MASTER

Planning and scheduling under uncertainty in oncology day care

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Planning and scheduling under uncertainty in oncology day care

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Abstract

This master thesis focusses on the planning and scheduling problem in oncology day care. It is performed within the settings of the Amphia hospital, Breda. Historic data and newly developed heuristics are used to come up with a tactical schedule to accommodate the real-time scheduling of patients. Simulation results show the new way of working leads to less patient waiting time and a better spread in nursing workload.

Preface

In this report the results from my graduation project at the Amphia hospital in Breda are presented. This graduation project is the final part of the study Operations Management & Logistics at the Eindhoven University of Technology.

I would like to express my gratitude to some people who played an important role during this master thesis project and during my study.

First of all, I would like to thank the supervisors of the TU/e for their role during the project. The role of my first supervisor, Nico Dellaert, was very important. His advice helped me in difficult times and he was always willing to see me when needed. I would also like to thank Uzay Kaymak for his role as a second supervisor during the project.

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I would also like to thank the people who played an important role during my whole study. I want to thank my parents and girlfriend, for their support during my study years and also my fellow students who were also very good friends.

Joost Menting
January, 2014

Management Summary

This master thesis is performed within the setting of the Amphia hospital, Breda. The Amphia hospital positions itself as one of the main national hospitals in the development of cancer care. The number of patients that is diagnosed with cancer increases annually by 5% and the complexity of cancer care increases due to an increasing variety in types of treatments. These developments have increased the complexity of the planning and scheduling of treatments in oncology day care. This problem is the main subject in this master thesis. We define the planning and scheduling problem of treatments as the problem of assigning treatments to particular days and timeslots.

Problem definition

In oncology day care patients receive chemotherapy treatments and other treatments by infusion, and leave the hospital on the same day. Relevant resources involved in the process are nurses, chairs, drugs and physicians. The number of available treatments has risen dramatically in recent years. Besides this the demand in oncology has seen a major shift from the inpatient setting towards the outpatient setting. Within the setting of the Amphia hospital this increase in complexity has led to an increase in peaks of nursing workload during a day. The current planning systems find it difficult to deal with the wide variety in treatments and resources involved.

We found that research on this problem is scarce. Only two studies apply optimisation techniques in the relevant setting. They both conclude that the problem cannot be solved by a single optimisation model, queuing model, or heuristic. The main difficulty according to literature is to incorporate the nursing capacity into a mathematical model. The difficulty here is that a nurse from oncology day care is responsible for multiple tasks at the same time. Both studies solved this problem by categorising treatment according to a certain aquity level, which stands for the amount of nursing capacity involved in each treatment. Both studies resulted in a 2-step approach to deal with the planning and scheduling problem. The main difference between the 2 solutions is that one study waits until all treatments are known, and creates a solution accordingly. The other study assumes an incoming treatment needs to be planned right away. Both studies found significant improvements in the resulting schedules compared with current practice.

Using the results from current literature and the problem statements from the Amphia hosptital, the following main research question is created.

What planning and scheduling tool can be used in oncology day care that reduces patient waiting times by improving the use of current resources?

By improving the use of current resources we mean increasing the resource utility and reducing the spread in workload. By increasing the resource utility the time that a patient needs to wait before his/her appointment can be planned is automatically reduced. By reducing the spread in workload the patient waiting time in the waiting room is decreased.

Conceptual model

The main findings from the literature study and the characteristics in the Amphia hospital together form the input for the development of a conceptual model to answer the main research question. A rolling horizon methodology is developed where a tactical schedule is created periodically and used in the real-time scheduling of patients. Excel VBA is chosen as a programming tool because of the practical advantage of the automation of manual tasks. The relevant resources incorporated in the development of the solution are nurses and chairs. The incorporated treatments are all treatments given in the oncology day care department. These include all intravenous treatments, taking blood samples, and also intake consultations. The following assumptions are the most important assumptions in the calculations of our mathematical models:

- All treatment durations are known and deterministic.
- Patients and drugs are present at the time a treatment starts.
- The available capacity can be altered.
- Treatments are divided in categories according to treatment time.
- The required nursing capacity for all treatments can be divided in 2 phases.

A mathematical model is created in Excel VBA to calculate the tactical schedule according to the input variables set by the user. The input variables are the amount of expected treatments and the probability distribution resulting from historical data. The tactical schedule does not apply optimisation techniques. The way in which the programme works is that it first creates an initial solution and then starts an iterative process to improve the solution. A heuristic is developed that improves the initial solution until improvement is no longer possible. The main objective value that the tactical schedule focusses on is the reduction in the overutilisation of nursing capacity. The resulting programme is able to generate tactical schedules using different capacity settings. Therefore the programme can also be used by management in order to determine the available capacity depending on an expected amount of treatments.

A second programme is developed in Excel VBA to accommodate the real-time scheduling of patients. The programme uses the tactical schedule as input and treatments can be scheduled according to reserved blocks. A problem arises when a request for treatment comes in that no longer fits in one of the available blocks. Scheduling rules that should be followed sequentially are developed to be able to plan every incoming request. As a result some treatments can be scheduled on different days or in different blocks.

Results

A simulation programme is developed in order to assess the quality of the developed solution compared with current practice. This simulation programme uses the amount of expected patients and the tactical schedule with capacity constraints as input. Depending on the amount of expected patients the programme generates a set of incoming patients according to a Poisson distribution. The programme then assigns all treatments to particular days and timeslots according to the developed scheduling rules.

It turned out that, especially in busy periods, our newly developed way of scheduling treatments performs better than the current way of working. The current way of working is hardly ever able to deliver feasible schedules, where our programme was able to generate 14 out of 15 feasible schedules. A feasible schedule is able to fit in all incoming requests for treatment. In terms of patient waiting time the performance is similar. According to the simulation results there seems to be an exponential relationship between the amount off scheduled patients and the waiting time per patients. Using our developed scheduling method, this critical value for amount of patients per day lies roughly around 40. When this amount is reached the schedule is full and every extra patient leads to a significant increase in patient waiting time. By increasing nursing capacity by 12,5% in a busy period the resulting patient waiting time is reduced by 25%. For the calm period generally the same conclusions can be drawn. Patient waiting times are low both in reality and in our results but in reality the schedules are hardly ever feasible. The fact that infeasible schedules are used makes a big difference in a busy period when all chairs are constantly occupied. It leads to situations where more patients are present for treatment than there are chairs available.

Recommendations and future research

Our simulation results show that there is a potential advantage in our newly developed way of planning and scheduling treatments. The following recommendations are made to implement the developed new way of working in the Amphia hospital:

- Management should be responsible for the generation of tactical schedules in Excel and the translation of the schedules in the current planning application.
- A new planning application should be created in order to accommodate the real-time scheduling of treatments.
- The planners are responsible for the real-time scheduling of patients and should make choices based on the developed scheduling rules.

Our research has resulted in the development of a new way of planning and scheduling treatments. New heuristics are developed that do not apply optimisation techniques but step by step procedures in order to find solutions that together provide an answer to our main research question. These programmes, that can be implemented directly in different oncology day care settings, are our main contribution to current literature. Due to assumptions made in our research, opportunities for future research are:

- Perform a time study in order to improve the accurateness of the probability distribution, used to divide treatments into different categories.
- Incorporate stochastic treatment times into the model in order to get a more accurate estimate of the real resulting patient waiting time.
- The incorporation of the other relevant resources into the model, for instance the pharmacy and the physician.

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1. Introduction

This master thesis concerns the problem of planning and scheduling treatments in oncology day care. In this unit outpatient cancer care is provided to patients that are treated for a variety of cancers, e.g. bowel, breast, prostate, and lung cancer. Developments in recent years in healthcare, and specifically in oncology, have increased the complexity of planning and scheduling treatments in these departments.

In recent years there has been a general increase in demand for healthcare, mainly caused by the aging of the population. Besides the aging of the population, the demand for oncology services will rise because of the age-sensitivity of cancer and the increase in cancer survivors (Erikson et al., 2007). Besides this, oncology care has seen a major shift from the inpatient setting towards the outpatient setting. According to Turkcan et al. (2011) “In the last two decades, chemotherapy administration has shifted from the inpatient setting to the outpatient setting due to sophisticated delivery methods, new oral preparations of drugs, and improved management of side-effects, enabling patients to tolerate their treatments without being hospitalised”. This shift in oncology towards the outpatient setting is also confirmed by Delaney et al. (2002); Hastings and Moore (2006).

Besides the increase in demand, the complexity of planning and scheduling in oncology day care is further increased due to the variety in types of treatments. Nowadays there are hundreds of different protocols that require different treatment methods and treatment durations. This number is still increasing due to current research. In practice this increasing complexity of the planning problem has led to some serious problems in the field. Studies show high fluctuations in workload of resources. Negative consequences that follow from this are long patient waiting times, higher patient dissatisfaction, irritated and sometimes stressed staff (Chabot and Fox, 2005; Hastings and Moore (2006).

These developments and problems that follow from it make the subject a relevant topic for research in the field of operations management and are the main reasons for choosing this field as a topic for the master thesis. The master thesis is performed in the Amphia hospital in Breda. In the next section the current situation at the Amphia hospital is described, starting with general information and then zooming in on oncology day care.

1.1. The Amphia hospital

The Amphia hospital originates from a merge of 3 separate hospitals in 2001. The location of the 3 former hospitals are still the 3 main locations of the Amphia hospital today. The three locations are called “Langendijk, Molengracht and Pasteurlaan”, named after the streets of the locations. Each location has its own specialities.
The Amphia has divided its organisation in 5 care centre divisions, each has its own manager. The divisions are: Innovation, Strategy, Quality, Control and Service. The different care units at the Amphia incorporate all the patient care delivered. There are 5 different main categories on which the hospital wants to focus. These are Oncology, cardiovascular, movement, women & child, healthy aging.

As can be seen oncology is one of the 5 main categories of care that the Amphia provides. This shows the importance of the oncology department within the Amphia hospital. The Amphia hospital positions itself as one of the main national hospitals in the development of cancer care. The number of patients that is diagnosed with cancer increases annually by 5% and the complexity of cancer care increases due to research results. Annually there are over 3000 patients diagnosed with cancer in the Amphia hospital. To provide optimal care the hospital has recently concentrated as much cancer care as possible on 1 location. They recently opened this new department of hematology/oncology to concentrate involved resources and shorten communication lines. The oncology day care is the only cancer care that is still provided at the “Langendijk” location.

1.2. Oncology day care

When a patient gets diagnosed with cancer it has a major influence on this person’s life. Cancer can be life threatening but in recent years continuous research has increased the chance that a patient can be cured. The first step after the diagnosis of cancer is the setup of a treatment plan. This is done by a team of specialists from different specialties (e.g. surgery, hematology, radiology, etc.). A treatment plan consists of surgery, radiotherapy, chemotherapy or a combination of the three. When a patient has followed the treatment plan the result is analysed. If a follow up treatment is necessary a new treatment plan is set up. If not, the patient is discharged. This general process that a cancer patient goes through is shown in figure 1.

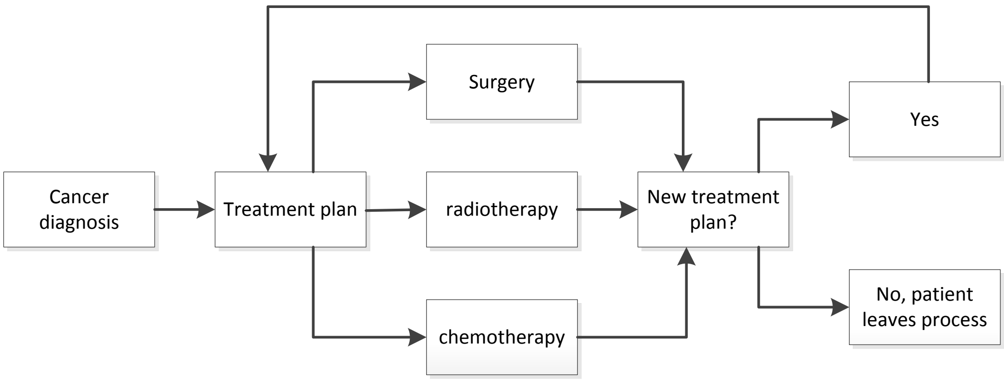

Figure 1: The general process that every cancer patient goes through

As shown in figure 1, chemotherapy can be one of the building blocks of a treatment plan for a cancer patient. The majority of chemotherapy treatments are given by infusion, and an increasing amount is given orally. The chemotherapy treatments given by infusion in the outpatient setting are the main subject of this thesis. The rest of the process in figure 1 is not within scope. These patients receive treatment at oncology day care. The general process of oncology day care is described in figure 2.

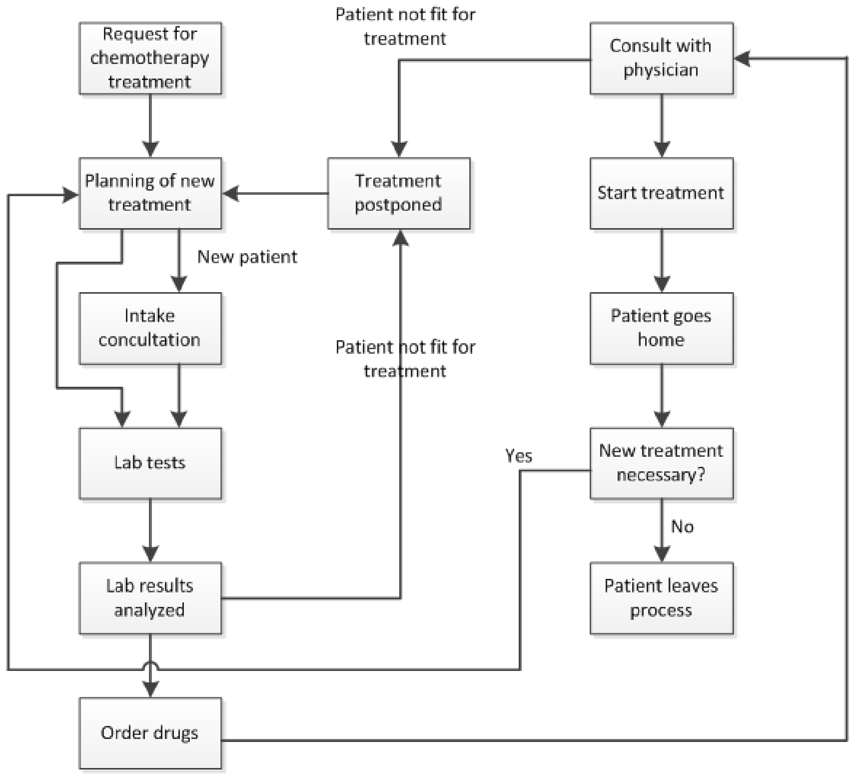

Figure 2: Oncology day care in the Amphia hospital

Every patient is assigned to a responsible oncologist. This oncologist determines the details of the treatment plan. A treatment plan can consist of multiple cycles. A cycle consists of a number of treatments with predetermined time intervals. The input for the process is a request from an oncologist to start a chemotherapy treatment. Depending on the type of treatment and input from the oncologist a number of chemotherapy treatments are planned. The first step for the patient is an intake. During a conversation with one of the nurses the patient receives all kinds of relevant information about the length of stay, how to deal with unwanted side effects like loss of hair, etc. An intake normally takes one hour. After the intake the patient starts with the planned treatments. Before a treatment starts most patients need to get blood and/or urine samples one day in advance of the treatment. From these samples the physician at the day care can decide to postpone a treatment. When this is done a new treatment needs to be planned, for instance one week later, to give the patient more time to recover. When the treatment is not cancelled a drug is ordered at the pharmacy, one day prior to the actual treatment. At the actual day of treatment some patients have a consult with their oncologist. During this consult it can also be decided to postpone a treatment. When this is done the drug often goes to waste because of the very short shelf life. When a treatment is not cancelled the patient is taken to the day unit by specialised nurses to receive the chemotherapy treatment. After the treatment the patient goes home and, if necessary, new treatments are planned. When the whole treatment plan is carried out the patient leaves the process. The effect of the treatment plan is analysed and possibly a new treatment plan is developed, as described in figure 1.

2. Literature research

A literature review is conducted on the topic of planning and scheduling under uncertainty in oncology day care. In this chapter the main findings from this literature review are summed up. These findings, combined with the characteristics of the Amphia hospital described in chapter 1, will serve as input for developing research questions for the master thesis in the next chapter.

2.1. General findings

Differences between the production industry and healthcare industry are important to keep in mind when applying theories from one setting to the other. Jan Vissers and Roger Beech discussed the differences and similarities in their book "Health Operations management" (2005). We analyzed that oncology day care has the same general similarities and differences with the production industry as the healthcare industry in general has. One main similarity is that in both settings equipment and staff are the necessary resources to function as means of production. Also the output requirements are up front specified for both the production industry but also at the oncology day care. Independent of the effect of chemotherapy the tasks of the unit are very clear before treatments start. The most important differences between oncology day care and the production industry are in the object of flow and the use of buffers. In the production industry materials flow through the processes and buffers can be used to stock (semi) end products. In oncology day care patients flow through the processes and it is not possible to stock end products. The only buffers that can be used are waiting times and lead times.

After this we zoomed in on methodologies applied by different healthcare departments to deal with the planning and scheduling problem. The studies found show a wide range of possible solutions for the planning and scheduling problem in healthcare. It depends on the characteristics of the department which methodology can be applied. Gupta and Denton (2008) define 4 different characteristics to classify different planning and scheduling systems found in literature:

- The arrival process. Requests for planning can be dealt with in batches, per unit, or in periodic periods.
- Service times are either known (deterministic) or random.
- Patient and provider preferences are either taken into account or not.
- Include either direct or indirect waiting times in the scheduling method. Here direct waiting time is the difference between an appointment time and the time when he/she is actually served by the service provider (time in waiting room). Indirect waiting time is the difference between the time that a patient requests an appointment and the time of that appointment (time on a waiting list).

