DESIGNING A BLUEPRINT SCHEDULE FOR THE PRE-TREATMENT PHASE APPOINTMENTS OF PATIENTS OF INSTITUUT VERBEETEN

Tactical multi appointment planning

A.G. Ploeg
August 2021

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Preface

In front of you lies my research; “Designing a Blueprint Schedule for the Pre-treatment Phase Appointments of Patients of Instituut Verbeeten”. I worked for Supply Value and was seconded to Instituut Verbeeten. This research is written to complete the master Industrial Engineering and Management at the University of Twente. I wrote my research in the period February 2021 to August 2021.

First, I would like to thank Geerten Peek for the opportunity to start my research at Instituut Verbeeten. From the moment I started at Supply Value, he was really helpful and searched for potential companies and projects. He introduced me to Aleksandra Leuverink, who was already doing an interesting project at Instituut Verbeeten. We figured out together how I could contribute with my research and expertise. I want to thank her for getting to know Instituut Verbeeten really quick and she was always there to answer questions about her project. I also want to thank Dave Dominicus for being my supervisor the first couple of months of my research and the weekly meetings we had. Moreover, I want to thank Evelien Peijs- van Mierlo for helping me out to understand the processes at Instituut Verbeeten. Because of all different tumour types and processes there were a lot of difficult terms and abbreviations. Especially, I want to thank Noura Marmouk for all the meetings and interesting conversations we had about the research. She knows a lot about Instituut Verbeeten and I learned a lot from her expertise in Lean Six Sigma. It is really valuable to hear about the implications of applying these methods in practise and to change processes step by step.

Second, I would like to thank my two supervisors from the University of Twente. Especially my first supervisor, Gréanne Leeftink. She always had valuable feedback and after each meeting I had fresh motivation to continue with my research. It is a long process with ups and downs, where she supervised me throughout the whole learning process. Moreover, I want to thank my second supervisor, Erwin Hans. I had a couple of meetings with him, when I needed some feedback. He always made time, even though it was a busy period and I learned a lot from him.

Finally, I want to thank all my friends and family motivating me throughout the whole process. It helped me to see things in perspective and realize I was doing the right thing. I enjoyed the research of designing a blueprint schedule and I hope you – the reader – will enjoy it as well. From now on, my student life is finished and I look back at it with a smile on my face.

Afien Ploeg

Utrecht, August 19, 2021

Management Summary

Introduction

Instituut Verbeeten provides radiotherapy for cancer patients. Before starting the radiotherapy, appointments of the pre-treatment stage must be scheduled. Instituut Verbeeten wants to optimize the blueprint schedule of pre-treatment appointments for their patient types with different stages and durations. In the Netherlands, access time norms are defined which determine a maximum number of days between referral and the start of the treatment. Currently, only 90% of the acute patients is treated within 24 hours, 94% of the subacute patients is treated within 7 days and 95% of the regular patients is treated within 21 days. **Therefore, this study focuses on designing a blueprint schedule in which multiple appointments are efficiently scheduled taking the nationwide norm regarding to access time in mind.** In the literature, outpatient services are frequently studied, and a need for coordinated care across multiple departments is acknowledged, but multi-disciplinary appointment planning is challenging because there are often more constraints such as interdependency between pre-treatment phase appointments. The contribution if this thesis is three-fold: 1. We develop a multi appointment blueprint schedule, a problem on the tactical multi appointment/disciplinary side of the planning, which is underexposed in the literature. 2. We focus on combining appointments to decrease access time and start a patients' treatment as soon as possible. And 3. We show the working of our models in a practical case with Instituut Verbeeten, which shows that the blueprint schedule for pre-treatment phase appointments can be obtained in their current practise.

Methods

We focus on mid-term planning and in particular the design of a blueprint schedule, for a flexible flow shop system, as certain patient types do not need all care pathway stages. Patient types have different tumour types and radiotherapeutic oncologists (RTO) have different tumour type specializations. All care pathways can be summarized to 19 patient types covering 90% of all patients. The patients of Instituut Verbeeten are referred patients from mostly MDOs (multi-disciplinary meeting) in a hospital. We have the data of patients referred between September 2020 and February 2021 from the hospital information system. The nationwide norm states that all patients with an acute condition are treated within 24 hours, patients with a sub-acute condition are treated within 7 days, and patients with other conditions (also known as regular patients) are treated within 21 days.

We do not take uncertainty into account in the model, because we aim to set a basis for the tactical multi appointment/disciplinary side of the planning and combining appointments. The model is static, where input parameters can be adapted to analyse the resulting blueprint schedule. The model minimizes the total sum of the starting times of the reserved appointments, such that patients can be treated as soon as possible. Constraints make sure appointments are reserved for the right patient types and resources. Furthermore, we designed a constraint making sure the sequence of the stages is right. We develop both an exact method as well as a constructive heuristic, and the performance of the blueprint schedule is measured. The exact method is an ILP, which is solved using Spyder with the programming language Python and the software package MIP and solver CPLEX. The constructive heuristic is a greedy approach, programmed in Python. The initial sequence of scheduling the patient types in the first available slot is from the patient type 0 to 18. However, also other sorting methods are analysed, namely starting with the patient type with the highest or lowest number of arrivals and a random sequence.

Experiment design

To show the working of the methods in practise, we perform experiments which vary in:

- The number of days of the planning horizon of the experiment (5, 10, 15 or 20 days)
- The flexibility of taking over tasks by RTOs (one single RTO is assigned to BVB time and first consultation for that same patient, or the BVB time can be executed by any RTO with the tumour type specialisation)
- The size of the case mix (the original case mix or a 50% increase in the original case mix)

Results

Table 0.1 Summary experiment results

Experiments	**Exact** **Objective function**	**Calculation time**	**Heuristic** **Objective function**	**Calculation time**
Flex, initial	77,041.00	2058.36	77,673.00	526.81
Fix, initial	77,212.00	2894.75	78,084.00	376.37
Flex, 1.5x	119,309.00	2194.5	120,197.00	851.88
Fix, 1.5x	119,557.00	2218.54	120,803.00	688.26
Random			78,005.00	488.42
High to low			78,394.00	478.62
Low to high			77.724,00	487.18

Table 0.1 shows the summary of the experiment results for a planning horizon of 10 days. The exact method outperforms the constructive heuristic by 1.36% on average, and can be solved to optimality

within 30 minutes. The constructive heuristic also provides good solutions, with an approximation ratio of 0.82% and a calculation time of 526.81 seconds. This is four times less than the calculation time of the exact solution method. The initial sequence of patient types for the constructive heuristic (as displayed in Table 0.1) gives the lowest objective value. Furthermore, the objective function value is higher when the BVB time has a fixed RTO, namely the same RTO as the first consultation.

Currently, Instituut Verbeeten can start the treatment of **94%** of the **subacute patients** within the nationwide norm of **7 days** and this research achieved to increase this ratio to **100%**. These subacute patients can be treated with a mean of **3 hours**, far within the nationwide norm. Furthermore, currently Instituut Verbeeten can start the treatment of **95%** of the **regular patients** within the nationwide norm of **21 days** and this research achieved to increase this ratio to **100%**. These regular patients can be treated with a mean of **5 hours**, far within the nationwide norm. This means a large decrease in processing time and patients can start their treatment earlier.

Next to this, we show that patients can start their treatment 2 time slots, so 30 minutes faster if the BVB time can be executed by any RTO instead of the RTO that performed the first consultation. Furthermore, our proposed model still creates a feasible schedule when the case mix is 1.5 times more than the original case mix. This however comes at the cost of less available pool time, for example for follow up appointments. These follow up appointments can be planned when there are less new patients arriving.

Discussion

In our work, we show the working of our developed methods for a practical case study with Instituut Verbeeten. This research can also be used for similar cases where a blueprint schedule is to be created. The important characteristic of this model is that it concerns multi appointment planning including different stages and patient types. The limitation of this research is that the model cannot be solved exactly for a planning horizon longer than 10 days, for which the constructive heuristic has been developed.

Further research is required to involve the patients' travel time. For example by including the home location of a patient and the location of the resources. We proved that the model gives a better solution if the BVB time can be executed by any RTO instead of the RTO that did the first consultation of a patient. Therefore, we advise Instituut Verbeeten to reserve the BVB time at any RTO that is available to create more flexibility in the planning and to treat patients as soon as possible. We cannot start with the new blueprint schedule in one day, because first the backlog needs to be decreased. This can be done by increasing the availability of the resources for a couple of weeks, to make sure the backlog is decreased before starting with the new blueprint schedule.

Finally, consultancy agencies can use this research to execute projects at other companies with similar planning issues. To this end, the model can be used and adjusted to other circumstances and requirements by changing the input parameters and some constraints.

List of Abbreviations

Abbreviation	Explanation
ADM	Administration
BVB	The Dutch abbreviation for radiation preparation treatment plan (Bestraling Voorbereiding Behandelplan)
IKNL	The Dutch abbreviation for Integral Cancer Centrum the Netherlands (Integraal Kanker Centrum Nederland)
FU	Follow up appointment
(M)ILP	(Mixed) Integer Linear Programming
Mamma	the Latin word for breast
MDL	The Dutch abbreviation of stomach, intestine and liver (Maag, Darm & Lever)
MDO	The Dutch abbreviation for multi disciplinary meeting (Multi Disciplinair Overleg)
MR	Mould Room, to position a patient in the right form for a scan
NP	First consultation of a new patient
NVRO	The Dutch abbreviation for Dutch Association for Radiotherapy and Oncology (Nederlandse Vereniging voor Radiotherapie en Oncologie)
RTO	the Dutch abbreviation of radiation oncologists (Radio Therapeutisch Oncoloog)

Contents

1 Introduction

Since the reform of the Dutch health insurance system in 2006, a gradual transformation of the supply side of the healthcare market has taken place (Schut & Van de Ven, 2011). The health insurance law ensures a basic insurance for citizens and results in more possibilities for them to make their own choices from healthcare providers and health insurance policies (Zorgverzekeringswet, 2021). This creates competition between healthcare providers and healthcare insurers. They can distinguish themselves by creating efficient healthcare systems. A popular way of such development is the use of Operation Research (OR), which provides methodologies and solution techniques to improve access and reduce costs in healthcare (Ahmadi-Javid, Jalali, & Klassen, 2017).

Healthcare is divided into outpatient and inpatient care, where outpatient care does not require an overnight hospitalization. Outpatient care becomes an essential part of the healthcare system as there is a greater focus on preventive medicine practices and shorter lengths of stay (Cayirli & Veral, 2003). On top of this, patients develop more complex diseases, creating a need for coordinated care across multiple departments (Mutlu, Benneyan, Terell, Jordan, & Turkcan, 2015). Outpatient appointment systems (OAS) have been studied for more than a half century, namely since the paper of Bailey (1952). Cayirli & Veral (2003) and Gupta & Denton (2008) review the literature and address open research questions related to OAS problems, but do not mention the coordinated care across multiple departments. Leeftink, Bikker, Vliegen, & Boucherie (2020) look at the multi appointment context and conclude that mid-term capacity planning is a promising direction for further research, such as blueprint schedule planning, patient admission planning, and temporary capacity changes.

This research is motivated by Instituut Verbeeten, which provide radiotherapy for cancer patients for more than 65 years. Where radiotherapy is the irradiation of mostly malignant diseases. These treatments can be performed separately, or in combination with other relevant cancer treatment modalities, such as surgery and chemotherapy. Before starting the radiotherapy, several preparation steps need to be performed also known as the pre-treatment stage. A couple of healthcare professionals are involved in the radiotherapy treatments. Radiation therapy technologists (RTT) image the scans, plan the treatment, and perform irradiation sessions. While the radiotherapeutic oncologists (RTO) perform the first consultation, tumour contouring, and follow up appointments. The research focuses on the pre-treatment patient planning of Instituut Verbeeten, including the first appointment, CT scan and preparation time.

Instituut Verbeeten wants to optimize the blueprint schedule of pre-treatment appointments of their patients. A blueprint schedule is a schedule with reserved time slots for certain patient types, given that the patients have not arrived yet. In this way, it is easier to plan arriving patients because time slots are already reserved. These patients have different care pathways, namely a specific sequence of operations, which is dependent on the characteristics of the tumour (such as tumour site, level of advancement, etc.), urgency level, amongst other factors (Vieira, 2020). The pre-treatment phase involves multiple appointments with different healthcare professionals. In an ideal situation, patients attend pre-treatment appointments on the same day, if necessary, because this decreases total travel and access time. Access time is the time from referral to the treatment. High access time and waiting time is generally undesirable in healthcare, but especially in radiotherapy (Simons, et al., 2017). Because local tumour control and survival rates are negatively affected by increased waiting time, especially for specific tumour sites (e.g., breast, head, and neck cancer) (Mackillop, 2007). Furthermore, patients have fear and feel insecure about their process which results in prolonged psychological distress, so it is desirable to start the treatment as soon as possible (Mackillop, 2007). In the Netherlands, timeliness standards are defined by the Dutch Society for Radiation Oncology (NVRO), which determine a maximum number of days between referral and the start of the treatment (Normeringsrapport, sd). Currently, only 90% of the acute patients is treated within 24 hours, 94% of the subacute patients is treated within 7 days and 95% of the regular patients is treated within 21 days. Therefore, this study focuses on designing a blueprint schedule in which multiple appointments are efficiently scheduled taking the nationwide norm regarding to access time in mind.

The problem we look at in this research is unique. First, because it focuses on the tactical side of the planning, namely addressing the organization of operations of the healthcare delivery process. In particular tactical planning deserves attention, as this level of control is underexposed in practice due to its inherent complexity (Hans, Van Houdenhoven, & Hulshof, 2012). Tactical implications of a strategic decision should be managed, because otherwise problems are likely to persist. Second, it concerns a multi appointment planning including doctors with different combinations of specialisations. Research often limit their scope to a single diagnostic resource type or procedure step due to complexity constraints (Marynissen & Demeulemeester, 2019). However, the pre-treatment includes multiple appointments which should be planned in a short time, to decrease access time and start the treatment as soon as possible. Reviews of multi disciplinary planning such as from Vanberkel, Boucherie, Hans, Hurink, & Litvak (2009) and Leeftink, Bikker, Vliegen, & Boucherie (2020) compile an overview of planning models, but little or no scheduling occurs. The contribution if this thesis is three-fold: 1. We develop a multi appointment blueprint schedule, a problem on the tactical multi appointment/disciplinary side of the planning, which is underexposed in the literature. 2. We focus on combining appointments to decrease access time and start a patients' treatment as soon as possible. And 3. We show the working of our models in a practical case with Instituut Verbeeten, which shows that the blueprint schedule for pre-treatment phase appointments can be obtained in their current practise.

The remainder of this paper is organized as follows: Section 2 describes related literature on multi appointment planning, followed by the problem description in Section 3. Section 0 elaborates on the case study settings and results. Finally, Section 4 describes the conclusion and discussion.

