 1:30 p.m.	11	3	3	**6**
1:30 p.m. to 2:00 p.m.	12	3	3	**6**
2:00 p.m. to 2:30 p.m.	13	4	4	**8**
2:30 p.m. to 3:00 p.m.	14	4	4	**8**
3:00 p.m. to 3:30 p.m.	15	4	4	**8**
3:30 p.m. to 4:00 p.m.	16	4	4	**8**
4:00 p.m. to 4:30 p.m.	17	4	4	**8**
4:30 p.m. to 5:00 p.m.	18	4	4	**8**
5:00 p.m. to 5:30 p.m.	19	4	4	**8**
5:30 p.m. to 6:00 p.m.	20	4	4	**8**

The clinic has N nurses that are full-time or part-time employees. On a daily basis, there are five nurses scheduled per station. Four of them are assigned with patients whereas the fifth extra nurse is there to accommodate any drop-ins and unscheduled patients which accounts for medical emergencies. This makes a total of ten nurses when considering both locations. In our case, it is assumed all 10 nurses are working in a single station. Understandably, these nurses begin their shifts at different times of the day and have lunches that overlap wisely. **Table 3.3**. shows how many nurses are available throughout the day, A_t. A first nurse begins at 7:00 a.m., the second and third nurse begin at 8:00 a.m., the fourth nurse begins at 9:00 a.m. and the fifth nurse begins at 10:00 a.m. According to the request of the clinic, the extra nurse who begins to work at 7:00 a.m. is not considered when making the schedule as he or she may be used to perform different tasks, or serve as a back-up to cover for a sick nurse. This is why **Table 3.3** only considers the nurses available and on the floor. There is a weekly rotation of nurses between stations such that their expertise and knowledge can be shared among one another. This serves as a balance for the social well-being of the staff. Since a previous assumption was made concerning the elimination of two distinct stations, this concept of staff rotation is not considered.

Table 3.4: Maximum of Patients Admitted per Time slot $t \in T$, per Station and in Total: M_t

Time	Time slot t	Station 1	Station 2	**Total:** M_t
8:00 a.m. to 8:30 a.m.	1	2	2	**4**
8:30 a.m. to 9:00 a.m.	2	2	2	**4**
9:00 a.m. to 9:30 a.m.	3	3	3	**6**
9:30 a.m. to 10:00 a.m.	4	3	3	**6**
10:00 a.m. to 10:30 a.m.	5	4	4	**8**
10:30 a.m. to 11:00 a.m.	6	4	4	**8**
11:00 a.m. to 11:30 a.m.	7	4	4	**8**
11:30 a.m. to 12:00 p.m.	8	2	2	**4**
12:00 p.m. to 12:30 p.m.	9	0	0	**0**
12:30 p.m. to 1:00 p.m.	10	0	0	**0**
1:00 p.m. to 1:30 p.m.	11	3	3	**6**
1:30 p.m. to 2:00 p.m.	12	3	3	**6**
2:00 p.m. to 2:30 p.m.	13	4	4	**8**
2:30 p.m. to 3:00 p.m.	14	4	4	**8**
3:00 p.m. to 3:30 p.m.	15	2	2	**4**
3:30 p.m. to 4:00 p.m.	16	0	0	**0**
4:00 p.m. to 4:30 p.m.	17	0	0	**0**
4:30 p.m. to 5:00 p.m.	18	0	0	**0**
5:00 p.m. to 5:30 p.m.	19	0	0	**0**
5:30 p.m. to 6:00 p.m.	20	0	0	**0**
				80

It is necessary to have nurses readily available to set up arriving patients, as well as to monitor the stability of the ones already there. A patient arriving for treatment will require the full attention of a nurse as they need to be installed for infusion whereas a nurse can overview up to four patients already receiving treatment. The maximum amount of patients admitted per time slot, M_t is a limit established by the head nurse of the oncology clinic and shown on **Table 3.4**. Due to the scheduling of lunch breaks, additional patients may not enter the system between 12:00 p.m. and 1:00 p.m. as the rest of the nurses working will be occupied by monitoring patients. This same idea applies between 3:30 p.m. and 6:00 p.m. The clinic can no longer admit additional patients for chemotherapy as some nurses are completing their shifts and the remaining nurses will be busy monitoring the patients already receiving chemotherapy. This information leads to conclude that only a maximum of $m_d = 80$ patients may be admitted per day for treatment and to be fair, each nurse will have a maximum of $m_n = 10$ patients to supervise per day. As previously mentioned, there are always four scheduled nurse plus an extra for emergencies. This additional nurse can also help supervise patients when needed.

The Segal Cancer Center's operations are defined as a primary care delivery model. Meaning that every patient is assigned a primary nurse with whom every subsequent appointment must be scheduled. This is unlike a functional care delivery model where patients may be paired up with a different nurse during their appointments [5]. At this clinic, every nurse $n \in N$ possesses a group of patients I_n specific to them. Understandably, a patient $i \in I$ is ideally scheduled if their primary nurse works on day $d \in D$, which is determined by the Boolean parameter B_{id}. To the best of their abilities, the schedules are made such that each patient is assigned to the primary nurse that will assist them throughout the rest of their appointments. On an exceptional basis, it is possible and acceptable if this cannot be done as it should not be a reason to delay a patient's infusion as this would lead to the detriment of the treatment. The decision variable Y_i monitors how often patient $i \in I$ is not scheduled with its primary nurse.

Table 3.5: List of Drugs that can Only be Ready as of 10:00 a.m.

Drug name
1. Abraxane
2. Alimta (Pemetrexed)
3. Caelyx (liposomal Doxo)
4. Gemcitabine
5. FOLFOX
6. Rituximab
7. Trastuzumab
8. Vadaza
9. Compassionate MK3475
10. MCG 1229
11. MCG 1307
12. NCIC LY16
13. MCG 1308
14. MCG 1323
15. MCG 1118
16. LUG GO28753

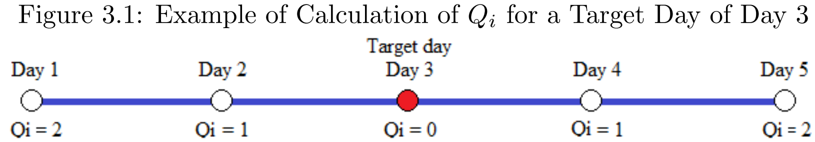
Since the pharmacy is operational only from 8:00 a.m. to 4:00 p.m., a few prescription drugs must be prepared on the previous day to fulfill the need of patients expecting to begin treatment at 8:00 a.m. There are although some restrictions set at the clinic pertaining 16 specific drugs listed in **Table 3.5** as they do not remain stable long enough to be prepared in advance and be stored overnight. They must be produced only a few hours before injection. Due to these restrictions, the oncology pharmacy has established booking restrictions based on the stability of these drugs. These special case patients $s \in S$ requiring any of these 16 prescriptions may only begin treatment as of 10:00 a.m.

When a patient approaches the clinic to book their chemotherapy appointments, they are given dates for the first three treatments only. When looking for an availability, it is preferable unless specified by the oncologist, to give them the earliest start day such that their three appointments can be completed as early as possible. The decision variable C_i records on which day the third appointment of patient $i \in I$ is completed.

To make a distinction between selecting the date of the appointment, which cannot be changed once it is set and the start time of the treatment that can be re-optimized, a first binary decision variable X_{ikd} is used to define the day $d \in D$ of the appointment $k \in K$ for patient $i \in I$. A second binary decision variable Z_{ikdt} is used to define the start time $t \in T$ on the day $d \in D$ of appointment $k \in K$ of patient $i \in I$.

There are three objectives simultaneously being optimized. Firstly, the model minimizes Q_i, the total amount of days by which the set of appointments of patient $i \in I$ is scheduled ahead or after the day prescribed by the oncologist. The **Figure 3.1** is used to explain this example. If a patient requires an appointment on day three and gets scheduled on day two or day four, this patient is delayed from the target day by one day. If that same patient is scheduled on day one or day five instead of the desired day three, this patient is delayed by two days. The best outcome would be to receive an appointment on the desired day as this would eliminate any delays. In order to be in control of this significant objective, the parameter m_i is introduced to place a limit to the amount of delay each patient can tolerate throughout the set of their three appointments.

Figure 3.1: Example of Calculation of Q_i for a Target Day of Day 3



Secondly, the model minimizes the occurrence of not being scheduled with the correct nurse. Therefore, it minimizes the value of Y_i. For example:

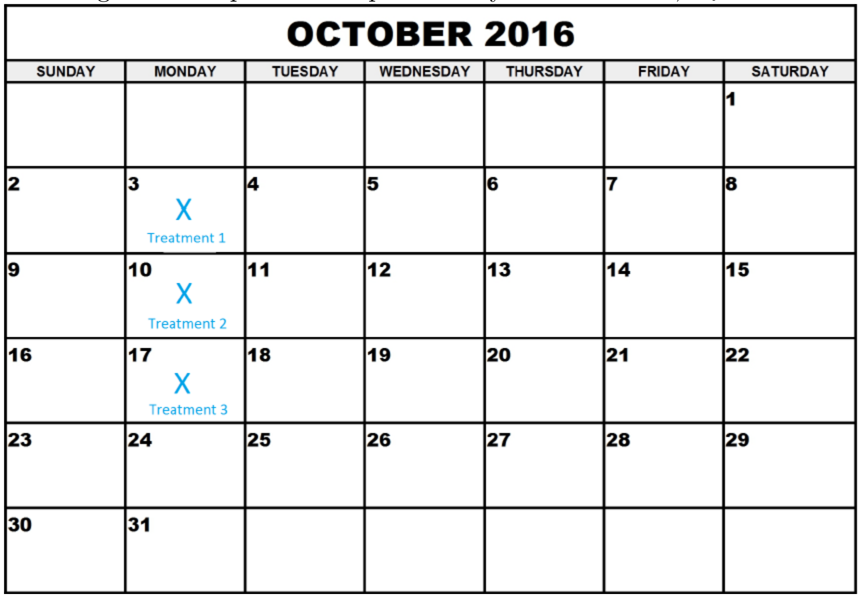
-If $Y_i = 0$, it is an optimal case, patient $i \in I$ was assigned with his/her primary nurse for all appointments.

-If $Y_i = 1$ this means that patient $i \in I$ was not scheduled with hi/her primary nurse on one occasion out of three appointments.

-The same goes for $Y_i = 2$ and $Y_i = 3$, meaning that patient $i \in I$ was not scheduled with its primary nurse two times and three times respectively.

Finally, the third objective of this model minimizes the completion time of all three appointments. For example, a patient who requires six days of rest between each appointment would ideally be scheduled according to **Figure 3.2**. Therefore, beginning on the first available day and completing all three treatments by the 17th of October is the minimal and optimal completion date for this patient. This means that patient $i \in I$ completed all three treatments by day 17.

Figure 3.2: Optimal Completion Day of Treatments, $C_i = 17$



OCTOBER 2016						
SUNDAY	MONDAY	TUESDAY	WEDNESDAY	THURSDAY	FRIDAY	SATURDAY
						1
2	3 X Treatment 1	4	5	6	7	8
9	10 X Treatment 2	11	12	13	14	15
16	17 X Treatment 3	18	19	20	21	22
23	24	25	26	27	28	29
30	31					

Unfortunately, due to the limitations of the system in terms of chemotherapy clinic operating hours, the amount of nurses available throughout the day to treat and supervise patients, as well as chair capacity, it is frequent that a patient must be treated on a different day than the one prescribed by the oncologist.

3.2 Mathematical Model

Using the above mentioned set of decision variables, the chemotherapy outpatient scheduling problem can be stated as follows:

$$\textbf{Minimize:} \sum_{i \in I} \Big(w_1 Q_i + w_2 Y_i + w_3 C_i \Big) \tag{3.1}$$

$$\textbf{Subject to:} \sum_{d \in D} d X_{ikd} = \sum_{d \in D} \sum_{t \in T} d Z_{ikdt} \qquad i \in I, k \in K \tag{3.2}$$

$$\sum_{d \in D} X_{ikd} = 1 \qquad i \in I, k \in K \tag{3.3}$$

$$\sum_{d \in D} \sum_{t \in T} Z_{ikdt} = 1 \qquad i \in I, k \in K \tag{3.4}$$

$$\sum_{k \in K} X_{ikd} \leq 1 \qquad i \in I, d \in D \tag{3.5}$$

$$\sum_{i \in I_n} \sum_{k \in K} Z_{ikdt} \leq 1 \qquad d \in D, t \in T, n \in N \tag{3.6}$$

$$t Z_{ikdt} + L_{ik} \leq 19 \qquad i \in I, k \in K, d \in D, t \in T \tag{3.7}$$

$$\sum_{k \in K'} \Big(\sum_{d \in D} dX_{ikd} \leq \sum_{d \in D} dX_{i(k+1)d} \Big) \qquad i \in I \qquad (3.8)$$

$$\sum_{i \in I} \sum_{k \in K} X_{ikd} \leq m_d \qquad d \in D \qquad (3.9)$$

$$\sum_{k \in K} \Big(\sum_{i \in I} Z_{ikdt} + \sum_{i \in I} \sum_{t'=max\{1,t-L_{ik}+1\}}^{t-1} Z_{ikdt'} \Big) \leq c \qquad d \in D, t \in T \qquad (3.10)$$

$$\sum_{i \in I} \sum_{k \in K} Z_{ikdt} \leq M_t \qquad d \in D, t \in T \qquad (3.11)$$

$$\sum_{i \in I_n} \sum_{k \in K} \sum_{t \in T} Z_{ikdt} \leq m_n \qquad d \in D, n \in N \qquad (3.12)$$

$$\sum_{k \in K} \Big(\sum_{i \in I} Z_{ikdt} + \frac{1}{4} \sum_{i \in I} \sum_{t'=max\{1,t-L_{ik}+1\}}^{t-1} Z_{ikdt'} \Big) \leq A_t \qquad d \in D, t \in T \qquad (3.13)$$

$$\sum_{k \in K'} \Big(\sum_{d \in D} dX_{i(k+1)d} - \Big(\sum_{d \in D} dX_{ikd} - R_{i(k+1)} \Big) \Big) \leq m_i \qquad i \in I \qquad (3.14)$$

$$- \sum_{k \in K'} \Big(\sum_{d \in D} dX_{i(k+1)d} - \Big(\sum_{d \in D} dX_{ikd} - R_{i(k+1)} \Big) \Big) \leq m_i \qquad i \in I \qquad (3.15)$$

$$\sum_{k \in K} \sum_{d \in D} \Big(X_{ikd} - \Big(B_{id} X_{ikd} \Big) \Big) = Y_i \qquad i \in I \qquad (3.16)$$

$$\sum_{d \in D} \sum_{t \in T} dX_{i3d} = C_i \qquad i \in I \qquad (3.17)$$

$$\sum_{k \in K'} \Big(\sum_{d \in D} \sum_{t \in T} dZ_{i(k+1)dt} - \sum_{d \in D} \sum_{t \in T} dZ_{ikdt} - R_{i(k+1)} \Big) \leq Q_i \qquad i \in I \qquad (3.18)$$

$$- \Big(\sum_{k \in K'} \Big(\sum_{d \in D} \sum_{t \in T} dZ_{i(k+1)dt} - \sum_{d \in D} \sum_{t \in T} dZ_{ikdt} - R_{i(k+1)} \Big) \Big) \leq Q_i \qquad i \in I \qquad (3.19)$$

$$X_{ikd} = 0 \qquad i \in I, k \in K, d \in W \qquad (3.20)$$

$$Z_{ikdt} = 0 \qquad i \in S, k \in K, d \in D, t = 1,2,3,4 \qquad (3.21)$$

The objective function **(3.1)** minimizes the sum of delays, the possibility of not being assigned to the primary nurse and the sum of completion time. It is affected by the weights w_1, w_2 and w_3 such that the objectives can be balanced and prioritized according to the preference of the decision maker.

This model allows to confirm the appointment date X_{idk} separately from the appointment time Z_{idkt}. It is then important that the two decision variables are linked through the set of constraints **(3.2)** to reflect the same day of appointment $d \in D$ for the same appointment $k \in K$ of the same patient $i \in I$. The following set of constraints **(3.3)** certifies that every patient is given an appointment date for each of their treatments, whereas **(3.4)** certifies that all the appointments are given a start time. The set of constraints **(3.5)** ensures that a patient cannot be scheduled to perform more than one chemotherapy treatment per day.

With **(3.6)**, the arrival of patients for their treatment must coordinate with the availability of their primary nurse since each one of them can only focus on one newly arriving patient per time slot. As specified by the head nurse, the set of constraints **(3.7)**, ensures that all the infusions are completed by 5:00 p.m., even though the clinic is open until 6:00 p.m. This allows the staff to catch up on any delays that may have accumulated during the day. The set of constraints **(3.8)** serves a logical purpose, the appointments must follow the same sequence as it is prescribed by the oncologist.

According to the preference of the decision maker, it is only possible to accommodate m_d patients per day with to the set of constraints **(3.9)**. Also, since the clinic deals with chair/bed resources, **(3.10)** verifies that the total amount of patients being set up and already receiving treatments does not exceed the total capacity of the system.

The clinic has established a maximum amount of arriving patients per time slot as seen on **Table 3.4** and the set of constraints **(3.11)**, implements this. To be fair to all the nurses, **(3.12)** controls the daily workload such that each nurse does not receive more than a certain amount of patients per day. Although **(3.11)** limits the amount of new patients admitted per time slot in the system, the set of constraints **(3.13)** confirms there is enough staff remaining to monitor the patients already installed for chair time.

The set of constraints **(3.14)** and **(3.15)**, provide a limit to the total amount of days by which the appointments of the set K of each patient may be delayed. The set of constraints **(3.16)** verifies how often a patient is scheduled for an appointment when his/her primary nurse is not working on that day. Furthermore, **(3.17)** records the day on which the third appointment of every patient is completed. Finally, to verify the amount of delays experienced by a patient throughout the scheduling of their set of appointments K, the set of constraints **(3.18)** and **(3.19)** are necessary.

With the set of constraints **(3.20)**, it is certain that there will be no appointments mistakenly scheduled on the weekend, when the clinic is closed. Also, due to the short shelf life of 16 specific drugs, the restrictions applied by the pharmacy and represented by **(3.21)** and affects the scheduling possibilities of these special cases. They can only begin treatment as of 10:00 a.m.