The characteristics that are relevant for oncology day care will be determined in the next chapter. Cardoen et al. (2010) did a literature review in operating room planning and scheduling. In their review they found 246 relevant studies, which shows the amount of research done only on this particular department. They mention a lot of different solution techniques used: e.g. mathematical programming methods, heuristics, simulation or analytical approaches. They also mention the difference in the inclusion of arrival and duration uncertainty. Many researchers prefer the deterministic approach due to computational complexity. However a stochastic approach is better to bridge the gap with reality.

2.2. Optimisation in oncology day care

The next step was to zoom in on the characteristics of oncology day care. We found only 2 studies that apply optimisation techniques in oncology day care to deal with the planning and scheduling problem. The first study is done by Turkcan et al. (2011). Their objective is to minimise the patients treatment delays because the primary goal of chemotherapy day care is to treat all patients according to the treatment plans set by the oncologist. In other words, their objective is to minimise indirect waiting time. They developed two models. The first model assigns different patients to particular days (the planning problem) and the other assigns patients to particular timeslots (the scheduling problem). The objective function of the first model minimises total staff overtime costs, staff idle time costs and total treatment delay. The objective function of the second model minimises the total completion time of all treatments on a particular day. After this a rolling horizon algorithm is given to apply the two models efficiently.

The other relevant study is the study of Hahn-Goldberg et al. (2012). They developed a method called dynamic template scheduling in which they deal with an offline and an online problem. They also created two optimisation models to deal with both problems. The first creates a pro-active template using deterministic optimisation. This means that an optimal schedule of an average day in chemotherapy day care is created. When requests for appointments come in, they are scheduled according to the available slots in the created schedule. Every planned request cannot be changed anymore. When a request comes in that does not fit in an available timeslot the second method is used and the schedule is dynamically updated. This means that the schedule at that time, with the already booked appointments and the available time, is updated, to come up with a new schedule that fits the request. They call this part the online problem. Their objective function is to minimise the makespan. This means that the time it takes to do all treatments is minimised. This automatically reduces indirect patient waiting times.

Both studies make different assumptions what leads to very different models and results. In the study of Turkcan et al. waiting lists for requests to start chemotherapy are allowed. In the study of Hahn-Goldberg et al. waiting lists are not allowed and incoming requests are scheduled right away. This difference cause the two models developed in the studies to be totally different. There are also differences in assumptions and constraints on resource capacity. The way to include nurse capacity is different and only one of the two studies includes the capacity of the pharmacy. Similarities are that both studies use historical data as input for their model. Both studies do not take emergencies or last minute cancellations into account. Important to note is that both studies agree on the fact that the characteristics of the planning and scheduling problem make it not likely that it can be solved by a single optimisation model, queuing model, or heuristic. Both studies developed 2 separate models that are connected by a programming tool.

2.3. Quantifying nursing workload

All relevant studies tried to capture reality as close as possible by including constraints on the relevant resources. The resource that is hard to capture by constraints is the capacity of the nurses. Studies show that it is hard to measure the workload of nurses objectively and that is why the emphasis in the literature study was on this subject. The difficulty here is that a nurse from oncology day care is responsible for multiple tasks at the same time. A nurse is responsible for monitoring and helping a number of patients and, at the same time, also for taking in new patients.

Literature shows this problem can be treated in different ways. The hardest part is to deal with the huge variety in different treatment types, each with its own nursing workload. This problem can be solved by categorising the treatments. A lot of the found studies develop their own "acuity-tool" that they can use to determine nursing workload. They develop 4, 5, or 6 different categories each with a different nursing workload. All the different treatments are divided among these categories. Other studies did not use any categories and came up with nursing workloads for each individual treatment type. The second problem that should be dealt with is how to assign these nursing workloads to the treatments or how to divide the treatments into categories. This can be done in two ways. Some studies did elaborate time studies to determine nursing workloads: Moore and Hastings (2006); Delisle (2009). Others used a team of experts and used their knowledge to develop different categories: Chabot and Fox (2005); Cusack et al. (2004); Green et al. (2012). The final distinction that can be made is in the type of activities that is included in the measurement. Most of the indirect activities are often incorporated as constant (e.g. setting up tubes, ordering supplies, communicating with other departments, documentation).

2.4. Quantifying workload of other resources

Other resources besides nurses that are relevant in the setting are chairs/beds, pharmacists and physicians. It is important to determine if a resource is only committed in the process of oncology day care. If not, the dependencies with other departments need to be taken into account which is very hard to model.

One resource that is only committed to oncology day care and is often used as fixed capacity is the availability of chairs/beds. For instance Turkcan et al. (2011) have a fixed amount for the number of beds/chairs while the number of nurses can be altered. Hahn-Goldberg et al. also use a fixed amount for the number of chairs/beds. Both studies do not take the difference between beds and chairs into account.

A resource that is often partly dedicated to oncology day care is the pharmacy. Turkcan et al. (2011) do not take this resource into account at all. They make the assumption that a drug is instantly available when it is needed. Hahn-Goldberg et al. take into account a fixed number of 5 servers that are dedicated to oncology day care.

The final resource that needs to be taken into account are the physicians. It is hard to put capacity constraints on this resource because they are not only committed to oncology day care. Patients often have a consult with their oncologist but sometimes with the physician of the day unit. In relevant studies this resource capacity is not taken into account in capacity constraints.

2.5. Variability and uncertainty

By variability we mean the characteristic that a certain variable can differ from its expected mean. By uncertainty we mean that a certain event has a probability of being cancelled.
The first type of variability is in the arrival process of requests for appointments. It depends on the assumptions made what type of arrival process can be used. Turkcan et al. (2011) assumed that capacity is too low to deal with all requests at once so a waiting list with requests exists. In this way the model can incorporate a queuing system where incoming requests could be determined by a distribution. Hahn-Goldberg et al. use a different view and assume that every incoming request

needs to be scheduled right away. In their model a waiting list is not allowed because this has a great influence on the health of the patient.

When a patient is scheduled there is the uncertainty that a treatment is cancelled because of the physical condition of the patient. There are some studies that mention this uncertainty but none of the studies found takes this uncertainty into account. Emergency patients are also not taken into account in relevant studies.

When it is decided that a treatment is not cancelled the patient is taken to a chair for treatment. There is always variability in treatment duration. This type of variability is already discussed in the chapter of determining nursing workload. There is patient specific variability and treatment specific variability. Patient specific means that one patient needs much more attention from a nurse than another because of a bad health status, bad vein access etc. Treatment specific variability means that one type of regimen needs much more nursing time than another.

Both variability and uncertainty are hard to take into account due to the lack of relevant data. For instance there is often no data for the real duration of a treatment or the waiting time before a treatment starts. If researchers need this data they need to do separate time studies or use input from experts. That is why almost all relevant studies use deterministic treatment times and do not take uncertainty in treatments into account.

2.6. Opportunities for future research

Literature gave us an extensive view on the current research done in the application of optimisation techniques in oncology day care. It also gave us an idea about possibilities for future research which are the following:

- The relevant studies strived for minimisation of treatment delay and minimisation of makespan. Future research could focus on other targets e.g. minimising the spread in capacity workload, maximising resource utilisation or minimising costs.
- Incorporate the indirect care of patients into the model to approach the real nursing workload in a better way.
- Include the capacity of the day care physician into the model, knowing that his/her capacity is completely devoted to chemotherapy day care.
- Include the uncertainty of emergencies and cancellations into the model.
- Include stochastic treatment times into the model.
- Incorporate distributions for the arrival process of requests. This can be one distribution for all days or different distributions for different days/weeks.

3. Research Project

The problem definition is stated in section 3.1, following from characteristics of oncology care described in the introduction. Together with the findings in the literature review this problem definition will serve as input for developing research questions in section 3.2. In sections 3.3 and 3.4 the research project is further described by defining the scope, important assumptions and the used research methodology.

3.1. Problem definition

The oncology day care department of the Amphia hospital faces numerous challenges. Three major challenges are identified that serve as input for developing research questions in this master thesis:

- There is no objective insight in the development of demand in the department, neither in the past nor in the future. Therefore it is unknown what recourses are necessary to deal with future demand.
- There is no objective method to measure the real workload of the department.
- There is no knowledge of how to design and implement a new way of planning that reduces the spread in workload and still takes into account relevant constraints.

3.2. Research questions

The main problem experienced by the staff of the department is the high spread in workload during a day and between days. This leads to stressed and unhappy staff and also to longer waiting times for patients. Therefore we decided to develop a research question that addresses this problem. As a cause of this problem we identified a mismatch between the required resource capacity and the available resource capacity during a day. The literature study showed this problem has been studied in the field of operations management and that it can be solved. These findings have led us to come up with the following research question:

What planning and scheduling tool can be used in oncology day care that reduces patient waiting times by improving the use of current resources?

By improving the use of current resources we mean increasing the resource utility and decreasing the spread in workload. By increasing resource utility the time that a patient needs to wait before his/her appointment can be planned is automatically reduced, this leads to a decrease in indirect waiting time. Additionally the decrease of the spread in workload leads to less delays in practise. A reduction of these delays automatically leads to a decrease in the time that patients spend in the waiting room, thereby reducing direct waiting time. In order to find an answer to the main research question a set of sub questions is developed. The sub questions are categorised to clarify the different steps that are performed during the thesis project.

Sub questions are developed that together lead to an answer to the main research question. The first step in the research was to get an idea about the amount of patients treated during recent years and the demand for oncology day care in the future. The sub questions that are answered in this first part are:

- *How has demand for oncology day care developed over the long term (years)?*
- *How does a short term forecast (Weeks) for demand look like?*

A very important and difficult step was to obtain an objective measurement of the workload for oncology day care. Literature showed the hardest workload to measure objectively is the nursing workload. In order to get a good understanding of the current workload the following sub questions are answered:

- *Which treatments are given and what resources are necessary for each treatment?*
- *How does the workload over time for nurses and chairs for individual treatments look like?*
- *How does the workload for the department as a whole look like during a day?*

The previous sub questions are answered in the analysis part of this research project. The next step was to design and build a mathematical model that models an alternative way of working. This should lead to less spread in workload and less patient waiting times while matching reality as close as possible. The next sub questions were developed in this part:

- *What general problem solving techniques found in literature can be applied to the situation in the Amphia hospital?*
- *How to define the objective of the mathematical model?*
- *How does the workload for resources look like when the solution of the model is applied?*

The outcome of the previous sub questions is a new way of working that should improve resource utilisation. The final step is to develop and run a simulation tool that measures the quality of new way of working by running historical data through the model. The outcome of the model can be compared with the outcome of the current way of working and the actual benefits of the new way of working become clear. The sub questions that are developed for this final part are the following:

- *How does an arrival distribution of patients look like according to historical data?*
- *How can the process of scheduling patients be simulated?*
- *How do the results of the simulation tool look like and what are the benefits compared to the current way of working?*

3.3. Research scope and assumptions

A variety of resources and care providers are involved in the process at oncology day care, depicted in figure 2. However not all the parties involved in this process are incorporated within the scope of this research. When a patient arrives at the department for treatment 3 resources are always involved:

- Chairs
- Nurses
- Drugs

For some patients the physician is also involved. The capacity of the chairs and nurses are fully devoted to the unit, and therefore the most important resources in this research. In the current situation in the Amphia hospital there are always 16 chairs and 4 nurses available. The capacity of the pharmacy, where drugs are prepared, is only partly dedicated to the unit and therefore not within the scope of this research. Only a fraction of the patients visit the physician and this resource is therefore also not within the scope of this research. This means in our results the scheduling of the treatment is leading and a visit to the physician is planned according to this treatment. This means it may occur that waiting time exists between the visit with the physician and the treatment.

There are different types of appointments and treatments provided at the unit, which all require capacity from the involved resources. The types of treatments that are within the scope of this research are:

- All treatments that are given by infusion at oncology day care.
- Intake consultations.

The treatments given by infusion can be chemotherapy treatments but also for instance blood thinners. All these treatments require both chair and nurse capacity. An intake consultation with a patient normally requires 1 hour of nursing time and therefore also has a major influence on the nurse capacity available for providing infusion treatments. The consult with the physician is not included due to the fact that the physician is also not included as a resource.

A number of assumptions are included in this research project. The assumptions influence the calculations in our mathematical models and most of them are not applicable to current practice. They are incorporated to reduce the computational complexity of the developed models. For these reasons, the following assumptions apply to this research project

- Patients are physically present and ready when their appointment is scheduled.
- Treatment durations and starting times are deterministic.
- There is no difference between patients that need a bed or a chair; every patient can use a chair.
- There is no difference in the capacity of different nurses.
- An intake is always 1 or more days before the first day of treatment.
- The probability for last minute cancellations is taken into account.
- Guidelines for the maximum workload are used, these are not restrictions. This means double bookings are allowed.
- Treatment plans set up by oncologists contain hard constraints. They are taken into account.
- Patient preferences and demands from other departments are soft constraints. They are partly taken into account.

The following restriction applies to this research project:

- The available data is limited. It contains all the treatments that are given during recent years. There is no data on direct waiting times or real treatment durations.

3.4. Research methodology

To describe the general methodology the research model of Mitroff et al. (1974) is used. The resulting model is given in figure 3.

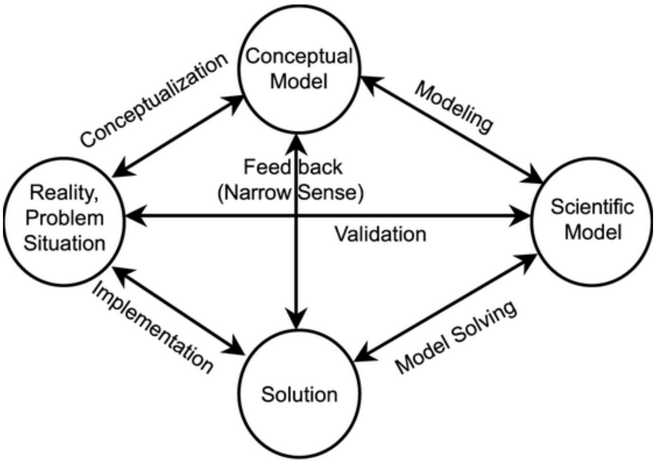

Figure 3: Research model developed by Mitroff et al.

During this research project the cycle is gone through one time except for the final step.

Problem situation: The first step is the description of the problem situation. Input from the organisation is used for this and the problem that will be tackled during the master thesis is identified.

Conceptual model: In the conceptual model we stated what resources, assumptions and restrictions are relevant and can be translated into parameters. We defined values for the parameters by performing a detailed analysis of the available data.

Scientific model: In the development of the scientific model the real situation is captured in a conceptual model using the relevant constraint and parameters.

Solution: The actual improvement of the current way of working lies in the design of new decision criteria. They are built into a mathematical model and lead to a solution that should be an improvement compared to the current way of working. This is tested by building a simulation model where the model output is compared with current practice.

The final step, the implementation phase, is not part of this research project.

4. Analysis of oncology day care

In this chapter the first two sets of sub questions are answered. To answer the first, a data analysis is done to give an idea about the development of demand during the past years. After this, multiple regression is used to design a forecast model for the short term future. The second set of sub questions considers the variety in different treatments provided. Again a dataset is analysed to determine different resources required for each treatment. After this it is possible to categorise the treatments and measure the actual workload of the department during a day.

4.1. Long term demand analysis

The available dataset contains all declarations of handlings at the oncology day care from January 2010 until March 2013. De dataset is analysed in Excel by counting all unique patients per day. This gives an idea about all relevant handlings that require nursing or chair capacity, including intake consultations, flushing of port-a-cads and taking blood samples. The results of the analysis are shown in figure 4. The results are also summarised in table 1.

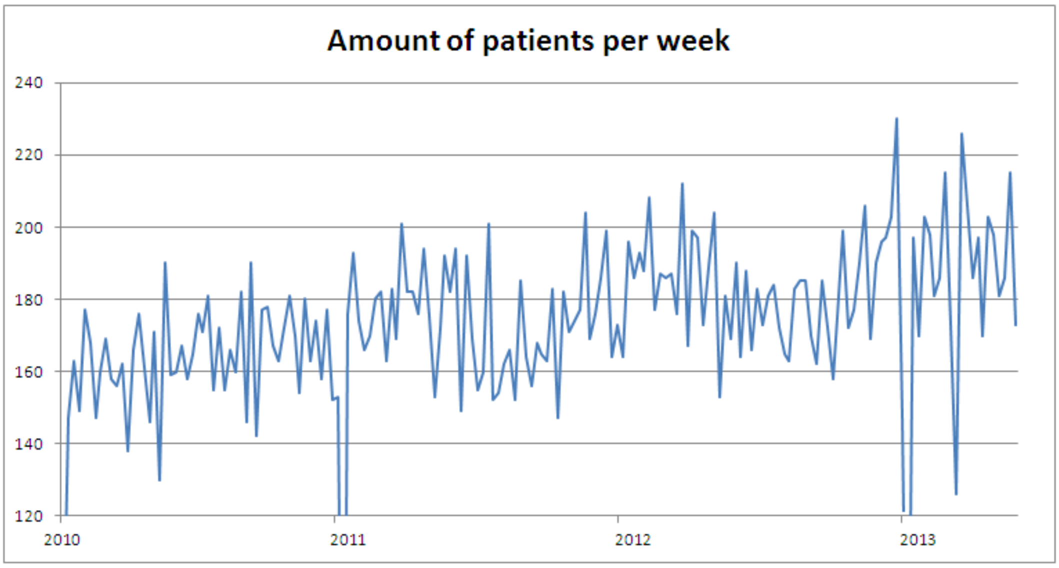

Figure 4: Demand for oncology day care, January 2010 - March 2013.

Table 1: Summarised findings demand analysis

Year	Average per week	Total amount of patients in year	% increase	Standard deviation
2010	162	8431		13,0
2011	171	9043	7,26	14,5
2012	180	9544	5,54	15,9
2013	189	10013 (estimated)	4,91	

The analysis resulted in 3 statements:

- An increasing linear trend of 9 patients per week per year is found.
- Standard deviation has increased with roughly 10% both in 2011 and in 2012.
- Suspicion rises about seasonality patterns. Both in 2011 and in 2012 there is a clear peak in the spring and a decrease of demand during the summer.

