Dynamic nurse assignment in chemotherapy outpatient clinics

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Dynamic Nurse Assignment in Chemotherapy Outpatient Clinics

Master Thesis

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Abstract

This master thesis focuses on the nurse assignment problem at oncology outpatient clinics. We perform a thorough review of the literature to determine how the current nurse assignment methods can be improved and we develop a dynamic nurse-to-patient assignment tool with the goal of improving both the nurses workflow and patients' continuity of care while accounting for the uncertainty of cancellations. Testing of the tool shows that a periodic review and modification of the nurse-to-patient assignments can simplify the assignment task and indeed improve the desired workflow and continuity of care.

Preface

This graduation project is the final part of my studies in Operations Management and Logistics at the Eindhoven University of Technology. I would like to express my gratitude to some of the people who played an important role during my time at TUe and this master thesis project.

First of all, I would like to express my deep gratitude to Nico, my supervising professor for his invaluable guidance during this project. I am extremely thankful for the opportunity to work with him on this project and for his immense patience, support and encouragement. I'd also like to thank my second supervisor, Claudia, for taking the time to supervise this project.

A big thank you to all my Eindhoven family, specially Chiara, Satya, and Andres, for making me feel at home at the other side of the world. Special thanks to Michael for believing in me and helping me keep sane during this project. And thanks to my classmates Mari, Ale, Bahim and Renee, for the endless moments of fun between our study sessions.

Above all, I want to thank my parents. Not only for the countless opportunities they have opened up for me, but for always pushing me forward, teaching me to never stop learning, for encouraging me to take on big challenges, pursue new adventures and for always believing in me. Thanks mom and dad for you unconditional love and support, I love you and I am grateful for you always.

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Chapter 1

Introduction

1.1 Introduction

Chemotherapy is one of the major treatment methods for cancer patients. Due to increasing need for cancer care and the growing shortage of registered nurses, patients experience long waiting times while clinics scramble to provide treatment to as many as possible while stretching their nursing staff.

The unique nature of cancer to each patient requires individualized treatment plans. Oncology clinics are often burdened with scheduling large volumes of patients for chemotherapy treatments under limited resources such as the number of nurses and chairs. The variable treatment times, cancellations and resource constraints make said scheduling a challenging task and resulting poor schedules negatively impact the workload and job satisfaction of nurses.

Nurses are the key resource delivering chemotherapy treatments. They are responsible for tasks like administering treatment, providing information about the procedure, and managing the side effects of drugs. A nurse's workload during their shift depends on several factors including the number of patients assigned to them and the attention required by those patients.

In a 2002 study, nurses reported greater job dissatisfaction and higher emotional exhaustion, which are strongly and significantly related with patient-to-nurse ratios, when they were regularly responsible for more patients than they could safely take care of during a shift. [4]

Throughout this thesis, we aim to tackle the nurse assignment problem at chemotherapy outpatient clinics. We look into the diverse mathematical techniques that are being used in healthcare operations and we develop different models with the goal of simplifying the assignment task and positively impact the nurses workload.

1.2 Background and Goals

Accessible health care requires a well-trained and well-motivated nurse workforce of an adequate size which is able to deliver safe and high-quality medical services. However, there is a concern that a gap may be looming between demand for and supply of nurses around the world. [24] In the Netherlands, there is a worrisome shortage of qualified nurses across several sectors, including special care departments like oncology clinics.[2]

In the oncology area, this shortage of nurses is met with the increasing demand for cancer treatment. Additionally, developments in the field have increased the complexity of planning and scheduling treatments at specialized clinics.

In current literature, there are many studies concerning patient scheduling at chemotherapy clinics, most of which focus on minimizing treatment delay and make-span. Intuitively, the priority is on the patient's satisfaction. However, the waiting time is not the only factor impacting a patient's experience at a health clinic. Improving the schedules and workflow for nurses can also enhance the patient's experience, the quality of the care they receive and, of course, the nurses' work conditions. The reduction of nurse overtime and a more balanced workload can reduce the chances of nurse burnout and boost performance.

Chemotherapy nurses have the flexibility of managing multiple patients. Ideally, a nurse should simultaneously monitor up to five people, but may monitor additional patients if needed. Because of the nature of their work, nurses often find themselves stretched to their maximum capacity and at high-risk of burnout.

When scheduling, it is important to take measures to provide safe working conditions to those delivering the treatment, as well as ensuring that each patient gets the attention they need. Changing the way that outpatient clinics approach the scheduling and planning of chemotherapy treatments by adding a special attention optimal nurse-to-patient assignment tools and focusing on nurses' workload can have a positive impact on the way the clinic operates and may bring benefits for all involved.

There are several papers that examine the performance of optimal scheduling models with a focus on workload and resource optimization as their objective functions. These objectives include: minimizing the aggregated workload for nurses, minimizing the instances in which a nurse monitors more than the ideal number of patients, and minimizing the clinic's overtime.

Some of the models that focus on workload incorporate acuity level constraints. In these models, each patient is assigned an acuity level that represents how much nursing effort they will require and the nurses have a predefined limit of aggregated acuity level they can monitor simultaneously. However, acuity levels are difficult to assess beforehand, as each patient may respond differently to chemotherapy treatment. In addition, the models incorporating acuity level set a fixed maximum workload for nurses, when in reality nurses will monitor more than the recommended number of patients if needed.

On a global scale, better workforce planning in nursing is crucial to reduce health inequalities and ensure sustainable health systems. [13] However, the ever-present need for better planning tools in healthcare and particularly chemotherapy outpatient clinics has been scarcely studied. Therefore we believe it would be valuable to contribute to this area of study and approach the problem accounting for uncertainty. As nurse-to-patient assignment is the final step of nurse planning, a lot of uncertainty arises from no-shows and cancellations as well as variable treatment duration. In this study we set out to design a nurse assignment tool that can support outpatient clinics in generating daily plans that can improve the quality of work of its nursing staff and the care their patients receive, while considering the uncertainty of cancellations on real-time oncology planning. This leads us to the following research question:

> How can current methods be enhanced so that an outpatient oncology clinic can improve nurses' workflow and increase quality of care for patients, while capturing the dynamic uncertainty of patients attendance?

In this project we will develop a patient-to-nurse assignment model that assumes a given patient schedule and nurse availability. With the goal of improving both the nurses' and the patients' experience, we set different objectives for the model: minimizing nurses' excess load (a nurse is said to have an excess load when the number of patients simultaneously assigned to them exceeds the recommended nurse-to-patient ratio), minimizing patient waiting time during treatment, balancing the workload across nurses, and minimizing the number of different nurses in charge of a patient during treatment.

To capture the variability that comes with oncology treatments, we will then develop a tool that combines the deterministic nurse assignment model with a patient scheduling model to account for cancellations and re-assign nurses throughout their shift.

It was decided to focus on this particular problem, as it has barely been studied in the literature and we believe that improved nurse-to-patient assignments can have a positive impact on nurses quality of work as well as patient satisfaction.

Chapter 2

Preliminaries

2.1 Chemotherapy Outpatient Clinics

Chemotherapy is one of the most common cancer treatments, along with surgery and radiotherapy. It is a systemic treatment that uses drugs to kill cancer cells. Chemotherapy treatments that were once delivered only in hospital environments are now administered mainly in outpatient environments, such as oncology offices, outpatient hospital departments, and even at patients homes. In outpatient chemotherapy clinics, the oncologists have direct control of drug administration, assistance is immediately available if problems arise, care is less expensive than inpatient services and overnight stays are avoided. Additionally, it simplifies the monitoring and control of treatment costs and allows treatment to be administered at the patients' convenience. [12]

When a patient is diagnosed with cancer, their responsible oncologist will design a treatment plan, which can include surgery, radiotherapy, chemotherapy or a combination of the three. Plans may also consist of multiple cycles, which in turn consist of a pre-determined number of treatment sessions spaced by predefined intervals. [20] Once this plan is defined, a patient will start their treatment at an oncology clinic.

Chemotherapy sessions are programmed in accordance to the patient's needs and the oncologist's advice. Figure 2.1 shows the typical flow of chemotherapy patients in an oncology clinic. For receiving treatment, all patients arrive to the clinic by appointment and are registered by the assistant. Before they may receive treatment, physicians will carry out blood tests to assess whether it is safe to undergo treatment or if their appointment needs to be postponed. Once the patient is cleared for treatment, the required drugs are prepared. Both the assessment and the drug preparation may be done one day in advance or earlier on the day of appointment. Finally, the patient will be assigned to a chair or bed, depending on the condition of the patient and the clinic's resources, where the treatment will be administered by a specialized nurse. [26]

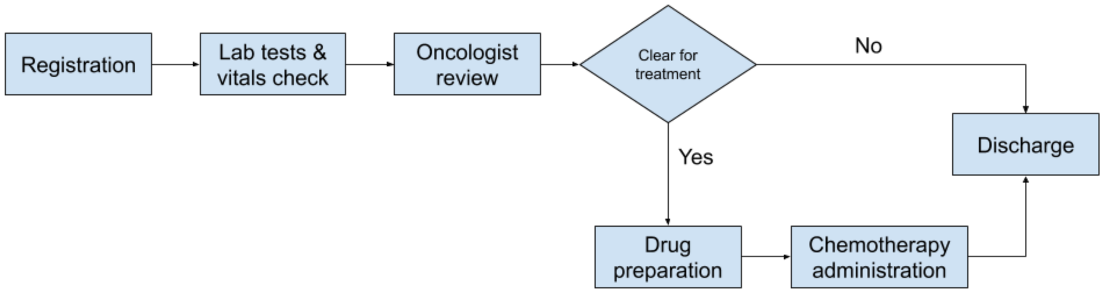

Figure 2.1: Patient Flow

Throughout this project, we will focus on the Chemotherapy Administration section of the process. Specifically, we will look into the resource assignment for this step. The drug preparation is omitted as are the lab tests, vitals checks and oncologist reviews. However, the result of the pre-tests and checks are reflected as no-shows or cancellations. The administration of treatment is performed by specialized nurses and is split into two sections: set-up and monitoring. The set-up is delicate and requires the full attention of one nurse, whereas in the monitoring phase a nurse can be responsible for several patients simultaneously.

While different hospitals might have slight differences in their processes, this is a general depiction of the patient flow and the results of the models described in further chapters will be applicable to most outpatient clinics for chemotherapy administration scheduling and nurse assignment. In most hospitals and clinics, the responsibility of balancing workloads during a shift falls to the charge nurse since they are the ones assigning patients to the allotted nursing staff. The tools that we will develop in this study will seek not only to improve the quality of the nurse assignments, but also simplify this task for the charge nurse or other administrative staff.

2.2 Overview of Nurse Planning

Registered nurses may work in different environments within the health care system. This includes outpatient clinics, different hospital wards and emergency departments, private practices, nursing homes, and private homes. For all these settings nurses require specific certifications and in some cases additional training. For outpatient clinics and other care providers mentioned, nurse planning is a vital part of their general resource capacity planning as nurses represent an essential and costly resource. In this section we provide an overview of resource capacity planning, with emphasis on nurse planning.