3.3 Computational Experiments and Analyses

This section analyzes and presents the computational results to demonstrate the capabilities and benefits of this mathematical model. The data used as input in this model is generated such that it reflects the reality of the Segal Cancer Center of the Jewish General Hospital. To model a potential schedule, the month of October 2016 is used as a template. For this example, the schedule is made over four weeks. Thus, Monday October 31st is considered as a day off and no one can be scheduled.

To verify the efficiency of the model, two tests as mentioned in **Table 3.6** are performed and analyzed. The first test does not allow any delays. Meaning that the adherence to protocol is perfectly respected for every patient. The second test will on the other hand allow patients to be affected at most by one delay over the course of their set of appointments K.

The values taken by the input parameters are shown in **Table 3.7**. The mathematical model will determine the appointment date and start time of three appointments per patient. A smaller scaled problem is

Table 3.6: Type of tests

Test	m_i
Test 1	0
Test 2	1

tested and analyzed, with 50 patients for a total of 150 appointments to be scheduled such that the adherence to protocol, the assignment of patients to their primary nurse and the completion time is optimized. Since the day is divided into 30-minute time slots, the model deals with 20 time slots representing the operating hours of 8:00 a.m. to 6:00 p.m.

Table 3.7: Values Taken by Parameters for **Test 1.** and **Test 2.**

Parameters	Values
I	50 patients who need to receive chemotherapy.
D	31 days in the month of October 2016.
K	3 appointments to be scheduled per patient.
T	20 time slots of 30 minutes.
N	8 nurses.
I_n	Every nurse is assigned a personal set of 6 to 8 patients, see **Table 3.8**.
W	On the dates: 1, 2, 8, 9, 15, 16, 22, 23, 29, 30 and 31 the clinic is closed.
S	16 patients out of 50 are considered to require special drugs and can only begin treatment as of 10:00 a.m., see **Table 3.8**.
R_{ik}	Rest period ranges between 1 day to 7 days, see **Table 3.9**.
L_{ik}	Appointment length ranges between 1 time slot to 14 time slot, see **Table 3.10**.
B_{id}	1, the nurse of patient $i \in I$ is available on day $d \in D$. 0, otherwise,, see **Table 3.11**.
M_t	See **Table 3.4**.
A_t	See **Table 3.3**.
m_n	8 patients per nurse per day.
m_d	50 patients per day at the clinic.
m_i	Has value 0 for Test 1 and has value 1 for Test 2.
c	30 chairs available in a day.

A total of eight nurses, some full-time and some part-time are modelled in this example. Every patient is randomly assigned to a primary nurse such that all the nurses are responsible for six to eight patients as it can be seen in **Table 3.8**. With the short shelf life of 16 specific drugs in mind, a distinction is made for 16 patients as they require special treatments that can only begin as of 10:00 a.m. This set of patients is also specified in this table. The ratio of having 16 special patients out of 50 patients may or may not be representative of the demand at the Segal Cancer Center, it was simply chosen for the sake of this example.

The resting period seen in **Table 3.9** shows the amount of days required between the first and second appointment as well as the resting period between the second and third appointment. It is randomly generated with the use of Microsoft Excel such that the values remain between one and seven. $R_{ik} = 1$ signifies that an appointment is required the next day and if $R_{ik} = 7$, an appointment is needed in a week.

Table 3.8: Patients with Special Drug Needs, S and Nurse Assignment to Patients, I_n

Special patients, S	3, 5, 7, 8, 9, 13, 15, 17, 18, 24, 25, 26, 30, 33, 34, 41
Patients of Nurse 1, I_1	16, 27, 34, 40, 41, 45
Patients of Nurse 2, I_2	3, 6, 15, 25, 37, 42
Patients of Nurse 3, I_3	2, 5, 13, 21, 28, 32
Patients of Nurse 4, I_4	9, 10, 11, 20, 33, 44
Patients of Nurse 5, I_5	8, 12, 31, 36, 48, 49
Patients of Nurse 6, I_6	1, 17, 19, 22, 43, 46
Patients of Nurse 7, I_7	4, 23, 24, 26, 39, 50
Patients of Nurse 8, I_8	7, 14, 18, 29, 30, 35, 38, 47

Table 3.9: Amount of Nights of Rest Required Before the Appointment $k \in K$ of Patient $i \in I$, R_{ik}

Patient $i \in I$	R_{i2}	R_{i3}	Patient $i \in I$	R_{i2}	R_{i3}
1	3	6	26	3	4
2	7	7	27	1	1
3	3	4	28	2	1
4	1	7	29	1	3
5	2	6	30	1	5
6	5	2	31	7	1
7	6	1	32	1	3
8	2	4	33	6	7
9	5	1	34	4	4
10	6	2	35	6	3
11	6	5	36	6	3
12	3	2	37	5	1
13	4	1	38	1	1
14	6	1	39	4	4
15	3	3	40	1	5
16	3	7	41	1	4
17	4	2	42	3	3
18	6	7	43	4	5
19	3	7	44	5	4
20	4	6	45	2	1
21	6	6	46	3	1
22	1	1	47	4	6
23	7	6	48	3	7
24	2	6	49	6	2
25	5	1	50	4	1

Every patient has a personalized regimen. The oncologists carefully diagnoses them and suggests infusions of different lengths as shown in **Table 3.10**. This data is also randomly generated with the use of Microsoft Excel to last between one time slot and up to 14 time slots which represents chair time ranging from 30 minutes to seven hours. To perform these chemotherapy treatments, the clinic is equipped with 30 chairs in this exercise.

Table 3.10: Amount of Time Slots Required for the Appointment $k \in K$ of Patient $i \in I$, L_{ik}

Patient $i \in I$	L_{i1}	L_{i2}	L_{i3}	Patient $i \in I$	L_{i1}	L_{i2}	L_{i3}
1	14	9	4	26	3	8	6
2	5	13	10	27	8	4	6
3	9	6	7	28	2	4	4
4	10	13	13	29	8	9	3
5	1	5	12	30	6	4	12
6	7	6	6	31	5	1	3
7	1	5	13	32	11	8	12
8	7	1	6	33	14	8	13
9	1	7	10	34	4	8	3
10	2	9	11	35	11	14	8
11	13	11	14	36	8	13	9
12	6	8	1	37	7	1	5
13	11	8	9	38	4	3	2
14	8	14	12	39	7	4	3
15	5	2	13	40	3	7	7
16	13	1	7	41	7	13	3
17	10	10	7	42	8	12	13
18	12	6	2	43	8	9	9
19	10	9	4	44	14	8	14
20	10	2	5	45	13	10	7
21	5	5	1	46	4	1	4
22	5	14	10	47	3	7	9
23	6	3	6	48	7	9	13
24	5	13	10	49	8	1	10
25	10	8	13	50	6	3	8

The individual capacity of each nurse is set to eight patients per day to control their workload, whereas the clinic is also limited to receive a maximum of 50 chemotherapy treatments per day. Since the primary care delivery model is implemented by the clinic, it is necessary to know when a nurse is working.

The **Table 3.11** shows the nurse's schedule on which the Boolean parameter B_{id} is based on. Thus, is it possible to know if the nurse of patient $i \in I$ is available on day $d \in D$ or not. This information is well known is advance and obtained from the head nurse who normally prepares the nurse's schedule six weeks ahead. The shift of the nurse is not distinguished in this table. It is simply known that they are working on that day.

To evaluate the performance of the optimization model, different convex combinations of the coefficients w_1, w_2, and w_3 are assigned to the three objectives. Each of the weights vary at the first decimal,

Table 3.11: Daily Nurse Availability for the Month of October 2016

Date:	3	4	5	6	7	10	11	12	13	14	17	18	19	20	21	24	25	26	27	28
Nurse 1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Nurse 2	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Nurse 3	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Nurse 4	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1
Nurse 5	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Nurse 6	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1
Nurse 7	1	1	1	1	0	1	0	1	1	1	0	0	1	1	1	1	1	1	1	0
Nurse 8	1	1	0	0	1	1	0	1	1	0	1	1	0	1	0	1	0	1	1	0

from 0 to 0.1 until 1 for a total of 11 possible weights per coefficient. Due to the structure of the problem, it is possible to deduce the minimum and maximum values of delays, $\sum_{i=1}^{I} Y_i$ and $\sum_{i=1}^{I} C_i$.- In Test 1, the minimal and maximal amount of delay possible is inevitably zero because of $m_i = 0$, meaning that every patient has perfect adherence to the prescribed protocol.

- In Test 2, the minimal amount of delay is also zero signifying perfect protocol adherence.

- In Test 2, the maximal amount of delay is 50. Meaning that every patient experienced 1 day of delay because of $m_i = 1$ during their three treatment.

- In both tests, the minimal value that Y_i can take is zero, meaning that every patient is assigned to their primary nurse for every appointment.

- In both tests, the maximal value that Y_i can take is 150, meaning that every appointment was scheduled with the wrong nurse.

- In both tests, the minimal value that C_i can take is 17 since at least one patient requires weekly treatments.

- In both tests, the maximal value that C_i can take is 28 since it is the extent of the planning horizon.

3.3.1 Test 1, $m_i = 0$

In this first test, since the impact of having no delays, $m_i = 0$ is being observed, the coefficient w_1 is set to zero while w_2, and w_3 vary. This represents a total of 11 scenarios. The results are shown in **Figure 3.3** and in further details in **Table 3.12**. This figure illustrates the trade-off between two conflicting objectives, maximizing the primary nurse assignment and minimizing the sum of completion time of the system while maintaining maximum protocol adherence. The negative correlation of these two variables is quite noticeable and are highly correlated with a coefficient of -0.7571. These calculations can be found in the Appendix, **Figure A.1** and **Figure A.2**. In the **Figure 3.3**, the emphasis is made on the makespan when in reality, the model calculates the completion time of the system shown in the black boxes beneath the yellow trend line. This is why the results obtained with the *instances 4 and 5* have the same makespan, yet differ in the amount of wrong nurse assignment because of the small difference in $\sum_{i \in I} C_i$ shown in the box.

Figure 3.3: **Test 1.** Trend on Delay of Data B and $m_i = 0$

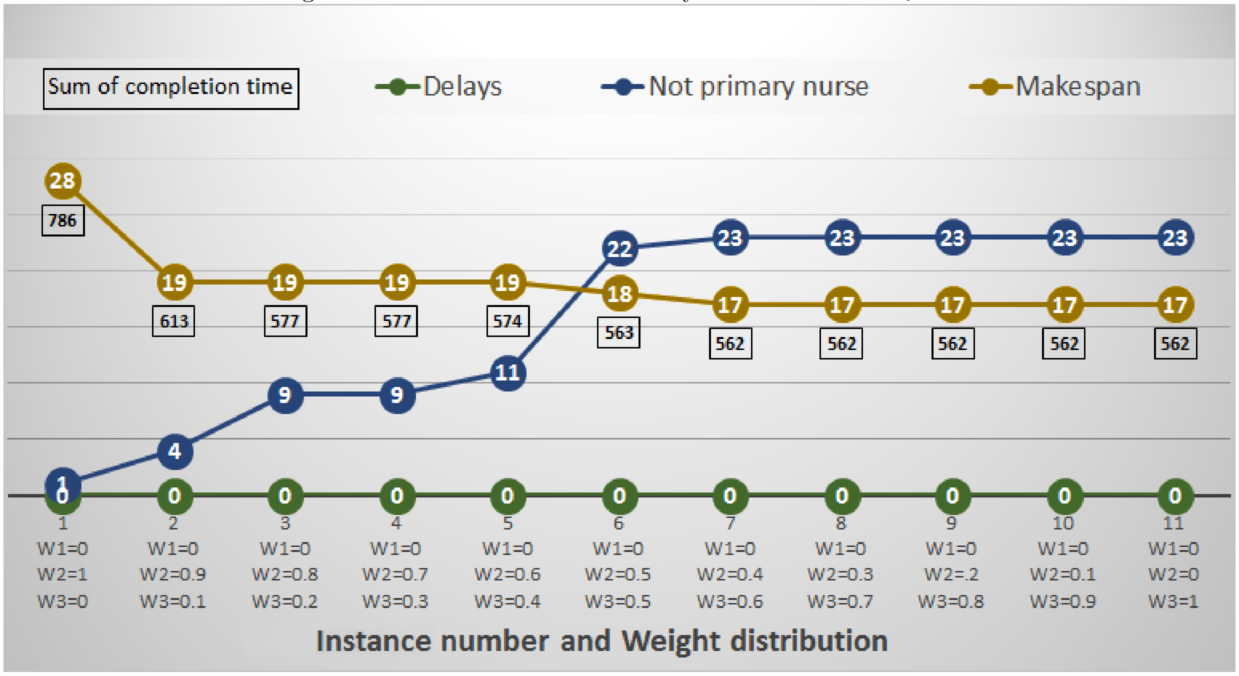


Table 3.12: Results from **Test 1.** with Different Combinations of Weights w_1, w_2 and w_3

Instance	w_1	w_2	w_3	Solving time (hh:mm:ss)	$\sum_{i \in I} Q_i$	$\sum_{i \in I} Y_i$	$\sum_{i \in I} C_i$	Makespan	Objective function
1	0	1	0	00:00:17	0	1	786	28	1
2	0	0.9	0.1	00:00:07	0	4	613	19	64.9
3	0	0.8	0.2	00:00:07	0	9	577	19	122.6
4	0	0.7	0.3	00:00:07	0	9	577	19	179.4
5	0	0.6	0.4	00:00:06	0	11	574	19	236.2
6	0	0.5	0.5	00:00:06	0	22	563	18	292.5
7	0	0.4	0.6	00:00:04	0	23	562	17	346.4
8	0	0.3	0.7	00:00:04	0	23	562	17	400.3
9	0	0.2	0.8	00:00:00	0	23	562	17	454.2
10	0	0.1	0.9	00:00:04	0	23	562	17	508.1
11	0	0	1	00:00:04	0	23	562	17	562

A lot of information can be extracted from this model. For example, it is interesting to see the results of *instance 1* and *instance 11* as they act like single objective optimization problems. When the decision making process emphasizes the need of being assigned to the primary nurse, $w_2 = 1$ and $w_3 = 0$, the optimal solution of *instance 1* reveals that one patient will not be assigned with its primary nurse, as seen in **Figure 3.4**. When looking deeper at the results obtained from the model, it is possible to pin point the affected patient and for which of the three appointments.

In this case, it is patient $i = 38$ who requires three appointments in a row as specified on **Table 3.9**.

Figure 3.4: **Test 1. Instance 1**, Amount of Patients Assigned to Each Nurse During the Month of October 2016

Date	Nurse 1	Nurse 2	Nurse 3	Nurse 4	Nurse 5	Nurse 6	Nurse 7	Nurse 8	Total Patients	Wrong Nurse
1										
2										
3	3	1	4		1	1	1	3	14	
4			1	2	1	2	1	4	11	
5	1	3	3	2	2	1	1	1	14	1
6	3	1	2		1		2		9	
7	2		1		1	2		2	8	
8										
9										
10		4	2	4			2	2	14	
11	4	2	3	1	3	2			15	
12	2	1		1	1		1	1	7	
13	2				2	2		3	9	
14				2	1	1	2		6	
15										
16										
17	1		2	2	1	1		1	8	
18		1						1	2	
19					2		1		3	
20				1				2	3	
21		2		1		2	3		8	
22										
23										
24		2				1			3	
25				1	1		1		3	
26						1	1	2	4	
27		1		1		1	2	2	7	
28					1	1			2	

Clinic is closed · Nurse day off

In terms of workforce management, this information can serve as an indicator to reassign this patient who needs three treatments over the span of three days to a different primary nurse since the part-time nurse 8 to whom this person is assigned in **Table 3.11** never works three days in a row. This simple modification could then lead to an optimal schedule which maximizes the assignment of patients to their primary nurse.

In the case where the minimization of the sum of completion time is emphasized in *instance 11* on **Figure 3.5**, the trade-off is clear. It is possible to complete all 150 treatments while maintaining perfect protocol adherence within 17 days, although 23 patients will be affected and not assigned to their primary nurse. That is a clear difference with *instance 1* that requires 28 days to complete all treatments such that only one patient is affected by a wrong nurse pairing.

The optimal weight distribution among the coefficients w_2, and w_3 is entirely subjective to the preference of the decision maker, which in this case is the head nurse of the Segal Cancer Center. It would although be suggested to follow the schedule obtained with the *instance 2*. Having a makespan of 19 days and wrong nurse assignment affecting only four patients is rather appealing. It would not be worth reducing the makespan by a single day and consequently affect the nurse assignment of 22 patients as seen in *instance 6*. When considering the result of the *instance 1*, having the amount of wrong nurse assignment reduced to one while significantly increasing the makespan to 28 days seems exaggerated as it only improves $\sum_{i \in I} Y_i$ by three.

Figure 3.5: **Test 1. Instance 11**, Amount of Patients Assigned to Each Nurse During the Month of October 2016

Date	Nurse 1	Nurse 2	Nurse 3	Nurse 4	Nurse 5	Nurse 6	Nurse 7	Nurse 8	Total Patients	Wrong Nurse
1										
2										
3	4	1	4	1	2	5	4	3	24	
4	2	2	1	2	3	1	2	7	20	
5	4	3	3	2		1	1	2	16	2
6	3	1	2	1	2	4	2		15	
7	1	2	1	1	1	2	1	2	11	3
8										
9										
10	2	6	2	4	5	1	2	5	27	7
11	1	2	3	1	1		5	2	15	7
12		1		2	2	3			8	3
13	1			1	2	1		2	7	
14				1					1	
15										
16										
17			2	2			1	1	6	1
18										
19										
20										
21										
22										
23										
24										
25										
26										
27										
28										

Clinic is closed | Nurse day off

3.3.2 Test 2, $m_i = 1$

The second test involves the possibility of experiencing one delay per patient, $m_i = 1$. Thus, all three weight coefficients w_1, w_2, and w_3 vary from 0 to 1. The results of 66 possible convex combination of weights are found in **Tables 3.13 and 3.14**.