4.2. Short term forecast

A multiple regression analysis is applied to come up with a short-term forecasting model to predict the number of patients/week in the near future. The predictor variables are:

- The quartile (to explain any seasonal patterns)
- The year (to explain the upward trend)
- If a week has 4 or 5 working days (to explain the high difference between weeks)

Values with standardised residuals > 2 are seen as outliers and deleted. There are a few weeks with extremely low number of patients. These are often weeks during the Christmas holidays where data was probably inaccurate.

Dummy variables are included for the quartile and the binary variable of 4 or 5 working days. The linear regression showed that quartile 1, 2, and 4 do not have a significant influence on the outcome of the model. That is why only a binary variable for quartile 3 (the summer period) is included.

The outcome of the multiple regression is the following equation:

$$Y = 168{,}12 - 6{,}93 * X1 - 20{,}0 * X2 + 8{,}33 * X3$$

In this equation:

- Y = the dependent variable, the amount of patients in a week
- X1 = a binary variable for quartile 3 (0=no, 1=yes)
- X2 = a binary variable for a week with 4 working days (0=no, 1=yes)
- X3 = a continuous variable for the year , where 2010 = 0.

The equation shows that the coefficients for X1 and X2 are both negative. The fact that the coefficient of X1 is negative and significant means that there are significantly less patients per week treated in quartile 3. The fact that the coefficient of X2 is negative means that in a week with 4 working days less patients are treated. And finally the fact that the coefficient of X3 is positive explains the positive trend of approximately 8,5 patients more per week per year.

We can conclude that both the seasonality and linear trend are confirmed by this regression. The quality of the model can be expressed in R^2. The outcome of the model is an R^2 of 0,35. This means that 35% of the variance in the model is explained by the variables in the model. Overall we are satisfied by the quality of the model. It is hard to come up with other variables that could further increase the quality. The output of the multiple regression is given in Appendix A as well as the checking of the assumptions. The resulting forecasting model will later be used in the mathematical model.

4.3. Treatment Analysis

At the department of oncology day care a lot of different treatments are provided. To get an idea about the real workload of the department we analysed what treatments are provided, which resources are involved in the process and what the treatment times are. When determining the scope of this research project 2 types of appointments were mentioned, intake consultations and all other treatments provided by infusion.

4.3.1. Intake consultation

An intake consultation is held before the chemotherapy starts. It normally takes one hour which includes the whole procedure and one nurse is involved. A chair is not involved because the consultations are done in a separate room. There is one nurse responsible for all the intake consultations during a day so in the current way of working 2 intakes cannot be done simultaneously. The intake consultation is standardised as much as possible which means it is assumed that intake consultations for different treatments all take one hour, despite the fact that some patients ask much more questions than others and need more time.

In the current situation intake consultations are planned at fixed timeslots:

- 10:00-11:00
- 13:30-14:30
- 14:30-15:30

Occasionally there are 4 intakes during one day. When this happens the fourth intake is planned in the timeslot 9:00-10:00. The planning decision on what date to plan an intake depends on when the first treatment is planned. A treatment is planned according to the treatment plan set up by an oncologist. The intake must take place at least one day before the first treatment.

The average amount of intake consultations during recent years is hard to determine because different codes are used for it. The data is not completely reliable and therefore the amount of intake consultations are captured manually for a shorter period from the planning system. In a busy period (May-June, 2013) the amount of intakes was 3,2 per day. In a less busy period (Jan-Feb, 2013) the average amount off intakes was lower (2,6 per day).

4.3.2. Infusion therapy

After the intake consultation a patients starts receiving infusion therapy on different dates. A rest period is often necessary for the patient to recover from the chemotherapy. Depending on the treatment a resting period is often 1 or 3 weeks. The types of resources involved and the treatment time are also dependent on the treatment. The treatment time varies from 15 minutes up to 8 hours.

For these reasons the first step in the analysis of infusion therapy is to determine how often particular treatments are provided. There is no data of applied treatments available. The only relevant registered data is the type of drug used and one treatment can consist of a combination of multiple drugs.

Currently in the Amphia there are 112 different treatments in oncology and 86 in hematology. This amount is constantly increasing due to research results. Both types of treatments are given in the day care centre. In order to determine how many times different treatments are provided the registered drugs in each treatment are analysed. From the combination of registered codes the used treatment schedule can be determined. As an example the following treatment is analysed:

Table 2: Example of registered data of 1 treatment

Date	Patientnumber	Drugs given
1-1-2013	X	12345
1-1-2013	X	45678
1-1-2013	X	67890

The used numbers in the example are fictional.
When a patientnumber is registered multiple times on the same day this means these registrations are all part of the same treatment. This treatment is then analysed by looking at the registered codes. When we add up these codes the sum equals to a particular treatment schedule. Often the applied treatment schedule is named after the used drugs. In the example the name of the used treatment schedule is "AC-Taxol-Trastuzumab". In this way a program is built in Excel that automatically determines the used treatment schedule depending on the used drugs in a treatment.

Due to medical innovation the applied treatments change frequently. Because our goal is get an idea about treatment used today we only analysed data from 2012 and 2013. The problem of different codes and different names used over the years for the same drug made the analysis more complicated. Therefore all different ways to register all different treatment had to be determined. As a result it turned out that for instance 1 treatment schedule has been registered in 5 different ways since 2012. Finally, the analysis resulted in a frequency distribution of all treatment schedules used. For 89,3% of the patients we were able to determine what treatment is given. The result is visualised in Appendix B.

4.4. Resource analysis

At this stage the frequency of used treatment schedules is known for the period January 2012 – March 2013. In order to translate the used treatment schedules into a workload for the department the workload for the relevant resources have to be determined. Relevant resources for all treatments involved are chairs and nurses.

4.4.1. Resource analysis – Chairs

The first relevant resource is the chair. One problem that had to be overcome was that sometimes different treatment times are used for the same treatment schedule. This is due to the fact that some patients have 3 weeks of resting period between 2 treatments and some patients have 1 week of resting period. To overcome this problem probabilities for 3 weeks and 1 week resting periods are determined according to historical data.

The workload for a chair equals the treatment time for a patient. The treatment times of all applied treatment schedules are known. This means that, based on results from the analysis in 4.3.2, the chair utility of any given day can be determined.

Based on treatment times different treatments can be categorised into groups. The groups differ from 15 minutes up to 8 hours. When we calculated the size of the groups of the analysed data we came up with a frequency distribution of the categories. The result of this analysis is given in table3.

Table 3: Categories of treatments based on treatment time.

Treatment time (minutes)	frequency	Probability
15	353	4,51%
30	0	0,00%
60	1062	13,56%
90	509	6,50%
120	1664	21,25%
150	669	8,54%
180	1000	12,77%
210	214	2,73%
240	1222	15,60%
270	39	0,49%
300	861	10,99%
330	62	0,79%
360	84	1,07%
390	4	0,06%
420	86	1,09%
450	4	0,06%

In our mathematical model this probability distribution represents the required chair capacity of an average incoming patient and can be used to estimate the workload of the department.

4.4.2. Resource analysis – Nurses

Besides the chairs the other relevant resource used during all treatments is the nurse. As mentioned in the literature review the utility of this resource is harder to determine because the nursing workload is different for each treatment.

When a treatment starts the first task of the nurse is to bring the patient from the waiting room to a chair. After this the following tasks are performed, all within the first 15 minutes of the treatment:

- Measuring pulse
- Set up the infusion
- Connect the first drug
- Enter all handlings digitally

After the first 15 minutes it depends on the treatment what further actions are required from the nurses. A lot of drugs given by infusion need to start slowly in order not to cause too much pain or an allergic reaction. The times at which the infusion speed can be increased is given in the treatment schedules. The lines need to be flushed between two drugs to prevent a chemical reaction before the drug enters the bloodline of the patient. During some treatments drugs need to be injected using a syringe. At the end of the treatment, the patient is decoupled from the infusion and leaves the day care centre. In short, a nurse is involved in all these treatment steps that take place at various times. As an example the nursing workload of a random treatment of 1 hour is given in figure 5. We define this as the time-phased nursing workload of a treatment.

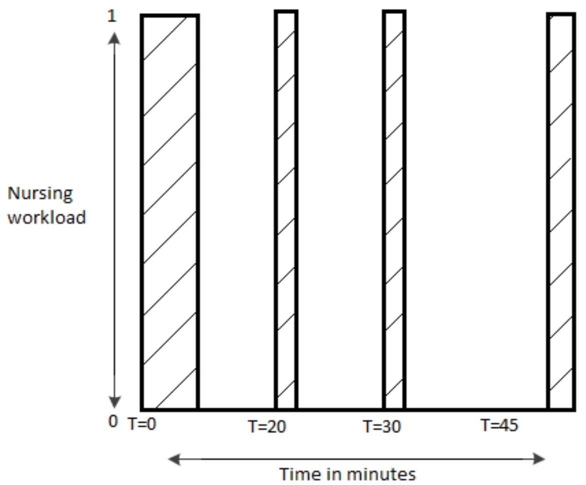

Figure 5: Example of time-phased nursing workload during a random treatment

A qualitative study is done to examine the time-phased nursing workload of the most important treatments by interviewing nurses. 3 different nurses were asked to determine the treatment times for each treatment schedule and the times at which handlings need to be done where nurses are involved. The main purpose of this was to check if the used treatment times for planning treatments are accurate and to get an idea about nursing workload during treatments. An example of an interview is given in appendix C. The outcome of these interviews is an accurate knowledge of the treatment times and the nurse utility during most of the treatments.

In order to give an accurate estimate of the nursing workload the nursing workload of all individual treatments needs to be incorporated. Due to the variety of different treatment schedules (approximately 200) this problem can be dealt with by categorising treatments according to nursing workload. This is also done in a variety of literature studies. After an analysis of the difference in nursing workload we decided to start with one category for all treatments. This means that the following important assumptions apply to all treatments:

- When a patients comes in, 1 nurse is required for the first 15 minutes of the treatment to handle different tasks.
- After the first 15 minutes, 0,125 nurse is required to deal with other activities during the rest of the treatment. In other words, 1 nurse can deal with 8 patients at a time excluding the first 15 minutes of treatment.

The value of 0,125 follows from current practice where, when 2 nurses are on a lunchbreak, the other 2 nurses are responsible for the treatments of a maximum of 16 patients simultaneously. In these breaks no incoming patients are scheduled. This means the workload per nurse per patient is than 1/8 = 0,125.

These assumptions make it able to model the fact that one nurse is responsible for different tasks at the same time. As an example the nursing workload of any treatment of one hour is given in figure 6.

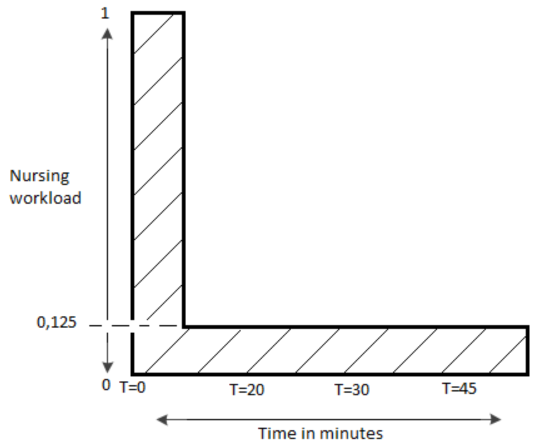

Figure 6: Time-phased workload used for all 1 hour treatments

4.5. Measuring Workload

In the resource analysis we decided to divide the treatments into categories based on treatment times. We also defined the nursing workload for each treatment where we made a difference between the first 15 minutes of treatment and the rest of the treatment. This allows us to come up with a tool to measure the workload of the department during any day.

In the current situation the workload of the department is measured in chair utility. This number does not represent the real workload of the department because often the nurses are the limiting factor. Therefore a measurement instrument is designed that expresses the workload of the department in nursing workload, while taking into account chair utility.

4.5.1. Calculation of workload

In order to give a mathematical representation of the workload the following variables are defined.

T Amount of timeslots
K Amount of chairs
N Amount of nurses
U_t Utilisation of nursing capacity in timeslot t $(t = 1 \dots T)$
R_t Required nursing capacity in timeslot t
A_t Available nursing capacity in timeslot t
P_t Number of patients that are in the second phase of treatment in timeslot t
N_t Number of new incoming patients that start treatment (first phase) in timeslot t
w^p Amount of nursing capacity required per timeslot for one patient during second phase
w^n Amount of nursing capacity required for one incoming patient during the first phase
Y_{nt} Binary variable. 1 if nurse n is working during timeslot t, 0 otherwise
Y_{nit} Binary variable. 1 if nurse n is responsible for an intake during timeslot t, 0 otherwise
Y_{nit} Binary variable. 1 if nurse n is on a break during timeslot t, 0 otherwise
${Y_{tk}}^{New}$ Binary variable. 1 if an incoming patient starts treatment in timeslot t on chair k, 0 otherwise
Y_{tk} Binary variable. 2 if chair k is occupied by a patient at the start of timeslot t, 0 otherwise
O_t Overutilisation of nursing capacity in timeslot t.

The workload of the department is expressed in the nursing workload in every timeslot. An expression of nursing workload is given in formula (1). It is calculated by dividing the required nursing capacity by the available nursing capacity.

$$U_t = R_t / A_t \quad (1)$$

In formula (2) and (3), the available nursing capacity and required nursing capacity are calculated respectively, which are necessary for formula (1).

$$A_t = \sum_{n=1}^{N} Y_{nt} - \sum_{n=1}^{N} Y_{nit} - \sum_{n=1}^{N} Y_{nbt} \quad (2)$$

$$R_t = w^p * P_t + w^n * N_t \quad (3)$$

The available nursing capacity in a timeslot is calculated by the number of working nurses in the timeslot minus the amount of nurses that are in an intake minus the amount of nurses that are on a break. The required nursing capacity depends on the number of patients in the first (N_t) and in the second (P_t) phase of treatment. Here the first phase of the treatment are the first 15 minutes, when the amount of nursing capacity required equals w^n. The second phase of treatment is the rest of the treatment, when the amount of nursing capacity required equals w^p. The values for N_t and P_t are calculated in formula (4) and (5) respectively.

$$N_t = \sum_{k=1}^{K} Y_{tk}{}^{New} \quad (4)$$

$$P_t = \sum_{k=1}^{K} Y_{tk} \quad (5)$$

As can be seen both N_t and P_t are calculated by a summation of the binary variables $Y_{tk}{}^{New}$ and Y_{tk} over all chairs. In formula 6 the overutilization in each timeslot is calculated.

$$O_t = if\ U_t > 1\ then\ U_t - 1, else\ 0 \quad (6)$$

There is overutilization when the value calculated in formula (1) exceeds 1. This overutilization, together with unexpected events, are the main causes for an increase in patient waiting times in the waiting rooms, simply because a planned patient cannot start treatment when there is no nurse available. Therefore this overutilization will later be used in the development of the objective function.

4.5.2. Graphical representation of workload

As a result it is possible to translate the daily planning list into a graphical presentation of workload for any day in the past. The input data required to calculate this are:

- Planning of treatments. Which treatment is planned at which timeslot, including intakes.
- Working shifts of nurses, including breaks.
- Values for constant input parameters w^p and w^n

Using the calculation the daily planning list is translated into a 2 dimensional matrix with timeslots on the y-axis and chairs on the x-axis (time is also on the y-axis in the current planning system). The matrix is than filled with values for $Y_{tk}{}^{New}$ and Y_{tk}. This matrix can then be used to calculate the required and available nursing capacity in every timeslot, using formulas (1-6). A graphical representation of this workload is given in figure 7.

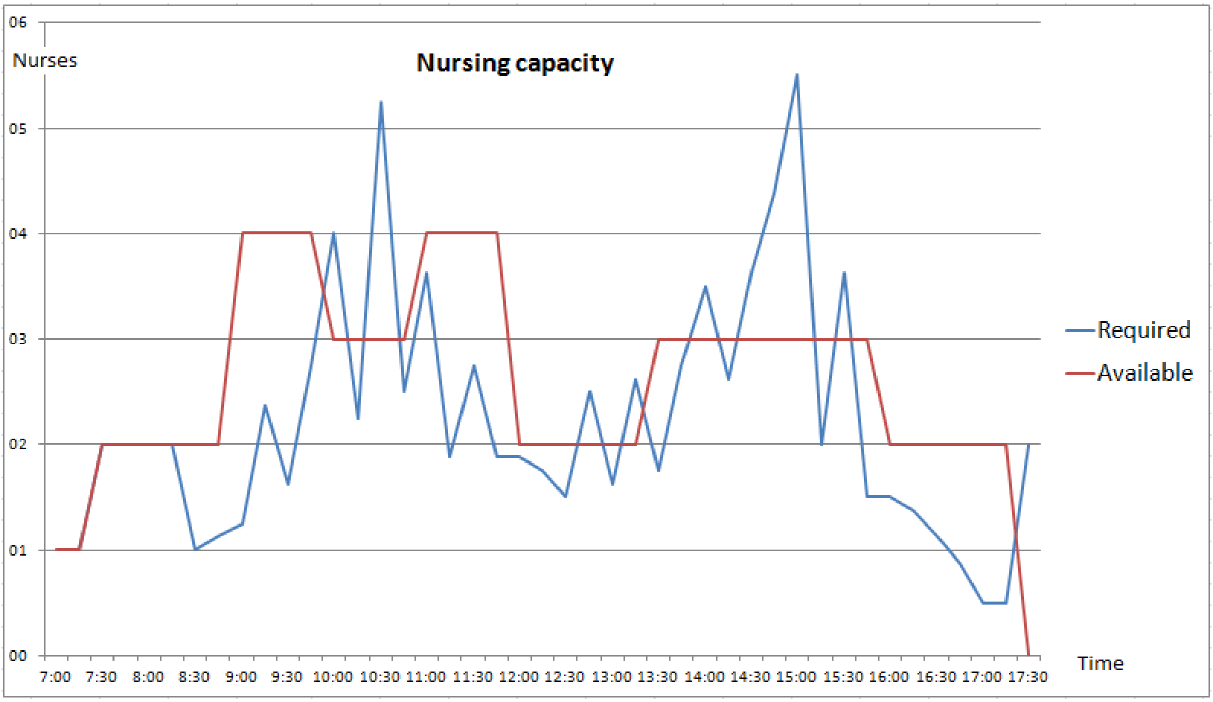

Figure 7: Example of nursing workload on 29-05-2013

This is an example of a day with a clear mismatch between available capacity and required capacity. The highest peaks caused by incoming patients are at timeslots when the available nursing capacity is much less. These peaks automatically lead to longer waiting times for patients and maybe overtime for nurses.

