TÉCNICO LISBOA

# A simulation model to support implementation of a combined walk-in and appointment system for CT scanning in a radiotherapy centre

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Thesis to obtain the Master of Science Degree in

**Biomedical Engineering**

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## Preface

This report is the final element of my studies to become an MSc. in Biomedical Engineering. Before I got a graduation assignment I was not sure whether its emphasis should be on solving a practical problem or doing research, since I am interested in both. The assignment I executed at the Netherlands Cancer Institute (NKI-AVL) in Amsterdam was an excellent opportunity to understand the importance of applying the research in the field and gave me an inside view of the clinical environment. This thesis was a challenging experience, not only because it was in a different setting from the university, different country and culture, but also because the research work was in the Operation and Research field, which I discover for the first time and got passionate about. Therefore, working on this thesis was a very nice experience for me. In the process of doing my research I got help from several people, whom I like to thank.

First, I want to thank to my supervisors in the University of Twente, Erwin Hans and Bruno Vieira. Erwin offered me the opportunity to execute my graduation project at a hospital in Amsterdam, with the unstoppable supervision of Bruno, who was also in the hospital always available for my doubts and with a truly dedication to the reading and correction of the thesis. I want to thank to my supervisor Mónica Oliveira, from Instituto Superior Técnico, for connecting me with Erwin Hans and for the availability to help me in the end of the thesis' delivery period.
All my thesis was written in the NKI-AVL hospital, and during that period Dr. Jeroen van de Kamer and Dr. Corine van Vliet-Vroegindeweij followed my work, helped me taking the most of the clinical field and gave crucial insights for the application of the simulation model to the hospital.
Having a chapter in the thesis about his work, I must also thank to Nikky Kortbeek for his availability and for helping me to understand part of his work.
Besides the people I worked directly with during my graduation project, I thank to my friends in Amsterdam, Anna, Ziva, Ale and João, for giving me motivation for the work week on weekdays. I also thank to my sister and parents, for the family support. Last but not least, I thank to my boyfriend Rui, who helped me a lot in the thesis structure, purpose and motivation, besides being always there for me.

**Resumo**

É comum os hospitais utilizarem um sistema de marcações para distribuir os pacientes pelos diferentes equipamentos de imagiologia. Esta política evita ter salas de espera lotadas e permite organizar a capacidade dos recursos envolvidos mais facilmente, equilibrando a carga de trabalho em cada dia de trabalho. Contudo, um sistema em que os pacientes podem ser atribuidos pelos equipamentos de imagiologia logo após a primeira consulta, sem hora marcada, apresenta benefícios tanto para o hospital como para os pacientes. De um ponto de vista logístico, as taxas de utilização aumentam, como consequência da inexistência de desperdício de tempo entre pacientes, evitando a tempos de folga e excedentes. Isto leva a uma menor necessidade de recursos e a uma maior facilidade em lidar com o não aparecimento de pacientes.

Neste trabalho temos como objectivo quatificar a vantagem de introducir pacientes sem marcação num sistema de marcação de pacientes para equipamentos de imagiologia. Para isto analisámos o caso de estudo de TACs do centro de radioterapia do AVL, utilizando o modelo “Walk-in Generator” [1] para obter as soluções iniciais de modelos de marcação de pacientes a serem posteriormente avaliadas através do modelo de simulação desenvolvido.

A melhor solução encontrada pelo modelo “Walk-in Generator” [1] utilizou a referência literária que espalha os intervalos de tempo para pacientes sem marcação ao longo de cada dia de serviço do equipamento. Esta solução apresentou uma redução de 1,5 dias nos tempos de acesso ao equipamento de imagiologia e um aumento de 49% na fracção dos pacientes sem marcação, satisfazendo a meta de nível de serviço estabelecida de servir 95% dos pacientes em 2 dias. Desenvolvemos, sobre métodos previamente validados, um modelo de simulação que é o primeiro a quantificar a vantagem de ter pacientes sem marcação num sistema de gestão de capacidade de recursos, em radioterapia.

**Palavras-chave**: alocação de recursos, horário de marcações, pacientes sem marcação, pacientes com marcação, simulação de eventos discretos, tempo de acesso, tempo de espera

**Abstract**

Hospitals often use appointment systems to assign patients to their imaging facilities. This policy avoids having crowded waiting rooms and allows them to organize the capacity of the involved resources more easily by balancing the workload on each working day. Although, allowing patients to walk into imaging facilities right after the first consultation, without an appointment, also lodge several benefits for both patients and hospitals. From a logistics' viewpoint, machines' utilization rates are increased; there is no waste of time after completing a service (thus avoiding slack and surplus times), fewer resources are needed for scheduling appointments and it is easier to deal with no-shows.