Table 3.13: Part 1. **Test 2.** Result of Analysis with Data B, and Maximum Delay per Person =1

Instance	w1	w2	w3	Solving time (hh:mm:ss)	$\sum_{i \in I} Q_i$	$\sum_{i \in I} Y_i$	$\sum_{i \in I} C_i$	Makespan	Objective function
1	1	0	0	00:03:35	0	16	845	28	0
2	0.9	0.1	0	03:04:23	0	1	1006	28	0.1
3	0.9	0	0.1	00:00:15	0	23	562	17	56.2
4	0.8	0.2	0	09:20:38	0	1	900	28	0.2
5	0.8	0.1	0.1	00:00:21	0	19	566	18	58.5
6	0.8	0	0.2	00:00:12	3	22	549	17	112.2
7	0.7	0.3	0	01:45:36	0	1	922	28	0.3
8	0.7	0.2	0.1	00:00:35	0	9	577	19	59.5
9	0.7	0.1	0.2	00:00:12	4	21	546	17	114.1
10	0.7	0	0.3	00:00:10	6	21	540	17	166.2
11	0.6	0.4	0	01:26:07	0	1	931	28	0.4
12	0.6	0.3	0.1	00:00:47	1	8	572	19	60.2
13	0.6	0.2	0.2	00:00:16	8	15	540	18	115.8
14	0.6	0.1	0.3	00:00:12	7	20	538	17	167.6
15	0.6	0	0.4	00:00:08	7	20	538	17	219.4
16	0.5	0.5	0	02:22:02	1	0	938	28	0.5
17	0.5	0.4	0.1	00:00:49	1	8	572	19	60.9
18	0.5	0.3	0.2	00:00:12	8	8	547	19	115.8
19	0.5	0.2	0.3	00:00:07	10	16	535	17	168.7
20	0.5	0.1	0.4	00:00:07	10	16	535	17	220.6
21	0.5	0	0.5	00:00:07	29	18	516	17	272.5
22	0.4	0.6	0	00:41:53	1	0	1023	28	0.4
23	0.4	0.5	0.1	00:00:36	9	3	560	19	61.1
24	0.4	0.4	0.2	00:00:13	14	5	540	19	115.6
25	0.4	0.3	0.3	00:00:10	12	12	535	18	168.9
26	0.4	0.2	0.4	00:00:07	22	14	523	17	220.8
27	0.4	0.1	0.5	00:00:12	29	17	516	17	271.3
28	0.4	0	0.6	00:00:07	29	18	516	17	321.2
29	0.3	0.7	0	03:53:55	1	0	939	28	0.3
30	0.3	0.6	0.1	00:00:20	13	1	556	19	60.1
31	0.3	0.5	0.2	00:00:24	16	3	541	19	114.5
32	0.3	0.4	0.3	00:00:12	23	4	532	19	168.1
33	0.3	0.3	0.4	00:00:11	29	11	519	17	219.6

Table 3.14: Part 2. **Test 2.** Result of Analysis with Data B, and Maximum Delay per Person =1

Instance	w1	w2	w3	Solving time (hh:mm:ss)	$\sum_{i \in I} Q_i$	$\sum_{i \in I} Y_i$	$\sum_{i \in I} C_i$	Makespan	Objective function
34	0.3	0.2	0.5	00:00:07	28	16	517	17	270.1
35	0.3	0.1	0.6	00:00:07	29	17	516	17	320
36	0.3	0	0.7	00:00:07	29	18	516	17	369.9
37	0.2	0.8	0	04:39:01	1	0	895	28	0.2
38	0.2	0.7	0.1	00:00:13	17	1	547	19	58.8
39	0.2	0.6	0.2	00:00:09	31	2	528	19	113
40	0.2	0.5	0.3	00:00:09	30	3	527	19	165.6
41	0.2	0.4	0.4	00:00:09	30	7	522	17	217.6
42	0.2	0.3	0.5	00:00:08	33	13	516	17	268.5
43	0.2	0.2	0.6	00:00:09	30	16	516	17	318.8
44	0.2	0.1	0.7	00:00:11	29	17	516	17	368.7
45	0.2	0	0.8	00:00:08	29	18	516	17	418.6
46	0.1	0.9	0	00:38:19	1	0	986	28	0.1
47	0.1	0.8	0.1	00:00:10	29	1	535	19	57.2
48	0.1	0.7	0.2	00:00:08	31	2	528	19	110.1
49	0.1	0.6	0.3	00:00:05	31	2	528	19	162.7
50	0.1	0.5	0.4	00:00:07	31	4	525	17	215.1
51	0.1	0.4	0.5	00:00:10	32	12	517	17	266.5
52	0.1	0.3	0.6	00:00:07	33	13	516	17	316.8
53	0.1	0.2	0.7	00:00:06	33	13	516	17	367.1
54	0.1	0.1	0.8	00:00:07	33	13	516	17	417.4
55	0.1	0	0.9	00:00:08	29	18	516	17	467.3
56	0	1	0	00:00:54	43	0	706	28	0
57	0	0.9	0.1	00:00:06	42	2	528	19	54.6
58	0	0.8	0.2	00:00:06	42	2	528	19	107.2
59	0	0.7	0.3	00:00:08	40	2	528	19	159.8
60	0	0.6	0.4	00:00:06	39	3	526	17	212.2
61	0	0.5	0.5	00:00:16	43	13	516	17	264.5
62	0	0.4	0.6	00:00:14	43	13	516	17	314.8
63	0	0.3	0.7	00:00:10	41	13	516	17	365.1
64	0	0.2	0.8	00:00:09	43	13	516	17	415.4
65	0	0.1	0.9	00:00:09	43	13	516	17	465.7
66	0	0	1	00:00:05	45	20	516	17	516

Figure 3.6: **Test 2.** Trend on Delay: 0 to 28

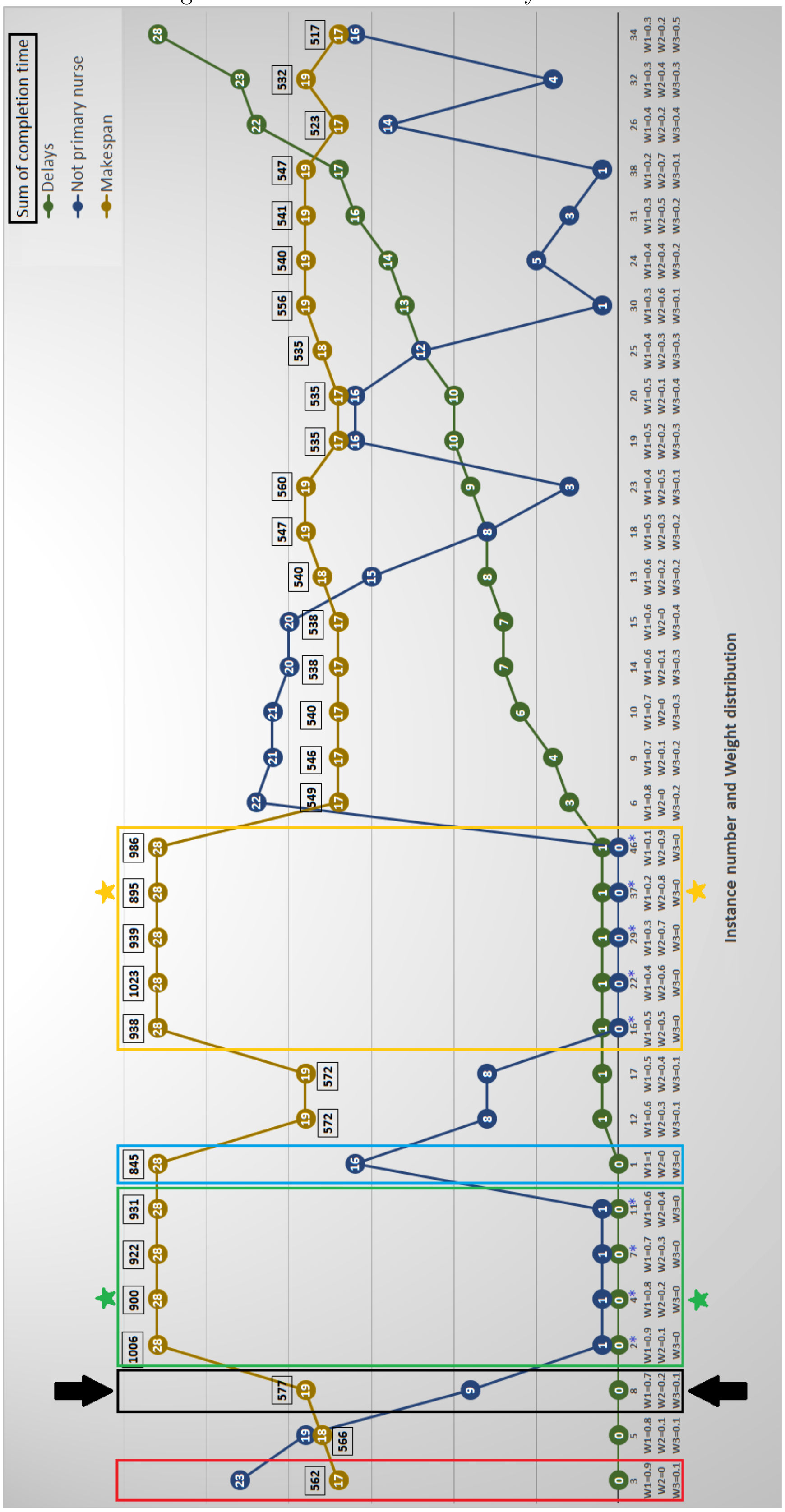
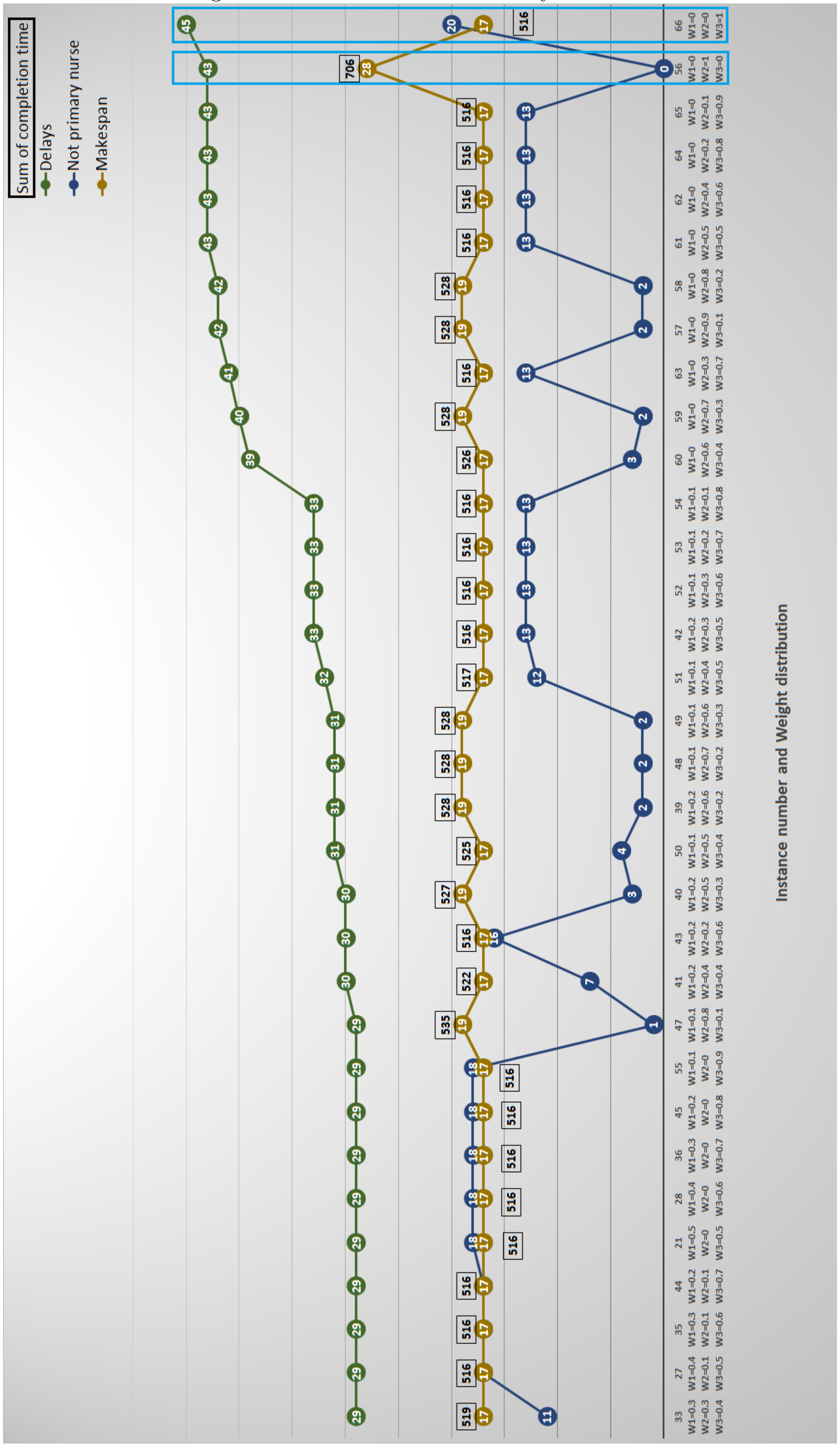


Figure 3.7: **Test 2.** Trend on Delay: 29 to 45



Through **Figures 3.6 and 3.7**, the negative relationship between primary nurse assignment and the makespan can further be examined. The output on this graph was ordered such that the tendency on delays could be observed in an increasing manner. The instances are graphed in an order different from the **Tables 3.13 and 3.14**. In this test, the correlation coefficient is calculated to stand at -0.61952 and demonstrates a moderate negative linear correlation, see Appendix **Figure B.1 and B.2** for the calculations. The negative linear correlation between these two different objectives indicates that there is some predictability. When one variable increases, the second variable decreases. It is then difficult to reallocate such that one criterion remains optimal without making the second criterion worse.

Throughout this test, *instance 1, instance 56* and *instance 66* outlined in blue act like single-objective optimization problems.

- *Instance 1* confirms that it is possible to experience zero delay.
- *Instance 56* confirms that it is possible to assign each appointment with the correct nurse.
- *Instance 66* confirms that it is possible to schedule all appointments within 17 days.

Of course, in each of these scenarios, trade-offs are made that do not advantage all three objectives simultaneously. It is although possible to see through *instance 3* outlined in red, two objectives being optimized at the same time. There are no delays and all the appointments are completed within the shortest makespan possible, 17 days. Consequently, the assignment of primary nurse is at its worse score with 23 appointments completed with the wrong nurse.

In the latter case of simultaneously optimizing the nurse assignment and the amount of delays, it is not possible through this scenario, but a few instances do come close. As it can be seen outlined in green, four instances attain zero delay with one wrong assignment, whereas five instances outlined in yellow, suffer of one delay with all nurse assignments done correctly. Through deeper analysis, it is possible to distinguish the best scenarios from these multiple solutions. The makespan may indicate 28 days for all of these instances, although when taking a closer look to the sum of completion time indicated in the box, it is possible to determine that *instance 4* and *instance 37* indicated by a green and yellow star have a better patient scheduling outcome. This indicates that most treatments began and were completed sooner.

Taking a closer look at the three weight coefficient of these outlined solutions, it is noticeable that w_3 often carries a null value. Signifying that the best output does not depend on the sum of completion time of the system. An optimized nurse assignment and adherence to protocol prime over minimizing the sum of completion time.

As it was mentioned previously, the optimal trade-off is subjective to the preference of the decision maker although the best recommendation would be to use the schedule obtained with *instance 8* indicated by the black arrows. Every single patient is scheduled according to the oncologist's prescribed regimen, thus attaining the best curative outcome. There are only nine wrong nurse assignments and the makespan is reasonably short with 19 days.

3.4 Contributions to Workforce Management

This section elaborates on the impact of using this tool on a daily basis. It demonstrates the quick decision making benefits and the possibility to guide nurse scheduling by first meeting the patient's needs.

The purpose of this optimization tool is to alleviate the workload and struggle of manually optimizing a schedule when so many variants are involved. This test was done on a blank canvas, meaning that all 150 appointments could be scheduled anywhere as availabilities abound everywhere. In a real-life scenario, this template would already be filled with existing appointments. This is why this model was created such that two distinct, yet similar decision variables are used to distinguish the date: X_{ikd} and the time : Z_{ikdt}. Any booked appointments would keep the same date as X_{ikd} would be set and the start time could be re-optimized through Z_{ikdt}, when new appointments are added.

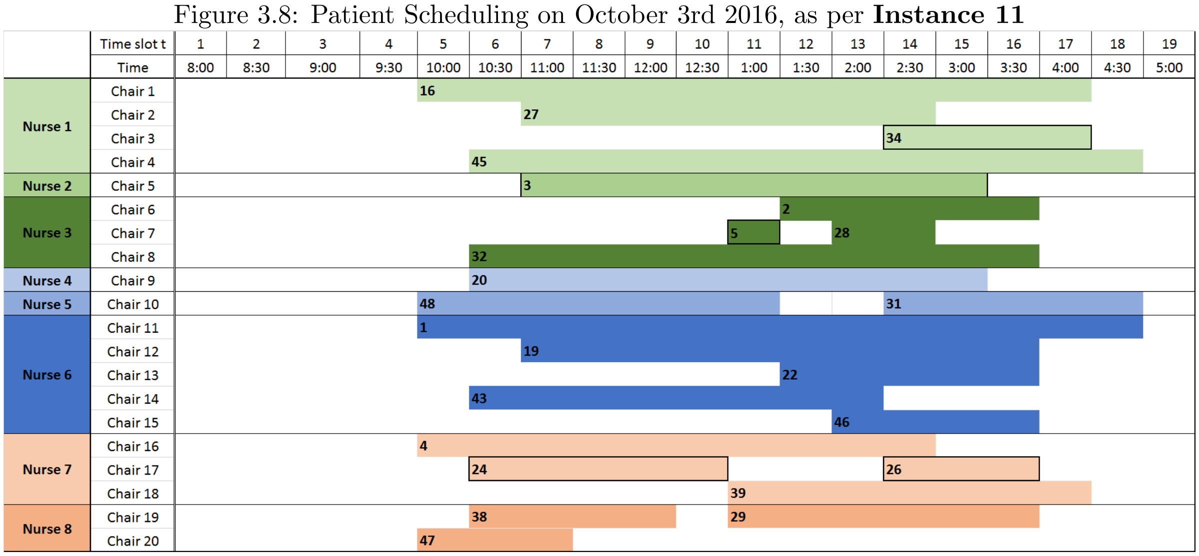
Some attention should be paid to the solving time. The instances indicated with an asterisk required between 38 minutes and up to 9 hours and 20 minutes to reach optimality with an average solving time of 3 hours and 5 minutes. The current test was done with a blank canvas; the solving time is understandably longer than a real-life scenario since the model needs to find the values of X_{ikd} for 150 appointments. This information would otherwise be known for all existing patients and would greatly simplify the problem as the model would mainly focus on finding appointment dates for the new request only, thus fitting three new appointments at a time and reschedule the start time of the appointments of the system.