4.6. Conclusions

In chapter 4 the current situation for oncology day care is analysed and quantified. Treatments are categorised according to treatment time and assumptions are made regarding the involved nursing capacity during treatments. This allowed us to develop a measurement tool that translates the daily planning into a graphical representation of nursing workload. The findings and calculations from this measurement tool are used as input for the development of a new planning tool in next chapters.

5. Conceptual model

In this chapter the general idea to capture the planning and scheduling problem in a mathematical model is presented. The relevant solutions from literature are analysed, based on these solutions a conceptual model for the Amphia hospital is developed.

5.1. Models from literature

The literature study showed that research on the operational improvement of oncology day care is scarce. Only 2 studies found actually applied used optimisation techniques to deal with the planning and scheduling problem. The first is the study by Turkcan et al. (2011). The second is the study conducted by Hahn-Goldberg et al. Both studies conclude that the problem is not likely to be solvable by a single optimisation model, queuing model or heuristic. The following information is additional to the literature review in order to give a clear idea about the methods and models used in the two studies found.

Turkcan et al. (2011) define the planning problem as the problem of assigning cycles of treatments to a sequence of days. They designed an integer programming model to assign new patients' treatments to days without changing the plans of existing patients (stage 1). As an input they use a set of new patients and a set of existing patients and solve the problem every Δ days. At stage 2 they solve the scheduling problem which they define as assigning patients to chairs, nurses and appointment times. They designed another integer programming model to deal with the scheduling problem. In this model they solve the scheduling problem for all the treatments known at that time at once. Both resources, chairs and nurses, are considered in the model. Due to the computational complexity of the second integer programming model they designed a third model that only considers the nurses. Finally they developed a heuristic to find appointment schedules in short computation times. This heuristic is similar to the longest processing time (LPT) rule, which is used to minimise the makespan in parallel machine scheduling. The programs are combined in a rolling horizon approach that is used to deal with the planning and scheduling problem. Results show that both the 3 developed integer programming models and the heuristic find feasible schedules that are better than current practice in terms of resource utilisation and patient waiting times.

Hahn-Goldberg et al. solved the planning and scheduling problem in a slightly different way. They use the planning rule that an incoming request must be scheduled right away. Therefore they do not use a method where they wait until all requests are known and create an optimal schedule for these requests. Instead they create an optimal planning schedule based on expected treatments, and call this the offline problem. This schedule is used during the actual planning of incoming treatments, the online problem. An online algorithm is written that assigns treatments to the actual timeslot. If there is a matching slot available the algorithm assigns it to the first available slot. If there is no matching slot available the algorithm calculates an updated template based on already planned treatments and expectations of future treatments to come. The available space in the schedule is reshuffled in order to make room for the incoming request. They measure the performance of the developed tool as the time it takes to complete all treatments on a given day. They compared a few days that actually occurred in the hospital with fictional schedules if their scheduling tool had been used. As a result they conclude there is significant improvement when their tool is used.

5.2. Conceptual model for the Amphia hospital

After the analysis of the current way of working in the Amphia hospital the conceptual model to deal with the problem in the relevant setting can be defined. An important decision that had to be made was to decide if appointments must be scheduled right away or if it is possible to wait until all requests are known. In the current way of working treatments are scheduled right away. Treatments are also not planned ahead because off the risk that a treatment is delayed for one week. The reason for this is when they would plan a 3-weekly cycle ahead, and one treatment is postponed for one week, all planned treatment need to be cancelled and planned again. For this reason we chose to use a similar approach as Hahn-Goldberg et al. where incoming requests are scheduled right away. This means we first solve the offline problem and define this solution as the tactical schedule. This tactical schedule is used during the actual planning of treatments, that is also captured in a mathematical model. Together the two programmes are combined in a rolling horizon methodology that captures the new way of working.

5.2.1. Tactical schedule

Hahn-Goldberg use optimisation techniques to create an offline schedule based on historical data. Due to the available dataset the approach of using historical data to come up with an offline schedule is also suitable for us. However the use of optimisation techniques is discussable. Writing an optimisation tool requires knowledge of a suitable programming language. Turkcan et al. use C^{++} and Hahn-Goldberg et al. make use of COMET. Due to the computational complexity both programmes take a very long time to come up with a solution. When software is written to come up with the best possible schedule all the possible schedules need to be compared and the best schedule is chosen. In our opinion it is too complex to calculate all possible schedules because of the number of possibilities. For instance when you need to plan 30 appointments there are also 164 empty timeslots. For the first timeslot on the first chair we can choose to schedule a treatments or leave it empty. Depending on your previous choice you make a choice for the next timeslot, and so on. Due to the complexity of the optimisation problem we decided to develop a heuristic that comes up with an initial solution and improves this solution step by step. It goes on until improvement is no longer possible. The advantage of using this method is that it is easier to capture in a mathematical model, computational times are much lower and it should still be able to come up with feasible solutions as long as the heuristic is “smart” enough. We define a feasible solution as a schedule that is able to fit in all incoming requests for treatments. A suitable programming language to model this heuristic is Excel, Visual Basic for Applications (VBA). The main advantage in this programming language is that it is very suitable to automate manual tasks. This makes it possible to design a heuristic “by hand” and then to automate this heuristic by writing it in Excel VBA.

5.2.2. Real-Time scheduling

The tactical schedule is used as a guideline in the real-time scheduling of treatments. As in the study of Hahn-Goldberg et al. a programme must be written to determine a suitable timeslot when there is no matching timeslot available anymore. Again, the use of Excel VBA is very suitable for this. This allows us to design scheduling rules and to capture these scheduling rules in a simulation programme. Here the design of these scheduling rules is essential for the quality of the final schedule, for these scheduling rules are used to overrule decisions made in the tactical schedule.

5.2.3. Rolling horizon methodology

A rolling horizon methodology is proposed to capture the development of a tactical schedule and the rules of real-time scheduling in 1 planning tool. The rolling horizon methodology starts by gathering input data for the development off the tactical schedule. The input data necessary are capacity restrictions and historical planning data. The necessary capacity restrictions are the following:

- Working shifts of nurses
- Amount of chairs
- Amount of Intake consultations and the time from which treatments can be planned

The historical planning data determines the amount of treatments and the type of treatments that are expected, based on the forecasting model described in chapter 4.2. The tactical schedule is created for the coming weeks (for instance 8) to initialise the programme. Then the created schedules are used for one week in the real-time scheduling. After 1 week it is checked if the input data to define the tactical schedule needs to be altered, and the tactical schedule that will be used for the next week is calculated again. The real-time scheduling programme is updated by creating 1 new week using the tactical schedule, and the real-time planning starts again for 1 week. At the end of the week input parameters are updated again, etc. In short, a conceptual model to deal with the scheduling problem in the Amphia hospital is defined in the form of a rolling horizon methodology. The resulting conceptual model is depicted in figure 8.

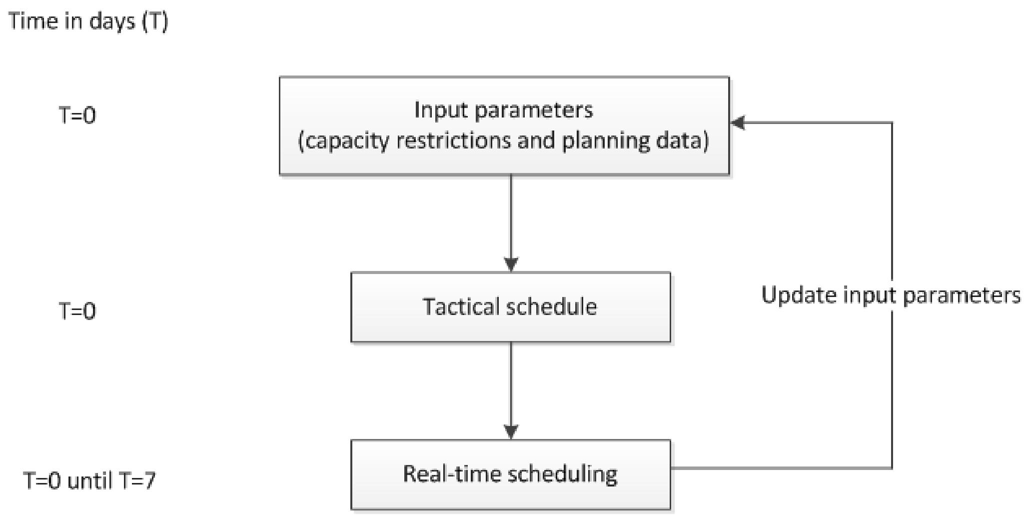

Figure 8: Conceptual model

5.3. Conclusions

In this chapter the conceptual model of our solution is developed. This is done by analysing the used methodologies in literature and the current situation in the Amphia hospital. The choice is made to develop a methodology that uses a tactical schedule in the real-time planning of treatments because treatments must be planned right away, before all treatments for this day are known. Excel VBA is chosen as a programming tool because of the practical advantage of the automation of manual tasks. This is important because a heuristic will be developed both for the development of a tactical schedule and the simulation of real-time scheduling. The design of the heuristics and the modelling in Excel VBA are discussed in the next chapters.

6. Tactical schedule

A heuristic is developed to calculate a tactical schedule depending on input parameters. The design of this heuristic in Excel VBA is explained in this chapter. The heuristic is part of a tool to come up with the tactical schedule. First, the goals of the tool and the heuristic are defined. Then the general steps of the tool are defined and finally the heuristic itself, that strives for a feasible solution, is explained.

6.1. Goals and demands

The demands for the outcome of this tool are important to keep in mind in the design. The most important practical demands for the Amphia hospital are that the tool is easy to use, produces an outcome in short computational times and that the input parameters for the capacity are dynamic. By dynamic input parameters for capacity we mean that the model should be able to run with different input parameters for working shifts of nurses, amount of nurses and amount of chairs. By doing this the tool can also be used by management in capacity planning when, on certain days, the amount of expected patients is higher or lower.

6.1.1. Objective value of heuristic

The heuristic itself should lead to schedules where the overutilization of nurses is reduced as much as possible. This automatically leads to less patient waiting time and a more balanced workload for the nurses. Therefore, when defining the objective variable of the heuristic, the focus is on the occasions where the available nursing capacity is lower than the required nursing capacity and therefore overutilization exists. To calculate the workload for nurses formulas from the measurement tool in chapter 4.5.1 are used. In these calculations the overutilization of nursing workload is calculated in formula (6).

$$O_t = if\ U_t > 1\ then\ U_t - 1, else\ 0 \qquad (6)$$

When these values for all timeslots during a day are summarised, we have a value for the total overutilization during this day. This value is visualised in the graph of chapter 4.5.2 as the sum of the points where the blue line lies above the red line.

However, to incorporate the different effect of 1 very high peak and 2 lower peaks, this value should be squared. For instance if 2 peaks occur (where $U_1 = 1.2$ and $U_3 = 1.2$) The first peak might be dealt with before the second peak occurs (when $U_2 = 0.8$). This causes less patient waiting time than when one peak ($U_1 = 1.4$) occurs. This is why the value for O_t should be squared. Next to this the formula is also multiplied by the number of nurses available in the timeslot because U_t represents a ratio. For instance if $U_1 = 2$ and $A_1 = 1$ this causes 1 timeslot of extra patient waiting time. However when $U_1 = 2$ and $A_1 = 2$ this causes 2 full timeslots of extra patient waiting time. For these reasons the objective value that is used in the decision process of the heuristic is presented in formula (7). The formulas (1-6) presented in chapter 4 are also still relevant in calculation off these values.

$$OV_t = {O_t}^2 * A_t \qquad (7)$$

When all these values calculated in the individual timeslots are summed up an objective value for the total daily schedule is created. This value is calculated in formula (8).

$$OV = \sum_{t=1}^{T} OV_t \qquad (8)$$

The objective of the heuristic should be to reduce this value calculated in formula 8 as much as possible. It should be noted that this value is not minimised because optimisation techniques are not used. This value is used in decision making of the heuristic in order to increase the quality of the schedule. The heuristic continues until improvement is no longer possible. The quality of the resulting schedule is measured in the value of the objective function in formula (8). A limit for this value can be determined to judge if the schedule is "feasible" or not.

6.2. General steps of the tool

As mentioned the heuristic works by improving the schedule until improvement is no longer possible. However before the actual heuristic starts, some general steps must be taken. The tool consists of the following general steps:

1. Gather input parameters from the user
2. Generate an inputlist of expected appointments
3. Generate an initial solution in which all the appointments are scheduled
4. Improve the initial solution

The first 2 steps are necessary to gather all the relevant input parameters. In the 3rd and 4th steps the actual scheduling of expected appointments is done to come up with a tactical schedule.

This chapter describes the "Tactical schedule" step from the conceptual model that is captured in a programming tool following these 4 steps.

Step 1 is necessary to generate a template with all the relevant formulas and capacity constraints in Excel. The following data needs to be entered in order to generate a template and the necessary formulas that are used in later steps.

- The total number of chairs *K*
- The time from which appointments can be planned in the morning
- The time the daycentre closes which is also the maximum end time for all treatments.
- The amount of nurses that are available and the working hours of all individual nurses
- The number of intakes on a day and their starting times
- The number of patients that 1 nurse can monitor in every timeslot, excluding incoming patients.

A template in which all expected appointments will be planned is created based on these input parameters. Also all the relevant formulas that are necessary in future decisions are created here. These are formulas 1 until 8, stated in previous chapters.

In step 2 the list of expected appointments is generated that later need to be planned into the generated template. The only input that is necessary here is the amount of expected patients for the future day. Based on this amount the probability distribution stated in chapter 4.4.1 is used to come up with the amount of treatments from each category that need to be planned into the schedule. The amount of expected patients that is necessary as input for this step can either be determined by management, based on experience, or by the forecasting model developed in chapter 4.2.

Step 3 and 4 are used in the actual scheduling of treatments in the template. Two separate heuristics are developed and written in Excel VBA, one for step 3 and one for step 4. They are explained separately in the next paragraphs.

6.3. Heuristic for the initial solution

In this paragraph step 3 of the tool to come up with a tactical schedule is translated into a heuristic that has been programmed in Excel VBA. Here the goal of this heuristic is to come up with a schedule where all the appointments are assigned to timeslots and chairs. The actual improvement (the alignment with available nurse capacity) off this schedule is done in step 4. For step 3, heuristic 1 is developed, which is also depicted in figure (9).

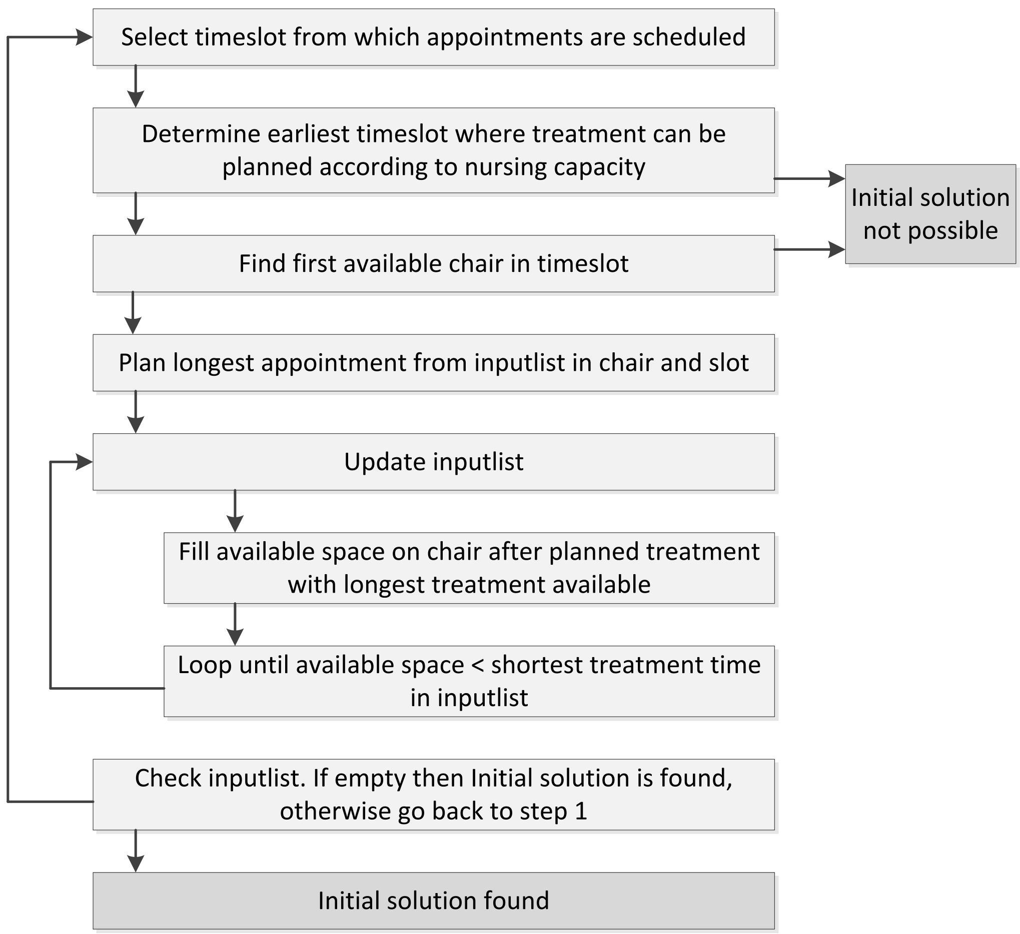

Figure 9: General steps of heuristic 1.

When the outcome of the heuristic is a feasible solution all treatments from the inputlist fit in the designed schedule. If either an available chair or timeslot is not found the heuristic stops and the appointments in the inputlist cannot be planned in the schedule. In this case capacity needs to be increased in order to fit in all treatments. This can be done by running the programme again from step 1. A more mathematical notation can be found in appendix D.