2 Literature

This section reviews the related literature on the topic multi-disciplinary appointment planning. Starting with the introduction of a Lean Six Sigma project of Instituut Verbeeten in Section 2.1. Next, Section 2.2 discusses the importance of appointment systems focussed on multi appointment planning. Thereafter, Section 2.3 gives an overview of the four-by-four generic framework of healthcare planning and control of Hans, Van Houdenhoven, & Hulshof (2012). Section 2.4 includes the possible characterstics of a model. Section 2.5 mentions possible solution methods and Section **Error! Reference source not found.** elaborates on the contribution of the literature to the research.

2.1 Lean Six Sigma

Currently, Instituut Verbeeten is working on a Lean Six Sigma project. This project aims at optimising the distribution of the first appointment across the locations of Instituut Verbeeten. Lean principles and tools play an important role in healthcare delivery in the improvement and quality of services (Spagnol, Min, & Newbold, 2013). The current Toyota Production System (Lean) has been in existence since 1945, so it is developed further in many years. Therefore, there is a high urgency in improving healthcare services compared to world-class manufacturing organisations where staff already understood the lean principles and the urgency for change (Young & McClean, 2009).

Lean thinking focusses on eliminating waste (Womack & Jones, 1997). These includes defects, overproduction, transportation, waiting, storage (buffers), movement and relocating, doing more than necessary and unused creativity and capacity. In the case of healthcare service, especially waiting, doing more than necessary and unused capacity are relevant. Waiting belongs to the patient access time and waiting time. So, the time until patient’s first consultation and the time between patient’s appointments. Doing more than necessary is the case in the patient registration and planning process. Sometimes processes can be simplified by eliminating or combining steps in, for example, the planning process. Furthermore, resources have to be used efficiently and unused capacity should not be the case. Eliminating waste involves five stages (Womack & Jones, 1997):

1. Specific value must be defined by the customer, in terms of specific products with specific abilities at specific prices.
2. The value stream must be identified with all the actions required to bring the product to the customer, with only activities that add value.
3. Create flow and eliminate the traditional batch process.
4. Get the customer to pull the product.
5. Perfection.

During the research, the focus is on eliminating waiting, doing more than necessary and reducing unused capacity to reach the lean goal to eliminate waste.

Six sigma identifies and aligns improvement initiatives with strategic objectives and business goals and look at key processes across the entire system (Sehwail & DeYong, 2003). Since introducing the initial 6-step process by Motorola University Design for Manufacturing training programme in 1988 (Watson & DeYong, 2010), Six Sigma became an extension to Total Quality Management (TQM) (Green, 2006). It became a business strategy focussing on improving understanding of customer requirements, business productivity and financial performance (Kwak & Anbari, 2006). The principle took shape in the electronics industries and in the last two decades, principles also been implemented in the context of, amongst others, hospitals (Sehwail & DeYong, 2003). Especially, the Define, Measure, Analyse, Improve and Control (DMAIC) approach works well for processes that can measure response variables, because it is an systematic, structured and on facts based method. The approach helps to base decisions on facts in stead of feelings or presumptions. During the research, the DMAIC approach is used as underlying thought to reach process improvement.

2.2 Importance of appointment systems

Healthcare providers differentiate themselves by creating efficient healthcare systems, where the use of Operation Research techniques is one way to improve access time and reduce costs. In recent years, there is an increased focus on outpatient services and a need for coordinated care across multiple departments (Mutlu et al., 2015). There are literature reviews available on outpatient appointment systems, such as Cayirli & Veral (2003) and Gupta & Denton (2008). However, these do not address multi appointment scheduling. A multi disciplinary care system is defined as a care system in which multiple related appointments are scheduled per patient, involving healthcare professionals from different facilities or with different skills. Leeftink et al. (2020) and Marynissen & Demeulemeester (2019) indicate the relevance of multi-disciplinary/appointment planning, which are becoming increasingly popular.

Although multi-disciplinary appointment planning is considered relevant, multi-disciplinary appointment planning is also much more challenging than single appointment planning, or multi appointment planning for a single discipline, for multiple reasons. For example, there are more constraints, such as precedence relations and resource availability, that must be considered. In addition, there is often the bullwhip effect, due to the variability that occurs in early stages of a patient's care pathway, which impacts potential efficiency in later stages (Samuel, Gonapa, Chaudhary, & Mishra, 2010). The bullwhip effect is a well-known and much studied inefficient outcome. Different involved disciplines often do not use the same information, resulting in the bullwhip effect (Leeftink et al., 2020). It also refers to the observation that the variability of orders in supply chains increases the closer one gets to the production source (Wu & Katok, 2006). This is linked to the patient's care multi stage care pathway. For example, Samuel et al. (2010) defined the bullwhip effect as the standard deviation ratio between the service rate and patient arrival rate. A care pathway is defined as a complex intervention for the mutual decision-making and organisation of care processes for a well-defined group of patients during a well-defined period of time (Vanheacht, De Witte, & Sermeus, 2007). Concluding, multi-disciplinary appointment scheduling is more challenging, due to the precedence relations and resource availability that must be considered.

2.3 Healthcare planning and control

Healthcare planning and control is divided into different hierarchical levels of control and managerial areas. Hans, Van Houdenhoven, & Hulshof (2012) introduces this four-by-four generic framework, shown by **Error! Reference source not found.**. The four managerial areas are medical planning, r esource capacity planning, materials planning and financial planning. This report focuses on resource capacity planning, namely dimensioning, planning, scheduling, monitoring, and control of renewable resources. Patients must be scheduled with multiple resources, such as staff and MRIs. Furthermore, there are four hierarchical levels of control, namely strategic, tactical, and offline/online operational. Since the focus is on resource capacity planning, the levels can be depicted in the following way. Strategic means long-term and relates to structural decision making, i.e., case mix planning: capacity dimensioning and workforce planning. This occurs about a year before patients are scheduled. Next comes tactical, which focuses on the implementation of the processes, such as block planning, staffing and admission planning. This takes place a few weeks before patients are scheduled. Finally, there is operational, divided into offline and online operational. Offline operational focusses on short-term decision making related to the implementation of the healthcare delivery process, such as appointment scheduling and workforce scheduling which is executed. Typically, this takes place about a few weeks before the appointments. Online operational decisions, such as monitoring and emergency coordination, are made on the same day or a few days in advance.

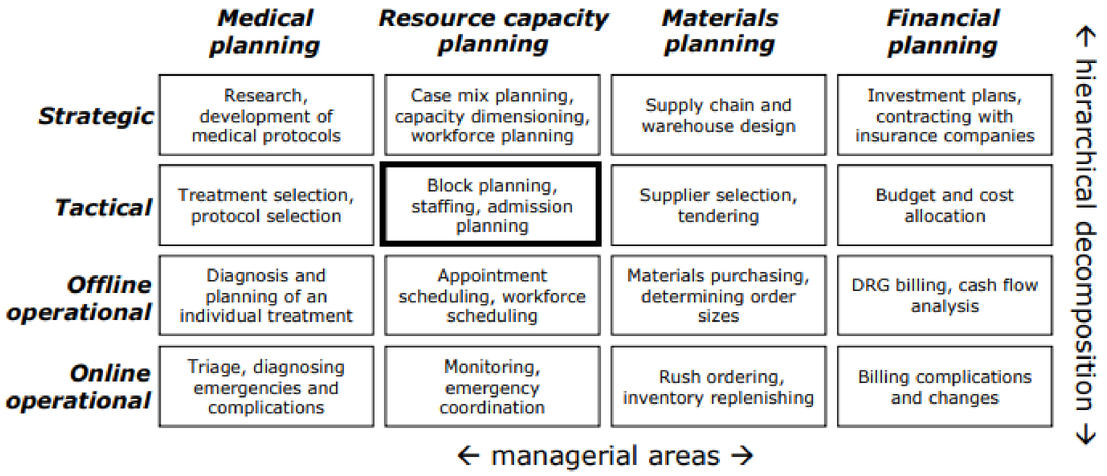


Figure 2.1 Framework for healthcare planning and control (Hans et al., 2012)

Patients are referred through MDOs of different hospitals. An MDO is a meeting with doctors from multiple disciplines (Multidisciplinair overleg, sd). During this MDO the decision is made if a certain patient is treated. The MDOs of the referring hospitals are held every week on the same days, so this part of the number of referred patients can be predicted. The goal is to match the planning to the schedule of the MDOs, so the focus of this research is on mid-term planning, namely tactical/capacity planning, shown by **Error! Reference source not found.** with the highlighted black border. The main o bjectives are to achieve equitable access and treatment duration for different kind of patient groups, to serve the strategically agreed upon a target number of patients, to maximise resource utilisation and to balance the workload (Hulshof, Boucherie, Hans, & Hurink, 2013). Capacity planning considers the allocation of resource capacity across specialties, patient groups or time slots by, for example, blueprint schedule and patient admission planning (Leeftink et al., 2020). The blueprint schedule consists of a description of the number of capacity or reserved time slots for specific patient types. These time slots can also be used for combined appointments. The patient admission policy describes the number and type of patients that can be admitted from the waiting list.

To match the planning to the schedule of the MDOs, the focus is on generating a blueprint schedule. The factors showed in Table 2.1Table 2.1 can be considered when modelling the key decisions to design the blueprint schedule (Hulshof, Kortbeek, Boucherie, Hans, & Bakker, 2012).

Table 2.1 Factors to consider when modelling key decisions of a blueprint schedule

Factor	**Explanation**
Number of patients per consultation session	To control patient access times and patient waiting times. When the number of patients increases access times probably decreases, but overtime tends to increase.
Patient overbooking	If patients do not show up, they cause unexpected gaps and increases resource idle time. To compensate no-show patients, patients can be overbooked, so planning more patients than the suggested number of planned slots. It provides benefits for facilities with high no-show rates.
Length of the appointment interval	This decision affects the resource utilization and patient waiting times. When the slot length decreases, resource idle time decreases, but patient waiting times increases.
Number of patients per appointment slot	It was common to schedule all patients in the first time slot of a consultation session. Nowadays, it became common to distribute patients evenly over the consultation session to balance resource idle time and patient waiting time.
Sequence of appointments	If there are multiple patient groups, the sequence of the appointments influences waiting times and resource utilization. Therefore, appointments can be sequenced based on patient groups.
Queue discipline in the waiting room	The higher the patient's priority, the lower the patient's waiting time. The queue discipline is

	often first-come-first-served (FCFS), but if emergency patients are involved, they often are the highest priority.
Anticipation for unscheduled patients	Some facilities have unscheduled patients, also called walk-in and urgent patients. They should anticipate on these patients by reserving specific time slots. Often, unscheduled patients arrive in varying volumes during the day and week.

There are several possible objectives in designing a blueprint schedule, namely combining consultations, minimising waiting time, or minimising access time. In the case of combining consultations, Dharmadhikari & Zhang (2011) suggest a simulation-based scheduling policy to benefit hospitals with patients requiring multiple appointments on the same day through block scheduling with priority (BSP). To minimise waiting time, Liang, Turkcan, Ceyhan, & Stuart (2015) use discrete event simulation to model patient flow in the oncology clinic and test the impact of various operational decisions on patient waiting times, resource utilization, and overtime. Finally, in the last case in minimising access time, Bikker, Kortbeek, Van Os, & Boucherie (2015) developed a model for the capacity allocation of physicians to their multiple activities, aligned with demand with capacity allocation in sequential stages. Furthermore, efficiency gains are possible when certain tasks can be substituted between clinical staff, either horizontally (equally skilled staff) or vertically (lower skilled staff) (Smith-Daniels, Schweikhart, & Smith-Daniels, 1988).

Vieira (2020) concludes that most of the studies presented in the literature about radiotherapy treatment focus on the scheduling of the radiotherapy treatment sessions, and only few studies focus on optimizing the pre-treatment stage. However, there are potential benefits that can be achieved by reducing access times before treatment. Therefore, our research focuses on novel scheduling techniques for the pre-treatment stage to reduce access times and start treatment as soon as possible.

2.4 Characteristics of a model

This section describes the possible characteristics of a planning model. First, Section 2.4.1 includes an overview about the possible uncertainties to consider. Next, Section 2.4.2 elaborates on designing a static or dynamic model. Finally, Section 2.4.3 elaborates on the different options in precedence relations and the effect on the planning model.

2.4.1 Uncertainty

When optimizing planning processes, not everything can be predicted and aspects including uncertainty results in variability. Researchers must decide whether to take this variability into account or not. For example, the following aspects can include variability:

2.4.1.1 Appointment's durations

The durations of patients' appointments can vary because every patient is unique and has other requirements for their treatment. Most of the time, this aspect is fixed, and uncertainty is not considered. The deterministic approach is often used where durations have for example a low variance and when there are multiple appointments per patient on one day, the stochastic approach is used (Leeftink, Bikker, Vliegen, & Boucherie, 2020).

2.4.1.2 Patient arrivals

The arrival of patients is not always the same. This variability is often considered. The deterministic approach results in information gathering before decisions are made and the stochastic approach is used when the future arrivals are unknown (Leeftink, Bikker, Vliegen, & Boucherie, 2020).

2.4.1.3 Resource capacity

The capacity of a hospital is not always the same due to for example illness and sabbaticals, which can have an impact on the utilisation of capacity of interrelated disciplines (Samuel, Gonapa, Chaudhary, & Mishra, 2010). The deterministic approach is used when there is enough capacity available and the stochastic approach is used where capacity is scarce, specifically for capacity planning problems because information concerning resource capacity is not yet known (Leeftink, Bikker, Vliegen, & Boucherie, 2020).

2.4.1.4 Care pathway

These variations are mostly from situations with long treatments. The deterministic approach is suitable for fixed care pathways with information gathered before the decisions are made and the stochastic approach is suitable for situations where changes in the care pathway can take place (Leeftink, Bikker, Vliegen, & Boucherie, 2020).

2.4.2 Static or dynamic planning

Tactical resource and admission planning approaches are static or dynamic (Hulshof, Boucherie, Hans, & Hurink, 2013). When planning is static, it results in long-term cyclical plans. However, when a planning is dynamic, it results in mid-term plans due to the variability in demand and supply. Hospital's population and treatments should be annually anticipated by hospital managers to redesign blueprint schedules as a hospital's population and treatments changes over time (Leeftink, Vliegen, & Hans, 2019). Currently, there is often a planning supervisor who counteracts the problems by manually adjusting the planning with constant active and time-consuming monitoring of the planning. However, this is very dependent on the expertise of the supervisor and leave days, or illness can lead to a significant decrease in resource efficiency. This is solved by a model with parameters that are dynamically changed to adapt to the stochastic arrival of patient (Vermeulen, et al., 2009). Other aspects with variability are durations of appointment, care pathways or capacity of resources. For example, a care pathway may be known upon patient arrival, become clear during the appointments, or may be modified during the multiple appointments. However, information on arrivals and care pathways is usually not yet available for mid-term decision making, so it must be predicted (Hans et al., 2012).