We begin with strategic planning, this refers to long term management and addresses structural decision making. It includes defining the clinic's goals and translate them into the design, dimension and development of the health care delivery process.[16]. Decisions in this phase are based on high level information and forecasts. An example of a strategic decision is the staffing, in this phase one can decide how many nurses will need to be hired as permanent staff and how many will be provided by a third-party agency, service agreements with said agencies will also be defined at this stage.

Moving on, the tactical planning translates the strategic decisions into policies that will guide and aid the operational planning decisions. During this phase blueprints for the care delivery processes are defined. In tactical planning, demand forecasts will be used to determine the number of nurses required in each shift, and temporary capacity expansion decisions like overtime or hiring external staff may be done. At this stage block staff planning and admission planning are done. Most academic literature on nurse planning is on patient scheduling.

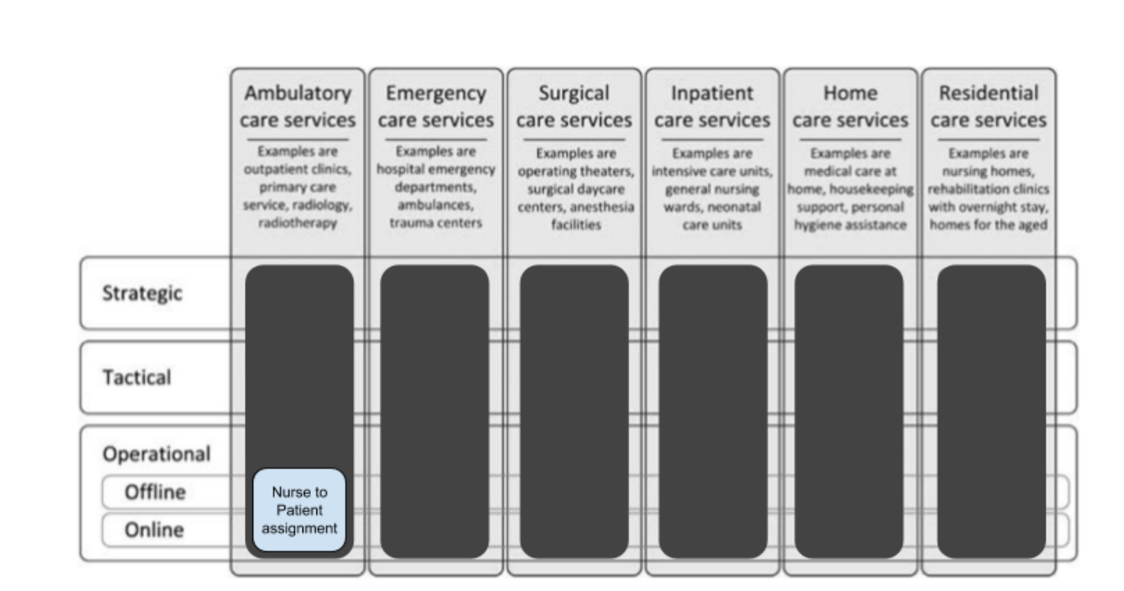

Figure 2.2: Taxonomy for resource capacity planning and control decisions in health care - adapted from Hulshof et al. (2012)

Operational planning (both 'offline' and 'online') refers to the short-term decision making related to the execution of the health care delivery processes. Following the tactical blueprints, execution plans are created at an individual nurse level. At this stage, schedules are known (except for last minute cancellations or add-ins). At this level, resource capacity flexibility is low, as it has been defined by decisions made at previous stages. Here we find the final phase of nurse planning: nurse assignment, where a charge nurse assigns each patient to a nurse at the beginning of a shift.

Offline planning refers to the planing of operations that has been done in advance. Examples of offline operational planning at an outpatient clinic include patient-to-appointment assignment and nurse-to-shift assignment.

Online operational planning is the set of control mechanisms that are used to handle and monitor the process, while reacting to unplanned cancellations, add-ins and variance in treatment duration. Real-time re-scheduling of certain patients or the dynamic re-assignment of nurses are examples of online operational planning. In practice, most nurse assignments are based upon either an intuitive judgment or a patient-ratio method, where each nurse is assigned the same number of patients. In many hospital units, nurses are rarely re-assigned to new patients. [23]

Throughout this thesis we will focus on the operational planning, specifically nurse-to-patient assignments. However, the results of sensitivity analysis that will be done for the different objectives in the deterministic nurse-to-patient assignment model may bring managerial insight useful for tactical decisions.

Chapter 3

Literature Review

For this project, an extensive amount of time was spent studying the literature. Since the project is not done in partnership with any external organization, having a comprehensive understanding of the work that has been done in the field of operations research within chemotherapy clinics was key to defining the problem statement and ensuring that this study could contribute to the general literature.

As healthcare systems around the globe face the challenge of delivering quality services while maintaining or even cutting the ever increasing costs, there is growing support for the view that traditional approaches to the management of healthcare systems are failing. In turn, mathematical modelling is increasingly being used to develop new answers to the complex issues in modern healthcare. [1] Because of this, one can find many studies applying different modelling techniques addressing operational capacity planning at different levels.

3.1 Mathematical Modeling in Chemotherapy Scheduling and Planning

In this chapter, we will give an overview of different modeling techniques that are being studied or applied in different areas of healthcare, with an emphasis on outpatient oncology clinics. We review the studies done specifically on patient scheduling and nurse assignment at chemotherapy outpatient clinics, putting an emphasis on the methods used to tackle uncertainty and the different objective functions that we found.

When studying the relevant literature on chemotherapy appointment scheduling and nurse assignment, we observe more and more models being developed and studied to aid healthcare clinics in their planning and scheduling. This of course includes the planning, scheduling and resourcing at outpatient clinics.

3.1.1 Patient Scheduling

Looking at patient scheduling, we found plenty of studies that use mathematical programming, constraint programming, queuing theory and heuristics. Many of these studies propose using templates or guidelines to reduce the complexity of the task for the schedulers, while others develop optimization models focusing on cost and waiting time reduction.

Accounting for Cancellations and Add-Ins

We see methods that attempt to strike a balance between optimality and practicality. When introducing uncertainty, calculating optimal schedules becomes computationally infeasible and in a practical setting, they can become useless. In their work, Hahn-Goldberg et al. [14] propose applying dynamic template scheduling, a technique that combines proactive and online optimization, to the chemotherapy scheduling problem. They assume deterministic treatment duration and punctual patient arrivals, but account for uncertain last minute add-ins and cancellations using a shuffling algorithm that re-schedules appointment start times within a predefined time limit. They first use an optimization model to generate and offline template and start filling in each incoming patient request. When a request can not fit in the original template, they create a new one using the optimization model and a revised set of appointments.

No-show patients and cancellations introduce significant uncertainty and limit accessibility to other patients by reserving appointment slots that go unused. To mitigate the negative effects, clinics often overbook patients. However, if done naıvely, overbooking can lead to longer patient waiting times and clinic overtime. Clearly, competing objectives must be well balanced for such a strategy to work. Studies such as Chakraboty [9], analyze the different objectives and propose policies to mitigate the impact of uncertainty.

Tackling Stochastic Treatment Lengths

Also attempting to acknowledge uncertainty, Berg et al. [8] formulate a two-stage stochastic mixed integer program for optimizing booking with no-shows and stochastic treatment lengths, in their study the objective is to maximize expected profit. Their model is based on an endoscopy outpatient clinic and it creates an optimal patient sequence. However, this assumes a single server and their model does not provide an optimal nurse assignment.

Bentayeb et al[7] present an alternate approach to uncertainty in treatment times. They performed data-driven study in which they use data mining and regression methods to create a prediction model for radiotherapy treatment duration and then said prediction model to generate a schedule.

Demir [5] seeks to tackle the uncertainty in pre-medication and infusion duration. He does so by formulating a two-stage stochastic mixed integer programming model for chemotherapy appointment scheduling problem under the limited availability of nurses and chairs. The objective of his model is to minimize the expected weighted sum of nurse overtime and patient waiting time. However, the computation times for the problem are significantly long, even for single-scenario problems.

In many healthcare settings, the equipment used is the key resource and thus there are also studies that focus the optimization around medical equipment. Legrain et al [17] optimize the use of the linear accelerators required in radiotherapy. This approach is very useful at clinics where the used equipment is expensive and scarce. In their study, they schedule patients on these machines taking into account priority for treatment, maximum waiting time before the first treatment, and the treatment duration. To account for uncertainty, they develop a hybrid method combining stochastic optimization and online optimization.

3.1.2 Nurse Assignment

In the literature, there are also papers addressing optimal nurse assignment. Nurse assignment is the final stage of nurse planning, during which each patient is assigned to a nurse at the beginning of the shift. Initial assignments often determine the amount of workload that each nurse will experience during a shift. [3] In general, the studies focus on patient scheduling but the models specify the nurse assignment in the generated schedules and some analyze nurse workload or overtime as a performance measure. Aside from lowering costs or shrinking patient waiting times, these papers mainly seek to reduce staff overtime and idle time. Some of the studies found implement acuity based assignments, this aims to account for the difference in nurses' skill level and patients' needs. There are also authors who implement the distances nurses must travel to tend to different patients.

Mobasher et al. [21] propose a multi-objective integer programming model for assigning nurses in operating suites, reducing nurse overtime and idle time. Their model is designed to assign nurses to different surgeries based on their specialties and skill levels, subject to a series of hard and soft constraints related to nurse satisfaction, idle time, overtime, and job changes during a single shift.

Liang and Turkcan [19] develop an acuity based multi-objective optimization model for nurse assignment, where the objectives are minimizing patient waiting times and nurse overtime. This model accounts for nurse skills and patient acuity, but it does not account for cancellations or variable treatment duration. In their study, they compare the performance of a functional care delivery method against a primary care functional method. Their model assumes a given patient schedule, but allows for delays in the start of treatment when caused by unavailability of nurses or chairs.

Acar [3] proposes a nurse-to-patient assignment that accounts for factors like patient acuity level and nurse travel distances. In this study, he developed different measures of what constitutes a "balanced" workload. Said measures were developed by working closely with nurses and through interviews.

Punnakitikashem et al [22] create an information technology (IT) prototype that aims to support charge nurses in their assignment task. Their tool was developed for a generic hospital setting and the MIP that is the underlying part of the IT tool has the objective of minimizing excess workload of the nurses. This tool does not account for uncertainty and is not directly applicable in a chemotherapy outpatient clinic setting.

Begen and Queyranne [6] consider the problem of scheduling medical procedures with discrete random durations with a single processor (or operating room). They propose a model that generates the optimal schedule with the objective of minimizing costs related to each treatment.

Rosenberger and Punnakitikashem [23] developed a stochastic integer programming model and use Benders' decomposition approach to solve this problem. Their objective function was to minimize excess workload on nurses where excess workload was defined as total patient workload assigned to a nurse in excess of the length of time from a time epoch until the next time epoch. Their model assigns patients to 2 different kinds of nurses, to comply with specific regulations. In their formulation the stochasticity comes in the expected number of patients (add-ins are allowed) and the level of workload that each patient would present.