This hypothesis was tested by observing the outcome of the longest instance, *instance 4* with weights: $w_1 = 0.8, w_2 = 0.2$, and $w_3 = 0$. Patients $i = 1$ to $i = 49$ were given their respective appointment dates according to the output of solving the blank canvas scenario. This allows the model to determine the treatment dates of only one new patient, patient $i = 50$ and the appointment start time of all other booked appointments including patient $i = 50$. Solving this test only required 1.02 seconds to reach optimality. This demonstrates that solving time will not be an issue in a real-life scenario. There is an added advantage to this separation method. In the case that a patient must absolutely be fit in the schedule on a given day, it is possible to set X_{ikd} for the first appointment and see the model resolve the rest.

In terms of efficiency, this tool greatly saves time by obtaining an optimal schedule within a few seconds. It brings a solution to the daunting task of scheduling patients, but it also has a benefit for nurse scheduling. Instead of firstly determining the schedule of the nurse and secondly determining the schedule of the patients, it is now possible to work in reverse such that the need of the patient is met by the schedule of the nurses. Taking a look back at *Figure 3.5*, it is now possible to determine the flaws. In *instance 11*, the scheduling tool prioritizes the wellbeing of the patient by having no delays and completing treatments as quickly as possible even if it affects the assignment of the primary nurse. If maximizing protocol adherence and minimizing makespan are the main objectives of the decision maker, it is possible to improve the nurse assignment objective by creating the nurse schedule after knowing the patient's appointment requirements. For example, the value of $\sum_{i=1}^{I} Y_i$ is greatly affected by the day off of nurse 5. Keeping in mind that patients come first, if this nurse was given a day off on the 5th or the 14th instead of the 10th, five additional patients would be properly scheduled with their primary nurse. The same goes for nurse 6. If this person was given a day off on the 11th instead of the 12th, three additional patients would be scheduled with their primary nurse and therefore improving the overall nurse assignment of the system.

The concept of establishing the nurse's days off after knowing the demand can further be applied to their hourly schedule. The **Figure 3.8** represents one of the busiest days of the month of *instance 11*, with 24 patients. The start time of treatment is specified for each patient and it is clear who is assigned to which nurse and on which chair. For example, patient $i = 16$ is required to begin treatment at 10:00 a.m. on chair 1 with nurse 1. It is also clear that patients who require special drugs are scheduled to begin after 10:00 a.m. and are distinguished by a black outline: patients 34, 5, 24 and 26.

Figure 3.8: Patient Scheduling on October 3rd 2016, as per **Instance 11**



Considering the start time of all the treatments on that day, it would be unnecessary to have nurses come in to work before 10:00 a.m. This information could serve to schedule early administrative tasks or meetings since patients would only arrive later. In order to accommodate every patient, each nurse is required to be present for the hours described in **Table 3.15**.

Table 3.15: Nurse Start Time and End Time Requirement for October 3rd 2016, as per **Instance 11**

	Start time	End time
Nurse 1	10:00 .a.m.	5:00 p.m
Nurse 2	11:00 a.m.	3:30 p.m.
Nurse 3	10:30 a.m.	4:00 p.m.
Nurse 4	10:30 a.m.	3:30 p.m.
Nurse 5	10:00 .a.m.	5:00 p.m
Nurse 6	10:00 .a.m.	5:00 p.m
Nurse 7	10:00 .a.m.	4:30 p.m.
Nurse 8	10:00 .a.m.	4:00 p.m.

On October the 10th, shown in **Figure 3.9**, nurse 1 and nurse 5 are absent and yet have patients assigned to them as outlined in red. By clearly seeing the workload of every other nurse, it is easy to evaluate who can accommodate these patients. A balanced although not unique schedule can be seen in **Figure 3.10**, where the grey chairs indicate patients who are not with their primary nurse. On this day, nurses are required to work according to the hours mentioned on **Table 3.16**. This mixed-integer linear programming model is able to create a schedule for the chemotherapy outpatient clinic while considering three objectives that are important to the Segal Cancer Center.

Figure 3.9: Patient Scheduling on October the 10th 2016, as per **Instance 1**

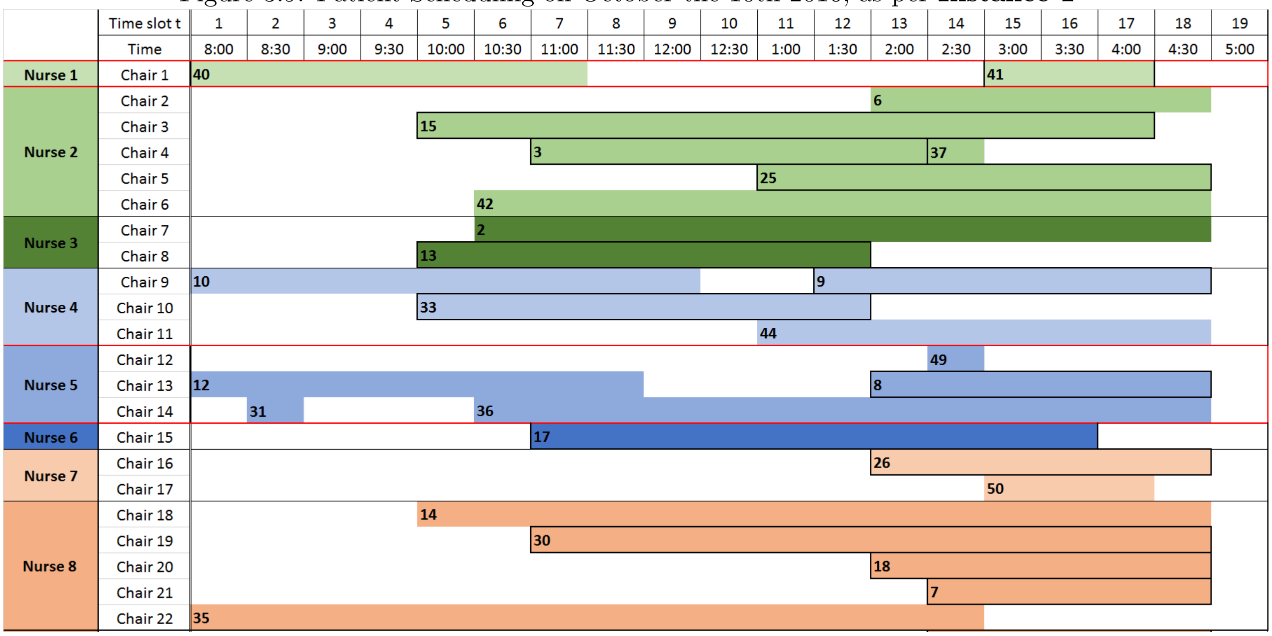


Figure 3.10: Patient Scheduling on October the 10th 2016, as per **Instance 1**, Manually Reassigned

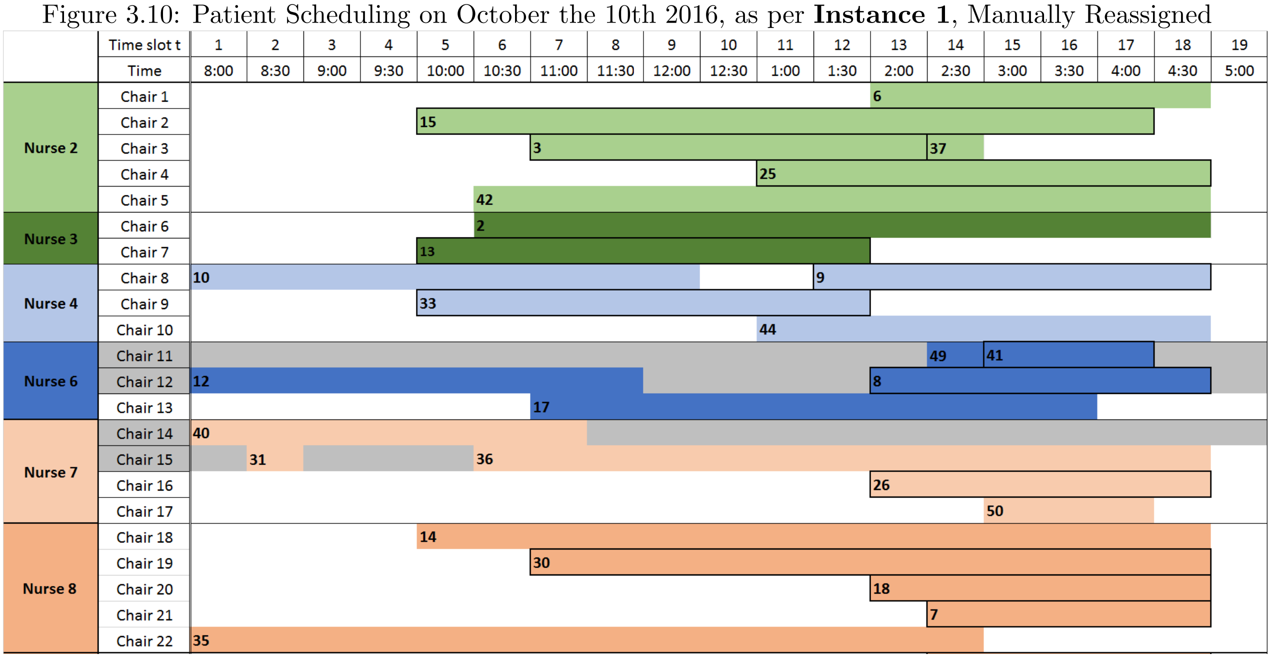


Table 3.16: Nurse Start Time and End Time Requirement for October the 10th 2016, as per **Instance 1**

	Start time	End time
Nurse 2	10:00 a.m.	5:00 p.m.
Nurse 3	10:00 a.m.	5:00 p.m.
Nurse 4	8:00 a.m.	5:00 p.m.
Nurse 6	8:00 a.m.	5:00 p.m.
Nurse 7	8:00 a.m.	5:00 p.m.
Nurse 8	8:00 a.m.	5:00 p.m.

3.5 Possible Improvements and Extensions

This section goes over the weaknesses of the model and suggests possible improvements to solve a more realistic chemotherapy outpatient scheduling problem.

The appointment start time obtained with this model is not a unique configuration. This mathematical model does not minimize nor maximize any aspect of treatment start time. With the current set of constraints, a schedule is simply obtained such that the resource limitations are respected. There are two additional plausible objectives that could add more value to this tool and further improve this model. For example, it could be interesting to include either of these:

-Minimization of the amount of chairs used per day to accommodate any walk ins or emergencies.

-Minimization of the daily completion time of treatment such that patients will arrive earlier and leave earlier.

Also, the concept of differentiating chairs from beds could be included as some patient are dependent on these beds while others can be accommodated by either of these two options. There is a major difficulty with this idea since the clinic unfortunately cannot always know in advance whether a patient will require a bed or not until their arrival.

The layout of the clinic was assumed to be undivided as it currently has two different work stations with an uneven amount of chairs and beds. Furthermore, a rotation of nurse between the two stations happens every two weeks. This may become a complication in a larger and busier scenario as it is not possible for a single nurse to attend patients located in two different places at once. An additional constraint would be required to monitor the station and amount of chairs required per nurse to take care of this issue.

The treatment length L_{ik} is assumed to be deterministic considering accurate protocols and established monographs that specify infusion procedures. It is nonetheless possible that an infusion lasts longer due to side-effects or a difficult set up.

Since this mixed-integer linear problem aims to optimize the single-stage of chemotherapy scheduling, earlier appointments happening on the same day with a different healthcare specialist such as an oncologist or any other specialist is not taken into consideration. Because of this, it is assumed that every patient will be arriving on time for their appointment, despite the fact that delays caused by traffic or previous appointment often occur in real life. A potential solution to this weakness is presented in the next chapter.

3.6 Conclusion

The focal point of this chapter was to set patient appointments in the single-stage environment of chemotherapy outpatient scheduling. A solution was proposed by developing a multi-objective mixed-integer linear program. The three targets of this scheduling tool were to:

-1. Maximize protocol adherence.

-2. Maximize primary nurse assignment.

-3. Minimize the sum of completion time which also affects the makespan of the system.

The results of computational experiments demonstrated the efficiency and speed of the suggested model. It was explained how the output can benefit in taking managerial decisions. Arrangements such as when to give a day off to a nurse and when to schedule their shifts start time can easily be determined. In conclusion, this multi-objective mixed-integer linear program has many advantages that can serve to schedule patients and nurses such that both parties can be satisfied.

This model allows to solve the chemotherapy outpatient scheduling problem. When it is used, the date and time of each appointment is known. The clinic will then immediately confirm the date that is obtained and disregard the appointment start time as it is only confirmed a few days before their treatment.

Chapter 4

Oncology Clinic Multi-Stage Scheduling Problem

The second focus of this thesis is the scheduling of the interdependent events that conclude to chemotherapy treatment. The Segal Cancer Center is divided in four main branches: the hematology clinic, the oncology department, the pharmacy and the chemotherapy unit. These four divisions greatly depend on one another. If any delay or interruption occur within the earlier stages, it will cause unnecessary patient wait time and affect the efficiency of the clinic. The proper coordination of these subsystems will reduce patient wait time, reduce staff idle time, positively impact efficiency and service level which will ultimately lead to an optimized oncology clinic. A mixed-integer linear program will demonstrate the possibility of abolishing the current two-day scheduling policy and easily complete all necessary tasks in a single day. The planning horizon of this scheduling problem is over the span of a single day and coordinates the activities of every patient.

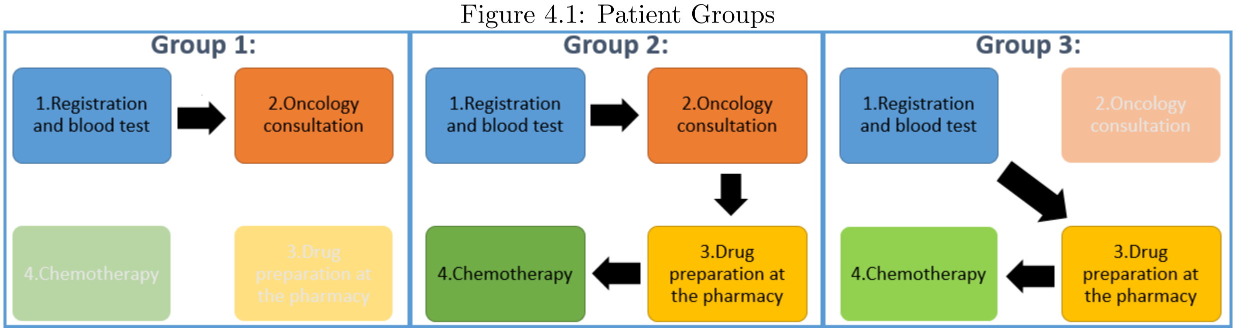
It is also an extension to a weakness mentioned in Chapter 3 as it is important to consider previous appointments that may affect the start time of chemotherapy treatments. Solving this real-world problem experienced at the Segal Cancer Center of the Jewish General Hospital in Montreal Quebec is the intention of this chapter.

4.1 Problem Definition

In April of 2014, due to complaints and extended patient wait time, the Segal Cancer Center had to modify its scheduling policy. A single day visit has been stretched out, on to two days. This represents the necessity of being at the clinic a first time to perform blood tests and complete a consultation with the oncologist if necessary. This is inconveniently followed by a second visit to the clinic to complete the chemotherapy treatment on the next day. In this manner, prolonged on-site wait time was converted to off-site wait time. This does not truly solve the issue. As it was surveyed by Lau [23], it would certainly be preferable to coordinate activities throughout the clinic such that everything can be completed in a single visit. This would increase patient satisfaction, overall convenience and eliminate the hassle of travelling twice to the clinic.

Chemotherapy is characterized by a regimen that consists of multiple infusions and frequent oncology examinations. Patients perform these follow ups at different intervals, which is decided by the oncologist. Three groups of patients are distinguished and seen in **Figure 4.1**. Group *G1* are the ones that come for an oncology appointment. Group *G2* are patients who need to complete an oncology consultation and receive chemotherapy treatment. Finally, group *G3* are patients who come to receive chemotherapy treatment only. The entire set of patient treated by the clinic is defined as $G = G1 \cup G2 \cup G3$.

Figure 4.1: Patient Groups



With the use of a mixed-integer linear programming model, the sum of completion time of each patient is minimized. With this approach, scheduling patients in a single day is easily done. On a daily basis, the clinic may receive between 100 to 250 patients scheduled to meet with an oncologist and 60 to 80 patients that require chemotherapy, thus either belonging to groups $G1$, $G2$ or $G3$.

As described in **Table 4.1**, this model must respect the capacity of the registration office, the fluctuating availability of oncologists, the production capacity of the pharmacy and the amount of nurses and chairs available to complete drug infusions.

Table 4.1: Material and Human Resources Required to Perform Daily Activities Through the Clinic

	Activities	Material resources	Human resources
Activity 1	Registration	Front desk	Secretary
	Blood Test	Examination room	Phlebotomist
	Await for blood test results	Waiting area	-
Activity 2	Oncology consultation	Examination room	Oncologist
Activity 3	Prescription preparation	Waiting area	Pharmacist / Pharmacy technician
Activity 4	Chemotherapy treatment	Chair / Bed	Nurse

- Upon arrival at the oncology outpatient clinic, the first activity applies to all three patient groups $G1, G2$ and $G3$. It is a sequence of three tasks, registering at the reception, performing a blood test and waiting for the results to be available as it is mandatory for the oncology consultation or prescription preparation by the pharmacy. With the current two-day system established by the clinic, it is common for a few patients of $G3$ to complete their blood tests on the previous day, at a CLSC as it may be more convenient than travelling to the Segal Cancer Center. Thus these patients upon arrival at the clinic must register at the reception and still wait for the blood test results as they must be retrieved from the Québec Health Record, a tool that allows healthcare professionals to have quick and easy access to health information of patients.

- The second activity, which is the consultation with an oncologist, applies to the patients of the sets $G1$ and $G2$. It is customary that an oncologist is assigned an examination room for the duration of their shift. Thus, it is unnecessary to validate the vacancy of an exam room as when an oncologist is available, the same goes for their assigned space.

- The third activity is the prescription preparation which is necessary to perform the chemotherapy treatment of patients $G2$ and $G3$. In the current two-day system, these patients do not stay and wait at the clinic for it as it is prepared during their off-site wait time. They simply head back home and arrive on the next day with their prescriptions ready for infusion. This will no longer be the case in the single day processing system as patients will be directed to the waiting area while the pharmacist validates the prescription and the pharmacy technician prepares it in a timely and orderly fashion.