6.4. Heuristic for improvement of initial solution

When an initial solution is found by heuristic 1, step 4 of the tool is used to improve it. In heuristic 1 the scheduling of appointments is not done by incorporating already scheduled treatments or expected treatments to come. Therefore the resulting schedule leads to high peaks in nursing workload. In order to improve the schedule the factors that cause the high peaks in workload need to be determined. As stated in other chapters, the variable that is crucial for the objective function is the utilisation of nursing capacity per timeslot, U_t. This variable is determined by the available and the required nursing workload in each timeslot. The available nursing workload in each timeslot is calculated based in the input by the user. The required nursing capacity is purely caused by how treatments are scheduled by the heuristic. Therefore the function that the heuristic needs to focus on is formula (3).

$$R_t = w^p * P_t + w^n * N_t \qquad (3)$$

Normally the factors w^p and w^n are set as 0,125 and 1 respectively. This shows the determining factor that causes the high peaks in nursing workload is the amount of incoming patients per timeslot. For this reason heuristic 2, that is designed to improve the initial solution, focuses on changing starting times of treatments in timeslots during a peak.

The way in which heuristic 2 works is that it tries to decrease the workload in the timeslot with the highest objective value, OV_{max}. The workload in this timeslot can be decreased by moving an incoming patient in this timeslot somewhere else. An incoming patient can be moved in a lot of different ways. In heuristic 2, 8 different methods off moving an incoming patient are tested. When none off the 8 ways is able to reduce the objective value the heuristic is done and the resulting schedule is the schedule with the best spread in nursing workload that the heuristic could come up with. The general way in which the heuristic works is depicted in figure 10.

The programme works with 2 schedules. This is used to check if a change in the schedule leads to improvements. Before a method is started, the best schedule found thus far is initialised. When the different methods lead to better schedules the best schedule is updated.

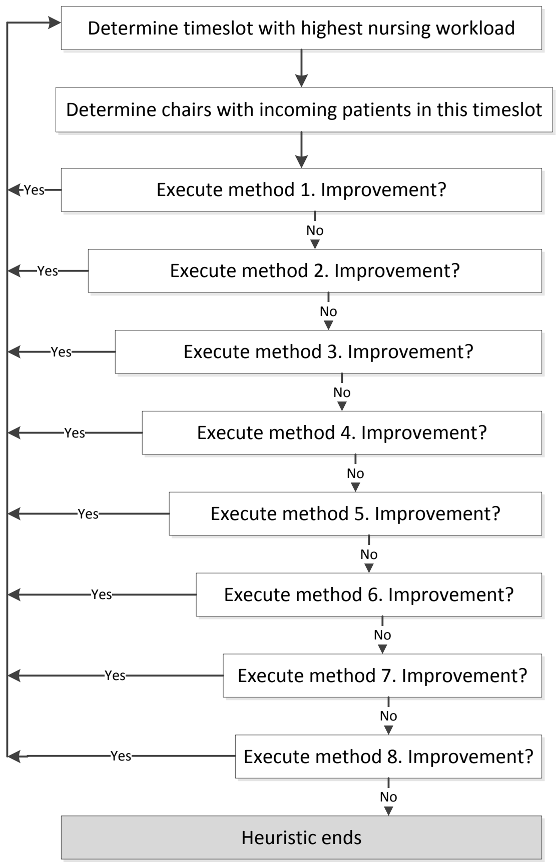

Figure 10: General steps of heuristic 2

6.4.1. Detailed description heuristic 2

8 different ways of rescheduling incoming patients are tried sequentially in heuristic 2. These 8 methods are chosen based on a manual improvement of the schedule. The choices made in this manual improvement are based on a rational analysis of the schedule. Some ways of rescheduling clearly showed more improvement than others and are therefore used in the heuristic.

Method 1

Method 1 moves an incoming patient from the busiest timeslot to one timeslot later, 2 timeslots later, 3 timeslots later, etc as long as the treatments on the chair are finished before the daycentre closes. Next, it checks if the changes made have led to a decrease in the objective value OV. If that is the case then method 1 has led to an improvement of the daily schedule and the method is run again. If the objective value is not decreased other chairs are checked for incoming patients in the busy timeslot. If they also do not lead to an improvement method 1 did not improve the schedule and another way of moving an incoming patient (method 2) is tried.

The way in which the method works is visualised in figure 11. There are three timeslots with an objective value of 113%. The earliest timeslot with this value is at time 12:30. Incoming patients in this timeslot are found on chair 12 and 16. All treatments on chair 12 are moved down until no longer possible. After each shift the resulting OV is compared with the OV before the shift. When the OV is decreased by the shift the best schedule is updated. When all options are checked the resulting OV is compared with the OV before the method is started. If this has led to a decrease in the OV the heuristic starts again in the first step, otherwise the appointments on chair 16 are shifted. If this also does not lead to an improvement method 1 is not able to improve the schedule and method 2 is started.

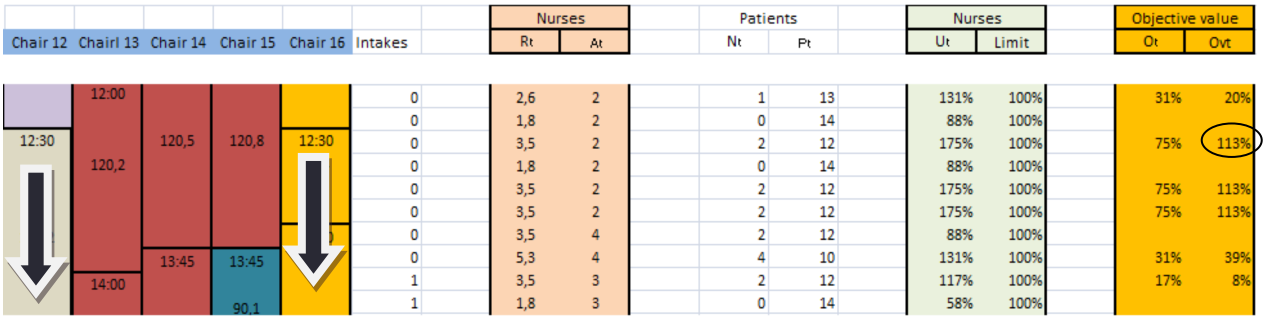

Figure 11: method 1

Method 2

In method 2 rescheduling is done by swapping different appointments on the same chair (figure 12). The method searches for an incoming patient in the busiest timeslot. The chair where the incoming patient starts his/her treatment is used to swap appointments. The last appointment on the chair is selected and moved to the first available timeslot on the chair. The other appointments automatically move to later timeslots to make room. Every time the resulting objective value is compared with the best objective value thus far. After 8 times the swapping is stopped (a chair is never occupied by more than 8 different patients during a day). When the swapping is stopped the initial objective value is compared with the best objective value found by the method. If the best objective value is lower the method has led to an improvement in the daily schedule and method 1 is started again. If not, the method does not lead to an improvement and method 3 is started.

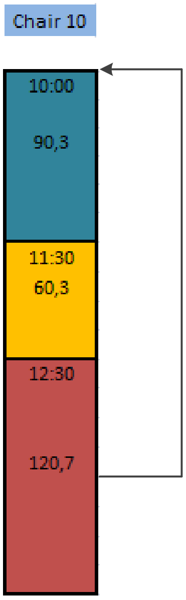

Figure 12: Method 2

In method 2 not all the possible sequences on the chair are tested. If there are for instance 5 different appointments with all different treatment times on the chair, there are $5! = 120$ different sequences in which the chair can be filled. It would be possible to test them all separately but then all the possible sequences need to be determined separately. This increases programming complexity.

Method 3

In this method two blocks are swapped with 1 other treatment where the treatment times of the 2 blocks combined equals the treatment time of the other treatment. The first step is again to determine the incoming patient that causes the high peak in workload. The treatment time of this appointment is added up to the block above the appointment on the same chair. Here this block can be a block of empty timeslots or another treatment. The next step is to search for other treatments in the schedule that have the same treatment time as the combination. The found treatment is swapped with the combination of the two others. Every treatment that has the same treatment time is swapped and every time the resulting objective

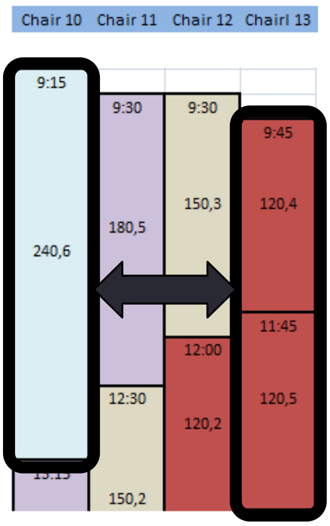

Figure 13: Method 3

value is compared with the best found thus far. When all possibilities are tried it is checked if the method has improved the schedule. If the method has improved the schedule method 1 is started again. If the method did not improve the schedule the next method, method 4, is started.

Method 4

In this method the sum of more timeslots are swapped with a treatment of equal treatment time. Two blocks before the incoming patient and the block itself are selected. Here the 2 blocks can either be a block of empty timeslots or another treatment. If two blocks cannot be found the method ends. These blocks are added up to the treatment time of the incoming patient. A treatment with the same treatment time as the combination is searched and again the two selections are swapped. For the rest the method works the same as method 3. All the treatments that can be swapped are tried and every time the resulting objective value is compared with the best found thus far. When all possibilities are tried it is checked if the method has improved the schedule. If the method has improved the schedule method 1 is started again. If the method did not improve the schedule the next method, method 5, is started.

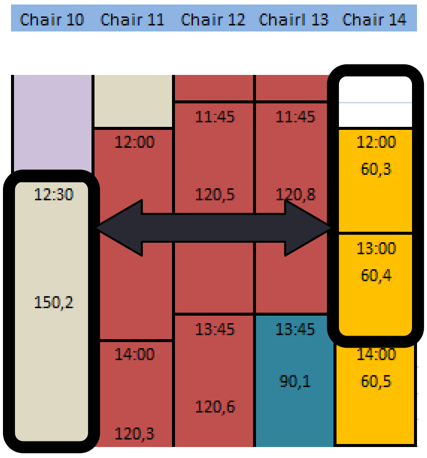

Figure 14: Method 4

Method 5

This method works the same as method 4. However in this method 1 block before the incoming patient, and one block after the incoming patient are added up to the treatment time of the incoming patient. Here, again, the 2 blocks can either be a block of empty timeslots or another treatment. If two blocks cannot be found the method ends. Method 5 also tries al the possible treatments and checks if the swapping leads to improvement of the schedule. If it leads to improvement method 1 is started. If it does not lead to improvement method 6 is started.

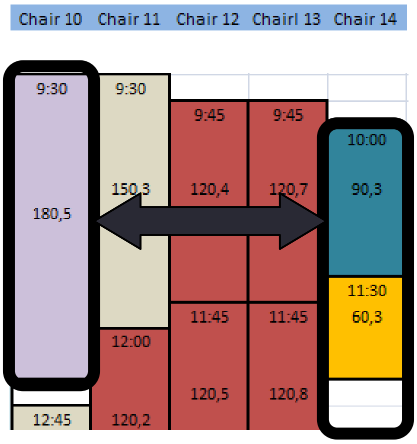

Figure 15: Method 5

Method 6

This method works in a similar way as method 4. Again 2 blocks above, and the incoming patient itself are selected. However in this method empty cells are not taken into account. This means if there is a block of empty cells the empty cells are deleted until another treatment is found. The treatment times of both treatments are added up and swapped with another treatment of the same treatment time. From the swapping part the method is identical to method 4. The only difference is that if it does not lead to improvement, method 7 is started.

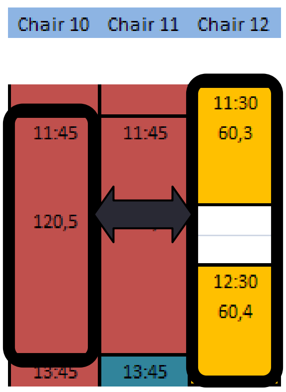

Figure 16: Method 6

Method 7

This method is a combination of method 1 and method 2. It again starts by defining the treatment that causes the high peak. It then moves the last appointment on the chair and moves it before the first, just is in method 2. However this time it is only done once instead of 8 times. The only purpose of this is to move the incoming patient that causes the peak to another timeslot. After this method 1 is started. This means the timeslot with the highest peak is determined again, and the appointment is moved down until no longer possible. When this is done the resulting best schedule is again compared to the best schedule before method 7 started. When it is improved method 1 is started. If it is not improved method 8, the final method, is started.

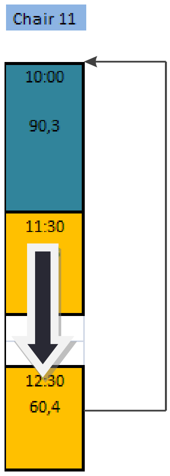

Figure 17: Method 7

Method 8

Method 8 it is the final method and the final hope to improve the schedule. It measures the treatment time of the incoming patient that causes the peak. Next it searches in the schedule for a block of empty timeslots that matches this treatment time. It swaps the treatment time with the found block. So in this method only the treatment that causes the peak is moved somewhere else. When this is done it checks the resulting schedule of before and after the swap. If the schedule is improved, method 1 is started. If it is not improved the heuristic ends. When method 8 finishes without starting method 1 the heuristic has found its best schedule.

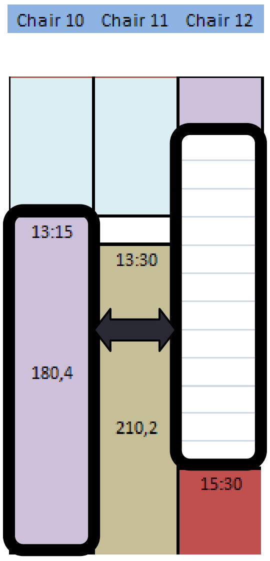

Figure 18: Method 8

6.5. Results

The generated tool is able to generate feasible solutions with different input parameters. An important difference with studies from literature is that we did not chose to minimise makespan. Instead, by using an initial solutions and the swapping of treatments, the resulting schedule always makes full use of the working shifts of nurses. An important effect of this is that mostly treatments are scheduled on for instance 14 instead of 16 chairs. This leaves 2 chairs available in the real time planning of patients in order to deal with the variety in treatments. The difference between the two ways of modelling is visualised in figure 19 and 20. The arrows show the difference in effects.

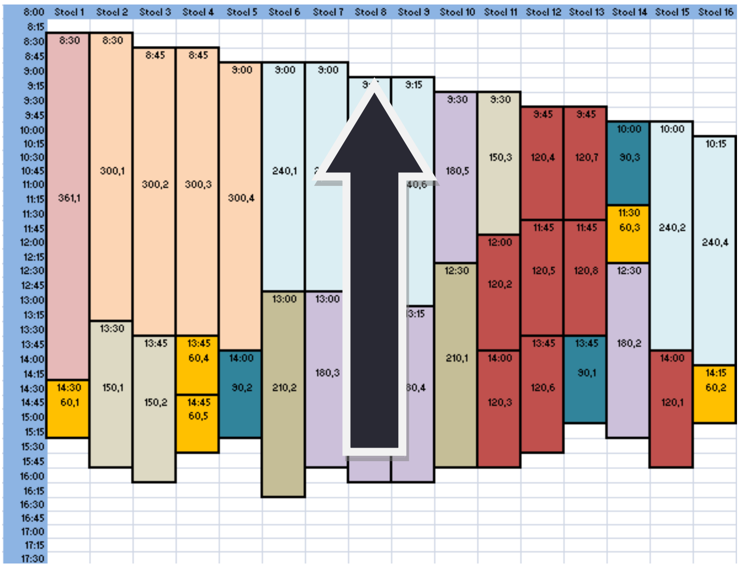

Figure 19: Resulting schedule from study from literature, where makespan is minimised

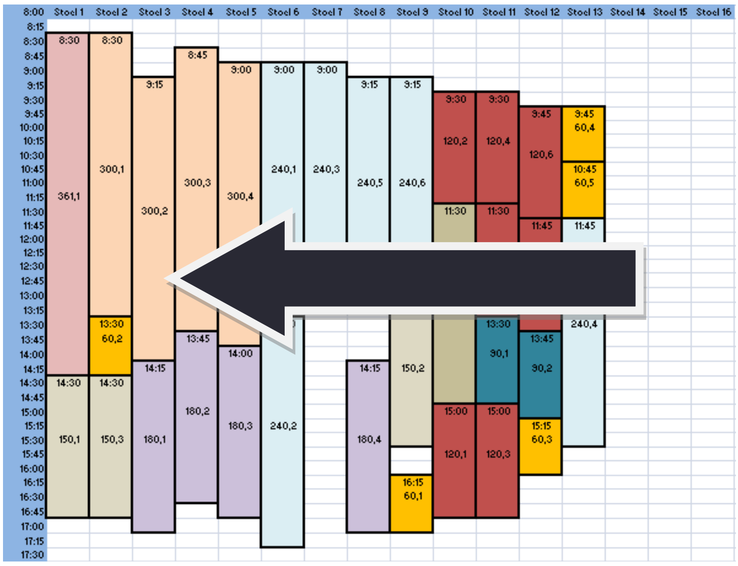

Figure 20: Resulting schedule from our programme, resulting in less chairs occupied

6.6. Conclusions

In this chapter the tool to come up with a tactical schedule has been explained. Using different input parameters the tool is able to generate schedules with acceptable values for the objective value. When the user decides the values are not acceptable he can increase capacity and run the tool again. The generated tactical schedule will be used in the real-time planning of patients, which is also the next step in the conceptual model. The Planning rules for the real-time planning of patients are explained in chapter 7, together with a simulation of the real-time planning.

7. Real-time scheduling

This chapter focuses on the real-time scheduling phase of the conceptual model. This phase is translated into a programme that can be used for scheduling patients. The programme uses the tactical schedule as input and plans according to this schedule together with some developed scheduling rules. The programme and the planning rules are explained in this chapter. The developed programme is also used in a simulation of the scheduling process to assess the quality of the total solution.