In addition, Walts and Kapadia [27] suggested an optimization approach for the patient classification system, where the objective was to minimize the total number of nurses needed by optimally assigning them to meet the acuity needs of the various clinical units in the hospital.

Queueing Theory

Queuing theory has been applied in the context of nurse staffing and nurse assignment, mainly in the setting of general hospitals where nurses can work in different wards or in emergency departments where the demand is uncertain. In general we see that the queuing models developed are with the goal of assessing or determining adequate staff levels. Yankovic and Green [28] develop a queuing model to determine adequate nurse staffing levels. Their two-dimensional model incorporates the demands for nursing care that result from changes in future expected occupancy and current patients' needs. De Vericourt [11] proposes a queuing model to evaluate whether or not ratio policies are effective at managing nurses' workload. He develops a queuing model to determine the ideal nurse staffing level, calculating the necessary and sufficient conditions under which the probabilities of excessive delay are kept below a certain level. Addressing the value that can be obtained from dynamic nurse assignment, Chan et al. [10] develop a model to dynamically assign nurses to different emergency departments at the beginning of each shift. The ability to reassign nurses at discrete intervals, rather than continuously, introduces a partial flexibility that provides an opportunity for reducing the expected waiting time of patients. They consider a multi-class queuing system, where patients of each class are different in terms of their average service times and waiting. We also found queuing models used to gauge overall clinic performance. For example, in her dissertation, Stevenson [25] seeks to asses and improve the efficiency at a phlebotomy outpatient clinic using queuing theory. She evaluated her models under five performance measures: mean waiting time, maximum waiting time, phlebotomist utilization, mean number of patients served and not served at the end of each day.

3.2 Different Objectives for Nurse Assignment

As it has been stated above, different studies have addressed nurse assignment as either a part of their patient scheduling strategies or specifically to improve the nurse-to-patient assignment. Throughout these studies we can observe a variety of nursing-oriented objectives.

Form the literature reviewed, the most popular objectives is Minimum Overtime. Most of the studies strive to reduce the time that nurses must work outside their regular shift, this of course may also improve nurses' work-life balance and reduce the clinic's costs as overtime hours might result in extra payments. The model proposed by Liang and Turckan [19], allows patients' treatment to go into overtime, and uses 2 different objectives: minimum waiting time for patients between their original scheduled time and the actual start of their appointment and minimum overtime for nurses. They define nurse overtime as the difference between the treatment completion time of the last patient assigned to the nurse and end of regular working hours for that nurse. In their objective they seek to minimize the total sum of nurse overtime. Banu[5] also focuses on overtime, using an objective that minimizes expected weighted sum of nurse overtime and patient waiting time in a stochastic model.

Other studies in literature strive to Minimize Nursing Overutilization. For example, in his 2014 thesis, Menting [20] defines a way of calculating nurse over-utilization in each time-slot. He then formulates a heuristic model that seeks to minimize overt-utilization. He uses a squared value for over-utilization as he argues that it is better to have multiple smaller peaks than one big one.

Some studies also combine several of these goals and create multi-objective models or define objective functions that combine different criteria. For instance, Hesaraki [15] in his 2019 dissertation, proposes a multi-criterion objective that aims to minimize nursing FTE, balancing the workload for nurses and reducing the number of nurse changes during a patient's treatment.

3.3 Opportunities for Future Research

After reviewing the existing literature we can say that most of the studies focus on the scheduling of patients and strive for the minimization of treatment delay and minimization of make-span. Very few models incorporate stochastic treatment duration but do so in computationally complex ways.

Further research could be done seeking different targets such as maximizing resource utilization, balancing resource utilization, minimizing costs and minimizing the spread in capacity workload. Additionally, more studies could incorporate nurse assignment into their models and evaluate nurse-workload focused objectives.

Specifically for chemotherapy outpatient planning, more research that includes the capacity of the clinic's oncologists could be done. Additionally, it would also be interesting to explore the use of queuing models to determine the necessary staff levels at chemotherapy clinics.

At an operational capacity planing level, we found that there are not many studies that tackle the nurse-to-patient assignment problem and to our knowledge there are no studies proposing methods for dynamic nurse assignment to tackle uncertainties.

Chapter 4

Research Design

4.1 Problem Definition and Research Questions

Oncology clinics everywhere face numerous operational challenges, mainly linked to the planning and scheduling. To improve operational efficiency at chemotherapy outpatient clinics, it is important to look at all stages of planning. The literature on this topic is in general scarce, but while there have been some recent studies on patient scheduling, nurse-to-patient assignment has not received much attention despite it having such a strong impact on a nurse's workload.

In particular, we found no literature regarding a dynamic nurse-to-patient assignment in a chemotherapy outpatient setting. The few studies we found on dynamic nurse assignment were focused on emergency departments or multi-disciplinary centers where nurses can be assigned to different departments at the beginning of their shifts, these studies apply queuing models and do not consider patient schedules.

Given the gap in the literature and the importance of a balanced workload we have decided to tackle the uncertain and dynamic nature of healthcare planning by focusing on the final stage stage of nurse planning: nurse-to-patient assignment.

The intended goals of this thesis project is to explore different models that could support clinics in their operational capacity planning, both offline and online. Additionally, we seek to contribute to the literature by performing a study in an area that has not received much attention. These goals lead us to the following research question:

> "How can current methods be enhanced so that an outpatient oncology clinic can improve nurses' workflow and increase quality of care for patients, while capturing the dynamic uncertainty of patients attendance?"

By improving nurses workflow we mean to create assignments that result in a more balanced workload across nurses and reduces nurses' excess load. As for increasing the patients' quality of care, we aim to do so with a better workflow for nurses and less nurse changes within treatments for each patient.

In addition to the main research question, for this study we pose the following sub-questions:

> "What are different objectives that clinics may use when assigning patients and how do these different objectives influence the performance measures like workload and continuity of care."

> "How can a continuous re-assignment of nurses at a chemotherapy outpatient clinic improve nurses' workflow and continuity of care?"

This sub-questions will support the development of an answer to the main research question.

4.2 Research Scope and Assumptions

There are multiple sub-processes within the patients' flow through the chemotherapy clinic. The main operational steps are the lab tests (which include taking vitals), a session with the oncologist, drug preparation by the pharmacy, setting up for the administration of treatment and finally the monitoring of said treatment.[15] These main steps are shown in figure 4.1. For this thesis, we will focus only on the last two steps: set-up and monitoring. This means that while there are several care providers and resources involved in the full process, only two clinic resources are within the scope of this research: chemotherapy trained nurses (who set-up and monitor treatment) and chairs (where the patients receive said treatment).

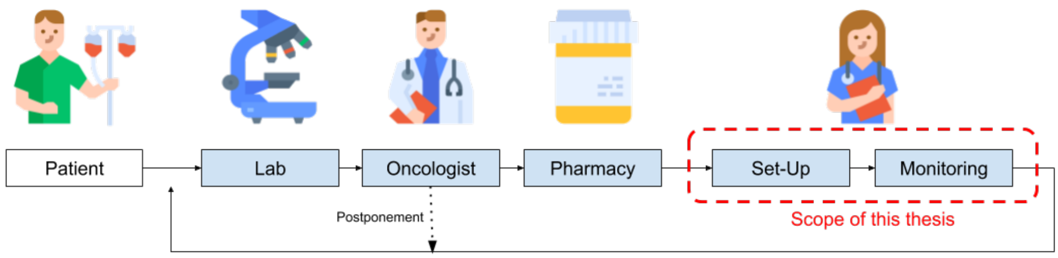

Figure 4.1: Process flow at a chemotherapy outpatient clinic

A number of assumptions are included in this research project, which influence the formulation of our mathematical models. We incorporate these assumptions to reduce the computational complexity of the developed models.

The assumptions we apply throughout this thesis are the following:

- All nurses have the same skill level and therefore any nurse has the ability to treat any given patient
- We consider 15 minute time-intervals, where a set-up time always takes one interval
- It is assumed that the clinic provides different types of treatments, each with its own treatment duration
- Each treatment type has a different duration. However, it is assumed that all treatment types require the same amount of nursing capacity per interval
- Because of the nature of the task, it is assumed that patient set-up takes up a nurse's full capacity. This means that when a nurse is assigned to a set-up they cannot monitor other patients during that time-slot.
- Unless a patient is a no-show, the patients arrive punctually to their appointment (no late arrivals)
- Some of the models will have additional assumptions, this will be noted in further chapters

4.3 Research Methodology

For a formal approach to the previously stated problem statement and research objectives, we adopt the research model proposed by Mitroff.

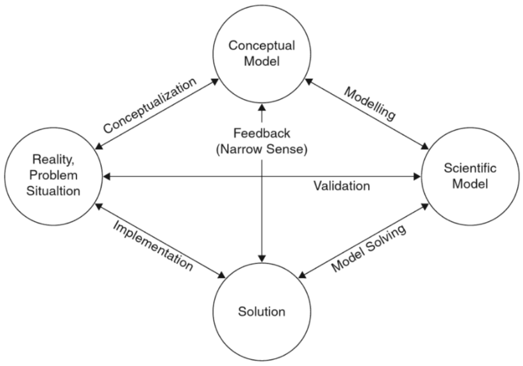

Figure 4.2: Mitroff's research model

We follow the loop presented in 4.2 starting from "Problem Situation" and we work our way towards "Solution". Because this thesis is an academic project done for the university, we do not reach the "Implementation" step.

The first step in this research model is to define the problem situation. We draw from the research that has been done concerning patient scheduling and nurse assignment at chemotherapy outpatient clinics and identify opportunities for further research. Once we identified the problem statement and the research goals, we design conceptual models where the desired inputs, outputs, objectives, and assumptions are defined. The next step is to translate the conceptual models into scientific ones. For this we define the mathematical formulation of the previously outlined conceptual models. Finally, we test the proposed models using simulation and testing different scenarios and by performing a sensitivity analysis.

Chapter 5

Mathematical Models

In this chapter we will describe the mathematical models that were developed to create a dynamic nurse assignment tool. A brief summary of each model follows:

Model 1 generates a nurse-to-patient assignment based on a given patient schedule and assuming deterministic treatment times and no cancellations. This model is meant to be run before the start of the work day and no changes are performed in the assignments throughout the day. With this model we analyse and evaluate the different objective functions.

Model 2 generates a weekly patient schedule based on a given number of request and assuming deterministic treatment times and no cancellations. The objective function of this model is to minimize patient waiting time and minimize nurses excess load. We also modify this model as **Model 2.2** to generate a new day schedule that can modify the original plan to account for cancellations.

Model 3: Dynamic Nurse Assignment Tool combines the previous models to account for the uncertainties of patient attendance. First we select a day from the weekly schedule generated with Model 2, then we use Model 2.2 to re-schedule patients based on known cancellations. Model 2.2 aims to minimize the change in initial appointment start times for patients and again minimize excess load for nurses. After this, we call model 1 for assigning nurses which will be re-run as more cancellations become known during the day. The nurse assignments are reviewed and, if required, improved every 2 hours.