2.4.3 Flow-shop, open-shop, or mixed-shop

Section 2.2 mentioned that multi-disciplinary appointment planning must consider constraints and precedence relations. Based on precedence relations, three different systems can be distinguished: flow-shop, open-shop, and mixed-shop. All three systems are shown in Figure 2.2. A flow-shop system (also called one-stop-shop) implies that patients undergo a predetermined sequence of activities at multiple facilities (Leeftink et al., 2020). Precedence relations between appointments are strict and form a predefined pathway. In the flow-shop context, integer linear optimisation (ILP) evaluated by discrete event simulation, and heuristic approaches are often applied. In an open-shop, patient appointments can be scheduled in any order and contain zero or only a few precedence constraints. The most used solution method for an open-shop problem is the (local search) heuristics. Finally, a mixed-shop is the combination of a flow-shop and an open-shop. They often have a fixed sequence, but the order is not fixed. This is usually solved by mathematical programming and heuristics. There is also a subcategory called flexible flow-shop, where the patient can skip stages and move to the next stage, especially relevant for personalised healthcare. However, this system is not reported on and is therefore identified as a gap in the literature.

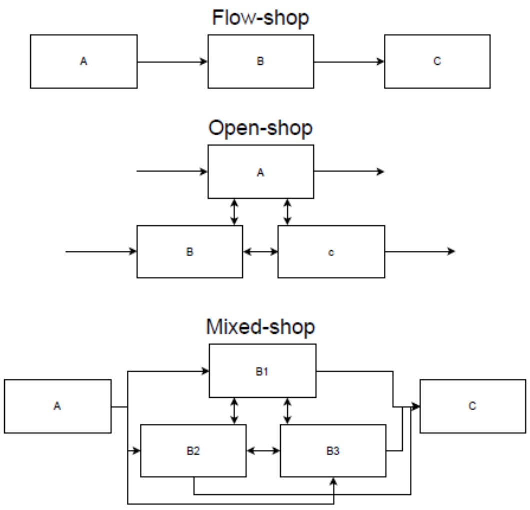


Figure 2.2 Visualisation of flow/open/mixed shop, based on (Leeftink, Bikker, Vliegen, & Boucherie, 2020)

2.5 Solution methods

Operation Research (OR) is used to optimize processes using techniques such as computer simulation, constructive heuristics, metaheuristics, and mathematical programming (Rajgopal, 2001). All techniques are applicable in different situations which will be explained. Typical objectives of the design of a blueprint schedule are to minimise patient waiting time, maximise resource utilization or minimise resource overtime (Hulshof, Kortbeek, Boucherie, Hans, & Bakker, 2012). When optimizing a model, different kinds of solutions can be achieved; feasible, infeasible, and optimal. The model can consist of multiple feasible solutions, which all satisfy the linear and non-linear constraints. One of the feasible solutions, is the optimal solution for which no better solution can be found. However, when a problem is big or complex, it is hard to find an optimal solution in reasonable time. In this case, a feasible solution can also be a good solution. When a model cannot be solved, it is infeasible (Feasible and infeasible solutions, sd).

Literature shows that computer simulation is the most popular method for solving strategic and tactical problems where patient flow and capacity allocation are the subjects of interest (Vieira, 2020). Computer simulation is the process of building an abstract model that mimics the behaviour of a real-world or theoretical system, executing the model on a computer and analysing the output (Law, 2007). Werker et al. (2009), Crop et al. (2015), and Joustra et al. (2012) used discrete-event simulation (DES) to model the pre-treatment phase of the radiotherapy process and test what could reduce patients' waiting times. Where Thomas (2003) uses Monte Carlo simulation modeling to calculate the number of linear accelerators needed to cover the demand in radiotherapy centers and determine the number of spare capacity to keep waiting times low.

Metaheuristics and constructive heuristics are used to optimize larger instances of the treatment scheduling problem, where the computation time of MILP models becomes intractable. Metaheuristics are general-purpose heuristic algorithms that iteratively improve a candidate solution, designed to solve a wide range of hard optimization problems without having to deeply adapt to the problem at hand (Blum & Roli, 2003). Petrovic et al. (2009) use a genetic algorithm to optimize pre-treatment patient flows by scheduling treatment efficiently. Constructive heuristics are heuristic methods to create and/or improve a candidate solution, step by step, according to a set of rules defined beforehand, which are built based on the specific characteristics of the problem to be solved (Solnon & Jussien, 2013). Constructive heuristics allow to build solutions based on empirical knowledge of the system. Petrovic & Leite-Rocha (2008) propose four constructive approaches for scheduling treatment sessions.

Furthermore, mathematical programming is most used to address operational problems where treatment scheduling problems is the subject of interest. Mathematical programming is an optimization method that aims to mathematically represent a decision problem by defining a set of constraints that bound the values of a set of decision variables, and an objective function to be either minimised or maximised until an optimal solution is found (Bradley, Hax, & Magnanti, 1997). Conforti et al. (2010), Castro & Petrovic (2012), and Burke et al. (2011) created mixed-integer linear programming (MILP) models to estimate optimal weekly linear accelerator schedules for irradiation sessions with a known population of patients. The models can find optimal solutions in a reasonable computation time.

2.6 Summary

This section includes a summary of the contribution of literature to this research. Lean thinking focusses on eliminating waste (Womack & Jones, 1997). These includes defects, overproduction, transportation, waiting, storage (buffers), movement and relocating, doing more than necessary and unused creativity and capacity. In the case of healthcare service, especially waiting, doing more than necessary and unused capacity are important. Furthermore, the Define, Measure, Analyse, Improve and Control (DMAIC) approach works well for processes that can measure response variables, because it is a systematic, structured and on facts based method. The approach helps to substantiate decisions on facts instead of feelings or presumptions. During the research, the DMAIC approach is used as process structure to reach process improvement.

There is a great focus on outpatient services and a need for coordinated care across multiple departments. Leeftink et al. (2020) addresses the multi disciplinary appointment context and elaborates on why this is an interesting area of research. Multi disciplinary appointment planning is challenging because there are precedence constraints and the bullwhip effect is often present, affecting potential efficiency in later stages of the patient's care pathway. The focus is on mid-term planning and in particular the design of a blueprint schedule, where multiple objectives are possible.

Furthermore, certain aspects should be considered when designing a blueprint schedule. We chose to not take uncertainty into account in the model, because we want to set a basis for the tactical multi appointment/disciplinary side of the planning and combining appointments. The uncertainty can be considered in further research. The model will be static, where input parameters can be adapted to analyse the resulting blueprint schedule. Moreover, the flexible flow shop will be considered because certain patient types do not need all care pathway stages. The solution of the model will be calculated through an exact model and a constructive greedy heuristic.

3 Problem description

This section focusses on the problem description. First, Section 3.1 describes the process of Instituut Verbeeten. Section 3.2 elaborates on the assumptions being made and Section 3.3 shows the mathematical model. Finally, Section 3.4 explains the constructive heuristic.

3.1 Process

This section includes an overview of the process within the case study, namely Instituut Verbeeten. Starting with Section 3.1.1 explaining the context. Next, Section 3.1.2 discusses the influx of patients. Section 3.1.3 elaborates on the possible care pathways of the case study. Finally, Section 3.1.4 describes the current situation.

3.1.1 Instituut Verbeeten

This research is conducted at Instituut Verbeeten, which provides radiotherapy for cancer patients for more than 65 years, where radiotherapy is the irradiation of mostly malignant diseases (Wie zijn wij?, sd). These treatments are performed separately, or in combination with other relevant cancer treatment modalities, such as surgery and chemotherapy. Radiation therapy technologists (RTT) image the scans, plan the treatment, and perform irradiation sessions. The radiotherapeutic oncologists (RTO) perform the first consultation, tumour contouring, and follow up appointments. In the remainder of this research, we focus on the RTOs. There are 17 RTOs at Instituut Verbeeten, who all have different specialisations. Appendix A shows the RTOs, their specialisations, and the total number of RTOs per specialisation.

Almost all RTOs have side activities, such as a study day or meetings of oncology related associations. The planning of this side activities is fixed because they are out of scope. In general, RTOs work from Monday to Friday and start their day on 8.30AM. In the morning they have appointments until 12.00AM, followed by a break from 12.00AM to 2.00PM. The first hour of the break is booked for meetings with other RTOs to discuss new patients and the second hour is booked for lunch. After the break, the RTOs have appointments until 5.00PM. Appendix B shows the division of the type of appointments of the even and uneven weeks of the RTOs where the side activities are called 'Meetings'. Moreover, the time slots reserved for administration (ADM), days free (RV) and study days (Study) are fixed.

Besides RTOs and RTTs, the Instituut has dieticians, dental hygienists, doctor's assistants, and social workers which are all out of scope. However, it should be kept in mind that some of these appointments are combined with appointments of RTOs. The result is that the planning should contain a certain level of flexibility to make this possible.

Instituut Verbeeten has three locations, in Tilburg, Breda, and Den Bosch (Wie zijn wij?, sd). All three locations provide radiotherapy treatment, but only in Tilburg resources concerning the CT scan is available. In addition, the radiotherapeutic oncologists (RTO) have consulting hours at the locations Gorinchem and Uden. Due to the pandemic starting in March 2020, a fixed division of RTOs to the locations of Instituut Verbeeten was introduced. Before the pandemic, the RTOs were flexible and may have had appointments at multiple locations. Appendix A shows which RTO is allocated to which location. Note that since March 2020, there have been no appointments at the locations Uden and Gorinchem.

3.1.2 Influx

With the exponential growth and aging of the world's population, the pressure on hospitals is increasing (Fendrich & Hoffmann, 2007). Every year, Instituut Verbeeten estimates the production for the next year. This is a prediction of the number of new patients to be admitted to the Instituut. The estimation considers the incidence rates of the IKNL (Integrated Cancer Centre the Netherlands). The IKNL data show an average growth rate of 2% for the four largest cancer groups of the Instituut, namely mamma (breast), lung, MDL (stomach, bowels & liver) and urology. They account for 88% of the hospital's total number of new patients. However, because of the pandemic the growth rate is not applicable and the division of the patients over the locations is different. Table 3.1 shows the overview of the realised production of 2019 and 2020 and the realised growth rate between 2019 and 2020.

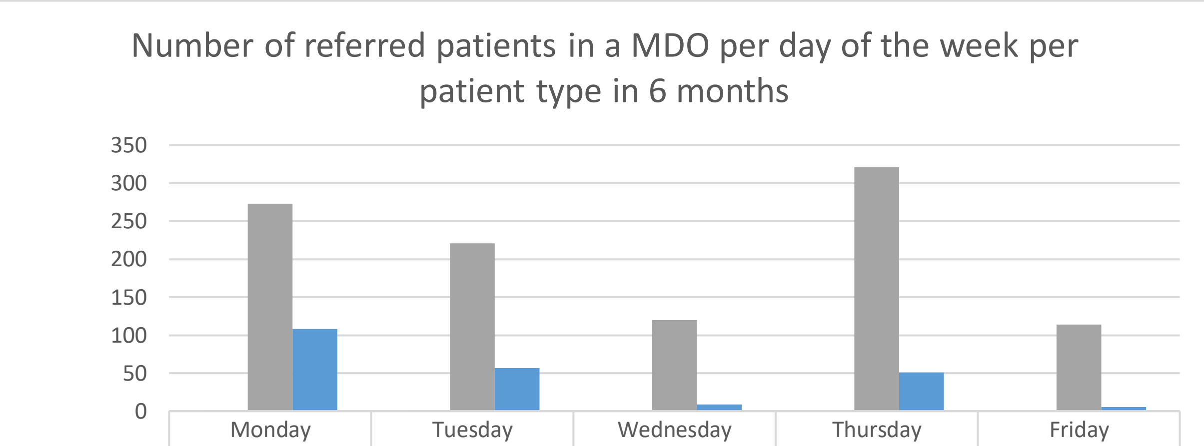
Table 3.1 Overview realised production 2019, 2020 and growth rate between 2019 and 2020 (hospital information system)

Location	**Realised production 2019**	**Percentages**	**Realised production 2020**	**Percentages**	**Growth 2019 vs 2020**
Tilburg	3461	66.5%	2898	56.4%	-16.3%
Breda	735	14.1%	1004	19.6%	36.6%
Den Bosch	698	13.4%	1117	21.8%	60.0%
Uden	228	4.4%	45	0.9%	-80.3%
Unknown	54	1.0%	62	1.2%	14.8%
Gorinchem	32	0.6%	8	0.2%	-75.0%
Total	5208		5134		-1.5%

Table 3.1 shows that in Tilburg with 56.4% the most patients are admitted. Furthermore, because of the pandemic there were no consultations in Uden and Gorinchem after March 2020. These patients were admitted to the locations Tilburg, Breda, or Den Bosch. This explains the number of new patients

at these locations. The patients of Instituut Verbeeten are referred patients from MDOs (multi disciplinary meeting) in a hospital or via other routes such as from a general practitioner.

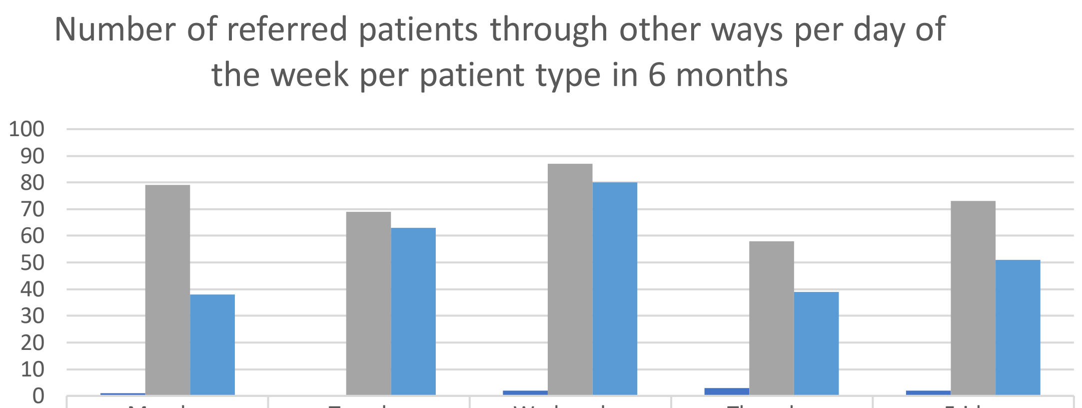
Due to the fixed schedule of the MDOs, there is a difference in the number of referred patients per day of the week. This is also visible in the data of patients referred between September 2020 and February 2021. The data shows that 66.6% of the referred patients come from an MDO and the rest through other means. Figure 3.1 focuses on this patient group, this are patients referred from an MDO, because the variability through the week depends on the fixed schedule of the MDOs. Figure 3.1 shows the number of referred patients in an MDO and Figure 3.2 shows all referred patients. A table is added below Figure 3.1 and Figure 3.2, to show the difference in referred patients per acuteness category. The number of acute referred patients is neglectable.



	Monday	Tuesday	Wednesday	Thursday	Friday
Acute	1	1			
Regular	273	221	120	321	114
Subacute	108	57	9	51	5

Figure 3.1 Number of referred patients in a MDO per day of the week per patient type in 6 months (n=1281, Sep. 2020 - Feb. 2021, hospital information system)

Figure 3.1 shows that there is a difference in variability of referred patients by day of the week. When patients are referred from an MDO, (sub)acute patients are mostly referred on Mondays and regular patients mostly on Thursdays. MDOs are typically scheduled for patient types on fixed days of the week, this explains the difference in the amount of referred patients per day of the week.