7.1. Scheduling Programme

A programme is developed in Excel to assess the quality of the new way of planning. As mentioned in the conceptual model of chapter 5 the scheduling programme is continuously used, incoming requests for treatment are scheduled right away. Once a week the programme is updated. Every time the programme is updated the number of expected patients for the new week needs to be estimated. This can either be done by management or by using the forecastmodel designed in chapter 4. Depending on the outcome off the tactical schedule, management can decide that the available capacity needs to be decreased/increased. When a final tactical schedule for the week is determined the scheduling tool is updated. A new week is generated based on the tactical schedule and all formulas and relevant dates. Now this generated week can be used in the real-time scheduling of treatments.

Two characteristics are important when a treatment needs to be scheduled. The preferred date and the treatment time. These are entered in the programme. The programme searches for the available options on this day, and the 2 nearest other days. The planner chooses one of the generated options if any are available. So far the scheduling of patients is straightforward. At a certain moment however, a request arises that no longer fits in one of the options. Therefore planning rules are developed that make sure a treatment can still be scheduled. When a treatment comes in that no longer fits in one of the reserved blocks, the available space is not reshuffled, as this would influence the tactical schedule that is generated and applied for this week. Available blocks of different treatment times or other days are used to fit in the request. There is also the available space on chair 15 and 16 that can be used for these requests.

The following scheduling rules are developed for the scheduling procedure. They should be followed sequentially. This means when a request comes in the treatment should be scheduled in one of the reserved blocks that fit. If this is not possible for some reason, the treatment should be scheduled on a different day. If this is also not possible a smaller block with empty space under it should be searched for, etc.

1. Schedule on preferred date in available blocks
2. Schedule in an available block on preferred day -1 or +1.
3. Schedule on preferred date on smaller block with empty timeslots under it.
4. Schedule on preferred date in block of 30 minutes longer
5. Schedule in available empty space between treatments
6. Schedule on the available empty chairs (mostly 15 and 16)
7. Overrule the reserved blocks and choose timeslots by hand

Scheduling rule 2 is the first alternative way of scheduling. This rule is chosen above others in order to lower the variety in amount of patients per day. It is not possible for all patients to be planned on alternative days. Some treatments have a stricter schedule than others. This option should be discussed by the planner with the responsible oncologist. In scheduling rule 6 the empty chairs are used. The presumption arises that making use of this available space should be suspended as long as possible. Then, if all the scheduling rules are not able to find available timeslots, the planner can overrule the reserved blocks and decide for him/herself where to schedule the appointment. In order to assess the quality of this new way of scheduling a simulation of the scheduling procedure is run.

7.2. Simulation of scheduling procedure

A simulation programme is developed in Excel VBA that schedules incoming requests according to the 7 designed planning rules. As an input to run a simulation of the scheduling process the following aspects should be known:

- Tactical schedule
- Probability of last-minute cancellations
- Incoming requests for scheduling

The tactical schedule is obtained by running the programme described in chapter 6. In the simulation this tactical schedule is used to generate new weeks, with relevant formulas for capacity etc. The probability of last-minute cancellations is important to take into account because this increases the required capacity. Many patients need to have blood samples taken the day before treatment in order to assess their physical health. For instance the haemoglobin value measures the concentration of red blood cells in the blood. Chemotherapy treatments often cause this value to decrease, which has a negative influence on the physical resistance of the patient. When the value is assessed to be too low, a chemotherapy treatment is postponed in order to let the patient recover. An oncologist can also decide the patient needs a blood transfusion. This treatment is also provided intravenously on the oncology day care department.

When, on a particular day, 35 patients were treated and 4 were cancelled on the day before the treatment, 39 patients had to be fit in the available schedule for this day. A cancelled treatment is digitally documented in the patient file but not in the planning system of the department. Therefore, in order to get an estimate of the probability of cancellation, a time study is done where the amount of cancellations on every day over a period of 8 months is counted. The faxes that were send to the pharmacy that stated the amount of cancellations for each day are gathered. This resulted in an average probability of 4,6% that a random treatment is cancelled. The influence of the type of treatment is not taken into account as a predictor variable in this analysis.

A Poisson distribution is used to create a list of incoming patients for the simulation programme. To test if a Poisson distribution is a good representation of real income flow of treatments the Chi-square test is done. The test is summarised in Appendix E. The outcome showed that the use of a Poisson distribution is appropriate. The reason to use a Poisson distribution and not real historic planning data is because the historic data is already influenced by the planners. Therefore the real treatment days can deviate from the preferred dates. The preferred dates of incoming patients are randomly generated.

7.2.1. Scheduling rules

The actual simulation of a period of scheduling is done in Excel VBA. The input required from the user is an average amount of patients per day, λ. A poisson distribution is used to generate the amount of incoming requests per day. When the amount of patients per day is known the probability distribution is used to generate a treatment time for each request. In this way an inputlist of treatment with a preferred day and a treatment time is created. The treatments in this list are scheduled according to the developed planning rules 1-7. The way in which a choice is made by running the simulation programme is explained for each planning rule. For each rule assumptions are made in order to capture the scheduling procedure in a simulation model.

Rule 1: Schedule on preferred date in available blocks

When a block is available on the preferred day one of these blocks is always chosen. The actual choice is random, each possibility has an equal probability.

Rule 2: Schedule in an available block on preferred day -1 or +1

When a block on the preferred day is not available options on other days are searched for. Currently the assumption is made that treatment days can only deviate 1 day from the preferred day and that it is possible for all type of treatments to be scheduled on one of these days. The probability to choose for day -1 or day +1 depends on the amount of available block on each day. It is calculated as follows:

$$P(choose\ day-1) = \frac{\#\ free\ blocks\ on\ day{-1}}{(\#\ free\ blocks\ on\ day{-1})+(\#\ free\ blocks\ on\ day{+1})}$$

$$P(choose\ day+1) = 1 - P(choose\ day-1)$$

When an alternative day is chosen the choice for the actual block is random again.

Rule 3: Schedule on preferred date on smaller block with empty timeslots under it.
Rule 4: Schedule on preferred date in block of 30 minutes longer
Rule 5: Schedule in available empty space between treatments

For these scheduling rules the same assumption as in rule 1 applies. When different options on the preferred day are found each option has an equal probability of being chosen.

Rule 6: Schedule on the available empty chairs

When none of the previous scheduling rules can be used to plan a treatment, the empty chairs are used. The procedure starts by searching for an available timeslot to start treatments according to nursing working at that time. A (maximum) value is used as a limit. When nursing utility is smaller than this value the timeslot is available to schedule an incoming patient. When a treatment of bigger than 240 minutes comes in the procedure starts searching in the morning and moves down. When a treatment of smaller or equal to 240 minutes comes in the search starts at the end of a day and moves up. This is because when a long treatment is scheduled in the morning, it normally finishes after the break when nurses are again available to start new treatments. All free chairs are searched for possibilities.

Rule 7: Overrule the reserved blocks and choose timeslots by hand
When incoming patient cannot be scheduled using any of the previous rules, the scheduling can still be done by choosing an available timeslot manually. Any timeslot that has enough empty timeslots after it can be chosen. In the simulation of the scheduling procedure this is incorporated by stopping the simulation procedure. The treatment is manually scheduled and the simulation is continued.

7.3. Performance measurement of the simulation

The resulting schedules of the simulation should be compared with real historic schedules using the same characteristics for the period. The goal of our tool is to come up with schedules that lead to a better spread in nursing workload. The objective value OV, calculated in formula 8 is used as an objective value to be reduced as much as possible. However the quality of the model cannot be easily interpreted by this value. Therefore the quality of the schedule is measured in the amount of time that nursing utility is smaller than 100%, nursing utility is between 100% and 120%, and finally the time that nursing utility is higher than 120%. Naturally the first value should be as high as possible and the second and third values should be as low as possible.

Besides these values the performance of the schedule can be translated in the waiting time for the patients. Here the assumption is made that the maximum utility of nursing capacity = 100%. This means that whenever the required capacity is higher than 100%, nurses do not work more efficient and are not able to deal with this higher workload. This means that when the maximum nursing workload of 100% is reached, the remaining workload is passed on to the next timeslot. This can lead to overtime of nurses. The formulas to calculate patient waiting time are the following.

$$TU_t = U_t + P_{t-1} \tag{9}$$

$$P_t = if\ TU_t > 1\ then\ (TU_t - 1) * A_t, else\ 0 \tag{10}$$

$$TW = \sum_{t=1}^{T} P_t \tag{11}$$

Where
TU_t = Total nursing utilization in timeslot t
U_t = Utilization of nursing capacity in timeslot t (before limit of 100% is applied)
P_{t-1} = Workload that is passed on from the previous timeslot due to the maximum of 100%
TW = Total patient waiting time during the day.

When the value for TU_t is known for a certain timeslot, the resulting workload that is passed on to the next timeslot can be calculated using formula (10). This amount of overutilization multiplied by the number of nurses gives the amount of waiting time caused by the workload in this timeslot. All these values for the individual timeslots are added up in formula (11) in order to give an estimate for the total resulting patient waiting time during the day.

7.4. Simulation results

The results of our simulation are compared with real historic planning data. The sets of incoming patients and results are adjusted in such a way that an objective comparison between the simulation results and the real planning results can be obtained.

The real planning results are adjusted in the following way:

- All 15-minute treatments are deleted. In the planning results they were scheduled at the end of the day, but in reality the patients came on different times. The real times are not known and therefore they are deleted. 15-minute treatments are also not incorporated in the simulations.
- When treatments did not fit in the schedule anymore they were cut up and divided over different chairs. These treatments are also deleted, otherwise they are seen as incoming patients in the measurement tool. In the simulation tool they are mentioned as treatments that cannot be scheduled

The set of incoming patients in the simulation is generated by the programme. This set is altered/generated in the following way:

- The amount of treatments on each day are generated using a Poisson distribution. This allows us to incorporate the variability in amount of treatments between different days.
- The probability of cancellations is incorporated in the total number of patients. This probability is 4,6% for all treatments. Therefore the total amount of incoming patients is multiplied by 1,046 in the simulations.
- The type of treatments and the dates are generated using the known probabilities. The probability for each treatment follows from historic data, and is given in table 3.
- The incoming patients arrive on random dates with equal probabilities. This allows the occupation of other dates to be incorporated in the decision making.

The quality of the developed scheduling tool depends on many factors in the decision making process of the tool. The rules applied in the creation of the tactical schedule and the real-time planning of treatments are already explained in the previous chapters. However the simulation allows us to test different settings in the programme. One important setting that is tested is how many blocks are scheduled in the tactical schedule. When this amount is low, more chairs are empty in the real-time scheduling of appointments. This makes the decision making in the real-time scheduling more important. When the amount is high the amount of space on empty chairs is reduced much more. This makes the decision making in the creation of the tactical schedule much more important. For these reasons 3 different methods are developed in the creation of the tactical schedule. The methods are based on the rounding of amount of treatments for each category that need to be scheduled in the tactical schedule. The 3 methods are:

1. RoundDown method: The amount of treatments per category in the tactical schedule is rounded Down.
2. RoundNormal method: The amount of treatments per category in the tactical schedule is rounded normally (< 0,5 is rounded down, ≥ 0,5 is rounded up)
3. RoundUp method : The amount of treatments per category in the tactical schedule is rounded up.

7.4.1. Simulation of busy period

The first simulation is done for a "busy" period. The historic data that is used for this busy period is May – June 2013. The average amount of treatments in this period (without 15-minute treatments) was 35 patients per day. This means that for the tactical schedule 35 treatments per day are scheduled. In the real-time planning a λ = 35*1,046 = 36,6 is used to generate the amount of incoming patients per day according to a Poisson distribution. By multiplying the probability of last-minute cancellations is also incorporated. The results from the 3 used simulation methods are given in the following tables 4, 5 and 6

Table 4: Simulation results using the RoundNormal method in a busy period

RoundNormal method						
	Patients		Nursing Utility (Hours)			Waiting time per patient(Hours)
Day	Scheduled	Not scheduled	<100%	100% - 120%	>120%	
1	44	3	7,5	0,75	2,25	0,56
2	41	0	7,75	1,25	1,5	0,26
3	41	0	7,5	1	2	0,49
4	37	0	8,5	1,25	0,75	0,11
5	33	0	9	1,25	0,25	0,08
6	39	0	8	1,5	1	0,20
7	36	0	8,5	0,5	1,5	0,18
8	33	0	9	1	0,5	0,12
9	31	0	10	0,25	0,25	0,02
10	36	0	9	0,75	0,75	0,11
11	37	0	8,5	1,5	0,5	0,09
12	36	0	8,75	0,75	1	0,14
13	38	0	8,75	0,75	1	0,19
14	37	0	8,5	1	1	0,08
15	36	0	9	1,5	0	0,05

The results using the RoundNormal method show there seems to be a relationship between the amount of patients and the waiting time per patient. Figure 21 shows the relationship is exponential.

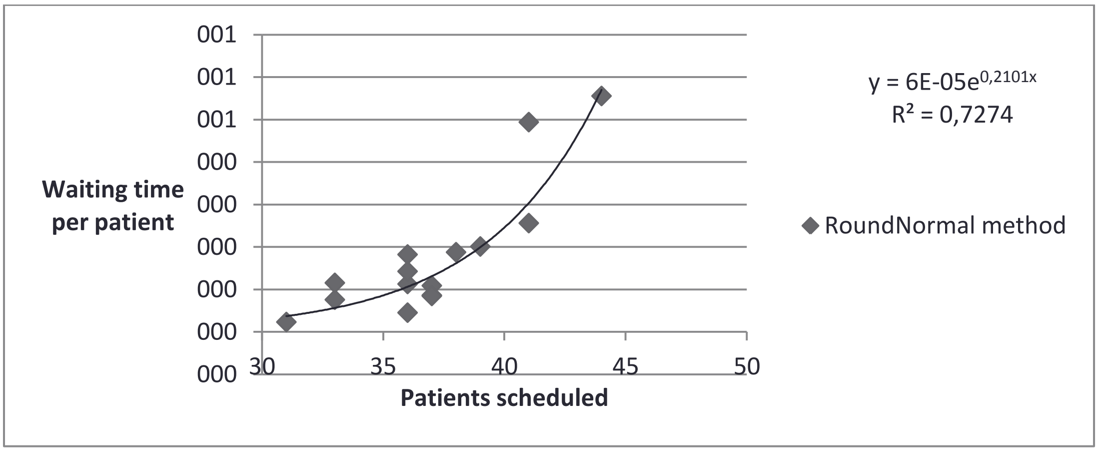

Figure 21: Exponential relationship between the amound of patients scheduled and the resulting waiting time per patient

The R^2 value of 0,73 shows a good model fit. However the amount of data used does not allow us to conclude that the relationship is true. The graph confirms the idea from practise that once a schedule has reached its limit every extra patient leads to a high increase in waiting time per patient.

Table 5: Simulation results using the RoundDown method in a busy period

RoundDown method						
	Patients		Nursing Utility (Hours)			Waiting time per patient(Hours)
Day	Scheduled	Not scheduled	<100%	100% - 120%	>120%	
1	39	1	7	1	2,5	0,51
2	41	0	7	1,5	2	0,55
3	35	0	8	2	0,5	0,19
4	31	0	9,5	0,75	0,25	0,07
5	41	0	7	1,25	2,25	0,34
6	36	0	7,5	2,5	0,5	0,15
7	39	3	7	0,75	2,75	0,51
8	36	0	8,5	1	1	0,18
9	38	0	8	1,75	0,75	0,20
10	39	0	7,75	2	0,75	0,20
11	32	1	8,75	1,5	0,25	0,13
12	28	0	10,25	0,25	0	0,00
13	36	0	8	2,5	0	0,14
14	40	0	7,25	2	1,25	0,22
15	44	0	6,5	0,75	3,25	0,66

Table 6: Simulation results using the RoundUp method in a busy period

RoundUp method						
	Patients		Nursing Utility (Hours)			Waiting time per patient(Hours)
Day	Scheduled	Not scheduled	<100%	100% - 120%	>120%	
1	40	1	7	1,25	2,25	0,43
2	39	1	7	2	1,5	0,42
3	35	0	7,75	1,75	1	0,12
4	37	0	8,5	1,5	0,5	0,09
5	34	0	8,5	1	1	0,18
6	40	1	7,25	1,25	2	0,48
7	34	0	8,5	1,5	0,5	0,09
8	32	0	9	1,5	0	0,06
9	33	0	8,25	1,25	1	0,15
10	31	0	9,75	0,75	0	0,01
11	34	0	8,5	1,25	0,75	0,14
12	33	0	8,25	1,75	0,5	0,09
13	35	0	8,5	2	0	0,05
14	41	0	7	1,75	1,75	0,40
15	37	0	7,75	1,5	1,25	0,30

When the results from the 3 methods are compared we conclude that the RoundNormal method performs best. The first important indicator that tells this is the ability to generate schedules that fit all the incoming treatments. Using the RoundNormal method only 1 schedule was not able to fit all incoming treatments, however demand on this day was extraordinary high (47 patients). Using both the other methods resulted in 3 schedules that were not able to fit in all treatments. It seems that the point where the schedule is full is reached earlier in the RoundUp and the RoundDown method. The second important indicator for the quality of the resulting schedules is the total amount of waiting time per patient. This is 2,67 hours (all days added up) for the RoundNormal method, 4,07 hours for the RoundDown method and 3,01 hours for the RoundUp method. Therefore it can be concluded that the RoundNormal method performs best.

The simulation results are compared with real planning data. As mentioned earlier, this data needs to be manually altered so it can be compared with our simulation results. All 15-minute treatments are deleted and cut up treatments are counted as treatments that do not fit in the schedule. When treatments do not fit in the schedule the schedule is not feasible. Ten days in the “busy” period are analysed manually and the results are given in table 7.