5.1 Model 1: Deterministic Nurse-to-Patient Assignment

Because of the focus on the nurse-to-patient assignment phase, it was decided that this model will work with an already generated patient schedule. Regarding the planning time-frame, it was the decided that the models will be used to plan only for a day. This is because of the uncertainty that comes with planning and scheduling at outpatient clinics, the closer to the date the more information the clinics have regarding nurse rosters and patient schedules. In practice, it is usually the charge nurse who is responsible for the assignments and does so at the beginning of the shift. In this project, the nurse-to-patient assignment model is designed to be run right before the work day starts. In the literature, we can observe a similar approach in Liang and Turckan[19].

We propose a purely deterministic nurse-to-patient assignment model given a patient schedule, nurse roster and chair capacity at the clinic. The model assumes that each nurse has the ability to treat any given patient and that the set-up time is 1 time-slot for every patient. Because of the nature of the task, this model also assumes that patient set-up takes up a nurse's full capacity. This means that when a nurse is assigned to a set-up they cannot monitor other patients during that time-slot. Additionally, for this model we assume deterministic treatment duration, punctual patient arrivals and no cancellations are considered. While popular in the literature, in this study we do not apply acuity based constraints as there is no universally-accepted objective way of assigning acuity for patients receiving chemotherapy treatment. However, a skill-acuity match constraint could be added to the model we propose.

While this model does not account for uncertainty, it can help simplify the charge nurse's task of assigning patients and generate better assignments.

The model is analysed under different objectives, both individually and in combination. The purpose of this is to assess what policies should a clinic take when assigning nurses. Different clinics might have different priorities and we hope that our analysis can bring managers a deeper understanding of the consequences of prioritizing certain performance measures over others. These objectives we analyse are:

- Minimizing the nurses' excess load (a nurse is said to have an excess load when the "ideal" nurse-to-patient ratio is exceeded)
- Balancing the excess load across nurses
- Balancing the general workload across nurses
- Minimizing the number of different nurses monitoring a patient throughout their treatment (seeking to increase continuity of care)
- Minimizing patient waiting time while in treatment

In the following sections we will describe the method employed for estimating the 'within-treatment' waiting times, outline the generated data set for testing and present the proposed model.

5.1.1 Estimating within-treatment waiting times

We employ a queuing model to describe the waiting time that patients experience while on treatment. Waiting time can occur throughout the chemotherapy administration because patients may require nurse assistance at different stages of their treatment. When nurses monitor several patients simultaneously, patients might experience delays before receiving nurse attention.

To estimate the aforementioned waiting time, we model the outpatient clinic as a unit where 1 nurse serves K patients as an M/M/1//K closed queuing system.

While on the monitoring stage of their treatment, patients may be in one of two states: stable or needy. Stable patients become needy after an exponentially distributed activation time with mean $1/\lambda$. Needy patients are attended by the nurse on a first-come-first-served basis and the duration of said service is exponentially distributed with mean $1/\mu$. Once treated, a patient becomes stable again. The exponential distribution assumption is common in hospital capacity planning and the wide range of possible patient needs and nursing tasks also suggests a high degree of variability in the health care process, which is consistent with the high coefficient of variation of the exponential distribution. [11] Below, we can see how the waiting time that a patient experiences during treatment (nurse response time) increases with the more patients assigned to a single nurse. These calculated waiting times will be used as constants in Model 1. As can be seen in figure 5.1, the waiting time experienced depending on the number of patients assigned to the same nurse is not linear. This is why this objective is different than minimizing the workload or the number of patients assigned to a nurse.

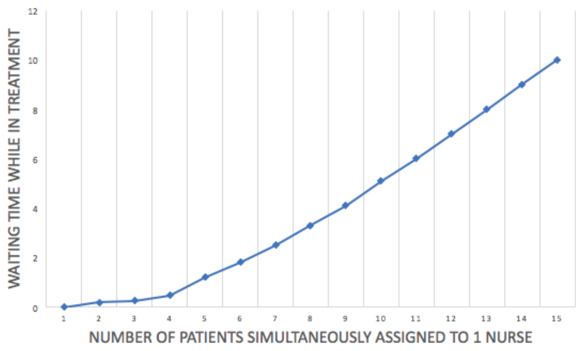

Figure 5.1: Waiting time experienced by a patient depending on the number of patients simultaneously assigned to a nurse

5.1.2 Treatment Duration and Pre-Set Patient Schedules

Because this thesis was done within an academic context, we did not have the opportunity to perform a case study at a clinic or analyse real data. For the purpose of testing our first model, we use data presented in other studies in the literature. We generate a data-set based on the data used by Liang and Turckan[19], the data we use for the computational studies can be found in appendix A.

5.1.3 Proposed Model

Parameters

$$
\begin{aligned}
P &: \text{ set of patients} \\
N &: \text{ set of nurses} \\
T &: \text{ set of time-slots} \\
C &: \text{ number of chairs available at the clinic} \\
M &: \text{ ideal number of patients assigned to one nurse during monitoring} \\
D_p &: \text{ duration of treatment, in number of time-slots, for patient } p \\
A_p &: \text{ scheduled treatment start time for patient } p \\
O_{n,t} &: \text{ excess load for nurse } n \text{ at time } t \\
MaxO &: \text{ maximum excess load for a single nurse} \\
U_{n,t} &: \text{ workload (in set-up equivalent load) of nurse } n \text{ at time } t \\
W_{n,t} &: \text{ patient wait time for nurse } n \text{ at time } t \\
Z_{p,n} &= \begin{cases} 1 & \text{if patient } p \text{ is assigned to nurse } n \text{ at any given time during their treatment} \\ 0 & \text{otherwise} \end{cases}
\end{aligned}
\tag{5.1}
$$

Decision variables

$$X_{p,n,t} = \begin{cases} 1 & \text{if patient } p \text{ is assigned to nurse } n \text{ in time-slot } t \text{ for monitoring} \\ 0 & \text{otherwise} \end{cases}$$

$$Y_{p,n,t} = \begin{cases} 1 & \text{if patient } p \text{ is assigned to nurse } n \text{ in time-slot } t \text{ for set-up} \\ 0 & \text{otherwise} \end{cases}$$

Objective Functions

$$\text{O1: } min \sum_{n}^{N} \sum_{t}^{T} O_{n,t} \tag{5.2}$$

$$\text{O2: } minmax \sum_{t}^{T} O_{n,t} \qquad \forall n \tag{5.3}$$

$$\text{O3: } minmax \sum_{t}^{T} U_{n,t} \qquad \forall n \tag{5.4}$$

$$\text{O4: } min \sum_{n}^{N} Z_{p,n} \qquad \forall p \tag{5.5}$$

$$\text{O5: } min \sum_{n}^{N} \sum_{t}^{T} W_{n,t} \tag{5.6}$$

$$\text{O6: } min \left(\sum_{n}^{N} Z_{p,n} \right) 0.5 + MaxO \tag{5.7}$$

Where Objective 1 (5.2) seeks to minimize the total excess load. Objective 2 (5.3) balances the nurses excess load by minimizing the highest excess load for an individual nurse and on a similar fashion, Objective 3 (5.4) balances and minimizes the workload across all nurses. Objective 4 (5.5) minimizes the number of nurses assigned to a patient during one treatment.Objective 5 (5.6) minimizes the total time patients might spend waiting while in treatment, we use a number of constraints to determine the number of patients assigned to each nurse in each time-slot and we penalize according to the constants we defined in section 5.1.1. Finally, Objective 6 (5.7) combines objectives 3 and 4 to balance and flatten the excess loads while keeping the number of nurses assigned to a single patient low to improve continuity of care.

Constraints

$$\sum_{n=1}^{N} X_{p,n,t} \leq 1 \qquad \forall p, \forall t = A_p + 1, t = A_p + D_p \tag{5.8}$$

$$\sum_{n=1}^{N} y_{p,n,t} = 1 \qquad \forall p, \forall t = A_p \tag{5.9}$$

$$\sum_{p=1}^{P} y_{p,n,t} \leq 1 \qquad \forall n, \forall t \tag{5.10}$$

$$X_{p,n,t} \leq 1 - \sum_{p=1}^{P} y_{p,n,t} \qquad \forall n, \forall t, \forall p \tag{5.11}$$

$$\sum_{p=1}^{P} X_{p,n,t} \leq M + 0_{n,t} \qquad \forall n, \forall t \tag{5.12}$$

$$\frac{\sum_{p=1}^{P} X_{p,n,t}}{M} + \sum_{p=1}^{P} Y_{p,n,t} \leq U_{n,t} \qquad \forall n, \forall t \tag{5.13}$$

$$\sum_{t=1}^{T} \sum_{n=1}^{N} X_{p,n,t} = \sum_{t'=t-1}^{t-D_p} \sum_{n=1}^{N} y_{p,n,t'} \qquad \forall p \tag{5.14}$$

$$\sum_{n=1}^{N} \sum_{p=1}^{P} y_{p,n,t} + \sum_{n=1}^{N} \sum_{p=1}^{P} X_{p,n,t} \leq C \qquad \forall t \tag{5.15}$$

$$X_{p,n,t} \leq Z_{p,n} \qquad \forall n, \forall t, \forall p \tag{5.16}$$

$$\sum_{n=1}^{N} Z_{p,n} \qquad \forall p \tag{5.17}$$

$$\sum_{t}^{T} O_{n,t} \leq MaxO \qquad \forall n \tag{5.18}$$

Constraints 5.8 and 5.9 ensure that patients have a nurse assigned to them during set up and all through the monitoring stage of their treatment. Because of the intensity of tasks required at the beginning of the treatment, a nurse can set-up at most one patient in any given time-slot, which is guaranteed by constraints 5.10 and 5.11. excess load occurs when a nurse has more than the ideal number of patients (M) assigned to them in a time-slot, constraint 5.12 calculates the excess load. Constraint 5.13 is used to calculate the workload for each nurse at each time-slot. We define a workload unit as the load equivalent for 1 set-up. Constraint 5.14 establishes the sequence between both stages of treatment; for every patient, the monitoring stage must start immediately after the set-up. All treatments are delivered on hospital chairs, constraint 5.15 ensures that the number of patients receiving treatment at any given time-slot does not exceed the number of chairs available in the clinic. Constraints 5.16 and 5.17 are used to count how many different nurses are assigned to each patient during treatment. Finally, constraint 5.18 determines the maximum workload for a single nurse.

5.2 Model 2: Weekly Patient Schedule

We develop a MIP that creates an optimal patient schedule for a work week. The model parts from a given number of requests, nurses and chairs. The model seeks to minimize nurses' excess load, because patients are prioritized in the system, which means that if there is chair availability then nurses are allowed to work over the recommended nurse-to-patient ratio in order to satisfy all patient requests. While this model was developed as a weekly scheduling tool, it could also be used to plan at different time horizons like a single day. In the next sections we will explain the data set that was created to develop and test the model and will present the mathematical model itself.