	Monday	Tuesday	Wednesday	Thursday	Friday
Acute	1		2	3	2
Regular	79	69	87	58	73
Subacute	38	63	80	39	51

Figure 3.2 Number of referred patients per day of the week per patient type in 6 months (n=645, Sep. 2020 – Feb. 2021, hospital information system)

Figure 3.2 shows the total number of referred patients through other ways than an MDO. We see that both subacute and regular patients are frequently referred on Wednesdays.

Furthermore, we look at the variability in the number of referred patients with specific tumour types. For example, Figure 3.3 shows that for example most pulmonary patients are referred in the beginning of the week and most Mamma patients are referred in the end of the week. These aspects can be considered when designing a blueprint schedule. Currently, Instituut Verbeeten does not consider the difference in new patients arriving per patient type and day of the week in the design of their appointment system.

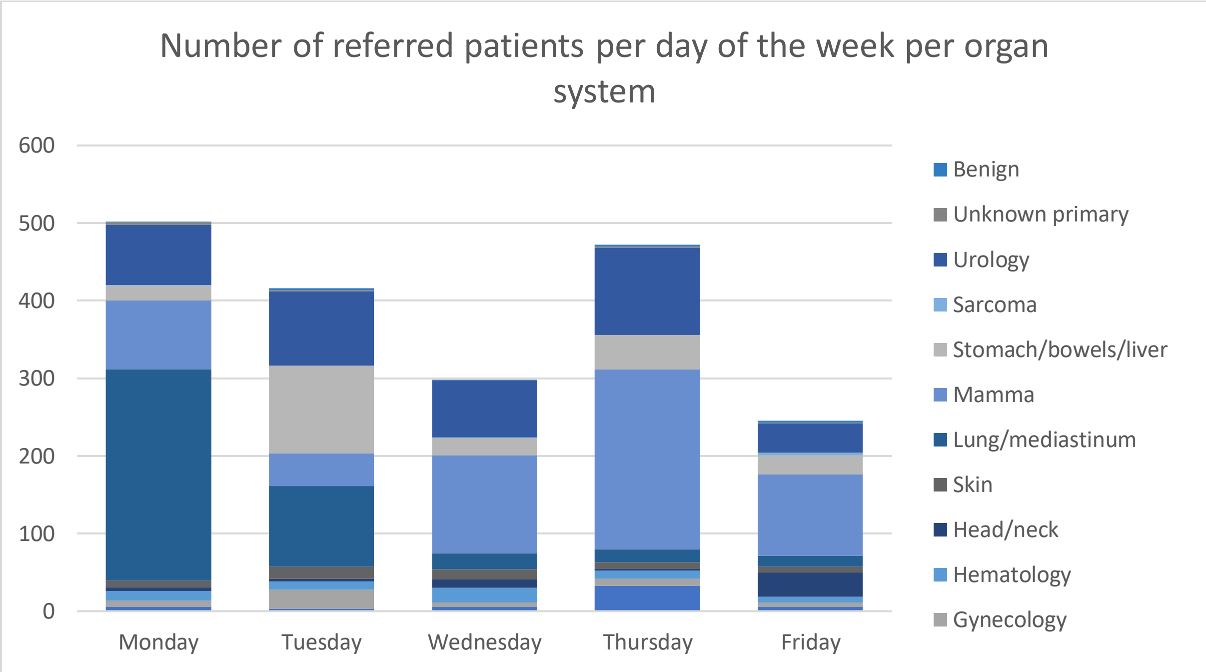


Figure 3.3 Number of referred patients per day of the week per organ system (n=1926, Sep. 2020 – Feb. 2021, hospital information system)

A new patient must be registered before the first consultation can be scheduled. They are registered in two ways: digital (through the doctor) or on paper (through the medical administration). The planner receives the registration and fills out the registration form. Sometimes it takes time to collect the patients' information and the planner must wait until this information is available. Some patients 'shop around' at different hospitals, for example for a second opinion. This means that some information must be requested from several hospitals. On average, one planner can handle 8-10 registrations per half working day, namely 4 hours. The second planner then focuses on actually planning the first few appointments. At this point, the planners reserve the appointments manually. They must check every RTO with the tumour type specialisation and search for the best combination of appointments for the pre-treatment phase.

3.1.3 Care pathways

Before a patient's radiation treatment starts, there are several stages, as shown in Figure 3.4. After the referral, a patient is scheduled for a first consultation with the doctor specialized in the patient's tumour type. The next step depends on whether the patient needs a mould for the radiation therapy. This is usually the case for patients who require treatment in the head and neck area. This appointment in the mould room can also be executed before the first consultation, as the patient's tumour type will already be known. However, we assume that the mould room can only be executed after the first consultation and before the CT scan. Usually the use of the mould room is not necessary and the next step for a patient is an appointment on the CT scan. Every patient needs a CT scan before treatment can begin. After the CT scan, the patient's doctor has time to prepare the treatment plan, also known as the radiation treatment plan (BVB). This time includes the contouring of the tumour that serves as the basis for the treatment plan, which is a detailed description of the radiation dose and the angels of the radiation beams. Almost all the care pathways phases have different durations in minutes, resulting in different types of care pathways.

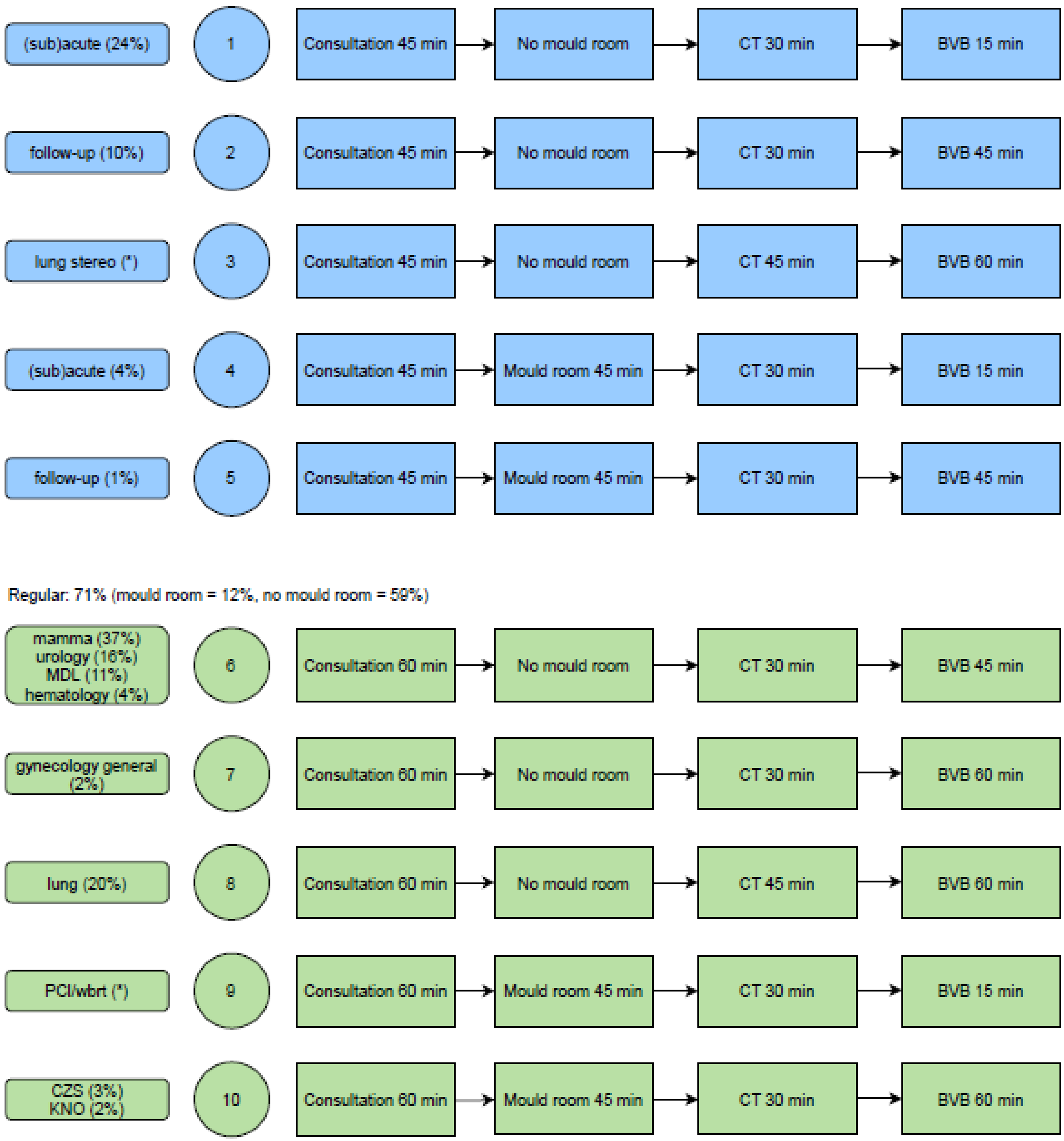


Figure 3.4 Care pathways of patients of Instituut Verbeeten, blue = (sub)acute patients, green = regular patients (n=4344, Jan. 2019 – Dec. 2019, hospital information system)

To gain some insight in the distribution of the patients, Figure 3.5 shows the distribution in numbers and percentages of the patients when they are (sub)acute or regular and whether they require an appointment in the mould room before the CT scan. This data is from all new patients in 2019. This distribution should be considered when designing the blueprint schedule.

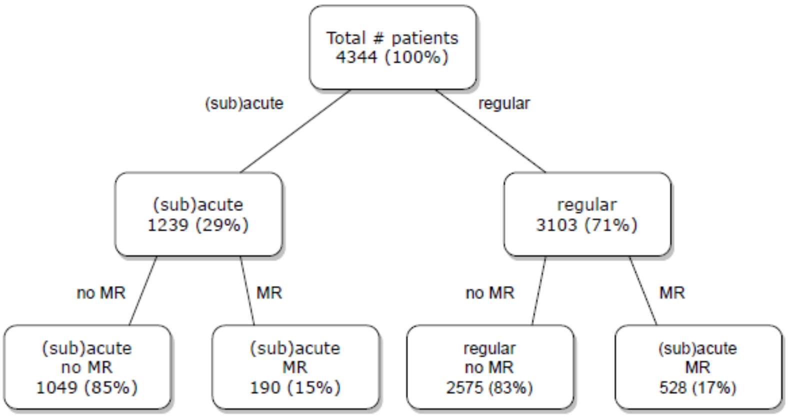


Figure 3.5 Distribution of the patients (n=4344, Jan. 2019 – Dec. 2019, hospital information system)

3.1.4 Current situation

Currently, there are a few aspects that stand out. As mentioned before, there are nationwide norms regarding the time frame in which the treatment of patients must start. However, at Instituut Verbeeten this is not always the case. There is no exact policy for the admission of acute and sub-acute patients. This means that the secretary does not consider the arrival of the patients who need to be treated within a few of days.

Table 3.2 Number of patients treated within nationwide norm, hospital information system

Type of patient	(80%) of the patients should be treated within:	Percentage treated within the nationwide norm:
Acute	24 hours	90.0%
Sub-acute	7 days	94.0%
Regular	21 days	95.0%

Table 3.2 shows the number of patients seen within the nationwide norm. This is calculated using the same data as the charts of referred patients, so patients registered between September 2020 and February 2021.

Instituut Verbeeten wants to put the patient first and therefore strives to combine appointments as much as possible. However, there is currently no policy on combining appointments and it requires some creativity from the planners to make this possible. At this point, it is hard for the planners to plan patients as soon as possible and let the patients start their treatment. It requires some creativity to make a efficient combination of multiple appointments. After some discussions with staff members of

Instituut Verbeeten, it can be concluded that improvement is possible, by standardizing the planning process and make it easier for planners.

3.2 Assumptions

Prior to this study, another study was conducted at Instituut Verbeeten focussing on the planning process up to the first consultation. For example, deciding where a patient has the first consultation. This depends on the location of the patient and which location is available for the tumour type of the patient. We do not focus on the allocation of the patient to a specific location, so the locations are out of scope and we assume the patients are at one location.

Moreover, it is assumed that the number per type of RTOs is known and appointment slots cannot be double-booked. There is no difference in service duration between different RTOs. The blueprint specifies the number of appointment slots in the RTOs' schedule that can be reserved by a particular type of patients.

It is assumed that appointments with other specialists are not a bottleneck for the planning, such as appointments with dieticians. Therefore, these are out of scope. Furthermore, there are a couple of appointments which are specific and performed only once a week, such as brachy therapy. This appointment is in collaboration with a hospital, so we assume that the planning of this appointment is fixed.

The care pathways showed by Figure 3.4 can be summarized to 19 patient types covering 90% of all patients. These patient types are summarized in Appendix C, including the tumour type, acuteness category and the duration per stage. The number of arrivals per day per patient type is known and we assume that patients arrive in the beginning of the day.

3.3 Mathematical model

In this section, the mathematical model is defined. First, Section 3.3.1 discusses the goal of the model and the result. Next, Section 3.3.2 defines the model with the sets and elements, input parameters, decision variables, constraints, and the objective function.

3.3.1 Goal

The goal of this mathematical model is to design a blueprint schedule for the RTOs, CT scans and mould room, where the number of visits to the hospital is minimised and the time between the appointments on the same day is also minimised. Preferably, (sub)acute and regular patients should start their treatment within the nationwide norm. As stated before, 90% of the patients are included in 4 care pathways and the other 10% are exceptions. The exceptions are covered by time slots reserved for pool time, which is discussed in Section 3.3.2.

3.3.2 Model

The optimization problem is modelled as a Mixed Integer Linear Programming (MILP) model because we want to solve the model optimally. We also design a constructive heuristic to compare both solution methods and calculation time. This means that some of the decision variables are constrained to be integer values as optimal solution. The model consists of multiple parts, namely sets and elements, input parameters, constraints, and the objective function. Section 3.3.2.1 discusses the sets and elements, then Section 3.3.2.2 elaborates on the input parameters. Next, Section 3.3.2.3 discusses the decision variables and Section 3.3.2.4 includes the constraints. Finally, the objective function is described in Section 3.3.2.5.

3.3.2.1 Sets and elements

The set notation is used, where D are the days, T are the time slots, R are the resources, P are the patient types and S are the stages, shown in Table 3.3. Every day has a fixed number of time slots and every time slot contains 15 minutes. The set with the resources covers all RTOs as well as the CT scans and mould room. Multiple patient types are created to distinguish between tumour types and acuteness. The last set contains the stages of each patient type, which also can be seen in Figure 3.4, so the first stage is the consultation, then optionally the mould room, CT scan and ends with BVB time.

Table 3.3 Sets and elements of model

Sets and elements	
$\boldsymbol{d}, \boldsymbol{d'} \in \{\mathbf{0} \dots \boldsymbol{D}\}$	Days, with D the number of days
$\boldsymbol{t}, \boldsymbol{t'} \in \{\mathbf{0} \dots \boldsymbol{T}\}$	Time slots, with T the number of time slots during a day
$\boldsymbol{r} \in \{\mathbf{0} \dots \boldsymbol{R}\}$	Resource types, with R the number of resource types
$\boldsymbol{p} \in \{\mathbf{0} \dots \boldsymbol{P}\}$	Patient types, with P the number of patient types
$\boldsymbol{s} \in \{\mathbf{0} \dots \boldsymbol{S}\}$	Stages of the care pathway, with S the number of stages

3.3.2.2 Input parameters

The input parameters contain all information regarding resources and patient types, also shown in Table 3.4. Starting with the arrivals of patient types per day in input parameter arr_d^p. Patients arrive during the whole day, but to simplify the problem, it is assumed that the arrivals are known in the beginning of the day. Next, the resources are not available every day and time slot, so these capacity properties are notated in cap_{dt}^r. Furthermore, every stage of every patient type needs a specific number of time slots per resource notated in $stage^{rps}$. The input parameter $time^{ps}$ contains the number of time slots needed per patient type and stage.