- The fourth activity is the chemotherapy treatment which is required for patients of the groups $G2$ and $G3$. To perform this step, a nurse must be available for setup and supervision for the duration of the infusion. Furthermore, a chair or a bed is essential for a comfortable treatment during this lengthy process.

As summarized in **Table 4.2** , the patients of $G1$ require the set of jobs $A1$: activity 1 and 2. The patients of $G2$ require the set of jobs $A2$: activity 1, 2, 3 and 4. Finally, the patients of $G3$ require the set of jobs $A3$: activities 1, 3 and 4. When a constraint must refer to all the activities, the set $A = A1 \cup A2 \cup A3$ will be used.

Table 4.2: Activities Required per Patient Groups

Activities	Patients $i \in G1, A1$	Patients $i \in G2, A2$	Patients $i \in G3, A3$
Activity 1	X	X	X
Activity 2	X	X	
Activity 3		X	X
Activity 4		X	X

The clinic continuously receives new appointment requests for which the trajectory and chemotherapy specifications are diverse. The tool developed in this model can only be used if the ensemble of the requests is known from the start. Realistically, this signifies that when a patient is asking to schedule an appointment, they will only know the date right away, but not the time. The clinic will collect all the requests and employ this tool once it has accumulated enough data to finalize the hourly schedule one day or two in advance, giving them the opportunity to contact each patient to confirm the time of their appointment.

The **Table. 4.3** describes the additional parameters and the decision variables of the mathematical model. Since the operating hours of the Segal Cancer Center are from 7:30 a.m. until 6:00 p.m., the timeline of this problem has been subdivided into smaller time slots of 15 minutes, for a total of 42 time slots $t \in T$. Where $t = 1$ represents 7:30 a.m. to 7:45 p.m. and $t = 42$ represents 5:45 p.m. to 6:00 p.m. This differs from chapter 3 due to the inclusion of oncology consultations. They are assumed to last one time slot. Thus having longer time slots would not be reasonable to model this situation.

Table 4.3: Parameters and Decision Variables of the Oncology Clinic Multi-Stage Scheduling Problem

	PARAMETERS
T	Set of time slots
$G1$	Set of patients who need to see the oncologist
$G2$	Set of patients who need to see the oncologist and receive chemotherapy
$G3$	Set of patients who need to receive chemotherapy
G	Set of patient $G1 \cup G2 \cup G3$
$A1$	Set of activities = 1,2
$A2$	Set of activities = 1,2,3,4
$A3$	Set of activities = 1,3,4
A	Set of activities $A_1 \cup A_2 \cup A_3$
r_t	Amount of patients that can be attended to per time slot t at the reception
$t1$	Amount of time slots for registration, blood test and result posting
$t2$	Amount of time slots required for an oncologist consultation
$p2_g$	Amount of time slots needed for drug preparation for the patient $g \in G2$
$p3_g$	Amount of time slots needed for drug preparation for the patient $g \in G3$
$c2_g$	Amount of time slots needed for chemotherapy treatment for the patient $g \in G2$
$c3_g$	Amount of time slots needed for chemotherapy treatment for the patient $g \in G3$
n_t	Amount of nurses available during time slot $t \in T$
o_t	Amount of oncologists available at time slot $t \in T$
p_t	Amount of pharmacy technicians available at time slot $t \in T$
c	Amount of chairs available
m	Maximum wait time between activities
	DECISION VARIABLES
C_g	The completion time for patient $g \in G$
Y_g	The total amount of time spent by patient $g \in G$ at the clinic
X_{tag}	A binary decision variable, 1 if at time slot $t \in T$, the activity $a \in A$ of patient $g \in G$ is scheduled to begin, 0 otherwise

There must always be someone present at the reception to greet, register and guide the patients arriving to the clinic. The capacity, amount of people that can be attended to per time slot $t \in T$ is described by r_t and is correlated to the amount of staff present at the reception.

Activity 1 of **Table 4.2** is expected to last $t1$ time slot and is assumed to be constant and identical for everyone. There are not many sources of variation at this point. After registering at the reception on the 7th floor of the Segal Cancer Center, the patient is directed to the hematology area next door. From there, a blood sample is taken and transferred to the core laboratory through a tube via, a pneumatic system. The results are then available through the hospital's information system within 30 minutes. Depending on their individual trajectory, a patient will either be seated in the waiting area of the 7th floor until meeting with an oncologist, or on the 8th floor to wait for their prescription to be ready for chemotherapy.

Activity 2 of **Table 4.2** applies to the people present for a consultation with an oncologist. The availability of these specialists varies widely since they are present for a specific amount of time that may vary from day to day or even from week to week. Due to additional commitments, such as teaching, completing research, giving conferences or the need of their expertise to complete surgery or consultation in different clinics, they do not have a constant schedule. The parameter o_t, specifies the amount of oncologists available per time slot $t \in T$ and can be deduced from the example of schedule shown on **Table 4.4**. In this problem, it is assumed that a patient may be assigned to any oncologist, when they are treated and followed up by the same person when possible. The duration of the consultation is assumed to be constant for everyone and require at most $t2$ time slots. During this time, the physician consults the patient and their file. The diagnostic and prescription are then recorded in the information system. From there, a patient may leave the clinic or head to the waiting area on the 8th floor for the prescription that will be required during chemotherapy.

Table 4.4: Amount of Oncologists Available per Hour, o_t

Time	Monday	Tuesday	Wednesday	Thursday	Friday
8:00 a.m.	0	3	1	0	1
9:00 a.m.	6	8	7	8	3
10:00 a.m.	6	9	8	8	4
11:00 a.m.	6	8	7	8	3
12:00 a.m.	4	5	5	4	2
1:00 p.m.	4	6	7	4	1
2:00 p.m.	3	6	7	4	1
3:00 p.m.	3	6	7	4	1
4:00 p.m.	0	2	3	2	0

The oncology clinic has its own pharmaceutical department. Upon receiving the prescription, the pharmacist validates it and transmits the instructions to the pharmacy technicians. Unlike the way it was modeled in [20], the pharmacy is affected by resource limitations. The parameter p_t accounts for the number of technicians available per time slot $t \in T$. While the drug is being processed, the patients are in the waiting area. The amount of time necessary to perform *Activity 3*, which is the drug preparation $p2_g$ for patients $g \in G2$ and drug preparation $p3_g$ for patients $g \in G3$ is different for each individual and depends on the prescribed regimen. With the knowledge of the industry, the amount of time required is accurately rounded up to the nearest 15-minute interval as it may vary between two minutes to 45 minutes to prepare a prescription, depending on the request. The possibility of delays due to misplaced files, phone call interruptions, additional prescription validation and other issues that may affect the preparation time are ignored in the parameters $p2_g$ and $p3_g$.

Additional limitations are considered in the infusion stage, something that was not done in [20]. A person who needs chemotherapy can only be scheduled per n_t, the amount of nurse available per time slot $t \in T$. It is conventional that a nurse must pay full attention to the patient they are setting up for infusion. Otherwise, they may simultaneously monitor the stability of four patients at their proximity. The infusion time required for *Activity 4* is predetermined by the oncologist and differs for every patient as it is a personalized treatment. The duration of each infusion is defined by $c2_g$ for patients $g \in G2$ and $c3_g$ for patients $g \in G3$. Once again, it is assumed to be deterministic as it is prescribed by the oncologist and based off reputable drug formularies. In reality, complications during setup or infusion such as side-effects or late patient arrival may prolong the infusion and delay any patient who was scheduled on that chair afterwards.

Once the prescription is ready, the nurse will direct the patient to a treatment chair in one of the two stations of the clinic. The number of chairs and beds c available to complete chemotherapy is a limiting resource as it can only accommodate one patient at a time. This is why their use must be optimized such that patients are not negatively affected.

The concept of wait time is introduced with the parameter m. Having some wait time may be necessary due to a lack of coordination between resources. Because of this, a patient may be affected by a maximum of m time slots between some activities. Having the ability to control this parameter guarantees a certain service level.

There is are two objectives to be optimized. First, the model aims to minimize the completion time C_g of every patient $g \in G$. In this manner, patients must enter and leave the system as soon as possible. By doing so, the probability of staff performing overtime will be reduced. For example:

-If C_g of $g \in G1 = 27$, this patient arrived to the clinic and was done meeting with the oncologist at $t = 27$.

-If C_g of $g \in G2 = 27$, this patient arrived to the clinic and completed their chemotherapy at $t = 27$.

-If C_g of $g \in G3 = 27$, this patient also arrived to the clinic and completed their chemotherapy at $t = 27$.

The second objective is to manage on site wait time as it will directly impact service levels. The decision variable Y_g will be minimized and represents the amount of time spent at the clinic by patient $g \in G$; the end time minus the time of arrival at the clinic. For example, if patient $g \in G1$ arrives to the clinic at $t = 4$ and requires the activities mentioned in **Table 4.5** to be completed, in an optimal setting this patient would be completing activity one during $t = 4, 5$ and 6, followed by activity two at $t = 7$ and leave the clinic at $t = 8$, such that $Y_g = 4$. In the case that $Y_g = 5$, it signifies the presence of idle time m throughout the process. This patient was in the waiting area longer than necessary before performing activity two as seen in **Figure 4.2**.

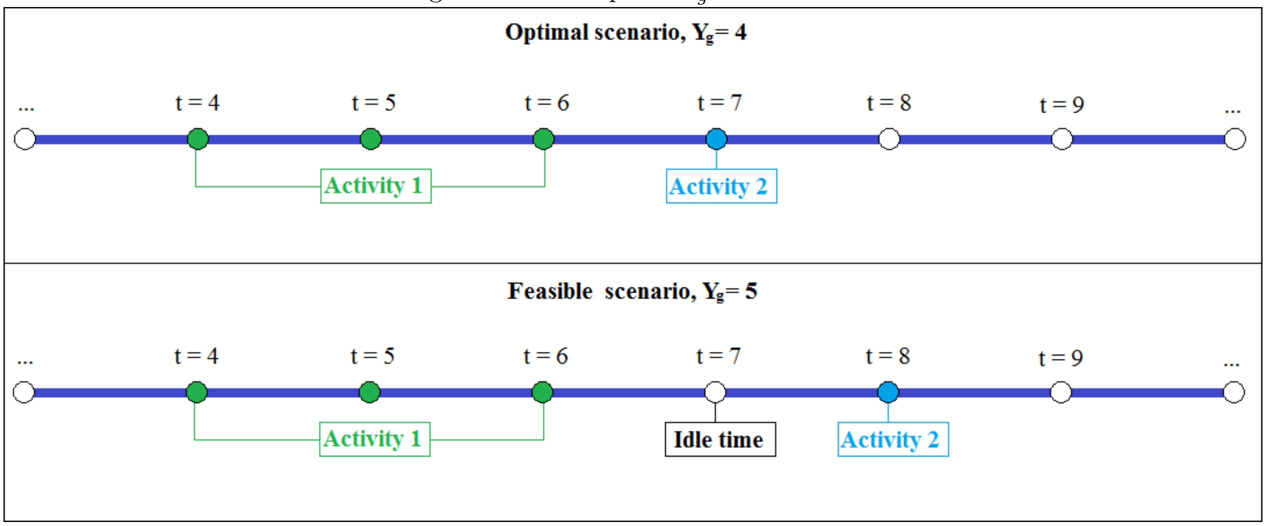
To keep track of the start time of each activity, the Boolean decision variable X_{tag} will indicate:

- 1, the activity $a \in A$ of patient $g \in G$ starts at time slot $t \in T$.
- 0, otherwise.

Table 4.5: Example of Time Required for Patient $g \in G$ to Complete *Activity 1* and *Activity 2*

Activity 1	Activity 2	Total
3 time slots (45 minutes)	1 time slot (15 minutes)	4 time slots (60 minutes)

Figure 4.2: Example of Y_g Calculation



4.2 Mathematical Model

Using the above-mentioned set of decision variables, the oncology clinic multi-stage scheduling problem can be stated as follows:

$$\textbf{Minimize: } \sum_{g\in G} C_g + \sum_{g\in G} Y_g \tag{4.1}$$

$$\textbf{Subject to: } \sum_{t\in T} X_{tag} = 1 \qquad a \in A, g \in G \tag{4.2}$$

$$\sum_{t\in T} tX_{t1g} + t1 \leq \sum_{t\in T} tX_{t2g} \leq \sum_{t\in T} tX_{t1g} + t1 + m \qquad g \in G1 \cup G2 \tag{4.3}$$

$$\sum_{t\in T} tX_{t2g} + t2 \leq \sum_{t\in T} tX_{t3g} \leq \sum_{t\in T} tX_{t2g} + t2 + m \qquad g \in G2 \tag{4.4}$$

$$\sum_{t\in T} tX_{t3g} + p2_g \leq \sum_{t\in T} tX_{t4g} \leq \sum_{t\in T} tX_{t3g} + p2_g + m \qquad g \in G2 \tag{4.5}$$

$$\sum_{t\in T} tX_{t1g} + t1 \leq \sum_{t\in T} tX_{t3g} \leq \sum_{t\in T} tX_{t1g} + t1 + m \qquad g \in G3 \tag{4.6}$$

$$\sum_{t\in T} tX_{t3g} + p3_g \leq \sum_{t\in T} tX_{t4g} \leq \sum_{t\in T} tX_{t3g} + p3_g + m \qquad g \in G3 \tag{4.7}$$

$$\sum_{g\in G} tX_{t1g} \leq r_t \qquad t \in T \tag{4.8}$$

$$\sum_{g\in G2} X_{t3g} + \sum_{g\in G2}\sum_{t'=max\{1,t-dp2_g+1\}}^{t-1} X_{t'3g} + \sum_{g\in G3} X_{t3g} + \sum_{g\in G3}\sum_{t'=max\{1,t-dp3_g+1\}}^{t-1} X_{t'3g} \leq p_t \qquad t\in T \tag{4.9}$$

$$\sum_{g\in G2} X_{t4g} + \frac{1}{4}\sum_{g\in G2}\sum_{t'=max\{1,t-dc2_g+1\}}^{t-1} X_{t'4g} + \sum_{g\in G3} X_{t4g} + \frac{1}{4}\sum_{g\in G3}\sum_{t'=max\{1,t-dc3_g+1\}}^{t-1} X_{t'4g} \leq n_t \qquad t\in T \tag{4.10}$$

$$\sum_{g\in G2} X_{t4g} + \sum_{g\in G2}\sum_{t'=max\{1,t-dc2_g+1\}}^{t-1} X_{t'4g} + \sum_{g\in G3} X3_{t4g} + \sum_{g\in G3}\sum_{t'=max\{1,t-dc3_g+1\}}^{t-1} X_{t'4g} \leq c \qquad t\in T \tag{4.11}$$

$$\sum_{g\in G1} X_{t2g} + \sum_{g\in G2} X_{t2g} \leq o_t \qquad t\in T \tag{4.12}$$

$$tX_{t2g} + t2 \leq 42 \qquad g\in G1\cup G2, t\in T \tag{4.13}$$

$$tX_{t4g} + c2_g \leq 42 \qquad g\in G2, t\in T \tag{4.14}$$

$$tX_{t4g} + c3_g \leq 42 \qquad g\in G3, t\in T \tag{4.15}$$

$$C_g = \sum_{t\in T} tX_{t2g} + do \qquad g\in G1 \tag{4.16}$$

$$C_g = \sum_{t\in T} tX_{t4g} + dc2_g \qquad g\in G2 \tag{4.17}$$

$$C_g = \sum_{t\in T} tX_{t4g} + dc3_g \qquad g\in G3 \tag{4.18}$$

$$Y_g = C_g - \sum_{t\in T} tX_{t1r} \qquad g\in G \tag{4.19}$$

The objective function is to minimize the total completion time and minimize the time spent in the clinic for every patient **(4.1)**. The set of constraints **(4.2)** ensures that all the activities $A = A1 \cup A2 \cup A3$ required by the patients $G = G1 \cup G2 \cup G3$ are scheduled.

Each patient group has a different trajectory and they must be scheduled accordingly. The set of constraints **(4.3)** verifies that the oncology consultation of patients $G1$ and $G2$ is scheduled chronologically either immediately after the registration or after being delayed by no more than m wait time.

Thus this same idea continues in **(4.4)**. A patient $g \in G2$ can only go to the 8th floor and wait for their prescription after seeing the oncologist. Only after the drug is prepare, patient $g \in G2$ can be set up for chemotherapy, **(4.5)**.

Patients $G3$ have a different trajectory, beginning with the set of constraints **(4.6)**. Their prescription can only be prepared after completing a blood test and the chemotherapy can only be performed after the prescription is ready, **(4.7)**.

The arrival rate of patients to the clinic is determined by the capacity of the registration office with the set of constraints **(4.8)**. Logically, a pharmacist must complete one prescription before preparing the next, **(4.9)**. The capacity and workload of the nurses is also monitored with **(4.10)**, making sure there are enough nurses working to accommodate newly arriving patients as well as to monitor existing patients. Finally, **(4.11)** ensures there are enough chairs to accommodate newly arriving patients and patients already being treated.

The amount of patients admitted for oncology consultations is also limited with the set of constraints **(4.12)**. In order to have all the patients out of the clinic by 6:00 p.m. such that overtime does not occur,**(4.13)** confirms that no oncology consultation will last past $t = 42$. This logic also applies with the set of constraints **(4.14)** and **(4.15)**, chemotherapy treatments may not be scheduled to last past 6:00 p.m. Every patient is ensured to complete their activities by the end of the day.

In order to calculate how much time each patient has spent in the clinic, the three set of constraints **(4.16), (4.17)** and **(4.18)** verify the completion time of the last activity of each patient. Finally, the set of constraints **(4.19)** calculate the difference between the time of departure and time of arrival at the clinic.

4.3 Computational Experiments and Analyses

This section presents the computational results of three tests and analyzes the solutions. To use this mixed-integer linear programming model, all the patient requests must to be known in advance. The input of preparation time $p2_g, p3_g$ and chemotherapy treatment time $c2_g, c3_g$ differ through these tests and are generated with the use of Microsoft Excel. The **Table 4.6** summarizes these differences.