5.3 Generating the Data Set

Because this thesis was done within the university, we were not able to use real data for the developing and testing of the models. However, we aim to create a realistic data-set for this purpose. In particular, we define specific assumptions as constraints that the data-set must respect:

- It is assumed that the clinic provides 5 different treatment types, each with its own expected treatment duration
- It is assumed that set-up time is 1 time-slot (15 minutes) for all treatment types
- We assumed that the arrival rate of patient requests follows a Poisson distribution with a mean arrival rate of 35 patients per week
- Here note that the word "arrivals" is used for newly arriving patients who will get their first treatment session, it is assumed that in total 7 sessions are needed for each patient.
- To determine the arrival rate for each treatment type, we multiply the total arrival rate with the percentage assumed of patients for each type. These percentages are random assumptions and can be found in table 5.1

Treatment Type	Treatment Duration in Minutes	Frequency	New Arrivals
Type 1	30	25%	8.5
Type 2	90	30%	10.5
Type 3	150	20%	7
Type 4	210	15%	5.25
Type 5	270	10%	3.5
Total Arrival Rate per Week			35

Table 5.1: Initial Values

Using the arrival rates shown in table 5.1, we calculate required number of appointment slots for a work week. For this calculation, both queuing theory and simulation tools are used. In Kendall notation, this process can be characterized as an M/D/c queue. When calculating number of appointment slots, the base time period is in weeks, process time is 1 time period and each time slot stands for parallel servers. To calculate minimum number of appointment slots per treatment type per week when the average waiting time for each treatment type is less than one week, equations 5.19 and 5.20 are used.

$$utilization = \frac{Arrivalrate * 7}{Servicerate} \tag{5.19}$$

$$Wq \approx \left(\frac{c_a^2 + c_e^2}{2}\right)\left(\frac{u^{\sqrt{2(m+1)}-1}}{m(1-u)}\right) t_e \tag{5.20}$$

Where c_a^2 and c_e^2 are coefficients of variation of the arrivals and service times. Because the arrival rates follow a Poisson distribution, and service times are deterministic, $c_a^2 = 1$ and $c_e^2 = 0$. Additionally, the processing time $t_e = 1$ and the number of parallel servers (m) is equal to the number of appointment slots. Since equation 5.20 is not exact, simulation is used to verify the results of both equations 5.19 and 5.20. Then, utilization of the appointment slots and waiting times of the new arriving patients are calculated. We set the available number of chairs and nurses at the clinic as the given minimum level needed to accommodate all expected requests.

5.3.1 Proposed Model

Based on the data generated in the previous section, there are 245 appointments to be scheduled in a week of 165 time-slots (5 working days of 8 hours each, plus 5 dummy time-slots at the end of the day). The clinic modeled has 5 nurses and 19 chairs which, as described in section 5.3, is the minimum required to accommodate all the incoming requests in a single week. As in all of our models, the recommended maximum number of patients that a nurse should simultaneously monitor is 5.

Parameters

$$\begin{aligned}
R &: \text{ set of requests for treatment}\\
T &: \text{ set of time-slots}\\
S &: \text{ set of treatment stages: Set-up} = 1 \text{ and Monitoring} = 2\\
N &: \text{ Number of nurses}\\
C &: \text{ number of chairs available at the clinic}\\
M &: \text{ ideal number of patients assigned to one nurse during monitoring, M=5}\\
K &: \text{ dummy variable, K=9999}\\
D_{r,s} &: \text{ duration of treatment, in number of time-slots, for patient request } r \text{ in stage } s
\end{aligned} \tag{5.21}$$

Decision Variables

$$\begin{aligned}
X_{r,s,t} &= \begin{cases} 1 & \text{if request } r \text{ is scheduled for treatment stage } s \text{ in time-slot } t \\ 0 & \text{otherwise} \end{cases}\\
Transition_{r,t} &= \begin{cases} 1 & \text{if transition occurs for request } r \text{ in time-slot } t \\ 0 & \text{otherwise} \end{cases}\\
O_t &: \text{ excess load for nurses at time-slot } r
\end{aligned} \tag{5.22}$$

Objective Function

$$\min \sum_{t}^{T} O_t \tag{5.23}$$

Constraints

$$\sum_{r}^{R} \sum_{s}^{S} X_{r,s,t} \leq C \qquad \forall t \tag{5.24}$$

$$\sum_{r}^{R} X_{r,1,t} + \frac{\sum_{r}^{R} X_{r,2,t}}{5} \leq N + 0_t \qquad \forall t \tag{5.25}$$

$$X_{r,2,t} \leq X_{r,2,t+1} + Transition_{r,t} \qquad \forall t, \forall r \tag{5.26}$$

$$\sum_{t}^{T} Transition_{r,t} \leq 1 \qquad \forall r \tag{5.27}$$

$$\sum_{t}^{T} X_{r,s,t} = D_r \qquad \forall r, \forall s \tag{5.28}$$

$$\sum_{t}^{T} X_{r,1,t} * M \geq \sum_{t}^{t+1} X_{r,2,t} \qquad \forall r, \forall t \tag{5.29}$$

$$X_r, 1, t \leq X_{r,2,t+1} \qquad \forall r, \forall t \tag{5.30}$$

$$\sum t^T \sum s^S X_{r,s,t*41} = 0 \qquad \forall r \tag{5.31}$$

First, we acknowledge that the nurse assignment step could have been added to this model by specifying which patients would be monitored and set-up by which nurse. Theoretically, this can be easily be done by adding one nurse set and then, changing the decision variable to X_r, s, t, n. However, in this instance the problem size becomes too big to efficiently run it on a frequent basis, so the decision was made to split the patient scheduling and nurse assignment into two models for sake of simplicity and practical benefits.

In the model defined above, constraint 5.24 ensures that the number of patients being treated at any given time-slot does not exceed the clinic's chair capacity as the patients can't be treated if they are not in a proper chair. Constraint 5.25 concerns the overall number of nurses needed in a certain time-slot. All nurses can treat any patient, regardless of their treatment type. However, patients in the set-up stage require the full attention of one nurse, while patients in monitoring require less attention and thus nurses can simultaneously monitor several people. Ideally, nurses would only monitor up to M patients at the same time, with this constraint we calculate the instances in which nurses are assigned to more than M patients. Constraint 5.26 is used in combination with constraint 5.27, it forces the model to schedule each request in continuous manner. Because the model schedules in terms of time-slots, it is important to ensure that each individual request is scheduled in consecutive time-slots as treatment can't be interrupted. Constraint 5.27 ensures that there is only 1 transition per request. "Transitions" in this model are used to mark the end of an individual patient's treatment. This constraint is needed so that Constraint 5.26 can work smoothly. Constraint 5.28 ensures that the patients are scheduled for the entire duration of their treatment. Constraint 5.29 and Constraint 5.30 are used to establish the precedence relation between both stages of treatment. Constraint 5.29 forces the model not to start stage monitoring before finishing stage set-up. Constraint 5.30 ensures that monitoring begins immediately after set-up ends. Constraint 5.31 ensures that treatments are scheduled in one single day, meaning that no request starts in one day and finishes on the next one. A work day would originally consists of 40 time-slots but one dummy slot is added at the end of each day (5 dummies in total) to represent the end of the work hours, where no request can be scheduled. Because Constraint 5.26 enforces continuity, all request must be scheduled before or after the end of each day, thus ensuring that no requests will be scheduled with an interruption.

5.3.2 Model 2.2

We modify model 2 to generate a daily schedule. The additional inputs for this model are: a day schedule generated by model 2, and a list of known cancelled appointments. The main modification is the added constraint **??** which allows the model to re-schedule patients by no more that one hour (or 4 time-slots) before or after their original appointment. Where A_r refers to the original appointment time for patient r and S_r to the new start time for patient r. We use this model to create a daily schedule after the initial set of cancellations becomes known.

$$|A_r - S_r| \leq 4 \qquad \forall r \tag{5.32}$$

5.4 Dynamic Assignment Tool: Tackling Uncertainty

For developing a tool that can handle the uncertainty of cancellations and no-show, we assume a scenario where some of the cancellations are known before the day starts and others become clear during the day. We assume that, because of the lab tests and oncologist visit that patients are required to go through before their treatment, we find out about a patient cancellation 2 hours (or 8 time-slots) before their scheduled appointment time. Re-scheduling patients is allowed only before the outset of the work day and at most 4 time-slots before or after their previously set start time. Every 2 hours throughout the day, the nurse-to-patient assignments are reviewed and possibly modified. The tool was developed drawing from the model proposed by Hahn Goldberg et al. [14] In their study, they use an deterministic optimization model to schedule the expected number of patients for a day, then as the actual requests for appointments arrive, they use the template to schedule them. When a request arrives that does not fit the template, they update the template online using the optimization model and a revised set of appointments. We adapt this technique to fit the nurse-to-patient assignment problem and instead of scheduling we re-shuffle nurses to improve their daily assignments. We give a conceptual representation of the tool in figure 5.2

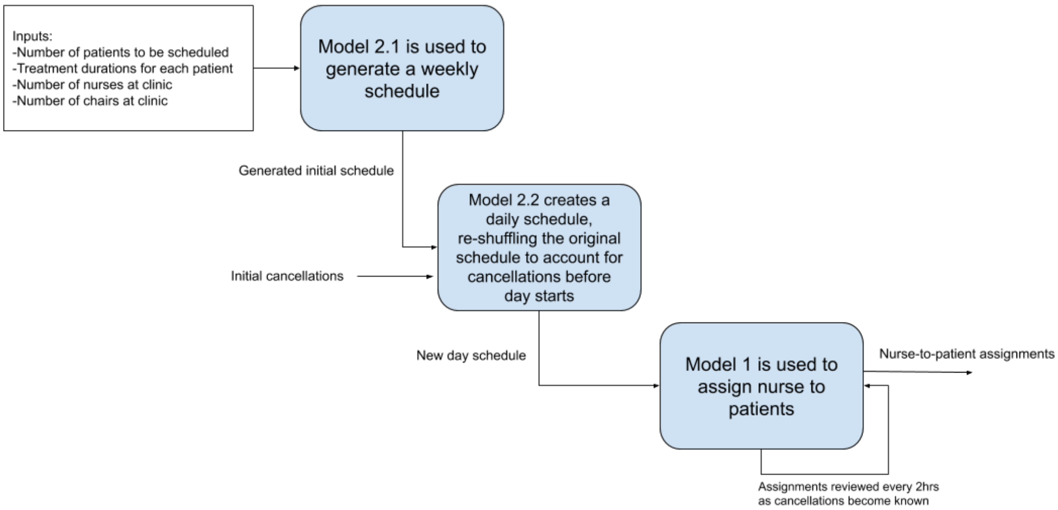

Figure 5.2: Dynamic Nurse Assignment Tool

Chapter 6

Strengths and Weaknesses of Proposed Models

In this chapter we review the strengths and weaknesses of the models described in chapter 5. We outline further improvements that can be done in each of the models and we reflect on their advantages.

6.1 Model 1: Deterministic Nurse Assignment

This deterministic nurse assignment MIP is very flexible in the sense that it can be easily modified to fit the needs of different clinics. For example, if the clinic works with patient acuity or the nurses have different skill sets for different treatments, then a acuity/skill matching constraint can be added. For this we would need a data matrix indicating whether a nurse is able to treat a certain patient (we will call this with the binary $Q_{n,p}$ which takes the value of 1 if nurse n can treat patient p) this variable would be added to the constraints multiplying by X_p, n, t. Additionally, the nurses availability can be added on a similar fashion,for this we would add a set indicating whether or not a nurse is available at a specific time-slot, this can be used to specify nurses shifts and breaks.