This research focusses on the pre-treatment phase of the care pathway of patients, so follow up appointments are not included. To make sure time slots are reserved for these types of appointments, we make use of time slots reserved for pool time. Pool time can be used for all other appointments than the pre-treatment phase of the care pathway of patients. The input parameter $MinPool$ states the minimum number of time slots reserved for pool time.

Table 3.4 Input parameters of model

Input parameters	
$\boldsymbol{arr_d^p}$	Number of patients of patient type p arriving on the beginning of day d
$\boldsymbol{cap_{d,t}^r}$	Capacity of resource r on day d and time slot t available or not (1=yes, 0=no)
$\boldsymbol{stage^{r,p,s}}$	Number of timeslots needed for an appointment at resource r to perform stage s of patient type p
$\boldsymbol{time^{p,s}}$	Number of timeslots needed for appointment for patient type p and stage s
$\boldsymbol{MinPool}$	The minimum number of reserved pool time slots

3.3.2.3 Decision variables

The decision variables values are unknown quantities before the model is solved and is estimated as an output when solving the model. This model uses four decision variables, shown in Table 3.5. Starting with $X_{d,t}^{r,p,s}$ which is a binary variable, so it can be either 0 or 1. This decision variable is 1 if time slot t on day d is reserved to start on resource r for patient type p and stage s. However, some constraints made it necessary to use an extra binary decision variable, namely $Y_{d,t}^{r,p,s}$ which is 1 if the time slot t on day d is reserved to take place on resource r for patient type p and stage s. For example, on d = 2 and t = 3 the reservation on a resource for a certain patient type and stage starts, then $X_{2,0}^{r,p,s}$= 1 and when the appointment duration is 3, then $Y_{2,0}^{r,p,s} = Y_{2,1}^{r,p,s} = Y_{2,2}^{r,p,s} = 1$. Figure 3.6 shows the example, where also a reservation is shown starting on d = 2 and t = 3.

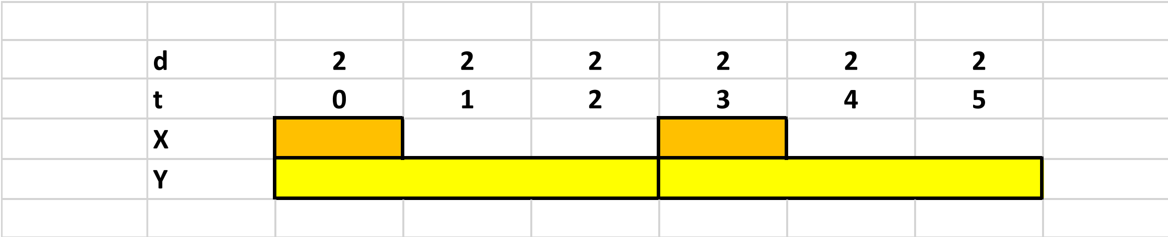


Figure 3.6 Example decision variable X and Y

The next binary decision variable is $P^{r}_{d,t}$, this variable is 1 when a certain time slot is used as pool time. As explained in Section 3.3.2.2, time slots reserved for pool time are used for all other appointments except for appointments of the pre-treatment phase, such as follow up appointments. Next, we use the decision variable $Q^{p,s}$ as slack variable. This variable is used in the constraint making sure that there are enough reserved time slots for all arriving patients. If there are less time slots reserved than the number of arriving patients, the slack increases. To ensure the slack variable is as low as possible, it is minimised in the objective function. Finally, the decision variable $AllStartingTimes$ is used to calculate the sum of the starting times of all reserved appointments.

Table 3.5 Decision variables of model

Decision variables	
$\boldsymbol{X^{r,p,s}_{d,t}}$	Stage s of patient type p is reserved to start on resource r on day d and time slot t (1=yes, 0=no)
$\boldsymbol{Y^{r,p,s}_{d,t}}$	Stage s of patient type p is reserved to take place on resource r on day d and time slot t (1=yes, 0=no)
$\boldsymbol{P^{r}_{d,t}}$	Resource r is reserved for pool time on day d and time slot t (1=yes, 0=no)
$\boldsymbol{Q^{p,s}}$	Slack factor for patient type p and stage s
$\boldsymbol{AllEndTimes}$	To calculate the sum of all the end times of the reserved time slots

3.3.2.4 Constraints

The next part of the model consists of multiple constraints, shown in Table 3.6. Starting with the capacity constraint (1), which ensures time slots can only be reserved for appointments or pool time if there is capacity on the resource. Constraint (2) checks that the number of reserved appointments of a certain patient type and stage is not higher than the number of arriving patients of that patient type. At the end of the planning horizon, every patient type needs enough reserved time slots to start appointments for every stage, this is fixed by constraint (3). Constraint (4) ensures time slots are only reserved for a certain patient type and stage if the resource can execute these. For example, the CT cannot perform the first consultation, but only the CT scan. Furthermore, as mentioned in Section 3.3.2.3, there are two decision variables $X_{d,t}^{r,p,s}$ (starting an appointment) and $Y_{d,t}^{r,p,s}$ (an appointment taking place) concerning whether a time slot is reserved or not. Constraint (5) makes sure that time slots are reserved with the right appointment duration, also visualized in Figure 3.6. Constraint (6) ensures time slots are reserved completely and not in parts divided over the day. There should be time slots reserved for all other appointments, such as follow up appointments. Therefore, constraint (7) ensures there are enough time slots reserved for pool time.

An important characteristic of this model is that we include multiple stages of a patients' care pathway. To ensure the sequence of the stages, we design the following two constraints (8+9). These constraints make sure that per patient type there are no more appointments of a certain stage than the previous stage. The constraint can be adjusted to the different patient types, because not every patient type needs every stage.

As mentioned in Section 3.3.1, the goal of this mathematical model is to design a blueprint schedule for the RTOs, CT scans and mould room, where the number of visits to the hospital is minimised and the time between the appointments on the same day is also minimised. To minimise the time between every appointment, constraint (10) is used to calculate the sum of the starting times of every appointment. Finally, a constraint (11) ensures that all variables should be nonnegative integers.

Table 3.6 Constraints of model

Constraints	
$$\sum_{p=0}^{P}\sum_{s=0}^{S} Y_{d,t}^{r,p,s} + P_{d,t}^{r} \leq cap_{d,t}^{r} \quad \forall r,d,t$$	Timeslots can only be reserved if there is capacity on the resource. If the timeslot is not already reserved and the capacity is available, the time slot can be reserved for pool time (1)
$$if\ time^{p,s} > 0:$$ $$\sum_{d=0}^{d'}\sum_{t=0}^{T}\sum_{r=0}^{R} X_{d,t}^{r,p,s} \leq \sum_{d=0}^{d'} arr_{d}^{p} \quad \forall p,s,d'$$	There are no more time slots reserved as the number of patients arriving per patient type and stage (2)
$$\sum_{d=0}^{D}\sum_{t=0}^{T}\sum_{r=0}^{R} X_{d,t}^{r,p,s} + Q^{p,s} = \sum_{d=0}^{D} arr_{d}^{p} \quad \forall p,s$$	Over the whole-time horizon, all arriving patients have time slots reserved for every stage (3)
$$X_{d,t}^{r,p,s} \leq stage^{r,p,s} \quad \forall r,p,s,d,t$$	Only reserve a timeslot if the resource can perform the patient type and stage and the patient type needs the stage (4)
$$Y_{d,t}^{r,p,s} = \sum_{tt=0}^{\min(t+1,stage^{r,p,s})} X_{d,t-tt}^{r,p,s} \quad \forall r,p,s,d,t$$	Ensure time slots are reserved with the right appointment duration (5)
$$\sum_{t=0}^{T} Y_{d,t}^{r,p,s} = stage^{r,p,s} * X_{d,t}^{r,p,s} \quad \forall r,p,s,d$$	Ensure time slots are reserved completely (6)
$$\sum_{d=5*x}^{5*(x+1)}\sum_{t=0}^{T} P_{d,t}^{r} \geq MinPool \quad \forall r,x \in \{0,\frac{D}{5}\}$$	The total number of time slots reserved for pool time per week can not be less then the minimum number of time slots for pool time per resource per week (7)

$\sum_{r=0}^{R}(\sum_{d=0}^{d'}\sum_{t=0}^{T}X_{d,t}^{r,p,s1} + \sum_{t=0}^{t'-time^{ps}} X_{d',t}^{r,p,s1}) \geq$ $\sum_{r=0}^{R}(\sum_{d=0}^{d'}\sum_{t=0}^{T}X_{d,t}^{r,p,s2} + \sum_{t=0}^{t'} X_{d',t}^{r,p,s2})$ $\forall p, s1 \in \{0, S-2\}, s2 \in \{1, S-1\} d', t'$	Ensure time slots for patient types with mould room are reserved in the right sequence of stages, there are no more patients in a stage than the previous stage (8)
$\sum_{r=0}^{R}(\sum_{d=0}^{d'}\sum_{t=0}^{T}X_{d,t}^{r,p,s1} + \sum_{t=t'}^{T} X_{d',t}^{r,p,s1}) \leq$ $\sum_{r=0}^{R}(\sum_{d=0}^{d'}\sum_{t=0}^{T}X_{d,t}^{r,p,s2} + \sum_{t=tt+time^{ps}}^{T} X_{d',t}^{r,p,s2})$ $\forall p, s1 \in \{0, S-2\}, s2 \in \{1, S-1\} d', t'$	Same constraint as (8), but in stead of checking from start to end of the day, this constraint checks the other way around, so from end to start of the day (9)
$AllStartingTimes \geq \sum_{r=0}^{R}\sum_{p=0}^{P}\sum_{s=0}^{S}\sum_{d=0}^{D}\sum_{t=0}^{T} X_{d,t}^{r,p,s} * ((d * T) + t)$	Calculate the sum of all starting times of the appointments (10)
$X_{dt}^{rps} \in \{0,1\} \quad \forall r, p, s, d, t$ $Y_{dt}^{rps} \in \{0,1\} \quad \forall r, p, s, d, t$ $P_{dt}^{r} \in \{0,1\} \quad \forall r, d, t$ $Q^{p,s} \in \mathbb{Z} \quad \forall p, s$ $AllStartingTimes \in \mathbb{Z}$	All variables should be nonnegative integers or binary values (11)

3.3.2.5 Objective function

The objective function is shown in Table 3.7. To make sure the model gives a feasible solution, a slack variable is introduced. This variable ensures sure that the model can be solved. We use the slack variable in Constraint (3), where we state that the total number of appointments per patient type and stage should be the same as the total number of patients arriving of that patient type. To make sure that all appointments are reserved, the slack variable is minimised in the objective function.

Furthermore, the goal of the model is to make it possible to schedule patients as soon as possible with minimal number of time between appointments of the pre-treatment phase. Therefore, the objective function also consists of the sum of all starting times of the reserved appointments.

Table 3.7 Objective function of model

Objective function	
$\min\left(10000000 * \sum_{p=0}^{P}\sum_{s=0}^{S} Q^{p,s} + AllStartingTimes\right)$	Minimise the total number of slack, this ensures that there are reserved time slots for all the arriving patients and minimise the starting times of the reserved appointments

The model is implemented in Spyder with the programming language Python and the model is solved with the MIP package. The default installation includes the COIN-OR Linear Programming Solver – CLP, namely an open-source linear programming solver. This solution method is an exact method and results in an optimal solution.

3.4 Constructive heuristic

As the computation time of the exact model of Section 3.3 increases with larger problem instances, we propose a constructive greedy heuristic to decrease the calculation time for larger instances. A constructive heuristic produces a solution to the model that may not be optimal but are sufficient given time constraints. We propose a constructive greedy heuristic, which means that the solution is build piece by piece. It starts with an empty solution and performs multiple steps to build the solution with no backtracking allowed. The solution of the constructive heuristic is used to compare to the schedule of the solution of the exact method. The pseudo code of the heuristic is included in Appendix D and the flow chart is shown in Figure 3.7.

The heuristic checks per day and per patient type the number of arrivals. Hereafter, the heuristic loops over each arrival and necessary stages and searches per stage the resources that can perform the appointment of this stage and patient type. The heuristic chooses the first available resource that can start the appointment the earliest and reserves the necessary time slots. It stores the reserved appointment in a list, which can in the end be visualized in a schedule. Next, the heuristic continues to the next stage of that patient type. When the last stage is reached, it continues to the next arrival of that patient type. If the last arrival is reached, it continues to the next patient type and otherwise to the next day.

The initial sequence of checking the patient types is a random approach, starting from patient type 0 to 18. However, we will also explore other sorting methods, such as starting with the patient types that have the highest or the lowest number of arrivals per week.

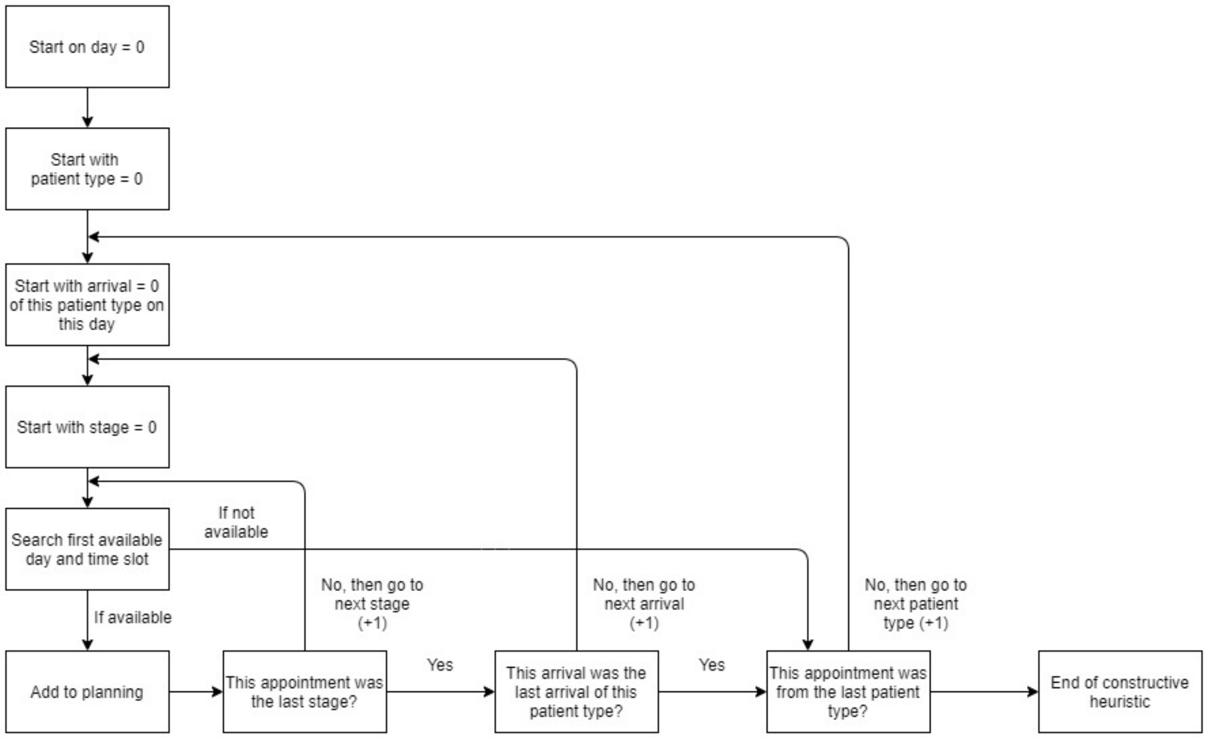


Figure 3.7 Flowchart of constructive heuristic

4 Case study settings and results

This section focuses on the case study settings in Section 4.1. Next, the model is solved for different settings and experiments are conducted in Section **Error! Reference source not found.**. The last part, S ection 4.3 elaborates on the results of the experiments.