Table 4.6: Type of Tests

Test	Chemotherapy treatment length, $c2_g$ and $c3_g$
Test 1	Generated data with mean ≈ 7 and standard deviation ≈ 4
Test 2	Generated data with mean ≈ 10 and standard deviation ≈ 7
Test 3	Generated data with mean ≈ 13 and standard deviation ≈ 8

The experiment was performed with the input seen in **Table 4.7**. This mathematical model can optimize and create a schedule to accommodate 280 appointments or more per day depending on the resource limitations. It determines the start time of every activity in the clinic, no matter the trajectory of the patient. It is tested with 200 patients of type $G1$, 40 patients of type $G2$ and finally 40 patients of type $G3$ such that the completion time and on site wait time is minimized. Since the clinic is open from 7:30 a.m. to 6:00 p.m., the timeline is divided in 42 time slots of 15 minutes.

The amount of resource available for the registration and chemotherapy treatments are slightly increased to solve this test. This allows to optimally schedule patient appointments and consequently coordinate the staff to match the demand.

At the reception, it is assumed that one employee may register and serve four patients per time slot. Since there are 280 patients that will arrive to the clinic over the course of the day, an inflated approximation would be to have three receptionists with the capacity of serving up to 12 patients per time slot as seen in

Table 4.7: Values Taken by Parameters for **Test 1, Test 2** and **Test 3**

	PARAMETERS
$G1$	200 patients who need to see the oncologist
$G2$	40 patients who need to see the oncologist and receive chemotherapy
$G3$	40 patients who need to receive chemotherapy
G	A total of 280 patients from the set of patient $G1 \cup G2 \cup G3$
T	42 time slots of 15 minutes
r_t	3 receptionists are assumed to be able to process 4 patients per 15 minutes, for a total of 12 patients per time slot
$t1$	2 time slots to register, perform blood test, and obtain results
$t2$	1 time slot to consult with the oncologist
$p2_g$	Preparation time ranges from 1 to 3 time slots, see **Table 4.9**
$p3_g$	Preparation time ranges from 1 to 3 time slots, see **Table 4.10**
$c2_g$	Chemotherapy treatment length ranges from 1 to 28 time slots, see **Table 4.9**
$c3_g$	Chemotherapy treatment length ranges from 1 to 28 time slots, see **Table 4.10**
o_t	Refer to table **Table 4.8**
p_t	Refer to **Table 4.8**
n_t	Refer to table **Table 4.8**
c	35 chairs available
m	Maximum wait time between activities is set to 0

Table 4.8. Of course, it is not feasible to have the same three employees working from 7:30 a.m. to 6:00 p.m. Their schedules will be made per the output and requirement of the model.

The purpose of this model is to prioritize the proper scheduling of patients such that the limiting resources can be adapted to the demand. Therefore, the capacity at the reception was slightly increased. This same idea is applied to the number of nurses available at each time slot n_t as their schedule can easily be modified to accommodate the need of patients. The head nurse always has eight nurses on the floor with an additional two for emergencies or administrative tasks. It is assumed that ten nurses are available throughout the day as seen in **Table 4.8**, even though they do not begin to work at the same time, nor end at the same time. The output of the model will determine the schedule of each nurse.

Contrarily to the reception and chemotherapy, the oncology department has a strict schedule to follow. Each physician supplies their availabilities to the oncology clinic and it is fixed. The staffing level used in this model is seen in **Table 4.8**. The pharmacy also has a strict schedule, but it is at least constant. At all time, there are $p_t = 5$ pharmacy technicians readily available to prepare patient prescriptions. This does not directly imply that five new prescriptions can be prepared at every time slot as some pharmacy technicians may still be busy with previous prescription.

The first activity, which is the registration and blood test is assumed to require two time slots $t1 = 2$ and remain constant for everyone. The second activity, which is the oncologist consultation is also assumed to be constant and require only one time slot $t2 = 1$ per patient. The amount of time required for the

Table 4.8: Staff Availability

Time slot	r_t	o_t	p_t	n_t	Time slot	r_t	o_t	p_t	n_t
1	12	0	0	10	22	12	9	5	10
2	12	0	0	10	23	12	6	5	10
3	12	3	5	10	24	12	6	5	10
4	12	3	5	10	25	12	6	5	10
5	12	5	5	10	26	12	6	5	10
6	12	5	5	10	27	12	6	5	10
7	12	8	5	10	28	12	6	5	10
8	12	8	5	10	29	12	6	5	10
9	12	8	5	10	30	12	6	5	10
10	12	8	5	10	31	12	6	5	10
11	12	9	5	10	32	12	6	5	10
12	12	9	5	10	33	12	6	5	10
13	12	9	5	10	34	12	6	5	10
14	12	9	5	10	35	12	6	0	10
15	12	8	5	10	36	12	6	0	10
16	12	8	5	10	37	12	6	0	10
17	12	8	5	10	38	12	4	0	10
18	12	8	5	10	39	12	4	0	10
19	12	8	5	10	40	12	0	0	10
20	12	8	5	10	41	12	0	0	10
21	12	9	5	10	42	12	0	0	10

prescription preparation $p2_g$ and $p3_g$ as well as the time needed for chemotherapy treatment $c2_g$ and $c3_g$ differs per patient according to their prescribed regimen. The data used for the tests can be seen in **Table 4.9 and 4.10**

For the chemotherapy process, all 30 chairs and five beds are included in this problem such that $c = 35$. Because of the processing time to complete prior activities, the earliest chemotherapy treatments may only begin is at $t = 3$. Since there are 35 chemotherapy chairs, the clinic has a total capacity of 39 time slots * 35 chairs for a total of 1365 time slots to accommodate patients in need of chemotherapy.

The concept of wait time introduced by the parameter m is set to zero to eliminate idle time. The exercise of setting $m = 1$ was not explored in this thesis, but could serve as an extension to this research. Realistically, adding the second term of minimizing $\sum_{g=1}^{G} Y_g$ in the three tests that were given as examples could have been omitted. Exploring this route was attempted, but did not turn out to be successful. Even though CPLEX is a strong and top of the line optimization tool, the solver was never able to find a feasible solution within 12 hours, even though an optimal schedule with $m = 0$ existed.

Table 4.9: Drug Preparation and Infusion Time for Patients $G2$

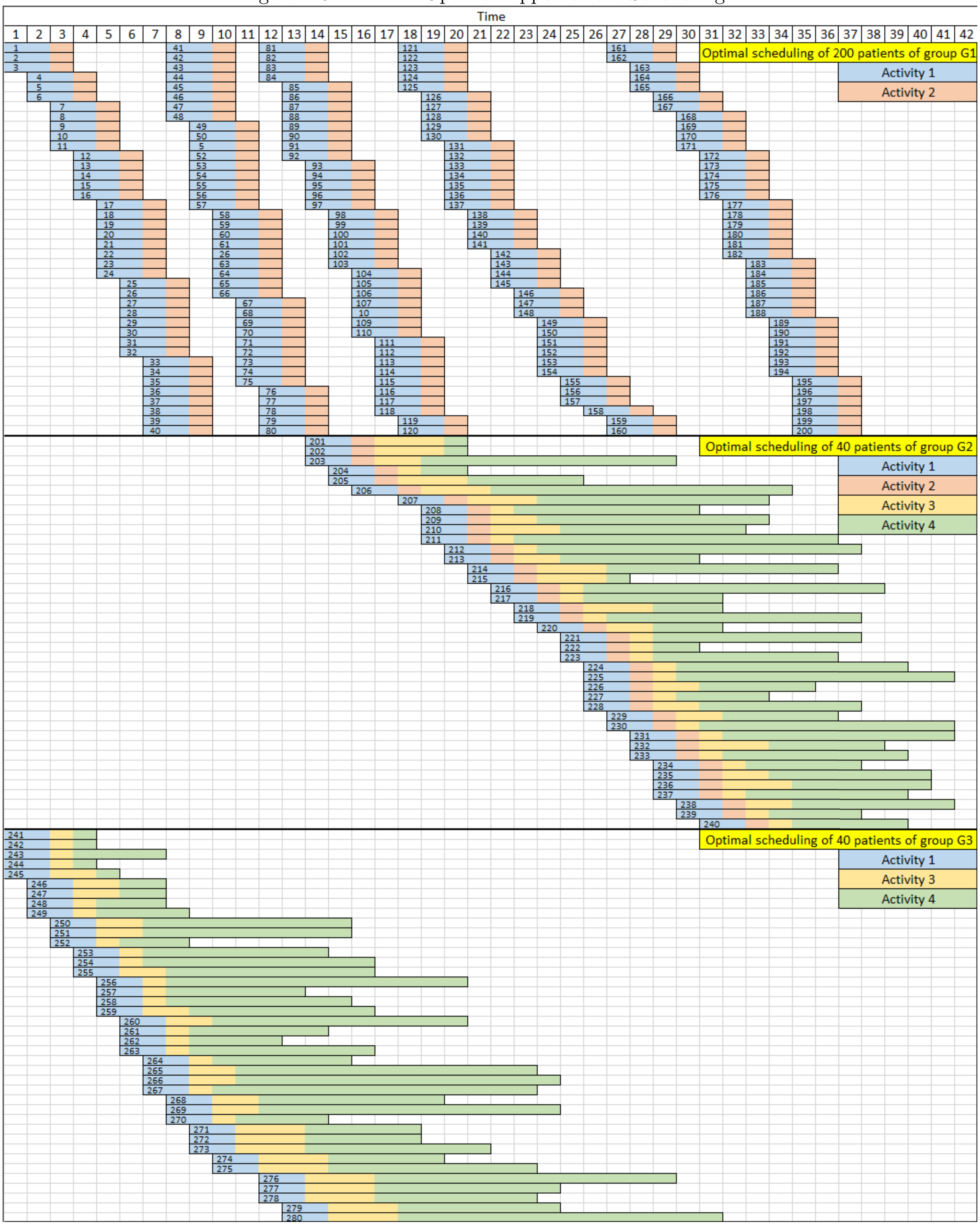
Patient	Test 1 $p2_g$	Test 1 $c2_g$	Test 2 $p2_g$	Test 2 $c2_g$	Test 3 $p2_g$	Test 3 $c2_g$
1	1	14	2	26	3	29
2	1	5	1	27	3	28
3	1	9	1	24	3	27
4	3	10	2	1	1	28
5	3	1	3	10	2	26
6	2	7	1	18	3	24
7	3	1	1	7	1	25
8	2	7	1	3	2	23
9	3	1	3	9	1	23
10	1	2	1	3	1	21
11	1	13	2	12	1	19
12	2	6	1	1	3	15
13	2	11	2	3	2	17
14	1	8	2	13	2	17
15	2	5	1	8	3	16
16	3	12	3	10	1	15
17	1	10	1	5	3	14
18	1	12	3	14	2	9
19	2	10	1	14	2	5
20	1	10	3	16	2	6
21	1	5	1	6	2	13
22	3	5	2	16	3	11
23	1	6	3	13	1	7
24	2	5	3	1	1	9
25	3	10	3	13	1	1
26	3	3	3	9	3	9
27	1	8	3	13	1	10
28	1	2	1	1	3	9
29	3	8	1	8	1	2
30	3	6	2	9	2	9
31	3	5	1	10	3	6
32	1	11	3	9	1	8
33	1	14	1	11	3	3
34	1	4	1	10	3	1
35	1	11	1	1	3	4
36	1	8	2	7	1	4
37	2	7	1	8	1	5
38	1	4	2	3	1	2
39	1	7	1	6	2	3
40	2	3	1	5	1	2

Table 4.10: Drug Preparation and Infusion Time for Patients $G3$

Patient	Test 1 $p3_g$	Test 1 $c3_g$	Test 2 $p3_g$	Test 2 $c3_g$	Test 3 $p3_g$	Test 3 $c3_g$
1	2	9	1	24	1	12
2	1	13	3	1	1	16
3	1	6	3	7	1	11
4	2	13	2	18	2	12
5	3	5	3	3	1	5
6	1	6	2	6	3	12
7	3	5	3	22	1	28
8	1	1	1	17	1	1
9	3	7	1	15	3	17
10	3	9	1	5	3	24
11	2	11	3	9	2	20
12	1	8	1	8	1	5
13	2	8	1	27	2	13
14	2	14	1	9	1	10
15	2	2	2	19	2	24
16	1	1	1	18	2	15
17	1	10	1	14	2	21
18	1	6	3	26	1	26
19	2	9	2	1	3	20
20	2	2	1	3	1	7
21	3	5	2	3	2	19
22	1	14	3	17	2	24
23	1	3	1	16	1	24
24	3	13	2	2	1	10
25	1	10	2	3	2	3
26	3	11	1	17	2	11
27	1	6	2	7	3	4
28	1	4	2	1	1	22
29	2	12	1	1	3	28
30	1	4	3	13	3	2
31	1	1	1	8	3	21
32	1	8	1	4	3	4
33	2	8	2	6	3	6
34	3	8	1	6	1	6
35	3	15	3	3	2	4
36	2	21	2	10	3	13
37	2	4	1	9	2	16
38	1	5	2	2	3	30
39	1	7	3	3	3	8
40	3	17	1	9	2	13

4.3.1 Test 1, Treatment Length with Mean ≈ 7 and Standard Deviation ≈ 4

Figure 4.3: **Test 1.** Optimal Appointment Scheduling



The first test is performed with chemotherapy treatments of shorter length, ranging from one to 21 time slots with a mean of seven time slots and standard deviation of four time slots. This comes up to a total demand of 619 time slots to complete chemotherapy, thus filling the chairs at 45.35% of their capacity. The optimal scheduling of the clinic's activities is seen in **Figure 4.3** and was solved within 172.14 seconds.

Every patient in the system has been numbered from one to 280 and is scheduled so no unnecessary wait time is incurred. With this figure, it is possible to see at what time each patient begins and completes every activity. Looking at patient 214, he or she must be at the reception at $t = 21$ which is 12:30 p.m. After registering and completing the blood test, an oncologist is available to meet this patient at $t = 23$ which represents 1:00 p.m. Upon the end of the consultation, this patient is directed to the waiting area while their prescription is being validated and made. Since it is known that this medication requires 45 minutes to prepare, the chemotherapy only begins at $t = 27$, 2:00 p.m. This patient is then properly installed by a nurse onto a chair and will receive their infusion over the course of the next 10 time slots to finally exit the clinic at $t = 37$ which is at 4:30 p.m. This patient entered the system at $t = 21$ to finally exit at $t = 37$ for a total of $Y_{214} = 16$ time slots and a completion time of $C_{214} = 37$ time slots.

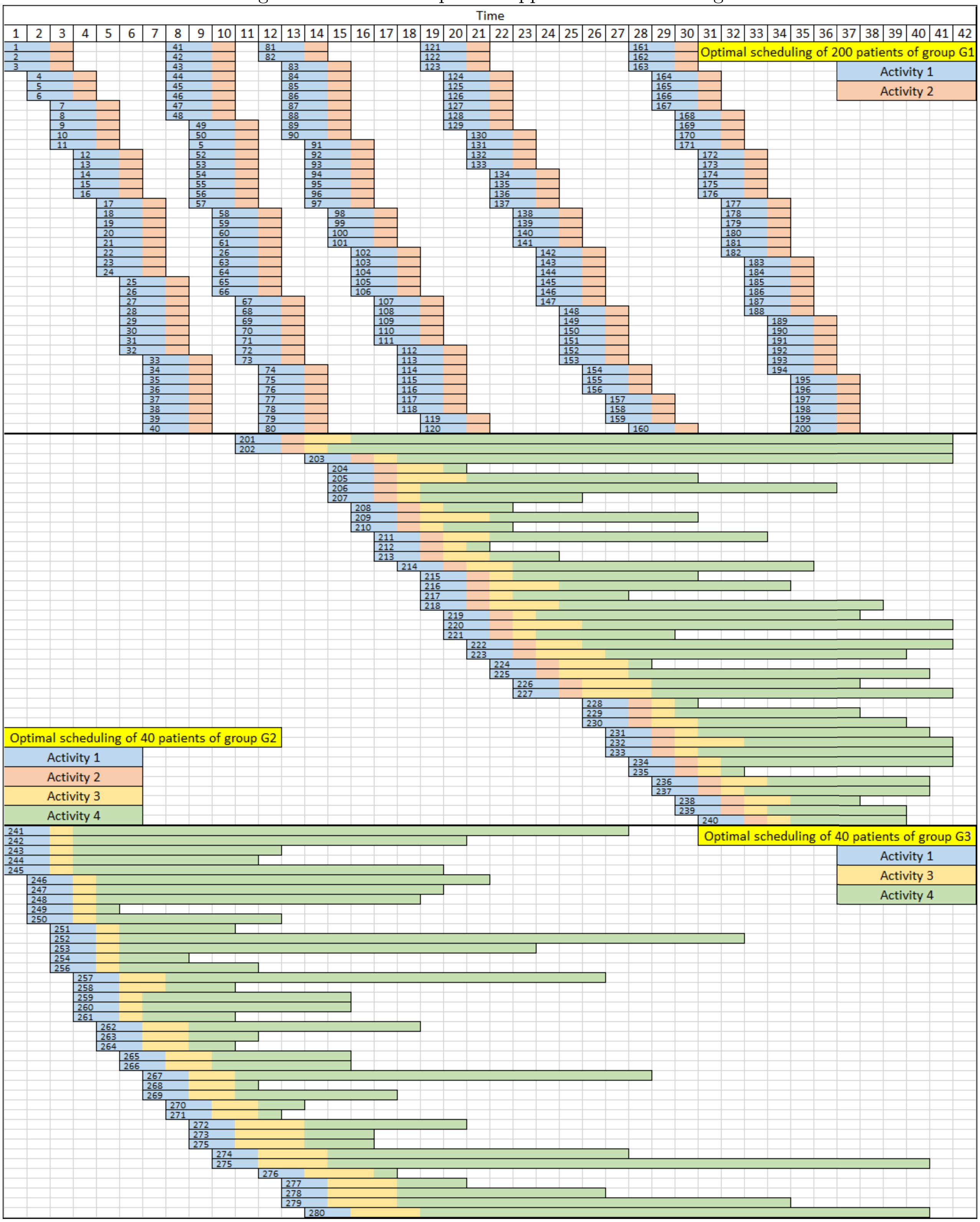
This scheduling tool may be impractical in a real-life scenario as it requires a list of appointment requests known in advance. It does not consider scheduling appointments as they arrive. The schedule that is obtained by using this mathematical formulation can although serve as a source of inspiration to formulate heuristics or rules to follow and achieve a feasible yet improved schedule in an online context. The following are observations that can be acknowledged and used.