This model is very simple and could be improved by accounting for stochastic treatment durations and probabilities for cancellations, for this project we attempted to develop said stochastic model. The first version of this stochastic model can be found in appendix B.

Because this model assumes both a given schedule and the available nurse capacity, the results that come from it are only valuable for online operations planning. This however, was the main goal of the model. A simple model that runs fast can be very helpful for charge nurses assigning patients to their staff.

6.2 Models 2 and 2.2: Patient Scheduling

The proposed MIP model uses time-slots and binary decision variables for each time-slot for scheduling. Thus, this model is quite flexible and can be modified for many different settings. For example, any scheduled staff breaks can be represented. Say, for instance, that nurses have a lunch break in the middle of the working hours, then constraint 5.31 can be modified to block those time-slots. Additionally, the model could also be used to calculate the optimal number of nurses required for a week given an expected amount of requests. This can be done by changing the set of nurses for an integer decision variable and minimize on it instead of minimizing excess load. For other treatment types, it is possible to add more stages per request by increasing the size of set s. The model can also be modified to allow the user to enter already scheduled request so that they are fixed and then schedule add-ins or remove cancellations. This can be done by adding a set of fixed appointments and the following constraint $\sum_s X_f, s, t \leq Scheduled_f t \forall f, t$ When this constraint is added, it is possible to use the model as an online scheduling tool. Additionally, for Model 2.2, it is possible to change the objective function to minimize the difference between patients' original appointment time and the new one. This instead of, or in addition to, restricting the range of time in which the appointment can be moved.

The model, of course, also has its weak points. First, the run-time of the MIP is very long, even with small instances, and the problem grows exponentially with the set sizes of requests, stages and time-slots. Furthermore, the accuracy of the model depends on the size of the time-slots and the expected patient arrivals. As time-slots gets finer and/or the expected number of request arrivals represents the reality better, the more accurate the solution obtained.

6.3 Model 3: Dynamic Nurse Assignment Tool

To further improve this tool we could generate the initial nurse assignment at the same instance as we create the daily schedule. As stated before, Model 2.2 can be modified to assign nurses as well. In this project we keep the models as two separate MIPs to reduce complexity and computational time.

The key improvement that this tool needs is a way to deal with stochastic treatment durations. Throughout this study, we assume deterministic treatment length, yet in reality treatments can last less or more than the scheduled time. For further research a heuristic could be developed for reassigning nurses when a treatment is delayed or ends early. Additionally, the original schedule could have additional penalties to avoid assigning a nurse for a set up right after they are assigned to a treatment that is expected to finish only one time-slot before the set-up should begin.

Chapter 7

Results

7.1 Analysing Different Objectives in a Deterministic Nurse Assignment Model

In this section, we will review different objective functions in Model 1. We evaluate the assignments generated by each objective function using the following performance measures: total excess load, maximum excess load for a single nurse, difference between highest and lowest excess load, maximum workload (measured in set-up load equivalents) for a single nurse, difference between highest and lowest workload, within treatment waiting time, sum of different nurses monitoring each treatment, and maximum number of nurses monitoring a single treatment. With each objective function, we present the different assignments generated based on the given schedule. Each of the four nurses was assigned a color and a name for ease of interpretation and the slots appointed for set-up are marked with a border. For all objectives, the model is coded in Python and solved using Gurobi Optimizer.The objectives tested are:

- Objective 1: minimize total excess load
- Objective 2: balance the excess load across nurses
- Objective 3: balance the workload across nurses
- Objective 4: minimize the number of different nurses assigned to a patient during treatment
- Objective 5: minimize the total time patients spend waiting while in treatment
- Objective 6: balance excess load and minimize the number of nurses assigned to a single treatment

First we run the model with Objective 1: Minimizing excess load. With this objective, we observe that adding or subtracting a nurse significantly impacts the objective value. However, while more nurses available, the model seeks to lower their excess loads and this results in higher number of different nurses overseeing a single treatment. The downside of using this objective function is that while it minimizes the total excess load, it disregards its spread. This means that a few nurses will get most of the excess load while other might not have any excess load during the shift or may even be idling at times.

To avoid overloading a minority of nurses, we also test Objective 2: balancing the excess loads across nurses. We do so by minimizing the maximum total excess load for a single nurse. With this objective, we observe a higher total excess load, but a lower excess load assigned to individual nurses.

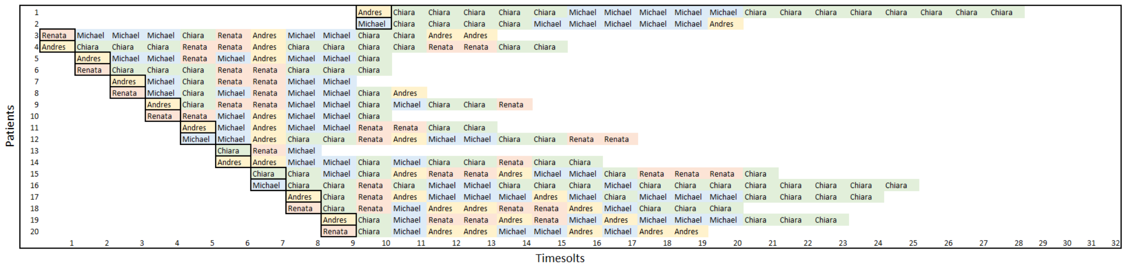

Figure 7.1: Objective: Minimize Total Excess Load

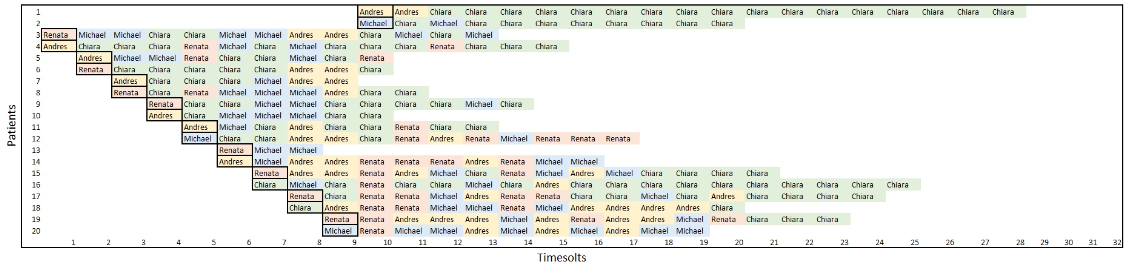

Figure 7.2: Objective: Balance excess Load Across Nurses

On a similar manner, we set an objective to balance workload across nurses (Objective 3). For this, we first calculate the workload for each nurse in each time-slot. We base this calculation on the load equivalent to 1 set-up. Then we set the objective function to minimize the maximum total workload for a single nurse. Because this model works with a set schedule of given patients, the required nurse workload is constant across all iterations. However, we will observe differences in the spread of workload across nurses and time-slots. While this objective evens out the workload across nurses achieving the same total excess load as Objective 2, it does not balance it resulting on some nurses carrying all the excess.

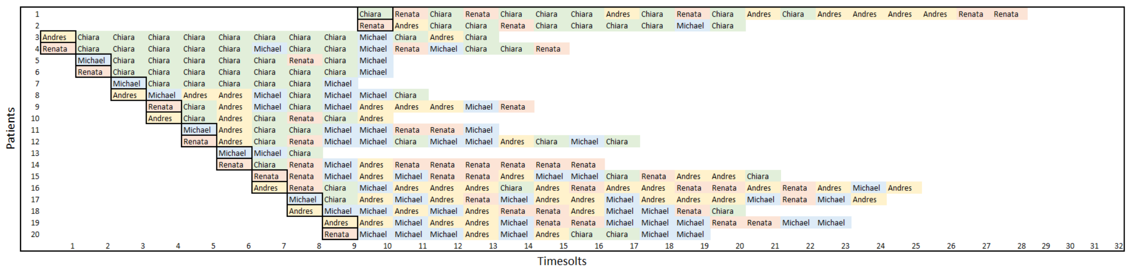

Figure 7.3: Objective: Balance Workload Across Nurses

When minimizing in-treatment waiting time, we look at the number of patients assigned to a nurse in every time-slot and we multiply the number by the constants calculated in section 5.1.1, we then minimize the total waiting time within treatment. When we use this as the model's objective, we can observe that the assignment results in the lowest possible total excess load and fairly balanced workload and excess load across nurses. This is because the fewer patients simultaneously assigned to one nurse, the lower the waiting time. However, we can see that there is a high number of different nurses monitoring each treatment.

Having many nurses in charge of one same patient at different instances of their treatment can become very confusing for both nurses and patient and may become a safety concern, so much so that at some clinics having the same nurse treat the patient during the entire treatment is a safety

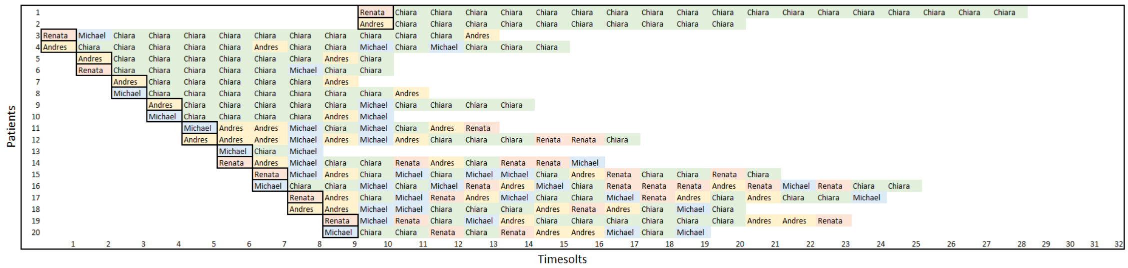

Figure 7.4: Objective: Minimize In-Treatment Waiting Time

and quality requirement[15]. Hesaraki[15] addresses this issue by minimizing the number of times the assigned nurse changes for each patient. In this study, we opt for minimizing the number of different nurses assisting each patient instead. This is because in Hesaraki's formulation changes are counted even when a nurse is reassigned to a patient at separate instances (eg. patient goes from nurse 1 to nurse 3 and back to nurse 1). This objective must be addressed in conjunction to other objectives or with a hard constraint on nurse workload. If one were to use only this objective without a hard capacity constraint, then the model would assign all of the monitoring to the first available nurse who would end up taking an extremely high workload while the rest of the nurses only perform setups and idle the rest of the time.

After testing the individual objective functions reviewed in this section, it was decided to combine the balancing of excess load and minimizing the number of nurses assigned to one treatment objectives. We believe that the combination of these two objectives would be the best to improve nurses' workflow and the patients' quality of care, as this multi-criteria objective aims to both balance and lower the excess load of the nursing staff while avoiding excessive nurse changes through a patient's treatment.

Balancing excess load was chosen over minimizing the total excess load because when minimizing the total it is possible that one or a few nurses get all the excess load which is a situation that a charge nurse would seek to avoid when assigning work. We chose balancing excess load over balancing the general workload for the same reason.