4.1 Case study settings

The problem description in Section 3 discussed the characteristics of the case study. The collected data is discussed in this chapter. The same sequence is used as the summary of the model in Section 3.3.2.

4.1.1 Sets and elements

We run the model for a planning horizon of 4 weeks, which is the same as 20 days, because we only consider working days. Each day is divided into 36 time slots of 15 minutes. The start time slot is at 8:30 AM and the last time slot ends at 5:30 PM. In total we have 20 resources, including 17 RTOs, 2 CTs and 1 mould room. All patients of Instituut Verbeeten are divided into 19 patient types, exceptions not included. Patient types are only included when they have at least one arrival per week. Per patient type it is known whether they need the mould room or not. Appendix C shows the used patient types. The model focuses on the pre-treatment phase, which starts with a first consultation, optionally followed by a mould room, then a CT scan and finishes with time for the RTO to prepare the treatment, namely BVB time.

4.1.2 Input parameters

The input parameters include all information regarding the number of arriving patients per patient type, the capacity per resource, the specialisation per resource and the number of time slots needed for each patient type and stage.

First, we calculated the number of arriving patients per patient type per day, based on historical data of Instituut Verbeeten. This historical data includes the number of patients arriving between September 2020 and February 2021. For every patient type, we calculate the number of arriving patients per day. Patient types arrive on specific days in the week, shown in Appendix E. These patient types are divided by tumour type, acuteness category and whether they need an appointment with mould room or not. An appointment with mould room is only considered when at least 20% of the patients needs it, otherwise it is an exception.

The second input parameter concerns the capacity of the resources. This parameter states for every day, time slot and resource whether there is capacity or not. At Instituut Verbeeten, many RTOs have side activities, which means that not every day has the same capacity available. Appendix B shows the availability of the resources, where the time slots reserved for administration (ADM), days free (RV) and study days (Study) are reserved and there is no capacity for appointments.

The third input parameter states per resource, patient type and stage whether they can execute it and how many time slots it take. Every RTO has different tumour type specialties, and this can be seen in this input parameter and in Appendix A. The fourth input parameter only includes the number of time slots needed to execute a stage per patient type and is also shown in Appendix C.

The final input parameter represents the minimum number of time slots per week and resource for pool time. These time slots are meant for all other appointments than the pre-treatment appointments which we focus on, such as follow up appointments, because there should be space left for these appointments. We assume 10 time slots pool time per week for each resource.

4.1.3 Constraints

Almost all constraints can stay the same, after implementing the data of the case study. We only must pay attention to the sequence constraints (8+9). Because not all patient types need all stages, the constraint is split in two constraints per kind of patient type. The first group of patient types includes the patient types that need all stages. Therefore, we have the following combination of stages: $s1 \in \{0,1,2\}$ and $s2 \in \{1,2,3\}$. The left-hand side of the constraint uses stages of $s1$ and the right-hand side of the constraint uses stages of $s2$. The constraint uses three combinations of stages, namely stage 0&1, stage 1&2, and stage 2&3. For example, the constraint makes sure that the number of appointments reserved for stage 0, on the left-hand side, is bigger than the number of appointments reserved for stage 1, on the right side.

Furthermore, there are some patient types that do not need stage 1, namely the appointment in the mould room. This means this stage is not included in the constraint. Therefore, we have the following combination of stages: $s1 \in \{0,2\}$ and $s2 \in \{2,3\}$. The constraint uses two combinations of stages, namely stage 0&2 and stage 2&3.

Finally, there is one patient type that only need stage 0 and 1, namely no CT scan and BVB time. This means we have the following combination of stages: $s1 \in \{0\}$ and $s2 \in \{1\}$. There is only one combination of two stages, namely stage 0&1.

4.1.4 Objective function and KPIs

The objective function minimizes the sum of all starting times of all reserved appointments. In this way, appointments are reserved as soon as possible, and patients can eventually start their treatment as soon as possible. Furthermore, the slack variable is minimised, such that there are enough reserved appointments to serve all arriving patients.

To measure the performance of the blueprint schedule, several KPIs can be designed. One of the KPIs calculates for every arrival the time between the arrival of a patient and the end time of the last stage. The mean and standard deviation are calculated to measure the performance of the blueprint schedule. The model checks for every day the number of arrivals per patient type and the number of appointments for the last stage of that patient type. If there are more arrivals than appointments for the last stage, it is assumed that the appointment for the last stage is performed the day after the arrival. This is included in the calculation of the times. After the calculation of the mean and standard deviation per patient type, insight is gained for which patient type patients can be treated earliest. Moreover, the standard deviation per patient type is used to gain insight for which patient type it is difficult to consequently plan them as soon as possible.

4.2 Experiment design

The goal of the model is to design a blueprint schedule in which patients' pre-treatment phase appointments are reserved as soon as possible, such that their treatment can start. We use two ways to solve the model; mathematical programming and the constructive heuristic. Section 4.2.2. elaborates on how these methods are applied in the experiment. In practise, every week is different with different arrivals, so the blueprint schedule should be tested for multiple situations. Section 4.2.2 discusses all chosen experiment settings.

4.2.1 Solution methods

The solution method mathematical programming is executed with the Python MIP-package. All sets, elements, input parameters, variables, constraints, and the objective function is given as input to the model and the program calculates an optimal solution. However, another way to solve the model is by a constructive heuristic. The solution of the constructive heuristic is used to compare with the blueprint schedule of the optimal solution calculated by mathematical programming. We expect that the calculation time of the constructive heuristic will be lower than the exact method and we want to know the difference. The constructive heuristic is explained in Section **Error! Reference source not found.** a nd the pseudo code is showed in Appendix D.

4.2.2 Experiment settings

The resulting blueprint schedule of both solution methods is tested for the following situations. First, if the BVB time should be performed by the RTO responsible for the first consultation or not. At this point, we assumed that the BVB appointment can be performed by any RTO with the required specialty. However, in practise the RTO that performs the first consultation of a patient, also performs the BVB appointment of the patient. We investigate the difference in performance in both situation but think the blueprint performs better when the BVB appointment can be performed by any RTO with the required specialty, because there is more flexibility in the planning. Therefore, we design a constraint that ensures that there are the same number of reserved appointments for the first stage and the last stage. So, we add the following constraint to the model:

$$\sum_{t=0}^{T} X_{d,t}^{r,p,0} = X_{d,t}^{r,p,3} \quad \forall r, p, d$$

Furthermore, we test the model by changing the input parameter responsible for the arrivals per patient type per week. Every week does not have the same number of arriving patients. Therefore, we adjust the arrivals per patient type per week to 1.5 times the original number of arriving patients. Hereafter, we can make a conclusion about the robustness of the planning, specifically if the model can still give a feasible solution.

Appendix F shows the experiment design, namely the settings per experiment. Section 4.2.1 elaborated on the difference between two solution methods, specifically the exact method and a constructive heuristic. Both are applied for all experiments with a maximum calculation time of 3600 seconds.

In the constructive heuristic, we also want to use strategies for the sequence of patient types. Initially, the constructive heuristic starts with planning patient type 0 on day 0. However, we also want to change this sequence. Therefore, the last three experiments (17, 18 and 19) use a different sequence of the patient types, namely:

- Experiment 17: Patient types are picked randomly.
- Experiment 18: Patient type with the highest arrivals per week is picked first, and the patient type with the lowest arrivals per week is picked last.
- Experiment 19: Patient type with the lowest arrivals per week is picked first and the patient type with the highest arrivals per week is picked last.

These three experiments are conducted with a planning horizon of 10 days, because these include the different availability of the resources for the even and uneven weeks. Moreover, we use the original case mix and a flexible, as it creates more flexibility in the planning.

4.3 Results

Appendix G shows the experiment results for every experiment and Table 4.1 shows a summary of the experiment results for the settings with 10 days. The first column of these tables includes the characteristics of the experiment, such that it is easily seen which experiment has which settings. These have the following options:

- The number of days of the planning horizon of the experiment (5d = 5 days, 10d = 10 days, etc.).
- If the BVB time is executed by the same RTO as the first consultation for that patient (flex = BVB time can be performed by any RTO with that specialisation, fixed = BVB time can only be performed by the RTO that executed the first consultation).
- The case mix, i.e., the number of arriving new patients (x1 = one time the original case mix, x1.5 = one and a half times the original case mix).

The objective function value is calculated by the sum of all ending times of all starting times of all appointments. By minimising this value, all appointments start as soon as possible. Furthermore, the slack variable is minimised, which ensures all appointments of all patient types are reserved. The slack variable is multiplied with a very big number, so if the objective function value is big, not all appointments are reserved.

Moreover, Appendix G includes for every experiment the results of the exact method and the constructive heuristic. The results are the value of the objective value, the approximation ratio, the calculation time, and the mean and the standard deviation of the number of time slots between the arrival and the last stage of a patient.

Table 4.1 Summary experiment results for experiments with 10d

Experiments	**Exact** **Objective function**	**Calculation time**	**Heuristic** **Objective function**	**Calculation time**
Flex, initial	77,041.00	2058.36	77,673.00	526.81
Fix, initial	77,212.00	2894.75	78,084.00	376.37
Flex, 1.5x	119,309.00	2194.5	120,197.00	851.88
Fix, 1.5x	119,557.00	2218.54	120,803.00	688.26
Random sort			78,005.00	488.42
High to low sort			78,394.00	478.62
Low to high sort			77.724,00	487.18

4.3.1 Difference between exact method and constructive heuristic

First, we want to know the difference between the solution of the exact method and the constructive heuristic. We expected that the exact solution will have a lower objective value and a less number of time slots between the arrival of a patient type and the appointment of the last stage, because the exact method gives the optimal solution. The experiments confirm these expectations, the objective value of the constructive heuristic is always higher than the objective value of the exact method.

We are also curious about the performance per patient type with the exact method and constructive heuristic. Therefore, Figure 4.1 shows the mean processing time per patient type. It shows the experiment with a planning horizon of 10 days, flexible RTO and the original case mix, solved with the exact method and constructive heuristic.

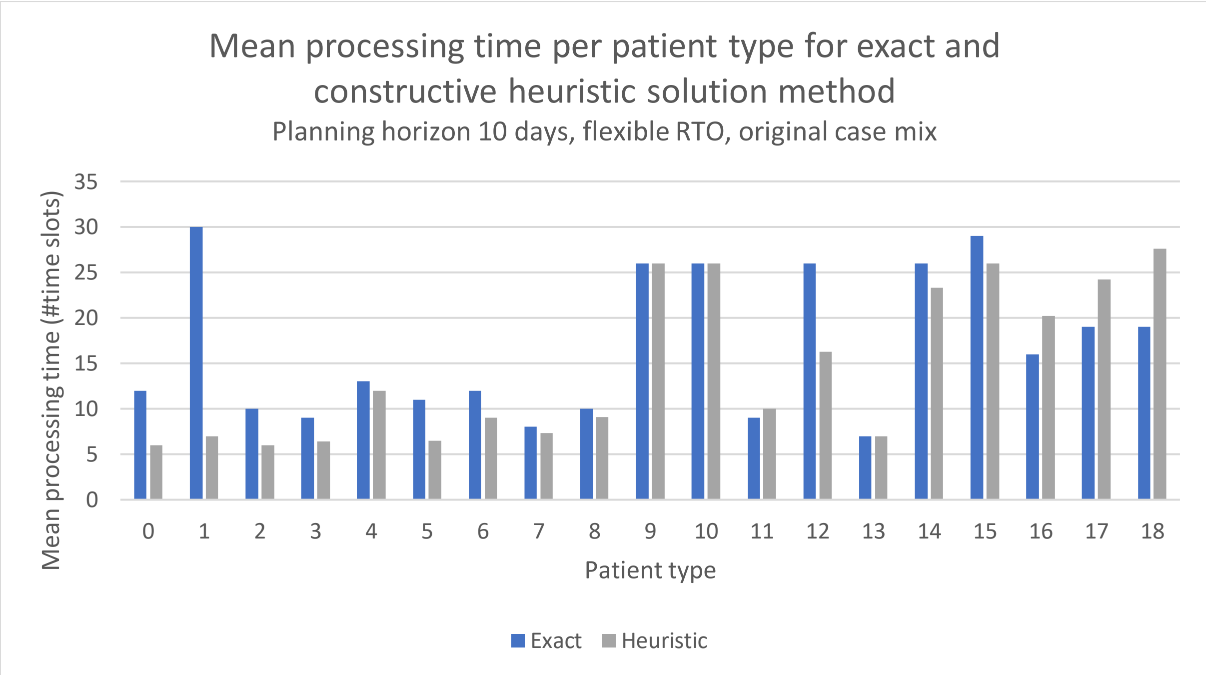


Figure 4.1 Mean processing times (# time slots) per patient type, planning horizon of 10 days, flexible RTO, original case mix

The constructive heuristic starts with planning patient type 0 on day 0 and then continues to the next patient type on day 0. Therefore, the mean processing times of the first patient types with the constructive heuristic is lower than the exact method. The last patient types have the highest arrivals per week, this explains why the objective function of the exact method is better, but the mean processing times of the exact method are most of the time higher than the mean processing times of the constructive heuristic.

The original constructive heuristic starts with patient type 0 and ends with patient type 18. However, we also want to know the effect of this sequence. Therefore, as mentioned in Section 4.2.2, we also conduct experiments with different strategies for patient type sequences. We use the original sequence of the heuristic, from highest to lowest number of arrivals, from lowest to highest number of arrivals and a random sequence. Then we investigate the mean processing times per patient type of these sequences. Figure 4.2 shows the mean processing times per sequence strategy, also shown in a table in Appendix H. We also add the mean processing times of the optimal solution with the exact method.