-Firstly, it is noticeable that patients of group $G3$ arrive to the clinic before patients of group $G2$. In fact, the reception does not serve any patient of $G2$ until every single patient of $G3$ has been admitted.

-Secondly, the patients of $G3$ seem to be ordered in a manner that prioritize patients with shorter pharmacy preparation time ahead of the ones who require longer preparation time.

4.3.2 Test 2, Treatment Length with Mean ≈ 10 and Standard Deviation ≈ 7

Figure 4.4: **Test 2.** Optimal Appointment Scheduling



The second test is performed with chemotherapy treatments of average length, ranging from one to 27 time slot with a mean of 10 time slots and standard deviation of seven time slots. This comes up to a total demand of 775 time slots to complete chemotherapy, thus filling the chairs at 56.78% of their capacity. The optimal scheduling of the clinic's activities is seen in **Figure 4.4** and was solved within 280.71 seconds.

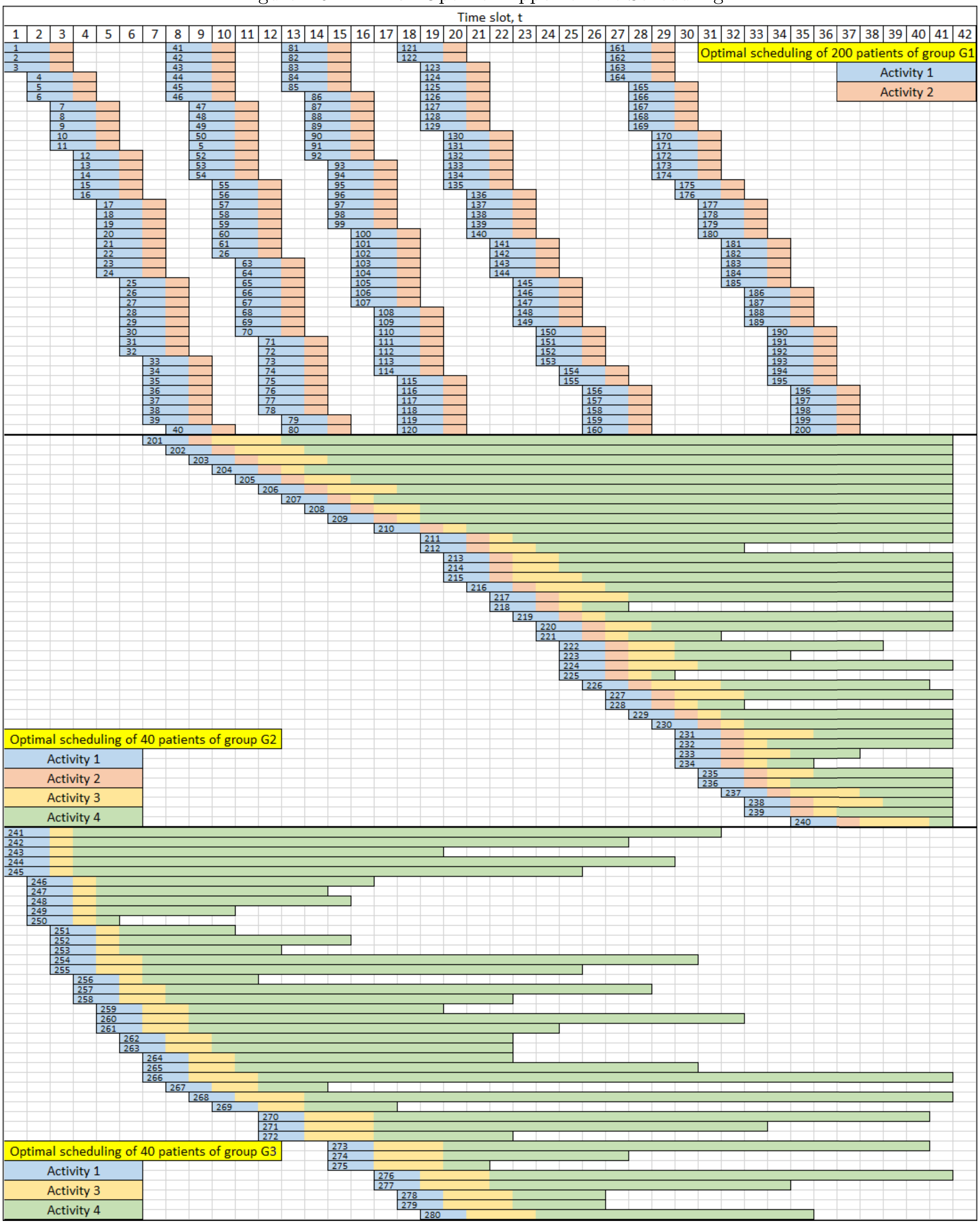
The two observations made in the first test are reinforced in this second evaluation. Most of the patients of group $G3$ are arriving to the clinic before patients of $G2$.

The prioritization of shorter pharmacy preparation time within $G3$ is quite apparent in this schedule. Since the amount of chair time available decreases as the day goes by, it is only normal that the model will encourage to use this resource as early as possible during the day. By completing prescriptions quickly, chemotherapy can begin sooner and chair idle time can be reduced.

The patients of $G2$ seem to be ordered in a way that prioritizes longest chair time first, but it is not entirely respected as it can be seen with patient 204. This person has a short infusion of 15 minutes, yet arrives at the clinic before other patients who require longer treatments.

4.3.3 Test 3, Treatment Length with Mean ≈ 13 and Standard Deviation ≈ 8

Figure 4.5: **Test 3.** Optimal Appointment Scheduling



The final test is performed with chemotherapy treatments that last much longer, ranging from one to 30 time slot with a mean of 13 time slots and standard deviation of eight time slots. This comes up to a total demand of 1072 time slots to complete chemotherapy, thus filling the chairs at 78.53% of their capacity. Since the parameter m is set to zero and eliminates patient wait time, solving this instance was infeasible. For this reason, the operating hours of the pharmaceutical department is extended until the end of the day. The optimal scheduling of the clinic's activities is seen in **Figure 4.5** and was solved within 806.41 seconds.

In this schedule, a pattern with $G2$ is clear. Patients who have longest treatments are admitted first and can be scheduled ahead of $G3$ patients. This is understandable as chair time has become a limiting resource in this scenario with higher demand.

Throughout all three tests, patients of $G1$ are simply fitted in whenever additional oncologists who are not busy with patients of $G2$ are free. There is no definite pattern observed.

4.4 Contributions to Workforce Management

This section illustrates the impact of using this tool to balance and guide staffing levels throughout the clinic. Although this model can only be applied in an offline setting, it can still be accommodated and benefit the clinic. When a patient is requesting an appointment, they would be given the date right away and the time would be confirmed later, a day or two before their appointment date. By doing so, the clinic has the time to accumulate requests and the oncology clinic scheduling model could be efficient.

The nurses, schedulers and receptionists spend so much time creating and restructuring patient schedules every day. This model supplies an optimization tool to significantly reduce the time spent on scheduling tasks, but also contributes to simplify decision making efforts of determining the best staffing level.

With the scheduling template obtained by using this model, the figures **Figure 4.6, Figure 4.7** and **Figure 4.8** display the amount of available resource per time slot and the actual use of them.

Figure 4.6: **Test 1.** Resources Available v.s. Resources Needed

Time	7:30	7:45	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	12:30
Time slot	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
Registration resource	12	12	12	12	12	12	12	12	12	12	12	12	12	12	12	12	12	12	12	12	12
Registration used	8	7	8	8	12	12	12	11	12	11	9	12	10	8	8	8	8	8	9	9	6
Oncology resource	0	0	3	3	5	5	8	8	8	8	9	9	9	9	8	8	8	8	8	8	9
Oncology used	0	0	3	3	5	5	8	8	8	8	9	9	9	9	8	8	8	8	8	8	9
Pharmacy resource	0	0	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5
Pharmacy used	0	0	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	4	2	2
Chair resource	35	35	35	35	35	35	35	35	35	35	35	35	35	35	35	35	35	35	35	35	35
Chair used	0	0	0	4	4	6	10	10	12	15	18	20	19	21	20	16	15	16	16	16	12
Nurse resource	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10
Nurse used	0	0	0	4	3	4	6	6	6	6	7	7	5	8	7	4	6	6	6	6	4
Total amount of patients in the clinic	8	15	23	28	34	40	47	46	48	51	52	55	55	53	49	45	44	46	46	45	39

Time	12:45	1:00	1:15	1:30	1:45	2:00	2:15	2:30	2:45	3:00	3:15	3:30	3:45	4:00	4:15	4:30	4:45	5:00	5:15	5:30	5:45
Time slot	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42
Registration resource	12	12	12	12	12	12	12	12	12	12	12	12	12	12	12	12	12	12	12	12	12
Registration used	6	6	7	6	6	6	6	6	6	6	6	6	6	6	0	0	0	0	0	0	0
Oncology resource	9	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	4	4	0	0	0
Oncology used	9	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	0	0	0	0	0
Pharmacy resource	5	5	5	5	5	5	5	5	5	5	5	5	5	0							
Pharmacy used	5	5	4	4	4	2	5	5	4	4	5	5	3								
Chair resource	35	35	35	35	35	35	35	35	35	35	35	35	35	35	35	35	35	35	35	35	35
Chair used	12	14	13	11	12	15	14	19	20	20	20	21	21	23	22	18	12	10	6	4	0
Nurse resource	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10
Nurse used	4	5	6	5	5	6	4	9	8	8	7	7	8	8	6	5	3	3	2	1	0
Total amount of patients in the clinic	39	38	36	34	35	36	38	43	43	43	43	44	42	41	34	24	12	10	6	4	0

Figure 4.7: **Test 2.** Resources Available v.s. Resources Needed

Time	7:30	7:45	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	12:30
Time slot	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
Registration resource	12	12	12	12	12	12	12	12	12	12	12	12	12	12	12	12	12	12	12	12	12
Registration used	8	8	10	10	11	10	11	10	12	11	9	10	11	9	8	8	8	8	9	9	6
Oncology resource			3	3	5	5	8	8	8	8	9	9	9	9	8	8	8	8	8	8	9
Oncology used			3	3	5	5	8	8	8	8	9	9	9	9	8	8	8	8	8	8	9
Pharmacy resource			5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5
Pharmacy used			5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	4
Chair resource	35	35	35	35	35	35	35	35	35	35	35	35	35	35	35	35	35	35	35	35	35
Chair used				5	10	14	17	19	21	23	22	20	17	19	22	19	18	20	21	22	20
Nurse resource	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10
Nurse used				5	7	8	7	7	8	8	8	7	5	7	8	6	6	8	8	8	7
Total amount of patients in the clinic			8	13	20	24	30	32	34	36	36	34	31	33	35	32	31	33	34	35	33

Time	12:45	1:00	1:15	1:30	1:45	2:00	2:15	2:30	2:45	3:00	3:15	3:30	3:45	4:00	4:15	4:30	4:45	5:00	5:15	5:30	5:45
Time slot	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42
Registration resource	12	12	12	12	12	12	12	12	12	12	12	12	12	12	12	12	12	12	12	12	12
Registration used	6	6	6	6	6	6	6	6	6	6	6	6	6	6							
Oncology resource	9	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	4	4			
Oncology used	9	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6					
Pharmacy resource	5	5	5	5	5	5	5	5	5	5	5	5	5								
Pharmacy used	5	5	5	5	5	4	2	3	4	3	3	3	2								
Chair resource	35	35	35	35	35	35	35	35	35	35	35	35	35	35	35	35	35	35	35	35	35
Chair used	21	22	23	24	25	24	23	23	24	23	25	25	26	26	25	24	20	19	15	9	
Nurse resource	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10
Nurse used	8	8	8	8	8	7	8	8	8	8	8	8	8	8	7	6	5	5	4	3	
Total amount of patients in the clinic	35	33	34	35	36	34	31	32	34	32	34	34	34	32	31	30	20	19	15	9	

Figure 4.8: **Test 3.** Resources Available v.s. Resources Needed

Time	7:30	7:45	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	12:30
Time slot	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
Registration resource	12	12	12	12	12	12	12	12	12	12	12	12	12	12	12	12	12	12	12	12	12
Registration used	8	8	10	8	11	10	11	9	10	10	9	12	8	8	11	8	10	10	10	9	6
Oncology resource			3	3	5	5	8	8	8	8	9	9	9	9	8	8	8	8	8	8	9
Oncology used			3	3	5	5	8	8	8	8	9	9	9	9	8	8	8	8	8	8	9
Pharmacy resource			5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5
Pharmacy used			5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5
Chair resource	35	35	35	35	35	35	35	35	35	35	35	35	35	35	35	35	35	35	35	35	35
Chair used				5	10	12	15	17	20	22	22	23	23	27	26	25	28	28	30	31	32
Nurse resource	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10
Nurse used				5	7	6	6	6	8	7	7	8	7	10	8	7	10	8	9	10	9
Total amount of patients in the clinic			8	13	20	22	28	30	33	35	36	37	37	41	39	38	41	41	43	44	46

Time	12:45	1:00	1:15	1:30	1:45	2:00	2:15	2:30	2:45	3:00	3:15	3:30	3:45	4:00	4:15	4:30	4:45	5:00	5:15	5:30	5:45
Time slot	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42
Registration resource	12	12	12	12	12	12	12	12	12	12	12	12	12	12	12	12	12	12	12	12	12
Registration used	6	6	6	6	6	6	6	6	6	6	6	6	6	6							
Oncology resource	9	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	4	4			
Oncology used	9	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6					
Pharmacy resource	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5
Pharmacy used	5	5	4	4	3	3	5	4	4	3	2	4	4	3	3	2	2	1	1		
Chair resource	35	35	35	35	35	35	35	35	35	35	35	35	35	35	35	35	35	35	35	35	35
Chair used	33	31	33	34	34	34	33	34	34	34	34	33	34	34	34	35	35	35	35	33	
Nurse resource	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10
Nurse used	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	9	9	
Total amount of patients in the clinic	47	42	43	44	43	43	44	44	44	43	42	43	44	43	43	43	37	36	36	33	

The proposed scheduling tool allows clinic executives to assess the trade-off between the cost of additional staff and the impact on customer service level and serving additional patients. They can also easily determine the adequate staffing requirement needed at the reception throughout the day and the number of nurses needed by first assessing the expected workload for the day.

As shown in Test 3, it became infeasible to schedule patients appropriately with chemotherapy chairs being filled at 78.53% of their capacity, the pharmacy was forced to remain open during a longer period of time. Paying attention to the usage level of the chairs may help set a threshold to be used to determine the necessity to postpone a patient to the next day, even though the chairs are not used at full capacity. However, it would be necessary to evaluate the clinics overtime cost to adjust and achieve a good threshold to see if it is worth delaying a patient's treatment.

Throughout the three tests, it is possible to see a correlation between the registration use and the amount of specialists available. The sum of oncologists and pharmacy technicians define the maximum number of patients that will arrive at the registration two time slots prior. This conclusion makes sense since these two resources act as the system's bottleneck. This information can be used to determine a suitable schedule for the receptionists of the clinic without even running the model.

It is visible that the oncology and pharmacy department are often used to the extent of their capacity. With this model, it is possible to test the impact of adding extra oncologists or pharmacy technicians and justify the benefit of doing so. Also, the impact of extending the operating hours of the pharmacy can be evaluated to possibly accommodate more patients in need of chemotherapy.

This model was purposely tested with more nurses than what is available. By doing so, it prioritized the need and scheduling of the patients. With the information that can be extracted from this tool and the knowledge that each patient being set up requires the full attention of a nurse while a nurse can monitor up to four patients already receiving treatment, it is possible to know exactly how much staff is needed per time slot. Because of this, proper lunch breaks can be scheduled and planned for moments when the chemotherapy department is less busy. An example of shifts and lunch break scheduling for the results of Test 1 is shown in **Figure 4.9**.

Figure 4.9: **Test 1.** Suggested Nurse Schedule to Match the Demand

Time	Amount of nurses needed	Amount of idle nurse	Nurse 1	Nurse 2	Nurse 3	Nurse 4	Nurse 5	Nurse 6	Nurse 7	Nurse 8	Nurse 9
			Amount of hours worked per nurse								
			7.5	7.5	7.5	7.5	7.5	7.5	7.5	4	3
7:30											
7:45											
8:00											
8:15	4										
8:30	4										
8:45	4										
9:00	5		Break								
9:15	6										
9:30	6			Break							
9:45	6				Break						
10:00	7										
10:15	7										
10:30	5					Break	Break				
10:45	8										
11:00	7										
11:15	4		Lunch					Break	Break		
11:30	6			Lunch							
11:45	6										
12:00	6										
12:15	6				Lunch						
12:30	4	1				Lunch					
12:45	4	1					Lunch				
13:00	6										
13:15	6										
13:30	5	1						Lunch			
13:45	5	1							Lunch		
14:00	7										
14:15	4		Break	Break	Break	Break					
14:30	9										
14:45	8										
15:00	8										
15:15	8										
15:30	7						Break				
15:45	8										
16:00	8										
16:15	6							Break	Break		
16:30	5	3									
16:45	3	1									
17:00	3										
17:15	2	1									
17:30	1										
17:45		1									

To match the optimal patient schedule obtained in Test 1, the clinic needs seven nurses to do full shifts and can use the help of two part time nurses to cover the shifts indicated in blue. Everyone gets a lunch and two breaks except the nurses with shorter shifts, without affecting the efficiency or service level of the system as they are planned accordingly. This also allows to notice when there are idle nurses. This information can be used by the head nurse to plan different tasks for these nurses if necessary. This same idea applies to scheduling the staff needed at the registration office. By knowing the demand, it is easier to schedule breaks and lunches.

By looking at the **Figure 4.6, Figure 4.7** and **Figure 4.8** it is possible to know how many chairs are needed to treat everyone. Test 1 shows that only 23 chairs out of 35 are being used, Test 2 only used 26 chairs and Test 3 used all 35 chairs. This could give some insights as per having too many or not enough chairs in the long run.

This tool saves time scheduling patients, but also has a benefit for staff scheduling. Instead of firstly determining the schedule of the staff and secondly fitting the schedule of the patients, it is done in reverse such that the need of the patient is met first and foremost.

4.5 Possible Improvements and Extensions

This section points out the weaknesses and possible improvements to make this oncology clinic scheduling model more resourceful.