We added the minimization of nurse's assigned to a single treatment to the excess load balancing objective because we observed that when minimizing both the general workload and excess workload, the number of different nurses assigned to one treatment goes up. We wanted to strike a balance between these two goals to create assignments that are better for both nurses and patients. To combine these two objectives we used the weighted sum method. Because we want to prioritize the excess load balance, we assign the total different nurses a coefficient of 0.5.

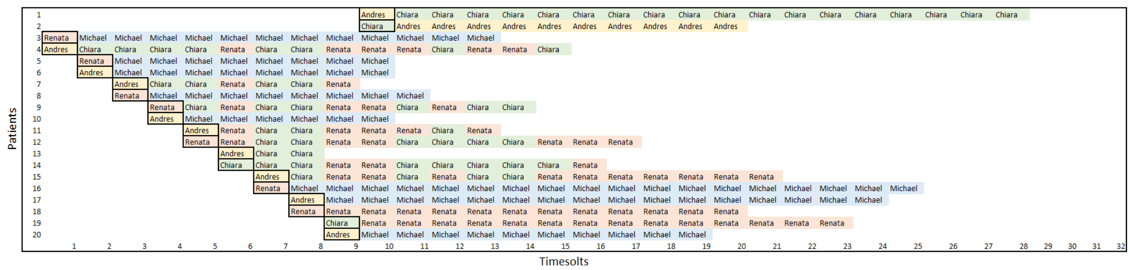

Figure 7.5: Objective: Balance Excess Load and Minimize Different Nurses per Treatment

In table 7.1 we can compare the value of the different performance measures when using different objective functions. In all runs, the given schedule input was the same (hence the steady total workload) and the number of nurses was always 4.

	Min Total Excess Load	Balance Workload	Balance Excess Loads	Min Waiting Time	Multi-Criteria
Total excess Load	17	20	20	17	24
Total sum of different nurses overseeing 1 treatment	68	66	61	73	27
Total Workload	63.2	63.2	63.2	63.2	63.2
Max Workload for a single nurse	19.6	15.8	21.8	17.2	19.4
Max Excess Load for a single nurse	8	10	5	6	6
Difference between min and max Workload	6.6	0	9.4	2.8	7.2
Difference between min and max Excess Load	8	9	0	3	0
Within Treatment Waiting Time	65.67	64.1	69.88	61.69	65.53
Max Nurses Monitoring per Treatment	4	4	4	4	2

Table 7.1: Performance measures resulting from different objective functions with 4 nurses

This table and performance measures help us understand how the different objective functions impact the nurses load and the continuity of care. When customizing this model for a specific clinic, their goals can be translated into the objective function. In some clinics balancing excess loads will be number one priority where for others the continuity of care might be prioritized. The comparison of the performance measures across objectives shows us how the different objectives compete, for instance a more balance workload or excess load will lead to more nurses assigned to one treatment. We also observe that balancing the general workload will not necessarily balance the excess load, this is because excess load is only possible during monitoring tasks while the general workload also considers the set-up tasks. As we can see with the multi-criteria objective tested here, if a clinic has several goals when assigning nurses, these can be grouped and assigned a weight depending on their priority.

7.2 Dynamic Nurse Assignment

To test the proposed dynamic nurse assignment tool, we generate a schedule for a clinic with 19 chairs and 5 nurses where 35 patients have been given an appointment for the day. For the cancellations, we use the data from Menting's study [20] and assume that any given treatment has a 4,6% probability of being cancelled. The patient mix is generated using the methodology in section 5.3 and can be found in appendix A.2.

A test is run for the scenario described above and we compare the initial solution, the solution after re-scheduling and at end of day after continuous re-assignment. The objective used for the nurse assignment in this tool Objective 6 which combines balancing excess load and minimizing different nurses per treatment. It is worth noting that the re-scheduling before the beginning of the work day is restricted to a maximum of 2 hours before or after the original appointment time. To evaluate the resulting assignments we use the following performance measures: average nurse utilization (a nurse is considered to be working at full capacity when they are assigned a load equal to 1 set-up), maximum excess load for a single nurse, difference between maximum and minimum excess load and workload, and number of different nurses assigned to one same treatment.

In the following example, we can observe the original schedule, the new schedule after cancellations at the beginning of the day and the changing assignments after the periodic nurse re-assignments. In this example scenario, two cancellations were known before the start of the day (patients 15 and 33), and the patients are re-scheduled accordingly). Then, after 2 hours cancellation for patient 20 becomes known and the nurses are re-assigned. Finally, the cancellation for patient 33 becomes certain 2 hours prior to the appointment and the nurses are re-assigned once again. Below, we can see the schedules and assignments throughout the day.

In figure 7.6 we can see the original schedule for the day. In the figure, we can identify the patients who were originally given an appointment but who resulted in a cancellation later on marked with a border.

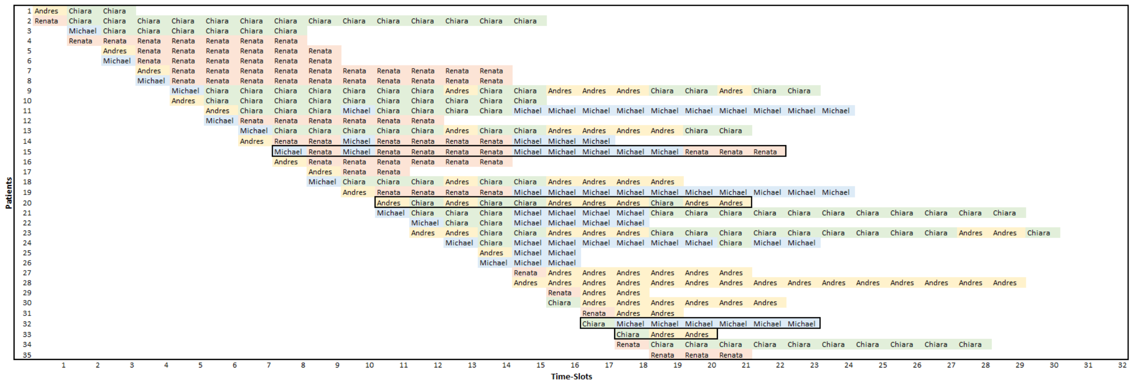

Figure 7.6: Original Schedule and Assignment

In figure 7.7 we can observe the changes in the patient's start times. Additionally, we can see that some nurses were assigned to patients' who later in the day cancelled, these are marked in the figure with a border. At this stage re-assignment was only done on the cancellations known before the start of the day.

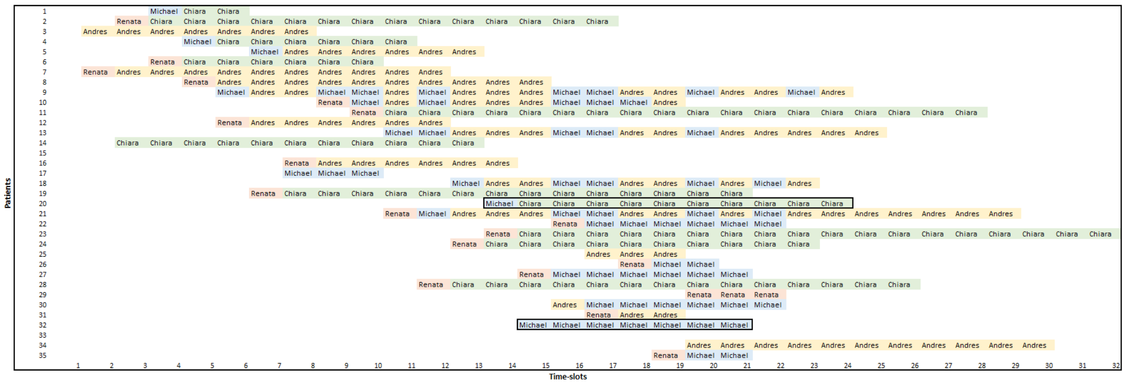

Figure 7.7: Schedule and assignments after re-scheduling

Finally, in figure7.8 we can see how the assignments look after reviewing and re-assigning nurses to account for cancellations every 2 hours.

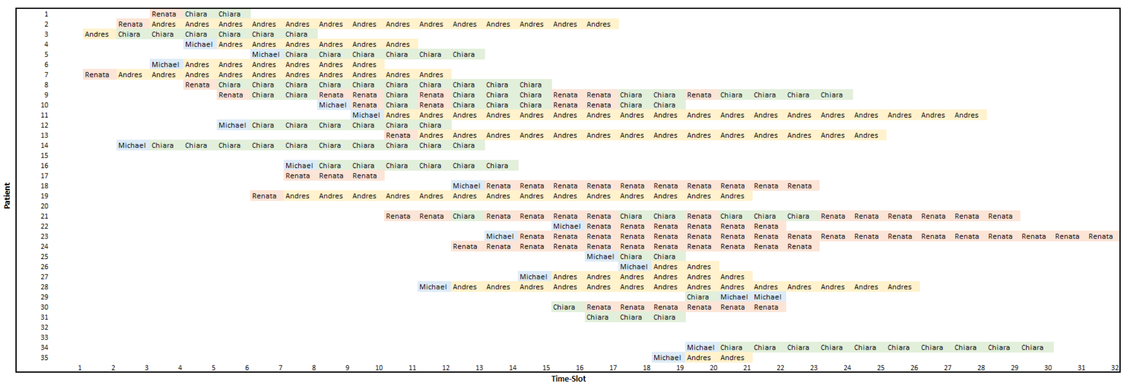

Figure 7.8: Full day schedule and assignments after periodic re-assignments

In table 7.2 we can observe the different performance measures for the full day. The "Original schedule" column shows the performance measures if the patient scheduling and nurse assignments were to stay as planned despite the cancellations and "Full day" shows how those same measures change after the initial patient-reschedule and periodic nurse re-assignment. In the middle, we also see how the second patient schedule and assignments would perform with the cancellations without modifying the assignments. As we can see, the workload remains constant because the measures are evaluated using only the patients that attended their treatment.

	Original schedule	After re-scheduling	Full day
Total Excess load	35	38	24
Max Excess Load for a single nurse	10	11	6
Difference between min and max Excess Load	3	2	0
Average nurse utilization	64%	64%	64%
Total sum of different nurses overseeing 1 treatment	41	35	34
Max nurses monitoring per treatment	2	2	2
Total workload	84,2	84,2	84,2
Max workload of a single nurse	25	24,6	23,8
Difference between min and max Workload	1,6	7,8	5,4

Table 7.2: Performance measures of daily assignments resulting from using the tool

As can be seen in table 7.2, the maximum workload for a single nurse is reduced as the nurses are re-assigned to account for cancellations, balancing the loads across the staff. The same happens with the difference between the nurse with the maximum excess load and the nurse with the minimum. However, we can see that when we re-schedule the patients, the maximum and total excess load go up, this is due to the second part of the multi criteria objective which minimizes different nurses observing a single treatment. It can be seen that once with the new schedule, the total and maximum excess loads decrease.