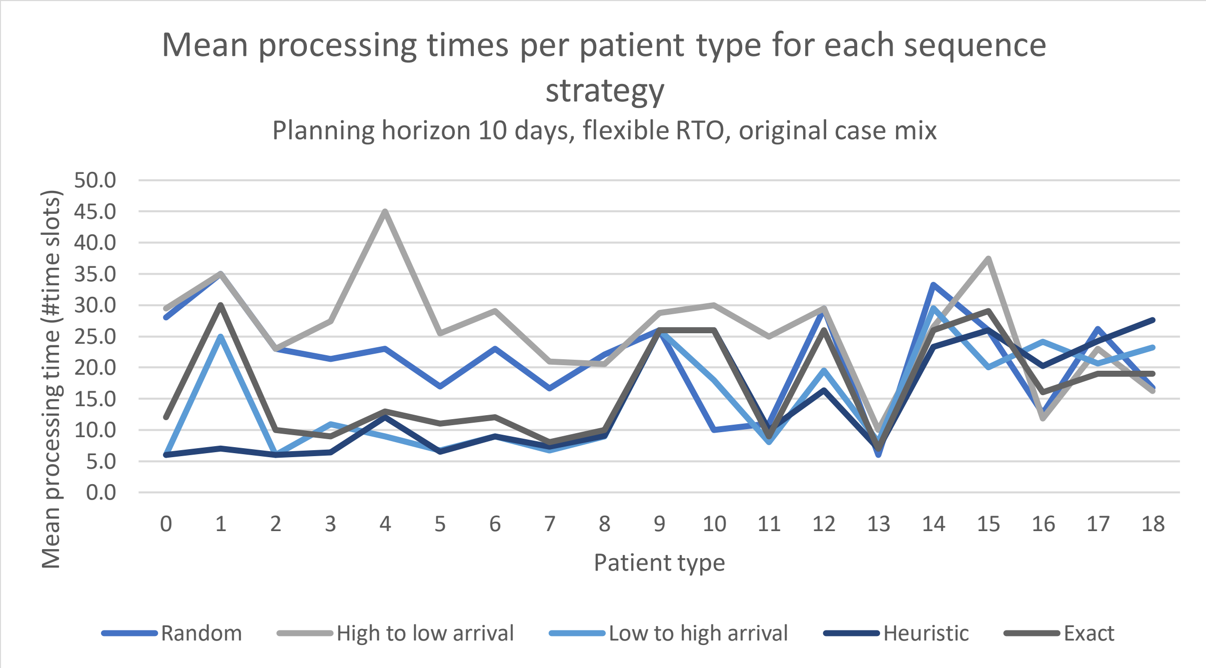


Figure 4.2 Mean processing times (#time slots) per sequence strategy

Figure 4.2 shows that the sequence high to low arrival give higher mean processing times for the first couple of patient types, namely the (sub)acute patient types. The (sub)acute patients have less arrivals and are planned later and this means that at this moment there are less time slots available, so the performance is worse. The lowest objective function value and mean number of time slots is of the exact method, namely 77,041.00 and 17.00 respectively. The lowest objective function value for the sequence strategies of the constructive heuristic is the original patient type sequence, namely 77,673.00 and 19.04. The worst solution sequence is the highest to lowest arrival sequence with 78,394.00 and 20.80.

There is a significant difference in the calculation time. The exact solution method takes, on average, four times the calculation time of the constructive heuristic. Figure 4.3 shows the calculation time per experiment, sorted from short to long planning horizon.

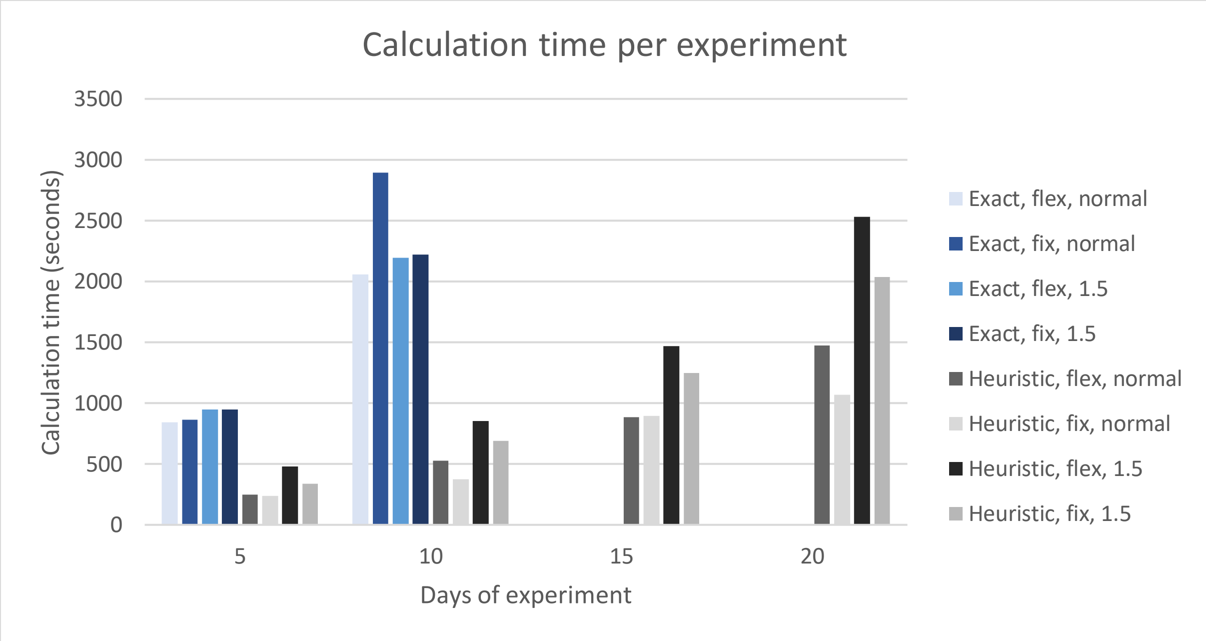


Figure 4.3 Calculation time (seconds) per experiment, sorted

Obviously, the calculation times increases when the planning horizon increases, because the problem becomes bigger. The calculation time of the constructive heuristic is sometimes four times lower than the calculation time of the exact method. Moreover, there is a significant difference in calculation time when the constructive heuristic has a flexible or fixed RTO. When the RTO is fixed, the constructive heuristic only needs to check the first available time slot of the fixed RTO for the BVB time. However, when the RTO is flexible, the constructive heuristic needs to check all RTOs for the first available time slot. The size of the case mix has a little influence on the computation time. On average, the calculation time is higher when we have one and half times the case mix, simply because the problem is bigger.

Due to the calculation time limit of 3600 seconds, the exact method cannot be solved to optimality for a planning horizon of 15 and 20 days. As within this time there is no feasible solution found for all instances, output on approximation ratio and upper bound solutions are not available.

4.3.2 Difference between fixed and flexible RTO for BVB time

Second, we want to know the effect of the fixed or flexible RTO for the BVB time. Currently, Instituut Verbeeten makes use of a fixed RTO. This means that the RTO that performs the first consultation of patient, also performs the BVB time of the patient. We want to evaluate if a flexible RTO will be an advantage for the time until a patient can start the treatment.

Table 4.2 Difference between fixed and flexible RTO for BVB time

Experiments	Objective function (sum of all starting times of all reserved appointments)		Mean number of timeslots between arrival and last stage	
	5 days	10 days	5 days	10 days
Exact, flex, original	17,402.00	77,041.00	17.00	17.00
Exact, fix, original	17,800.00	77,212.00	18.00	18.00
Exact, flex, 1.5	27,705.00	119,309.00	24.00	24.00
Exact, fix, 1.5	27,739.00	119,557.00	24.00	25.00

In Section 0 we concluded that the exact method performs better than the constructive heuristic. Therefore, Table 4.2 shows the experiments with the exact method. We see that the objective function value is worse when the BVB time has a fixed RTO. This is also the case for the mean number of time slots between arrival and the last stage.

The calculation time of the exact method is higher, when the BVB time is performed by the same RTO as the first consultation of a patient. However, when the constructive heuristic is used, the calculation time is less when the BVB time is performed by the same RTO as the first consultation of a patient. This can be explained by the fact that the constructive heuristic only checks the first available time slot for the same RTO as the first consultation. If the RTO is flexible, the heuristic must check every resource to find the resource than is available first.

The exact method has a higher calculation time when the RTO is fixed, and the constructive heuristic has a lower calculation time when the RTO is fixed. However, when the BVB time can be performed by any RTO with the required specialization, this results in a better performance in terms of access times and more flexibility in the planning, so we prefer a flexible RTO.

4.3.3 Difference between original case mix and 1.5 times the case mix

Third, we want to know the effect of a difference in the arrivals of patient types per week. Therefore, we use the original case mix and 1.5 times the original case mix. We use the same distribution per day of the week as the original case mix. We expect that the performance of the planning will be worse when we use the 1.5 times original case mix, because the planning is fuller, and it is harder to reserve time slots as soon as possible for arriving patients.

The mean number of times slots between arrival and last stage with a original case mix is 17.97 time slots. When the 1.5 times case mix is used, it increases to 22.82 time slots. This means there is almost a 5 time slot difference in the mean number of time slots between arrival and last stage, representing an additional waiting time of 75 minutes. The standard deviation between arrival and last stage with a original case mix is 8.87 time slots and with 1.5 times the case mix, 11.24 time slots. This results in a difference of 2 time slots, representing 30 minutes waiting time. Furthermore, there are less time slots available for all other appointments, such as follow up appointments.

4.3.4 (Sub)acute and regular patients and nationwide norm

To assess the adherence to the access time norms of (sub)acute and regular patients, we evaluate the experiment for 10 days, with flexible RTO performing the BVB time and the original case mix. These settings reflect the current situation, and are solvable with the exact method.

The mean number of time slots between arrival and the last stage for **subacute patients** with the **exact method** is 12.78 time slots, which is the same as 192 minutes or 3 hours. Furthermore, the maximum number of time slots between arrival of a subacute patient and the last stage is 48 time slots (720 minutes/12 hours). With the **constructive heuristic** the mean number of time slots between arrival and the last stage is 7.70 time slots (116 minutes/2 hours), and the maximum number of time slots between arrival and the last stage is 12 time slots (180 minutes/3 hours). Therefore, all patients can be treated the next day they arrive and within the nationwide norm of 7 days for subacute patients with both the exact and heuristic outcomes. The constructive heuristic gives a better performance for subacute patients, because the heuristic plans the patient types from patient type 0 to 18 and the first 8 patient types are subacute patients.

We also analyse the performance of the blueprint schedule for regular patients. The mean number of time slots between arrival and the last stage for **regular patients** with the **exact method** is 20.30 time slots (301 minutes/5 hours). Furthermore, the maximum number of time slots between arrival and the last stage is 32 time slots (480 minutes/8 hours). The mean number of time slots between arrival and the last stage with the **constructive heuristic** as solution method is 20.66 time slots (310 minutes/5 hours), and the maximum number of time slots between arrival and the last stage is 34 time slots (510 minutes/8.5 hours). This means all patients can be treated within the nationwide norm of 21 days with both the exact and heuristic outcomes.

We also experimented with a 50% case mix increase. In all experiments and for both patient types ((sub)acute and regular), all patients can still be treated within the nationwide norm. The highest mean amount of time slots between the arrival and last stage of a patient is 25 time slots (100 minutes/6 hours). However, this also means there are less time slots available for all other appointments, such as follow up appointments.

4.3.5 Interpretation of results

Appendix I shows the optimal blueprint schedule of this research and case study. Each type of appointment has a different colour in the blueprint schedule, where the yellow time slots are reserved for meetings. The breaks and free time are also showed in the planning. We used the solution of the exact method because this solution is optimal. Furthermore, the planning horizon of 10 days is used, because it includes the different availability of resources for even and uneven weeks. Every RTO should be flexible and perform the BVB time of any patient with the tumour type of its specialisation.

When we focus on the visualization of the planning, a couple of things stand out. First, the CT scan is almost always occupied in the beginning of the week. This is due to the number of arrivals per day, in the beginning of the week there are more arrivals. The follow up appointments have less urgency than the new patients who must start their treatment soon. Therefore, we advice to plan more follow up appointments in the end of the week. In this way, the patients arriving in the beginning of the week can start their treatment as soon as possible. Another possible solution is that we create an additional patient type corresponding to follow up appointments, also including a certain arriving day and tumour type. In this way, we create reserved appointments for follow up appointments. Because the CT scan are some days fully reserved, it highlights the importance of efficient planning of resources. Currently, Instituut Verbeeten checks manually the availability of resources and picks the best day and time slot. Sometimes this results in empty time slots of 15 minutes in which no CT scan appointment can be planned, because it always takes at least 30 minutes to execute an CT scan.

Furthermore, the starting times of the appointments is minimised, this automatically results in reserving the first appointments in the morning and the BVB time in the afternoon. To create more flexibility when planning patients, we can also let patients arrive in the lunch break. This forces the model to also reserve first appointments in the afternoon. We only considered patients arriving at the beginning of the day, but this could be adapted.

5 Conclusion and discussion

This section concludes this research. Starting with the conclusion in Section Conclusion5.1. Followed by the limitations in Section 5.2 and the future research suggestions in Section **Error! Reference source not found.**. Finally, the recommendations are discussed in Section **Error! Reference source not found.**.

5.1 Conclusion

This research proposes a ILP formulation and greedy heuristic for the tactical multi appointment planning problem. This problem is unique, as it focuses on the tactical side of the planning, which deserves attention because this level of control is underexposed due to its inherent complexity (Hans, Van Houdenhoven, & Hulshof, 2012). Second, it concerns a multi appointment planning including doctors with different combinations of specialisations, which deserves attention because researchers often limit their scope to a single diagnostic resource type or procedure step due to complexity constraints (Marynissen & Demeulemeester, 2019). Third, we show the working of our models in a practical case with Instituut Verbeeten, which shows that the blueprint schedule for pre-treatment phase appointments can be obtained in their current practise.

Currently, Instituut Verbeeten can start the treatment of **94%** of the **subacute patients** within the nationwide norm of **7 days**. However, the goal is to start treatment as soon as possible. This research achieved to increase this ratio to **100%** of the **subacute patients**. These subacute patients can be treated within a mean of **3 hours**, far within the nationwide norm. Furthermore, currently Instituut Verbeeten can start the treatment of **95%** of the **regular patients** within the nationwide norm of **21 days.** This research achieved to increase this ratio to **100%** of the **regular patients**. These regular patients can be treated within a mean of **5 hours**, far within the nationwide norm. This means a large decrease in processing time and patients can start their treatment earlier.

Next to this, we proved that patients can start their treatment faster if the BVB time can be executed by any RTO instead of the RTO that performed the first consultation. The objective function is lower when the RTO is flexible, and it takes on average one time slot less between the arrival of a patient and the last stage. The objective value with a fixed RTO is worse than the objective value with a flexible RTO. The mean number of time slots between arrival and last stage with a fixed or flexible RTO is respectively 18 and 17 time slots. The research also showed that the model still creates a feasible solution when the case mix is 1.5 times more than the original case mix. Consequently, there is less pool time available, for example for follow up appointments. These follow up appointments can be planned when there are less new patients arriving.