Table 7: Real planning results in a busy period

Real planning results						
	Patients		Nursing Utility (Hours)			Waiting time per patient(Hours)
Day	Scheduled	Not scheduled	<100%	100% - 120%	>120%	
1	39	1	8,5	0	2	0,31
2	32	3	8,75	0,5	1,25	0,11
3	33	1	8,25	1,5	0,75	0,20
4	38	5	8,75	0,75	1	0,50
5	35	2	8,5	0,5	1,5	0,20
6	29	1	8	0,75	1,75	0,27
7	31	5	8,75	0,75	1	0,11
8	31	0	8,75	0,5	1,25	0,09
9	31	3	9,25	1	0,25	0,08
10	28	4	9,75	0,25	0,5	0,07

When the results from reality are compared with our simulation results the following conclusions can be drawn:

- Only for day 8 the schedule was feasible. For the other days many treatments needed to be cut up in order to fit in the schedule, even though the average amount of patients per day is lower (35,2).
- The total amount of waiting time per patient is 1,53 for 10 days. This would be 2,29 for 15 days.

During the analysis of May and June 2013 it turned out that only 3 schedules where feasible. The cutting up of treatments is an accepted procedure to deal with treatments that do not fit in the schedule. When this is done the amount of patients in reality does not correspond with the amount of patients in reality. In practice this has led to situations where 16 chairs are occupied in the schedule but in reality 20 patients were present for treatment.

7.4.2. Busy period with increased capacity

The simulation results show that the amount of resulting patient waiting is still significant for some days. In an attempt to decrease these values capacity can be increased. Simulations are run using 2 was of increasing capacity:

1. Add more nursing capacity
2. Add extra chairs

In the previous simulation the following nursing work shifts are used:
Nurse 1: 7:00 – 15:30
Nurse 2: 7:30 – 16:00
Nurse 3: 9:00 – 17:30
Nurse 4: 9:00 – 17:30
In a new simulation with increased nursing capacity the following work shifts are used:
Nurse 1: 7:00 – 16:30
Nurse 2: 7:00 – 16:30
Nurse 3: 8:30 – 18:00
Nurse 4: 8:30 – 18:00

Using these shifts the working hours for each nurse are increased from 8 to 9 hours a day. It means nursing capacity is increased by 12,5%. Again, λ = 35*1,046 = 36,6 is used for the generation of the set of incoming patients. The results are given in table 8. The RoundNormal method is used to determine the amount of treatments in the tactical schedule.

Table 8: Simulation results using the RoundNormal method in a busy period with increased nursing capacity

Busy period with increased nursing capacity						
	Patients		Nursing Utility (Hours)			Waiting time per patient(Hours)
Day	Scheduled	Not scheduled	<100%	100% - 120%	>120%	
1	38	0	8,75	1,75	0,5	0,07
2	32	0	9,75	1,25	0	0,02
3	31	0	10	1	0	0,02
4	33	0	9	1	1	0,20
5	36	0	8,75	1	1,25	0,26
6	33	0	9,5	1,5	0	0,04
7	38	0	9	1,25	0,75	0,16
8	41	0	8,75	0,5	1,75	0,37
9	35	0	8,75	2	0,25	0,10
10	36	0	9,25	1,75	0	0,04

Increasing nursing capacity clearly has a positive impact on the workload of the department. Not once was the simulation tool not able to schedule a treatment. This is caused by the fact that more patients can come in at the same time. For instance in the morning 3 or 4 patients can come in 8:30 instead of 2, with the old working shifts. The later closing time of the department also increased chair capacity by 16*2 = 32 timeslots. The sum of waiting times per patient is 1,29 for 10 days, which equal 1,94 for 15 days. This value is roughly 25% less than the total sum using the same settings and lower nursing capacity. A graph with the resulting estimated exponential equations is given in figure 22. Here the results of the busy period with the RoundNormal method, increased nursing capacity, and reality are depicted. On the X-axis the amount of patients is depicted and on the y-axis the amount of average waiting time per patient. The resulting schedule from reality performs worse because the amount of waiting time increases earlier. When increasing the nursing capacity the model gave the best results.

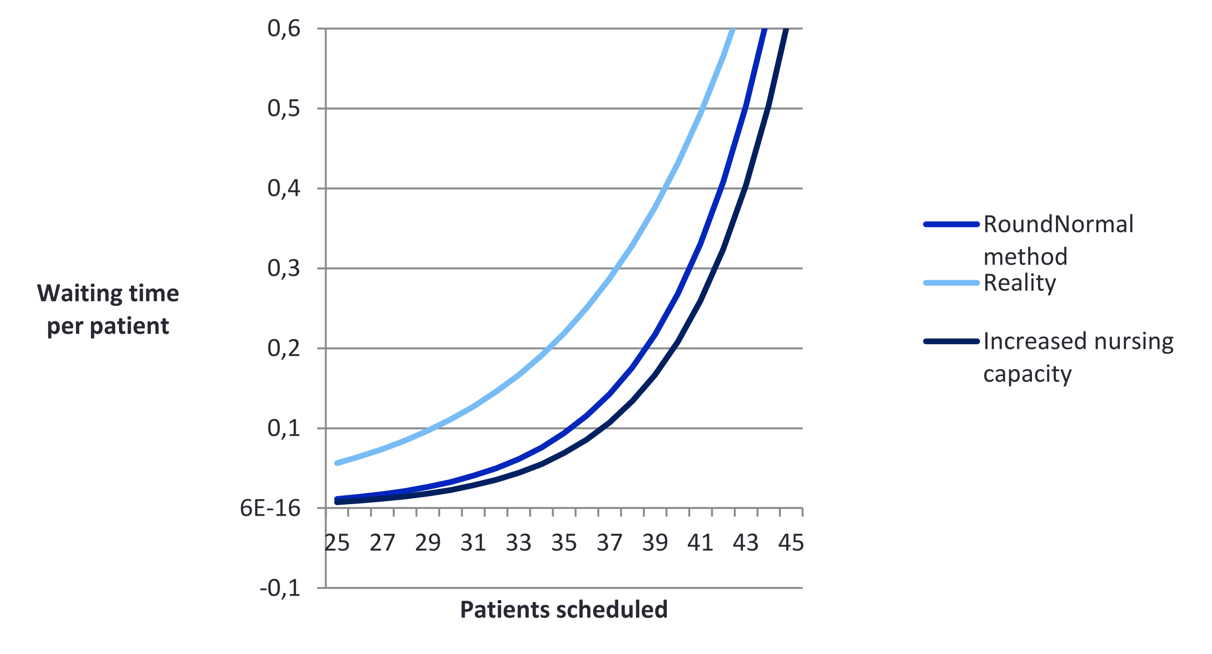

Figure 22: Estimated exponential equations for 3 methods

In the second simulation the capacity is increased by increasing the amount off available chairs from 16 to 17. The used working shifts for the nurses are the same as in the first simulations. The tactical schedule resulting from programme 1 is exactly the same as in the previous simulation with similar working shifts. This is because the chair utility is decreased to the left, and chair 15, 16, and 17 are not relevant in the tactical schedule. They become relevant in the decision making process of programme 2, the simulation programme. The results from the simulation are given in table 9.

Table 9: Simulation results using the RoundNormal method in a busy period with increased chair capacity

Busy period with increased chair capacity						
	Patients		Nursing Utility (Hours)			Waiting time per patient(Hours)
Day	Scheduled	Not scheduled	<100%	100% - 120%	>120%	
1	31	0	10	0,5	0	0,01
2	36	0	8,5	1	1	0,23
3	36	0	9	0,25	1,25	0,15
4	34	0	9,5	0,75	0,25	0,04
5	36	0	9,25	0,75	0,5	0,04
6	40	0	7,75	0,25	2,5	0,50
7	39	0	8	1	1,5	0,28
8	32	0	8,75	1,5	0,25	0,09
9	36	0	8,25	1,25	1	0,15
10	33	0	9	1	0,5	0,07

The most important effect off using an extra chair is that the probability that a feasible schedule can be created is increased. In our simulation, due to the extra chair, it was always possible to generate a feasible solution. The only difference in the decision making process compared with the first simulation is that one extra chair is used. The use of this chair has no influence on earlier decisions. The sum of waiting times for all days is 1,57 for 10 days, which equals 2,35 for 15 days.

7.4.3. Simulation of calm period

For the busy period our simulation results show that our new way of scheduling has a positive influence on the spread in workload. The main difference is in the ability of generating feasible schedules. We also want to analyse the differences in a calm period, when the average amount of incoming patients is lower.

For the generation of incoming patients λ = 28*1,046 = 29,3 is used in the simulation. Again, the RoundNormal method is used in the simulation. For the real planning data one week in July and one week in August are used. The average amount of patients per day in this period was 28. The results are given in table 10 and 11.

Table 10: Simulation results using the RoundNormal method in a calm period

Calm period, simulation results						
	Patients		Nursing Utility (Hours)			Waiting time per patient(Hours)
Day	Scheduled	Not scheduled	<100%	100% - 120%	>120%	
1	33	0	8,5	1,75	0,25	0,09
2	33	0	8,75	1,75	0	0,04
3	28	0	10,25	0,25	0	0,00
4	28	0	10,25	0,25	0	0,00
5	26	0	10,25	0,25	0	0,01
6	24	0	9,75	0,75	0	0,02
7	27	0	10	0,5	0	0,02
8	23	0	9,25	1	0,25	0,12
9	31	0	9,5	1	0	0,03
10	33	0	9,25	1,25	0	0,05

Table 11: Real planning results in a busy period

Calm period, Real planning results						
	Patients		Nursing Utility (Hours)			Waiting time per patient(Hours)
Day	Scheduled	Not scheduled	<100%	100% - 120%	>120%	
1	21	3	10,5	0	0	0,00
2	25	3	10,25	0	0,25	0,01
3	24	1	10	0,25	0,25	0,01
4	27	1	9,25	1	0,25	0,07
5	21	4	10	0	0,5	0,04
6	28	3	9,75	0,5	0,25	0,04
7	28	3	9,25	0,75	0,5	0,04
8	27	1	10,25	0,25	0	0,00
9	30	1	8,5	1,25	0,75	0,07
10	26	0	9,5	0,75	0,25	0,03

The first aspect that should be mentioned is that still the real planning data show a lot of days with infeasible schedules. Apparently in the current way of planning the cutting up of treatments also needs to be used when there are less patients. In this situation it does not really lead to problems because the average waiting time is very low, so the nurses should be able to deal with extra patients. The simulation results show only feasible schedules with also low patient waiting times.

7.5. Conclusions

In this chapter the real-time scheduling phase of the conceptual model is discussed. A new scheduling tool with relevant scheduling rules is developed in Excel 2010. A simulation programme is written in Excel VBA in order to analyse the results for this new way of scheduling. It turned out that, especially in busy periods, our newly developed way of scheduling treatments performs better than the current way of working. The current way of working hardly ever is able to deliver feasible schedules, where our programme was able to generate 14 out of 15 feasible schedules using the RoundNormal method. In terms of patient waiting time the performance is similar. The RoundNormal method performs better than the other 2 methods in terms of waiting time and generating feasible schedules. According to the simulation results there seems to be an exponential relationship between the amount of scheduled patients and the waiting time per patients. Using the RoundNormal method, the critical value for amount of patients lies roughly around 40. When this amount is reached the schedule is full and every extra patient leads to a significant increase in patient waiting time. For the calm period generally the same conclusions can be drawn. Patient waiting times are low both in reality and in our results but in reality the schedules are hardly ever feasible. The fact that infeasible schedules are used makes a big difference in a busy period when all chairs are constantly occupied. It leads to situations where more patients are present for treatment than there are chairs available.

8. Implementation

This chapter focusses on the practical issues of the new way of scheduling treatments in the oncology day care department. Recommendations are made regarding the implementation of the new way of planning. Here the characteristics of the Amphia hospital are central. Recommendations regarding the usage of the tool, the improvement of input data, and general improvements of the new way of working are defined.

8.1. Implementation in current practice

The resulting products of this master thesis are two programmes that together can be used in the new way of scheduling patients. Programme 1 is used to generate tactical schedules, programme 2 is used to facilitate the real-time scheduling of patients. Both programmes are run in Excel 2007 or Excel 2010 using the written programmes. The tactical schedule needs to be executed at most once a week. This can be done by the management of the department. Based on the expected amount of patients in a future week and the resulting tactical schedule, management can decide to increase the available capacity of chairs and/or nurses and run the model again. When the available capacity for the future week is determined, the resulting tactical schedule can be used in the real-time scheduling of patients. The generation of the tactical schedule should be under the responsibility of the managers of the department. The management can run the programme in Excel and use the resulting schedule in other software.

In our solution the real-time scheduling of patients is done in Excel. However in reality the real-time scheduling is done in the planning application of the hospitals electronic system. A new planning application should be created that allows planners to keep working in the hospitals electronic system. In this application the different timeslots should be reserved for different types of treatment according to the tactical schedule. When a request for an incoming patient comes in the planners determine an appropriate timeslot according to the designed scheduling rules. However the planners should also be able to overrule these reservations when none of the defined planning rules provides a solution.

8.2. Closing the gap between theory and current practice

The simulation results can differ from the results in reality due to some practical issues. The first factor that can cause a difference is the probability distribution for the different categories. This distribution is determined based in historic data from the last 1,5 years. Changes in treatments plans due to research results and wrong declarations of treatments can be a cause for a difference between the probability distribution and reality. In our simulation we assume that the probability distribution is correct. Therefore a new data analysis should be done (for instance every 6 months) in order to update the probability distribution.

The second factor that causes a difference between theory and current practice is the assumption of deterministic treatment times. In our model we assume that a treatment starts and finishes exactly the time that it is scheduled. In reality these times will be different due to the late arrival of patients, physical reactions during treatments, etc. Therefore, when future research is done on the topic, stochastic treatment times and starting times should be incorporated in the calculation of the resulting workload for the department.

The third important factor that should be incorporated are other relevant resources that influence the planning of the department. In the current situation these are the pharmacy and physician of the department. The pharmacy is responsible for the on time delivery of the required drugs. In our simulation model we assume that all drugs are delivered on time. An easy extension of the model would be to incorporate a probability that drugs are not on time. A fraction of the patients has an appointment with the physician of the department before their treatment starts. This appointment influences the possibilities for starting a treatment. In our model we assume the choice for starting a treatment is leading, and that an appointment with the physician does not necessarily take place right before the treatment starts. It means that in our model we allow that a patient has to wait for 15 minutes between the appointment with the physician and the start of the treatment. In future research the model can be extended by incorporating the capacity of the physician. A probability that a random patient needs an appointment with the physician can be incorporated according to historic data.

8.3. Conclusions

For the implementation of our developed solution in current practice the two developed programmes need to be incorporated in the current way of planning and scheduling treatments. Management should be responsible for the generation of tactical schedules in Excel and the translation of the schedules in the current planning tool. The planners are responsible for the real-time scheduling of patients and should make choices based on the developed scheduling rules.

In order to close the gap between theory and current practice, future research should focus on the updating of input data, incorporate stochastic treatment times and the incorporation of other relevant resources.

9. Conclusions

In this chapter the developed research questions are answered. The main findings are used to answer the sub questions sequentially. In the end this leads to an answer for our main research question.

9.1. General conclusions

This master thesis studies the problem of planning and scheduling treatments in oncology day care. The problem of planning and scheduling treatments concerns the assigning of treatments to a particular treatment day and timeslots. The amount of previous studies that have focussed on this problem is scarce and the studies found conclude that the problem cannot be solved by a single optimisation model, queuing model, or heuristic. Two relevant studies were found that developed solutions for the problem in a similar setting. Turkcan et al. (2011) developed a mathematical model in which they captured the problem. They solved the problem using the objective of minimising the patients treatment delays. Hahn-Goldberg et al. (2012) developed a method using an offline and an online solution. Their objective was to minimise the makespan. Here the makespan is the amount of time that is necessary to complete all treatments taking into account relevant capacity constraints. The main difference between the 2 studies found is that the first generates a solution when all treatments that need to be scheduled are known. The second study uses the scheduling rule that a treatments must be planned right away, before all treatments are known. Because of the current situation in the Amphia we used the second approach, where an incoming patient needs to be scheduled right away. According to the results from the literature study relevant research questions are developed and answered during this master thesis.

The following set of sub questions was developed because there was no objective measurement of development in demand for the oncology day care department over a long term period.

- *How has demand for oncology day care developed over the long term (years)?*
- *How does a short term forecast (Weeks) for demand look like?*

Historical data is analysed in order to get an idea of demand developed from 2010 until 2013. The analysis showed there is a linear increasing trend in the amount of patients treated per week. It also showed that seasonality patterns are relevant in the demand and the standard deviation is increasing. To answer the second question a multiple regression model is developed to come up with a short-term forecasting model. The predictor variables in this model are the year, the quartile and the fact that a week has 4 or 5 working days. The model has an an R^2 of 0,34 which means that 34% of the variance in the model is explained by the variables in the model.

The second set of sub questions was developed in order to obtain an objective measurement of the workload for oncology day care.

- *Which treatments are given and what resources are necessary for each treatment?*
- *How does the workload for nurses and chairs for individual treatments look like?*
- *How does the workload for the department as a whole look like during a day?*

The treatments are categorised according to treatment time in 15 categories each with its own probability. Assumptions for chair and nurse utilization are made in order to develop a measurement tool to measure the workload of the department. As a result the workload of the department is measured in the utilization of nursing capacity. The measurement tool showed a big difference between the available nursing capacity and the required nursing capacity in current practice.

The next set of sub questions is set up to develop a conceptual model and to come up with a mathematical model to calculate a tactical schedule that can be used in real time scheduling.

- *What general problem solving techniques found in literature can be applied to the situation in the Amphia hospital?*
- *How to define the objective of the mathematical model?*
- *How do the workload for resources look like when the solution of the model is applied?*

The developed conceptual model incorporates three main steps in order to deal with the planning and scheduling problem. The three steps are the gathering of input parameters, the calculation of a tactical schedule and the real-time scheduling of patients. A mathematical model is built in Excel VBA to calculate a tactical schedule according to input parameters. The model is dynamic in the sense that capacity of chairs and nurses are adjustable. Also the amount of expected patients is adjustable. A heuristic is developed that strives for an improvement of the schedule according to the objective value, which focusses on a reduction in the overutilization of nursing capacity. The heuristic follows an iterative process and goes on as long as a reduction is possible. The resulting tactical schedule can be used in the real-time scheduling of patients.