As it was previously explained, testing with model with $m = 1$ was not done through this thesis due to the difficulty of obtaining a feasible solution within 12 hours. This can be explained by the innumerable amount of additional possibilities this parameter adds. If $m = 1$, patients of $G1$ may experience one time slot of delay between activity 1 and activity 2. A patient of $G2$ may be scheduled per eight additional configurations. For example, a patient may be delayed between activities 1 and 2 only, or between 2 and 3 only, furthermore between 3 and 4 only, or a subset of them, or even between all the activities. The **Table 4.11** shows the extent of these possibilities. Considering these additional configurations, it is comprehensible that CPLEX struggles to determine a feasible schedule. Nonetheless, it would be interesting to see if a modified mathematical formulation that includes delays may positively impact the sum of completion time of the system.

In this model, any oncologist can be assigned to examine or follow up a patient. This does not reflect the true operations of the clinic as it would be important to pay attention to the concept of primary oncologists in the same manner a primary nurse is assigned to its respective patient.

To simplify this problem, the concept of time slot was introduced. It is quite efficient, but exaggerates the amount of time truly required to perform different activities throughout the clinic. For example, an experienced oncologist will not require 15 minutes to perform a follow-up, but on the contrary, may need more time for the first visit of a new patient that needs to be diagnosed and explained their treatment. A

Table 4.11: Possible Delay for Patients of $G2$

Between activities 1 and 2	Between activities 2 and 3	Between activities 3 and 4	Total
			no delay
x			1 delay
	x		1 delay
		x	1 delay
x	x		2 delays
	x	x	2 delays
x		x	2 delays
x	x	x	3 delays

possible solution would be to shorten each time slot to ten minutes or even five minutes. Of course, this will affect the solving time, but will give a more realistic feel to this scheduling tool.

The reality of the pharmacy department will also be enriched as prescription preparation time vary between two to 45 minutes. Additionally, since the shelf life of certain drugs allow for long period of storage, it is possible to prepare multiple batches at the same time. Any additional dose will be stored until a patient in need of the same drug arrives later in the day, thus eliminating the need of waiting for it to be prepared as it is already available.

Another interesting direction and extension of this work would be to combine the two models described through this thesis into one model. This would allow to determine optimal treatment dates according to the oncologist's recommendation and primary nurse availability as well as coordinate the clinic as a whole to schedule all additional activities and accommodate patients no matter their trajectory.

4.6 Conclusion

This model provided an extension to Chapter 3. It is important to consider previous obligations in the clinic that may affect the start time of chemotherapy treatments on that day.

This optimization method involving the use of a multi-objective mixed-integer linear programming model clearly shows that coordinating the four main branches of the Segal Cancer Center will lead to the abolishment of the current two-day scheduling policy and easily schedule all necessary tasks in a single day. This chapter took an integrated approach to solve the oncology clinic multi-stage scheduling problem.

With the help of three numerical examples, it was shown that using this scheduling tool will have a positive impact in the field of healthcare scheduling. There will be a better coordination between departments, reduce the amount of on site wait time for patients, establish a better balancing of resource utilization and minimize the sum of completion time and idle time of staff.

Chapter 5

Pharmacy Interruptions

This chapter goes over an important observation made in at the Segal Cancer Center. If the clinic were to implement either of the scheduling models expressed in this thesis, they would have to begin by working on the bottleneck of the system, the pharmaceutical department.

The team of oncologists of the Segal Cancer Center must consult up to 250 patients per day. These may be cancer survivors returning for regular check ups, newly diagnosed patients, and patients that are being monitored as they are going through chemotherapy. On a daily basis, there are 80 patients scheduled to receive drug therapy that may or may not have seen their oncologist on the same day.

These 80 patients that require chemotherapy are the ones affected by the two-day scheduling policy. Before this change, they were arriving early at the clinic, perform their blood tests and meet with their oncologist if necessary. After these two steps, patients were waiting for their prescription to be ready for chemotherapy and were quickly accumulating in crowded waiting areas.

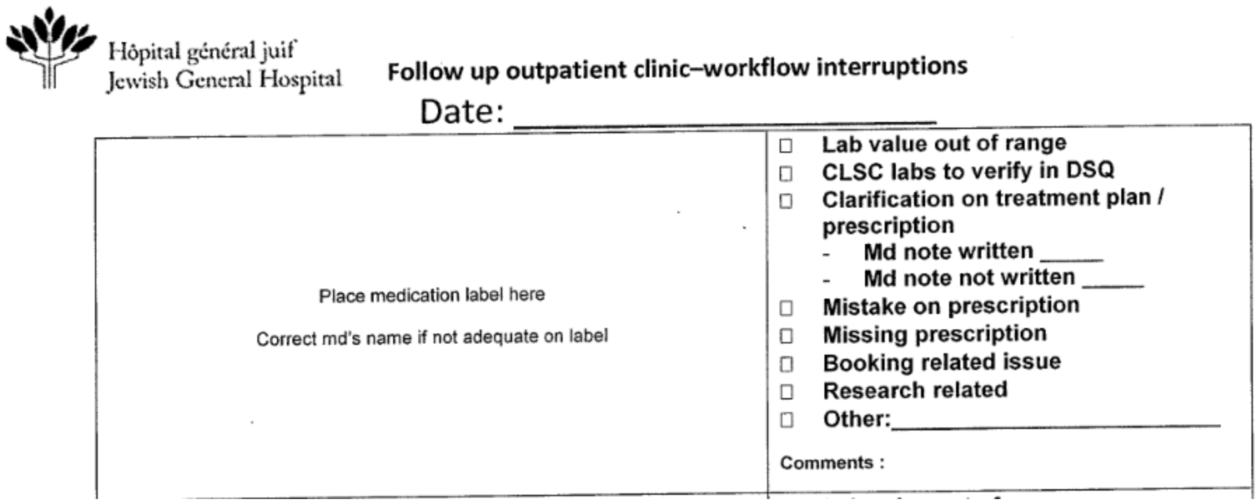
The blood test results and oncologist recommendation would reach the pharmacy, which would then trigger the drug validation by the pharmacists. Although it was known that these patients required chemotherapy, preparing a drug ahead of time is not recommended as they do not remain stable for a long time and are very costly to produce. It is important for the pharmacy to reduce as much as possible the waste of drugs, as well as their time as it would result in them having to re-create another drug to replace it if the blood test results are different from expected or in case that the oncologist makes treatment adjustments.

With the intention of reducing delays and shortening patient wait time, it was established that the pharmacy of the clinic, which is the bottleneck of the system needed some inspection. Since it was not possible to accelerate the process of drug preparation, the only way to mitigate long wait time and crowded waiting area was to send these 80 chemotherapy patients back home such that they would arrive the next morning and their prescription would be ready for infusion. Although it has proven to reduce the crowd at the clinic, these patients must inconveniently travel twice for something that was normally completed in a single day. Paying close attention to the bottleneck was necessary.

To understand the cause of delays experienced by the pharmacy, during the period of November

13th 2015 until December 18th 2015, the pharmacists were requested to complete the "Follow up Outpatient Clinic Workflow Interruptions" paper form seen in **Figure 5.1**.

Figure 5.1: Follow up Outpatient Clinic Workflow Interruptions Form



Hôpital général juif
Jewish General Hospital

Follow up outpatient clinic–workflow interruptions

Date: ____________________

Place medication label here Correct md's name if not adequate on label	☐ **Lab value out of range** ☐ **CLSC labs to verify in DSQ** ☐ **Clarification on treatment plan / prescription** - **Md note written** _____ - **Md note not written** _____ ☐ **Mistake on prescription** ☐ **Missing prescription** ☐ **Booking related issue** ☐ **Research related** ☐ **Other:**____________________ **Comments :**

The purpose of this experiment was to pinpoint the major causes of interruptions such that they could eventually be minimized and eliminated. This form only required a few seconds to fill out as the pharmacists upon experiencing a delay would stick a copy of the patient's prescription and select the appropriate cause of delay among:

-Receiving lab values out of range such that the current prescription is not appropriate to be administered,

-CLSC lab results to be verified in the Québec Health Record as some patients who do not require a consultation with their oncologist could visit the closest clinic to perform blood tests

-Requiring clarifications on the treatment plan or prescription from the oncologist,

-Noticing a mistake on the prescription that needed further clarifications,

-Not receiving any prescription to prepare,

-Booking related issues.

After tabulating the paper forms, collecting and analyzing follow up notes, pharmacy notes and verbal orders found on Endovault, it was possible to define the three main causes of interruptions for the 219 cases reported during that period. It was clear that interruptions experienced in the pharmacy were made by obtaining lab values out of range in 40.10 % of the time, additional clarification on the treatment plan or prescription was required in 30.59% of cases and mistake on prescriptions were made in 11.42% of the time. With this analysis, it was also possible to determine which oncologists were more troublesome such that they could refine their working practices and receive some coaching. In June 2016, upon discussing and presenting the results with the director of the Segal Cancer Center and the oncology pharmacy coordinator, it was determined that the oncologists and pharmacists would work together to establish guidelines that would diminish these three issues.

Chapter 6

Conclusion

Two serious issues in healthcare scheduling are tackled in this thesis. It is shown that optimization methods such as mixed-integer linear programming models can have a positive impact in the field of oncology clinic multi-stage scheduling and chemotherapy outpatient scheduling. With the seriousness of a disease like cancer, it is crucial to ease the pain and keep chemotherapy treatments stress free for these patients. By eliminating exaggerated on-site and off-site wait time and scheduling patient appointment with familiar nurses, we know that we could somewhat contribute to the well being of these people.

6.1 Future Directions and Extensions

An interesting extension to this thesis would be the combination of both models such that the entire clinic can be optimized at once. Assigning patients to their oncologists and primary nurse correctly, while respecting the chemotherapy protocol and considering the multiple possible trajectories.

Another extension would be to consider the wait time parameter m of the oncology clinic multi-stage scheduling model. It would be interesting to see if allowing patient wait time would have a positive impact on the system. Unfortunately, with the current formulation, obtaining a feasible solution in a reasonable amount of time was not possible.

Additional weaknesses addressed in the previous sections may be sources of inspiration for extending this research. The timeline of this problem was divided in 30-minute time slots and 15-minute time slots. Possibly a smaller and more precise time line may help to assess the real processing capacity of the oncologists and pharmacy drug preparation. The pharmacy has the ability of completing more than a single batch of a drug at a time and the knowledge of shelf life of these drugs can be used as an advantage to make this subsystem more efficient. The division of the chemotherapy unit in two stations was ignored and will be a challenge to consider due to the rotation of nurses and uneven number of chairs and beds.

6.2 Summary of Contributions

The contributions of this research are specific to scheduling applications in oncology outpatient clinics. It is a field that has seen a significant increase in demand due to the aging population and needs improvements. In recent years, healthcare providers realized the importance of having efficient systems to accommodate more patients while minimizing costs and maximizing the quality of their services.

To the best of our knowledge there is limited research in the literature in term of chemotherapy appointment scheduling while maintaining the assignment of primary nurses to their patients and simultaneously respecting the target day of chemotherapy treatment prescribed by the oncologist.

There are also only a few studies focused on optimizing the flow of the interdependent events that ultimately lead to chemotherapy treatments. This includes the coordination of the clinic's reception, the hematology clinic, the oncology department, the pharmacy and the chemotherapy unit. Each of these departments deal with specific resources limitations and constraints that must be considered to obtain an efficient system. Unfortunately, the scientific community has mainly focused on optimizing single-stages of this scenario. These two gaps in the literature are filled with the topics of this thesis.

The solutions found with both of these mixed-integer linear programming models can provide input for the clinic's workforce management. It will be possible to properly coordinate the schedule of the staff by establishing breaks and lunches when the demand is lower. Additionally, it will be easy to analyze and justify the impact of adding or eliminating a staff member.

Appendix A

Figure A.1: **Test 1.** Coefficient of Correlation Data Compilation

Wrong nurse	Make span					
X Values	Y Values	X - M_x	Y - M_y	(X - M_x)^2	(Y - M_y)^2	(X - M_x)(Y - M_y)
1	28	-14.545	9.182	211.57	84.306	-133.554
4	19	-11.545	0.182	133.298	0.033	-2.099
9	19	-6.545	0.182	42.843	0.033	-1.19
9	19	-6.545	0.182	42.843	0.033	-1.19
11	19	-4.545	0.182	20.661	0.033	-0.826
22	18	6.455	-0.818	41.661	0.669	-5.281
23	17	7.455	-1.818	55.57	3.306	-13.554
23	17	7.455	-1.818	55.57	3.306	-13.554
23	17	7.455	-1.818	55.57	3.306	-13.554
23	17	7.455	-1.818	55.57	3.306	-13.554
23	17	7.455	-1.818	55.57	3.306	-13.554
Mean = 15.55	Mean = 18.82			Sum = 770.73	Sum = 101.64	Sum = -211.91

Figure A.2: **Test 1.** Coefficient of Correlation Calculations

Result Details & Calculation

X Values
$\sum = 171$
Mean = 15.545
$\sum(X - M_x)^2 = SS_x = 770.727$

Y Values
$\sum = 207$
Mean = 18.818
$\sum(Y - M_y)^2 = SS_y = 101.636$

X and Y Combined
N = 11
$\sum(X - M_x)(Y - M_y) = -211.909$

R Calculation
$r = \sum((X - M_y)(Y - M_x)) / \sqrt{((SS_x)(SS_y))}$

$r = -211.909 / \sqrt{((770.727)(101.636))} = -0.7571$

Appendix B

Figure B.1: **Test 2.** Coefficient of Correlation Data Compilation

Wrong Nurse	Make span					
X Values	Y Values	$X - M_x$	$Y - M_y$	$(X - M_x)^2$	$(Y - M_y)^2$	$(X - M_x)(Y - M_y)$
16	28	6.121	8.576	37.469	73.544	52.494
1	28	-8.879	8.576	78.833	73.544	-76.142
23	17	13.121	-2.424	172.166	5.877	-31.809
1	28	-8.879	8.576	78.833	73.544	-76.142
19	18	9.121	-1.424	83.197	2.028	-12.991
22	17	12.121	-2.424	146.924	5.877	-29.385
1	28	-8.879	8.576	78.833	73.544	-76.142
9	19	-0.879	-0.424	0.772	0.18	0.373
21	17	11.121	-2.424	123.681	5.877	-26.961
21	17	11.121	-2.424	123.681	5.877	-26.961
1	28	-8.879	8.576	78.833	73.544	-76.142
8	19	-1.879	-0.424	3.53	0.18	0.797
15	18	5.121	-1.424	26.227	2.028	-7.294
20	17	10.121	-2.424	102.439	5.877	-24.536
20	17	10.121	-2.424	102.439	5.877	-24.536
0	28	-9.879	8.576	97.59	73.544	-84.718
8	19	-1.879	-0.424	3.53	0.18	0.797
8	19	-1.879	-0.424	3.53	0.18	0.797
16	17	6.121	-2.424	37.469	5.877	-14.839
16	17	6.121	-2.424	37.469	5.877	-14.839
18	17	8.121	-2.424	65.954	5.877	-19.688
0	28	-9.879	8.576	97.59	73.544	-84.718
3	19	-6.879	-0.424	47.318	0.18	2.918
5	19	-4.879	-0.424	23.803	0.18	2.07
12	18	2.121	-1.424	4.5	2.028	-3.021
14	17	4.121	-2.424	16.984	5.877	-9.991
17	17	7.121	-2.424	50.712	5.877	-17.264
18	17	8.121	-2.424	65.954	5.877	-19.688
0	28	-9.879	8.576	97.59	73.544	-84.718
1	19	-8.879	-0.424	78.833	0.18	3.767
3	19	-6.879	-0.424	47.318	0.18	2.918
4	19	-5.879	-0.424	34.56	0.18	2.494
11	17	1.121	-2.424	1.257	5.877	-2.718
16	17	6.121	-2.424	37.469	5.877	-14.839
17	17	7.121	-2.424	50.712	5.877	-17.264
18	17	8.121	-2.424	65.954	5.877	-19.688
0	28	-9.879	8.576	97.59	73.544	-84.718
1	19	-8.879	-0.424	78.833	0.18	3.767
2	19	-7.879	-0.424	62.075	0.18	3.343
3	19	-6.879	-0.424	47.318	0.18	2.918
7	17	-2.879	-2.424	8.287	5.877	6.979
13	17	3.121	-2.424	9.742	5.877	-7.567
16	17	6.121	-2.424	37.469	5.877	-14.839
17	17	7.121	-2.424	50.712	5.877	-17.264
18	17	8.121	-2.424	65.954	5.877	-19.688
0	28	-9.879	8.576	97.59	73.544	-84.718
1	19	-8.879	-0.424	78.833	0.18	3.767
2	19	-7.879	-0.424	62.075	0.18	3.343
2	19	-7.879	-0.424	62.075	0.18	3.343
4	17	-5.879	-2.424	34.56	5.877	14.252
12	17	2.121	-2.424	4.5	5.877	-5.142
13	17	3.121	-2.424	9.742	5.877	-7.567
13	17	3.121	-2.424	9.742	5.877	-7.567
13	17	3.121	-2.424	9.742	5.877	-7.567
18	17	8.121	-2.424	65.954	5.877	-19.688
0	28	-9.879	8.576	97.59	73.544	-84.718
2	19	-7.879	-0.424	62.075	0.18	3.343
2	19	-7.879	-0.424	62.075	0.18	3.343
2	19	-7.879	-0.424	62.075	0.18	3.343
3	17	-6.879	-2.424	47.318	5.877	16.676
13	17	3.121	-2.424	9.742	5.877	-7.567
13	17	3.121	-2.424	9.742	5.877	-7.567
13	17	3.121	-2.424	9.742	5.877	-7.567
13	17	3.121	-2.424	9.742	5.877	-7.567
13	17	3.121	-2.424	9.742	5.877	-7.567
20	17	10.121	-2.424	102.439	5.877	-24.536
Mean = 9.87	Mean = 19.42			Sum = 3579.03	Sum = 1018.12	Sum: =-1182.60

Figure B.2: **Test 2.** Coefficient of Correlation Calculations

Result Details & Calculation

X Values
$\Sigma = 652$
Mean = 9.879
$\Sigma(X - M_x)^2 = SS_x = 3579.03$

Y Values
$\Sigma = 1282$
Mean = 19.424
$\Sigma(Y - M_y)^2 = SS_y = 1018.121$

X and Y Combined
$N = 66$
$\Sigma(X - M_x)(Y - M_y) = -1182.606$

R Calculation
$r = \Sigma((X - M_y)(Y - M_x)) / \sqrt{((SS_x)(SS_y))}$

$r = -1182.606 / \sqrt{((3579.03)(1018.121))} = -0.6195$

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