The model with a flexible RTO for the BVB time and a planning horizon of 10 days can be solved exactly within 30 minutes. The blueprint schedule is a tactical decision, and Instituut Verbeeten adjusts the blueprint schedule once every half year. Furthermore, if changes should be implemented such as missing RTOs, the model is easily used and does not take a lot of time to run. Finally, the model can also be solved by the constructive heuristic and results in a good solution with an approximation ratio of 0.82% on average and a calculation time of 526.81 seconds. This is four times less than the calculation time of the exact solution method.

5.2 Recommendations and limitations

The recommendations and limitations can be divided into three stakeholders. Namely, for science, Instituut Verbeeten and the company facilitating the research.

First, we focus on the recommendations and limitations for science. This research can be used for similar settings where a blueprint schedule is to be created. The important characteristic of this model is that it concerns multi appointment planning including different stages and patient types. Every patient type needs different stages and different durations for these stages. Furthermore, not all resources can perform all stages and patient types, because of there specialisation. The limitation of this research is that the model cannot be solved exactly for a planning horizon longer than 10 days. However, the model can also be solved by the constructive heuristic with an approximation ratio of 0.82%. This constructive heuristic can also solve the model for a planning horizon longer than 10 days within reasonable time. For further research, advanced computers can be used to solve the model exactly for a planning horizon longer than 10 days. Moreover, we used a fixed sequence of stages and some patient types did not need all stages. It could be interesting to change the sequences, because sometimes the CT scan can also be executed before the first consultation. This probably results in more flexibility in the planning. Finally, we could not benchmark our greedy heuristic to the best practise available in the literature, simply because this research is unique and not researched before.

Second, we focus on the recommendations and limitations for Instituut Verbeeten. This is the environment of the case study and where the blueprint schedule is being implemented. Instituut Verbeeten mentioned they first want to focus on subacute patients. This can be implemented by first only reserving appointments for patient types with subacute condition. In this case, the model can be used to indicate the necessary reserved time slots for each resource. The other appointments are reserved as they did before. If this part of the blueprint schedule is implemented and subacute patients can be treated earlier, the model can be extended with patients with other conditions (regular).

As noted, before there is another research conducted to optimize the allocation of patients to locations close to their home location. We did not consider the home location of the patients. So, a next step could be including the home location of a patient and integrating the project to this research. Therefore, a constraint should be added concerning location constraints. In this way, an allocation of patients is taking place. We also need to add some time constraints if we add the location of the patients. There should be some time between appointments at different locations. For example, a first consultation in Breda and a CT scan in Tilburg cannot be reserved right after each other. Furthermore, patients with a certain tumour type or acuteness category need other time constraints, these can also be added.

The research sets a good blueprint schedule to start with and insights can be used to make it work. Moreover, this research focuses on the pre-treatment phase of the patient. However, there are other appointments, such as follow up appointments, influencing the planning. At this point, the model reserves time slots as pool time to reserve for follow up appointments or other appointments, for example if there are more arrivals of new patients than expected. The model minimises the starting times of the pre-treatment phase appointments. Therefore, these appointments start as soon as possible and there are more time slots reserved for pool time at the end of the day. If a patient arrives in the middle of the day, there is possibly no space left on the same day. However, we reached 100% of the patients starting their treatment within the nationwide norm. The focus of this research is on the blueprint schedule of the planning. This means we do not focus on planning the patients but consider the consequences when making decisions in the blueprint schedule.

We proved that the model gives a better solution if the BVB time can be executed by any RTO instead of the RTO that did the first consultation of a patient. Therefore, we advice to reserve the BVB time at any RTO that is available to create more flexibility in the planning and to treat patients as soon as possible. We aware of the fact that the RTOs find it hard to implement this, because RTOs preferably execute the first consultation and the BVB time of their patients. However, we know this research gives a good insight into the possibilities. We advice to make a plan to convince the RTOs about the advantages of a flexible RTO for the BVB time.

Furthermore, we only consider the case mix with a certain number of arrivals per day per patient type. This means the blueprint schedule is also created with this case mix. If the amount of arrivals per patient type per day is exactly the same, the blueprint schedule works well. However, we also want to know what the blueprint schedule looks like with other arrivals. We varied in the number of patients by multiplying the number by 1.5, but we did not change the arrival days of the patient types. Further research is required, to experiment with other arrival days of patients and reflect on the results. This is also the case with experiments with the blueprint schedule. Further research is needed to measure the performance of the blueprint schedule with random arrivals.

An important aspect when implementing the blueprint schedule at Instituut Verbeeten is the current backlog. Currently, Instituut Verbeeten struggles with planning patients' appointments within the nationwide norm. At this point, it takes sometimes 20 days before the patient can start the treatment. We cannot start with the new blueprint schedule in one day, because first the backlog needs to be decreased. This can be done by increasing the availability of the resources for a couple of weeks, to make sure the backlog is decreased before starting with the new blueprint schedule. As mentioned in the beginning of this section, Instituut Verbeeten can first start to implement the blueprint schedule for the subacute patients.

Lastly, we focus on the recommendations and limitations for the company facilitating the research. This company is a consultancy agency and can use this research to execute projects at other companies with similar planning issues. We stated that multi-disciplinary appointment planning problems are becoming increasingly popular and much more challenging than single appointment planning, or multi appointment planning for a single discipline. Therefore, the model can be used and adjusted to other circumstances by changing the input parameters and some constraints. The software Spyder with the programming Python can be used by anyone, because it is an open source software.

In short, this research can be used for similar instances where a blueprint schedule is created for multi appointment planning including different stages and patient types. The model can be solved exactly with a planning horizon up to 10 days and a constructive heuristic can be used for a planning horizon longer than 10 days. The research can be used at Instituut Verbeeten with predicted improvements of 100% adherence to the target access times, and a next step could be including location of the resources and home location of patients. Finally, the research can be adjusted and used by the company facilitating the research to execute projects at other companies with similar planning issues.

6 References

Ahmadi-Javid, A., Jalali, Z., & Klassen, K. J. (2017). Outpatient appointment systems in healthcare: A review of optimization studies. *European Journal of Operational Research, 3*(34), 3-34.

Bailey, N. T. (1952). A Study of Queues and Appointment Systems in Hospitals Out-Patient Departments, with Special Reference to Waiting-Times. *Journal of the Royal Statistical Society: Series B (Methodological), 14*(2), 185-199.

Bikker, A. I., Kortbeek, N., Van Os, R. M., & Boucherie, R. J. (2015). Reducing access times for radiation treatment by aligning the doctor's schemes. *Operation Research for Health Care*(7), 111-121.

Blum, C., & Roli, A. (2003, September). Metaheuristics in combinatorial optimization: Overview and conceptual comparison. *ACM Comput. Surv., 35*(3), 268-308.

Bradley, S. P., Hax, A. C., & Magnanti, T. L. (1997). *Applied Mathematical Programming* (1 ed.). MA: Addison-Wesley Publishing Company.

Burke, E. K., Rocha, P. L., & Petrovic, S. (2011). An integer linear programming model for the radiotherapy treatment scheduling problem. *CoRR*, abs/1103.3391.

Castro, E., & Petrovic, S. (2012). Combined mathematical programming and heuristics for a radiotherapy pre-treatment scheduling problem. *Journal of Scheduling, 15*(3), 333-346.

Cayirli, T., & Veral, E. (2003). Outpatient scheduling in health care: A review of literature. *Production and Operation Management, 12*(4), 519-549.

Conforti, D., Guerriero, F., & Guido, R. (2010). Non-block scheduling with priority for radiotherapy treatments. *European Journal of Operational Research, 201*(1), 289-296.

Crop, F., Lacornerie, T., Mirabel, X., & Lartigau, E. (2015). Workflow optimization for robotic stereotactic radiotherapy treatments: Application of constant work in progress workflow. *Operations Research for Health Care*(6), 18-22.

Dharmadhikari, N., & Zhang, J. (2011). Simulation optimization of blocking appointment scheduling policies for multi-clinic appointments in centralized scheduling systems. *International Journal of Engineering and Innnovative Technology (IJEIT), 2*(11).

Feasible and infeasible solutions. (sd). Retrieved August 9, 2021, from Optekk: https://www.opttek.com/documentation/engine/WebHelp/Feasible_and_infeasible_solutions.htm

Fendrich, K., & Hoffmann, W. (2007). More than just aging societies: the demographic change has an impact on actual number of patients. *Journal of Public Health, 15*(5), 345-351.

Green, F. B. (2006). Six-sigma and the revival of TQM. *Total Quality Management and Business Excellence, 17*(10), 1281-1286.

Gupta, D., & Denton, B. (2008). Appointment scheduling in health care: Challenges and opportunities. *IIE transactions, 40*(9), 800-819.

Hans, E. W., Van Houdenhoven, M., & Hulshof, P. J. (2012). A framework for healthcare planning and control. In *Handbook of healthcare system scheduling* (pp. 303-320). Springer, Boston, MA.

Hulshof, P. J., Boucherie, R. J., Hans, E. W., & Hurink, J. L. (2013). Tactical resource allocation and elective patient admission planning in care processes. *Health Care Management Science, 16*(2), 152-166.

Hulshof, P. J., Kortbeek, N., Boucherie, R. J., Hans, E. W., & Bakker, P. J. (2012). Taxonomic classification of planning decisions in health care: a structured review of the state of the art in OR/MS. *Health Systems, 258*(1), 129-175.

Joustra, P. E., Kolfin, R., van Dijk, N. M., Koning, C. C., & Bakker, P. J. (2012). Reduce fluctuations in capacity to improve the accessibility of radiotherapy treatment cost-effectively. *Flexible Services and Manufacturing Journal, 24*(4), 448-464.

Kwak, Y. H., & Anbari, F. T. (2006). Benefits, Obstacles and future of Six Sigma approach. *Technovation, 26*(5-6), 708-715.

Law, A. M. (2007). *Simulation Modeling & Analysis* (4 ed.). New York, NY, USA: McGraw-Hill.

Leeftink, A. G., Bikker, I. A., Vliegen, I. M., & Boucherie, R. J. (2020). Multi-disciplinary planning in health care: a review. *Health Care Management Science, 9*(2), 95-118.

Leeftink, A. G., Vliegen, I. M., & Hans, E. W. (2019). Stochastic integer programming for multi-disciplinary outpatient clinic planning. *Health Care Management Science*(22), 53-67.

Liang, B., Turkcan, A., Ceyhan, M. E., & Stuart, K. (2015). Improvement of chemotherapy patient flow and scheduling in an outpatient oncology clinic. *International Journal of Production Research, 53*(24), 7177-7190.

Mackillop, W. J. (2007). Killing time: the consequences of delays in radiotherapy. *Radiotherapy and Oncology, 84*(1), 1-4.

Marynissen, J., & Demeulemeester, E. (2019). Literature review on multi-appointment scheduling problems in hospitals. *European Journal of Operational Research, 272*, 407-419.

Multidisciplinair overleg. (sd). Retrieved August 9, 2021, from Medical Groep: https://www.medicalgroep.nl/multidisciplinair-overleg/

Mutlu, S., Benneyan, J., Terell, J., Jordan, V., & Turkcan, A. (2015). A co-availability scheduling model for coordinating multi-disciplinary care teams. *International Journal of Production Research, 53*(24), 7226-7237.

Normeringsrapport. (sd). Retrieved August 9, 2021, from Soncos: https://www.soncos.org/kwaliteit/normeringsrapport/

Petrovic, D., Morshed, M., & Petrovic, S. (2009). Genetic algorithm based scheduling of radiotherapy treatments for cancer patients. In C. Combi, Y. Shahar, & A. Abu-Hanna, *Artificial Intelligence in Medicine* (pp. 101-105). Berlin Heidelberg: Springer.

Petrovic, S., & Leite-Rocha, P. (2008). Constructive and grasp approaches to radiotherapy treatment scheduling. In *Advances in Electrical and Electronics Engineering - IAENG Special Edition of the World Congress on Engineering and Computer Science 2008* (pp. 192-200).

Rajgopal, J. (2001). Principles and application of operation research. In K. B. Zandin, *Maynard's Industrial Engineering Handbook* (pp. 27-44). New York: McGraw-Hill.

Samuel, C., Gonapa, K., Chaudhary, P. K., & Mishra, A. (2010). Supply chain dynamics in healthcare services. *Int J Health Care Qual Assur, 23*(7), 631-642.

Schut, F. T., & Van de Ven, W. P. (2011). Effect of purchaser competition in the Dutch health system: is the glass half full or half empty. *Health Economics, Policy and Law, 6*(1), 109-123.

Sehwail, L., & DeYong, C. (2003). Six Sigma in health care. *Leadership in Health Services, 16*(4), 1-5.

Simons, P., Backes, H., Bergs, J., Emans, D., Johannesma, M., Jacobs, M., . . . Vandijck, D. (2017). The effects of a lean transition on process times, patients and employees. *International Journal of Health Care Quality Assurance, 30*(2), 103-118.

Smith-Daniels, V. L., Schweikhart, S. B., & Smith-Daniels, D. E. (1988). Capacity management in healht care services: review and future research directions. *Decision Sciences, 19*(4), 889-919.

Solnon, C., & Jussien, N. (2013). *Constructive Heuristic Approaches.* Ltd: John Wiley & Sons.

Spagnol, G. S., Min, L. L., & Newbold, D. (2013). Lean principles in Healthcare: an overview of challenges and improvements. *IFAC Proceedings Volumes, 42*(24), 229-234.

Thomas, S. (2003). Capacity and demand models for radiotherapy treatment machines. *Clinical Oncology, 15*(6), 353-358.

Vanberkel, P. T., Boucherie, R. J., Hans, E. W., Hurink, J. L., & Litvak, N. (2009). A survey of health care models that encompasses multiple departments. *International Journal of Health Management and Information, 1*(1), 37-69.

Vanheacht, K., De Witte, K., & Sermeus, W. (2007). *The impact of clinical pathways on the organisation of care processes.* KU Leuven, Belgium.

Vermeulen, I. B., Bohte, S. M., Elkhuizen, S. G., Lameris, H., Bakker, P. J., & La Poutré, H. (2009). Adaptive resource allocation for efficient patient scheduling. *Artificial intelligence in medicine, 46*(1), 67-80.

Vieira, B. (2020). *Logistical Optimization of Radiotherpay Treatments.*

Watson, G. H., & DeYong, C. F. (2010). Design for Six Sigma: caveat emptor. *International Journal of Lean Six Sigma, 1*(1), 66-84.

Werker, G., Sauré, A., French, J., & Shechter, S. (2009). The use of discrete-event simulation modelling to improve radiation therapy planning processes. *Radiotherapy and Oncology, 92*(1), 76-82.

Wie zijn wij? (sd). Retrieved from August 9, 2021, from Instituut Verbeeten: https://www.verbeeten.nl/over-ons/wie-zijn-wij.aspx

Womack, J. P., & Jones, D. T. (1997). Lean thinking – banish waste and create wealth in your corporation. *Journal of the Operational Research Society, 48*(11), 1148-1148.

Wu, D. Y., & Katok, E. (2006). Learning, communication, and the bullwhip effect. *Journal of Operations Management, 24*(6), 839-850.

Young, T., & McClean, S. (2009). Some challenges facing Lean Thinking in healthcare. 309-310.

Zorgverzekeringswet. Retrieved March 24, 2021, from Zorgwijzer: https://www.zorgwijzer.nl/faq/zorgverzekeringswet