The final set of sub questions is generated in order to develop a new procedure for the real-time scheduling of treatments.

- *How does an arrival distribution of patients look like according to historical data?*
- *How can the process of scheduling patients be simulated?*
- *How do the results of the simulation tool look like and what are the benefits compared to the current way of working?*

For the arrival process of patients a Poisson distribution is used the generate the amount of patients per week. To generate a relevant category the probability distribution is used. New scheduling rules are developed to assign patients to timeslots. This new way of planning is modelled in a simulation tool in Excel VBA in order to test the quality of the new way of working. Three different methods to generate the tactical schedule are tested in the simulation. It turned out that the RoundNormal method performed best. 14 out of 15 planning days generated feasible schedules. In a similar period in reality only 1 out of 10 days the schedule was feasible. In terms of patient waiting time the two methods performed similar. This means that in reality, where treatments that do not fit in the schedule are cut up, it leads to much more waiting time than in our simulation model. By increasing nursing capacity in a busy period the resulting patient waiting time is reduced by 25% in a busy period. Increasing chair capacity does not lead to a reduction in patient waiting time, but increases the probability that the result from the real-time scheduling is feasible. In a calm period the comparison between the simulation results and reality are similar. The main difference is again in the fact that the current way of scheduling is not able to generate feasible schedules, where our simulation is able to generate feasible schedules for all simulated days. The resulting patient waiting times are again comparable.

9.2. Final statements

We conclude this master thesis with the assessment of the simulation results while incorporating the assumptions made. Our results show that the new way of planning and scheduling is able to generate feasible schedules that lead to less patient waiting time and less spread in nursing workload, especially in busy periods. A negative consequence of the new way of working is that the patient has less influence on the day of treatment. However we believe that patient service will improve using the new way of planning and scheduling because a patient will start his/her treatment on time and the nurses are able to spend more time on the actual treatment of patients.

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Appendix A: Multiple regression output and assumptions checking

Multiple regression output in Excel (in Dutch)

Gegevens voor de regressie	
Meervoudige correlatiecoëfficiënt R	0,592
R-kwadraat	0,350
Aangepaste kleinste kwadraat	0,339
Standaardfout	14,427
Waarnemingen	176

Variantie-analyse

	Vrijheidsgraden	*Kwadratensom*	*Gemiddelde kwadraten*	*F*	*Significantie F*
Regressie	3	19283,224	6427,741	30,884	0,000
Storing	172	35797,316	208,124		
Totaal	175	55080,540			

	Coëfficiënten	*Standaardfout*	*T- statistische gegevens*	*P-waarde*	*Laagste 95%*	*Hoogste 95%*
Snijpunt	168,118	1,943	86,546	0,000	164,284	171,953
Dummy Quartile 3	-6,933	2,671	-2,595	0,010	-12,205	-1,660
Dummy 4 working days	-20,009	4,214	-4,748	0,000	-28,327	-11,692
Year	8,327	1,101	7,562	0,000	6,154	10,501

Checking of the assumptions for multiple regression

Assumption 1: Values for residuals are normally distributed

To check this assumption the values for the residuals are divided in 5 categories and a histogram is created that shows the frequency of the categories:

Category	Frequency	*%*
-2	3	1,71%
-1	24	13,71%
0	121	69,14%
1	23	13,14%
2	4	2,29%

Figure A: Frequency of categories

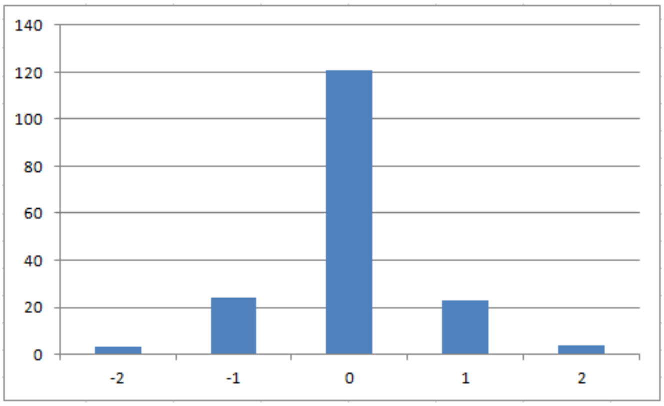


Figure B: Histogram of categories

The frequency distribution shows that the residuals are very clearly normally distributed. In a perfect normal distribution 68,2% lies within the “0 category”. In our analysis this is 69,14%. In a perfect normal distribution 95,4% lies within one of the 3 categories -1, 0 or 1. In our analysis this is 95,99%. Therefore we conclude that there is no reason to believe that the residuals are not normally distributed.

Assumption 2: Variance of residuals is constant, no heteroscedasticity in residual plot.

To check if this assumptions holds a scatterplot of the standardised residuals is given in figure C. From this plot we conclude that variance does not decrease or increase during time. Therefore we conclude that this second assumption is also met.

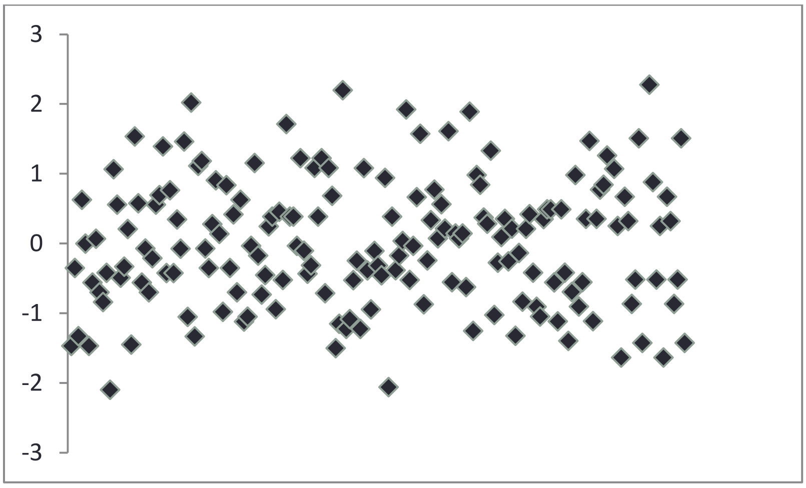


figure C: Scatterplot of standardised residuals

Assumption 3: Values of residuals are independent.

This assumption can also be checked from the scatterplot in figure C. It shows no patterns of increase or decrease of residuals during time. Therefore we conclude that this assumption is also met.

Assumption 4: Relationship between variables is linear.

To check this assumption a scatterplot of the relevant X variables and Y variable is given. The only relevant X variable to check is “year” because the other variables are binary variables. The plot is given in figure D.

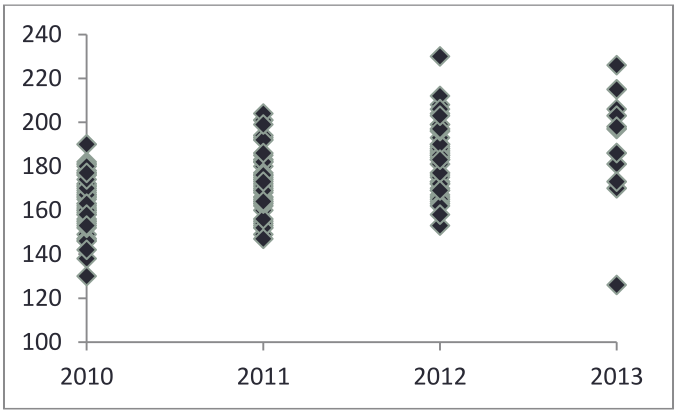
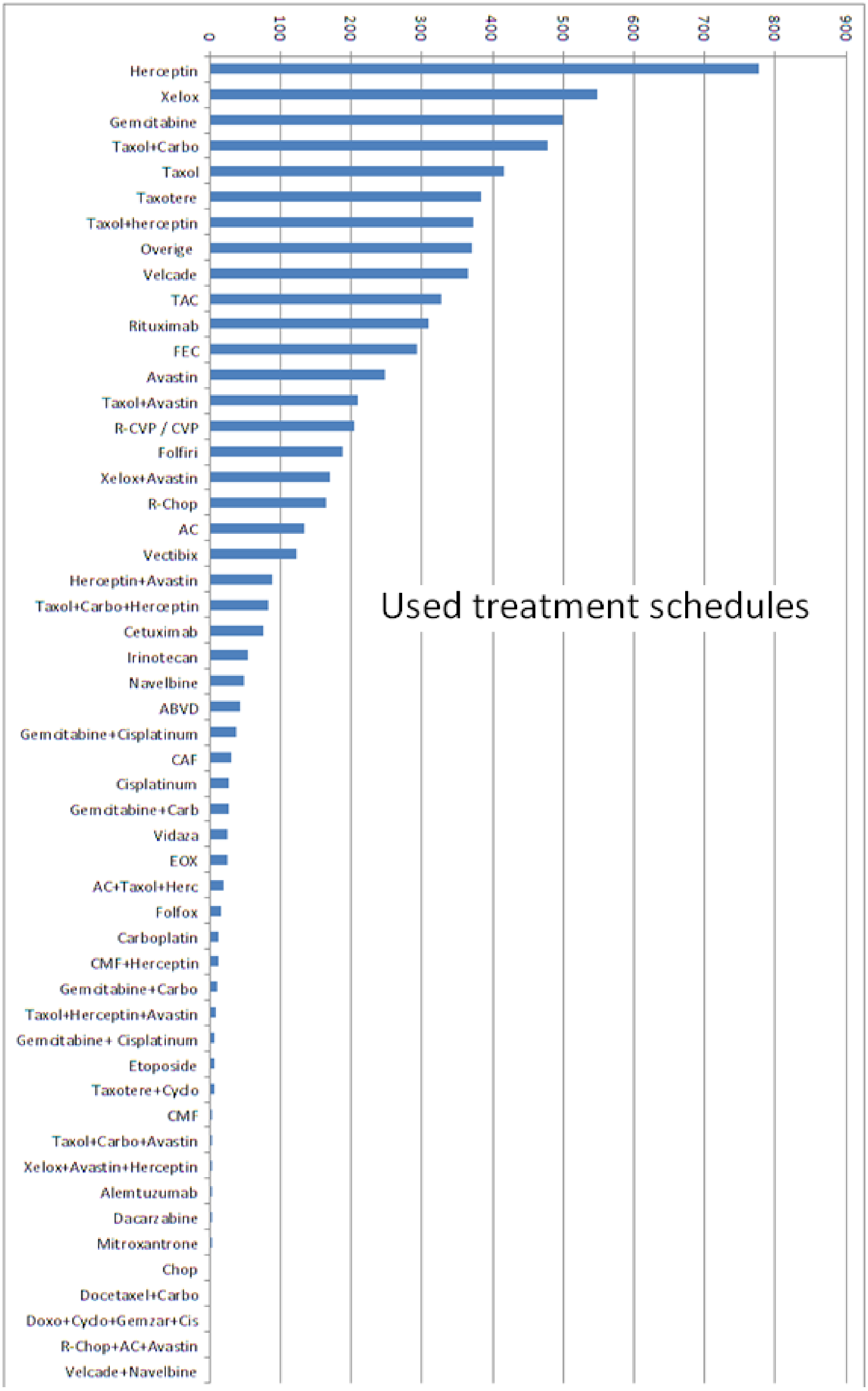


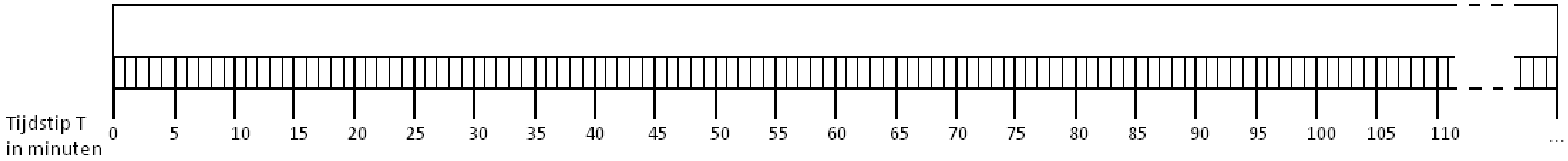
Figure D: X-variable “year” plotted against the Y-variable “number of patients/week”

There is no reason to believe the assumption of linearity is not met given this plot. Therefore we conclude that all 4 assumptions for applying multiple aggression are met and it is allowed to use it.

Appendix B: Analysis of frequency of used treatment schedules



Appendix C: Example of interview in Dutch



Activiteiten

Toedieningsschema …

1. Patiënt naar stoel
2. Lijnen doorspoelen
3. Pols en tensie meten en invoeren
4. Patiënt aanprikken en infuus aansluiten
5. Anti-emetica toedienen (push of infuus)
6. Chemo aanhangen
7. Zorgactiviteiten registreren op cow
8. Snelheden verhogen
9. Infuus verwijderen en patiënt naar huis

Ingevuld door …

Datum …

Totale tijdsduur behandeling (tijd die patiënt op de stoel zit) …

Verschil in tijdsduur tussen de eerste gift en daarna? ..

Voorbereidingstijd …

Hoe groot is het risico dat behandeling uitloopt door allergische reactie? …

Hoe groot schat je de belasting in, vergeleken met andere behandelingen op een schaal van 1 – 5? (aantal handelingen dat je uit moet voeren, gegevens invoeren, etc.)

0 0 0 0 0
Laag Hoog

Appendix D: Mathematical representation of heuristic 1

Heuristic 1 is designed to come up with an initial solution for the tactical schedule. This heuristic is written in Excel VBA. The following notation gives an idea about how the heuristic works in Excel VBA. This is not how the actual programme looks like.

Notation

T	Amount of timeslots
T^s	The timeslot from which appointments can be planned
K	Amount of chairs
N	Amount of nurses
U_t	Utilization of nursing capacity in timeslot t $(t = 1 \dots T)$
R_t	Required nursing capacity in timeslot t
A_t	Available nursing capacity in timeslot t
P_t	Number of patients that are already in a chair in timeslot t
N_t	Number of new incoming patients that start treatment in timeslot t
w^p	Amount of nursing capacity required per timeslot for one patient after the first timeslot
w^n	Amount of nursing capacity required for one incoming patient during the first timeslot
Y_{nt}	Binary variable. 1 if nurse n is working during timeslot t, 0 otherwise
${Y_{tk}}^{New}$	Binary variable. 1 if an incoming patient starts treatment in timeslot t on chair k, 0 otherwise
Y_{tk}	Binary variable. 1 if chair k is occupied by a patient at the start of timeslot t, 0 otherwise
C_{max}	The limit of nursing capacity for planning another patient in a timeslot
O_t	Overutilization of nursing capacity in timeslot t.
OV_t	Value for objective function in timeslot t
OV_{max}	Timeslot with the highest objective value
OV	Objective value for the total schedule on a day
L	Set of appointments in inputlist
L_{max}	Appointment from inputlist with longest treatment time in minutes
S_k	Available space in minutes after a treatment on chair k
L^A	Appointment from inputlist with longest treatment time **and** is smaller than S, in minutes
L^S	Appointment from inputlist with shortest treatment time in minutes

Heuristic 1

1: Set $T_1 = T_s$
2: Set $t = 0$
3: Set $k^{free} = 0$
4: Set $t = 1$
5: Set $k = 1$
6: **Do**
7: **If** $U_t < C_{max}$ **then**
8: **Set** $t^{free} = t$
9: go to step 13
10: **else** $t = t + 1$
11: **end if**
12: **until** $t = T + 1$
13: **If** $t = t + 1$ go to step 32
14: **Do**
15: **If** ${Y_{tk}}^{New} = 0$ and $Y_{tk} = 0$, **then**
16: **Set** $k^{free} = k$
17: go to step 20
18: **end if**
19: **until** $k = K + 1$
20: **If** $k = K + 1$ go to step 32
21: Plan L_{max} starting in timeslot t^{free} and chair k^{free}
22: Delete L_{max} from inputlist L
23: **Do**
24: Determine S_k
25: Plan L_A on chair k
26: Delete L_A from inputlist L
27: **Until** $S_k < L_S$
28: **If** $L = empty$ **then**
29: go to step 32
30: **else** go to step 1
31: **end if**
32: end sub

The heuristic starts by setting the timeslot from which appointments can be planned as the first timeslot. After the value for some variables are set in step 2 until 5. In step 6 until 12 the first timeslot where an appointment can be planned according to nursing capacity is determined. In step 14 until 19 the first empty chair is determined. Now an available timeslot and an available chair are known. If either an available chair or timeslot is not found the heuristic stops and the appointments in the inputlist cannot be planned in the schedule. This is assured by step 13 and step 20.

In step 21 the appointment from the inputlist with the longest treatment time is planned in the available timeslot on the available chair. The list is updated in step 22. In step 23 until 27 the available space after the planned appointment on the same chair is filled by the longest available appointment in the inputlist until the available space is smaller than the shortest appointment in the inputlist.

In step 28 the inputlist is checked. If it is empty heuristic 1 is done and an initial solution is generated. If it is not empty the heuristic loops back to step 1. The heuristic stops when either the initial solution is generated and the inputlist is empty or when an available timeslot or chair cannot be found and no initial solution can be generated.

Appendix E: Test if Poisson distribution can be used for incoming requests

A poisson distribution is used to generate incoming patients for the simulation of the scheduling procedure. To check if a Poisson distribution can be used a Chi-square test is performed. The amount of patients from feb-2013 until may-2013 is used in the test. During this period the average amount of patients per day was 41, this means $\lambda = 41$.

H_0: There is no significant difference between the observed and expected frequencies

If H_0 is not rejected there is no reason to believe a poisson distribution may not be used.

Critical value in Chi-square test: $\chi_c^2 = \sum \frac{(O_i - E_i)^2}{E_i}$
In this formula:
O_i are the observed frequencies
E_i are the expected frequencies
c = degrees of freedom = amount of different outcomes – 1

We tested for the possible outcomes from 1 until 80. This means c = 80 – 1 = 79

Using a 5% significance level the critical value for $\chi_{80}^2 = 102$.

For the data from feb – may the $\chi_c^2 = 75{,}94$.

Here $\chi_c^2 < 102$.

Therefore H_0 is not rejected and there is no reason to believe a Poisson distribution cannot be used.