To evaluate the impact of re-assigning nurses without the ability to re-schedule patients. We simulate 5 different sets of cancellations and run our model on the schedule that can be found on appendix A.2. We compare the performance measures of the original assignments with the ones resulting from periodic re-assignment. While the original schedule is always the same, the performance measures for the assignments will change because different appointments would be cancelled. We then take the mean of the improvements (i.e. decrease) on the different performance measures. The results are shown in table 7.3.

	Mean Improvement on Performance Measure
Total Excess load	2
Max Excess Load for a single nurse	3
Difference between min and max Excess Load	3
Average nurse utilization	1%
Total sum of different nurses overseeing 1 treatment	5
Max nurses monitoring per treatment	0.68
Max workload of a single nurse	1
Difference between min and max Workload	7

Table 7.3: Mean performance measure improvement between original schedule and periodic re-assignment

As we can observe, periodically reviewing and modifying nurses' assignments as the cancellations become know can improve the staff's work by spreading the excess load across all nurse and can enhance the continuity of care by reducing the number of different nurses that a patient interacts with during their treatment. This is a particularly valuable insight because while it is difficult for clinics to re-schedule patients on the same day, the nurse staff tends to be fixed. Having a tool that allows the charge nurse to quickly and easily enter the cancellations and generate a new nurse assignment every couple of hour can be very valuable for a clinic as this is shown to improve the load of nurses and continuity of care and it can also ensure that no nurses are idle, specially if the cancellations are more frequent or if the clinic has a higher number of nurses.

Chapter 8

Conclusions

8.1 General Conclusions

This master thesis focuses on the study of operations planning at chemotherapy outpatient clinics, specifically nurse assignment. From our extensive review of the literature, it is clear to us that despite the increasing interest in studying operations and capacity planning in a chemotherapy outpatient clinic setting, studies focusing on nurse assignment are notably scarce. Because of this, we set out to search for ways to contribute to this gap in the literature and we posed the following research question and sub-questions:

- How can current methods be enhanced so that an outpatient oncology clinic can improve nurses' workflow and increase quality of care for patients, while capturing the dynamic uncertainty of patients attendance?
  - What are different objectives that clinics may use when assigning patients and how do these different objectives influence the performance measures like workload and continuity of care.
  - How can a continuous re-assignment of nurses at a chemotherapy outpatient clinic improve nurses' workflow and continuity of care?

As clarified in chapter 4. by improving nurses workflow we mean to create assignments that result in a more balanced workload across nurses and reduces nurses' excess load. As for increasing the patients' quality of care, we aim to do so with a better workflow for nurses and less nurse changes within treatments for each patient.

Based on the results of of the developed assignment model and dynamic nurse assignment tool, we can conclude that a continuous review and modification of nurses' assignments can improve workflow and continuity of care in a very simple manner. The results show that this constant re-assignment can decrease and balance the excess loads while also reducing the number of different nurses a patient interacts with during one same treatment. With 35 patients, the nurse assignment model takes less than a minute to generate the optimal nurse assignment with and it can run in under 15 minutes for up to 62 patients. This quick and easy to use tool, can simplify the charge nurse's task of assigning work to their staff while also producing better assignments. While for this study we programmed the model on python, the same tool can be developed in excel, which is widely-used software and would make the tool more user friendly.

For developing the main tool and investigating the first research sub-question, we studied the different assignments generated by our model given different objective functions. To define the objective functions, we drew from goals that clinics may have when assigning work. For instance, balancing workload and excess loads are common targets in both practice and literature. For continuity of care, we proposed counting the different nurses assigned to a patient throughout the treatment rather than counting the nurse change. With the aim of contributing a new kind of objective function to the literature, we propose adding an objective that minimizes the waiting time that patients experience during their treatment. This relies on the nurses' response time which in turn depends on the number of patients they simultaneously monitor. Nonetheless, we expect that nurses' response time is not lineal and so for this project we use a queuing model to estimate these response times. When we tested this objective, we found that it could potentially be very useful in practice as it tends to balance general workload reduce excess loads. Unfortunately, we cannot be certain of the effectiveness of using this objective. To properly test this idea, a case study is needed to understand the needs of patients during their treatment and the response time of the nurses depending on their workload. This would allow for more realistic constants in the model and thus better results.

After studying the literature, developing and testing the tools developed in this project we can say that there is room for improvement on the current methods for nurse assignment currently being used at oncology clinics. While there are many existing tools for patient scheduling such as excel models, off-the-shelf or in-house developed software, the nurse assignment is usually done by hand. This is because, as the last step of operations planning, nurse-to-patient assignments are subject to plenty of uncertainty and clinics rely on the experience of charge nurses to make the adequate calls when designating the work to their staff. Yet, we believe that this manual method can be improved by creating tools that are fast and can be tailored to the clinic's specific needs. The dynamic assignment tool developed in this thesis, shows that optimization models run periodically to tackle variability can better the continuity of care and workflow of nurses.

8.2 Future Research

8.2.1 Full Picture of the Clinic

Regarding planning at chemotherapy outpatient clinics, we found that most of the studies focus on the scheduling of patients and strive for the minimization of treatment delay and minimization of make-span. There is opportunity to do more research that includes the capacity of the clinic's oncologists, lab and pharmacy and how the availability and performance of these resources impact the patient scheduling and the nurse staffing levels needed. Lastly, it would be interesting to explore the use of queuing models to study the patients' flow through a clinic and how this impacts the different resources.

8.2.2 Objectives for Optimal Nurse-to-Patient Assignment

Further research could be done seeking different objectives such as maximizing resource utilization or balancing resource utilization. Additionally, more studies that focus on patient scheduling could incorporate nurse assignment into their models and evaluate nurse-workload focused objectives.

What we see as a big opportunity for further research is the development of an objective function that can account for nurse response time, thus addressing the wait that patients experience during treatment. In this project we used a queuing model to develop an objective that minimizes this waiting time. Nevertheless, we believe that a case study done in partnership with a clinic is needed in order to properly develop such objective. This would require an analysis on what kinds of needs arise from patients during treatment and a time study to determine how often they occur and how long do nurses take to attend each type of need.

8.2.3 Tackling Uncertainty

We encountered very few models that incorporate stochastic treatment duration and those that do, do so in computationally complex ways. There is a lot of room for research regarding uncertainty, particularly regarding treatment time. Because of this, a good step forward would be developing tools that can improve patient scheduling and/or nurse assignment while accounting for variable treatment duration and well as cancellations and add-ins.

8.3 Final Remarks

Our results show that the periodic re-assignment of nurses is an easy way for clinics to improve continuity of care and nurses' workflow at outpatient clinics and the developed dynamic tool can be a strong upgrade on the current manual and static processes.

We reckon that the use of mathematical modelling can enhance the methods presently used at outpatient chemotherapy settings, specially when developed in partnership with a specific clinic so that the models can properly account for the clinic's configuration, needs and goals.

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Appendix A

Data Generated and Used

A.1 Data used for testing Model 1

For testing the different objectives in the deterministic nurse assignment model, we adapt the data used by Liang and Turckan [18]. The data set is small but is ideal for running, comparing and illustrating the resulting assignments form different objectives.

Patient Number	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Appointment Time	10	10	1	1	2	2	3	3	4	4	5	5	6	6	7	7	8	8	9	9
Treatment Duration	18	10	12	14	8	8	6	8	10	6	8	12	2	10	14	18	16	12	14	10

Table A.1: Data adapted from Liang and Turckan 2015

A.2 Data generated for testing Dynamic Nurse Assignment Tool

A.2.1 Patient mix for testing tool with re-scheduling

Treatment Type	1	2	3	4	5
Duration in time-slots	2	6	10	14	18
Number of patients	8	10	8	5	4

Table A.2: Patient Mix

A.2.2 Schedule used to test Dynamic Nurse Assignment Tool without re-scheduling

Patient	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35
Appointment Time	3	2	1	4	6	3	1	4	5	8	9	5	10	2	0	7	7	12	6	13	10	15	13	12	16	17	14	11	19	15	16	14	0	19	18

Table A.3: Initial Schedule

Appendix B

Stochastic Programming Model

We model the stochastic problem as a two-stage SMIP, the first stage decision is on the sequencing of patients and the second stage decision is on the nurse assignment.

We modify the initial models to account for stochastic treatment duration as well as no-shows. This new model considers the probabilities for different scenarios where the different treatments can deviate from their planned duration. For this model, we also assume an already generated patient schedule.

B.0.1 Additional Parameters

$$D_p : \text{planned duration of treatment, in number of time-slots, for patient } p$$

$$V_p : \text{Deviation, in number of time-slots, from planned duration of treatment}$$

$$K_p = \begin{cases} 1 & \text{if patient } p \text{ attends their appointment} \\ 0 & \text{if patient } p \text{ is a no-show} \end{cases}$$

Decision variables:

$$X_{p,n,t} = \begin{cases} 1 & \text{if patient } p \text{ is assigned to nurse } n \text{ in time-slot } t \text{ for monitoring} \\ 0 & \text{otherwise} \end{cases}$$

$$Y_{p,n,t} = \begin{cases} 1 & \text{if patient } p \text{ is assigned to nurse } n \text{ in time-slot } t \text{ for set-up} \\ 0 & \text{otherwise} \end{cases}$$

$$\text{O1: } minQ \tag{B.1}$$

$$\text{O2: } min \sum_{n}^{N} Z_{p,n} \qquad \forall p \tag{B.2}$$

$$\sum_{n}^{N} X_{p,n,t}^{w} \leq 1 \qquad \forall p, \forall t = t(A_{p,t}^{w}) + L_{p}^{w} \tag{B.3}$$

$$\sum_{t}^{T} \sum_{n}^{N} y_{p,n,t}^{w} = 1 \qquad \forall p \tag{B.4}$$

$$\sum_{p}^{P} y_{p,n,t}^{w} \leq 1 \qquad \forall n \tag{B.5}$$

$$X_{p,n,t}^{w} \leq 1 - \sum_{p}^{P} y_{p,n,t}^{w} \qquad \forall n, \forall t \tag{B.6}$$

$$\sum_{p}^{P} X_{p,n,t}^{w} \leq M + 0_{n,t}^{w} \qquad \forall n, \forall t \tag{B.7}$$

$$\sum_{n}^{N} X_{p,n,t}^{w} = \sum_{t'=t-1}^{t-L_{p}^{w}} \sum_{n}^{N} y_{p,n,t'}^{w} \qquad \forall p \tag{B.8}$$

$$\sum_{n}^{N} \sum_{p}^{P} y_{p,n,t}^{w} + \sum_{n}^{N} \sum_{p}^{P} X_{p,n,t}^{w} \leq C \qquad \forall t \tag{B.9}$$

$$\sum_{n}^{N} y_{p,n,t}^{w} = A_{p,t}^{w} \qquad \forall r \forall t \tag{B.10}$$

$$X_{p,n,t}^{w} \leq Z_{p,n}^{w} \tag{B.11}$$

$$\sum_{n}^{N} Z_{p,n}^{w} \qquad \forall p \tag{B.12}$$

$$L_{p}^{w} = (D_{p} + V_{p}^{w}) * K_{p}^{w} \tag{B.13}$$