In this work, we aim to quantitatively assess the improvement of having walk-in patients in a capacity allocation solution for imaging devices through the analysis of an appointment system combining walk-ins and appointments that maximizes the number of walk-in patients. We analyse the case study of the CT-scanning at the radiotherapy department of the AVL. To this end, we use a 'Walk-in Generator' model [1] to obtain a capacity allocation solution for the two types of patients, which was quantitatively evaluated through a discrete-event simulation model.

The best capacity allocation solution obtained with the 'Walk-in Generator' model was the one using a literature benchmark with spread time slots through the work day. This solution showed a reduction of 1,5 days in the access times, an increase of 49% in the fraction of walk-in patients served and satisfied the service level target of serving 95% within 2 days. We build upon previously validated research works and develop a model that, for the first time, quantitatively assess the advantage of having walk-in patients in the managing of resources' capacity allocation.

**Keywords**: Resource allocation, appointment schedule, walk-ins, appointments, discrete-event-simulation, access time, waiting time

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*NKI-AVL: Netherlands Cancer Institute - Antoni van Leeuwenhoekziekenuis*

*RT-AVL: Radiotherapy department of Antoni van Leeuwenhoekziekenuis*

*RT: Radiotherapy department*

*RTTs: Radiotherapy specialists*

*OR: Operation research*

*CT: computed tomography*

*PET-CT: positron emission tomography computed tomography*

*MRI: magnetic resonance imaging*

*CAS: capacity appointment schedule*

*MDP: Markov decision process*

*GA: genetic algorithms*

*TTS: time slot type specification*

*FCFS: first come, first served*

*AT: access time*

*WT: waiting time*

*FWI: fraction of walk-in patients*

*SL: service level*

*UT: utilization rat*

# Chapter 1 - Introduction

The work hereby presented fulfils the requirements of the degree of Master of Science in Biomedical Engineer, in the Clinical Engineering field, from Instituto Superior Técnico (IST), in Portugal, in collaboration with the University of Twente, in the Netherlands. It was tutored by Prof. Dr. Erwin Hans from the University of Twente, and Prof. Dr. Mónica Oliveira from the IST. The research work was developed in the radiotherapy (RT) department of the Netherlands Cancer Institute-Antoni van Leeuwenhoek (NKI-AVL), in Amsterdam, the Netherlands, under the supervision of Dr. Corine van Vliet-Vroegindeweij, Dr. Jeroen van de Kamer, and daily supervision of Bruno Vieira.

## 1.1 Research context: NKI-AVL

The NKI-AVL is a comprehensive cancer centre, located in Amsterdam, combining hospital (AVL) and research laboratories (NKI) under one roof in a single independent non-profit organization. The RT department treats more than 5000 new patients per year using state-of-the-art technology and treatment techniques. The department alone houses over 325 staff members, most of whom are radiation therapy technologists (117), radiation oncologists (24), medical physicists (11) and researchers (55).

## 1.2 Motivation and problem description

On a worldwide scale, healthcare institutions are trying to reduce costs while maintaining the same quality of care. It is known that costs in health systems are mainly associated with the need for highly qualified staff and the use of very expensive resources.

While health systems face increasing waiting times for several medical services, it is known that long waiting time can have a negative impact on patient's health outcome [2]. Therefore, there has been an increasing pressure to reduce patients' waiting times in hospitals without incurring additional costs.

The imaging track is a critical part of health systems' management. It is a necessary path for many treatment modalities and its resources are usually expensive and with a very limited in capacity. Thus, an efficient capacity management of the devices used in imaging facilities is a task of increasing importance in healthcare management that has shown solid improvement in reducing waiting times for treatment [2].

Hospitals often use appointment systems to assign patients to their imaging facilities. This policy avoids having crowded waiting rooms and allows them to organize the capacity of the involved resources more easily by balancing the workload on each working day. Allowing patients to walk into imaging facilities right after the first consultation, without an appointment, may lodge several benefits for both patients and hospitals. We define this type of accessibility as "walk-ins". From a patient's perspective, the number of visits to the hospital is reduced; the access time (time between an appointment request and the actual appointment) is eliminated and consequently, the psychologic distress of having to wait for a cancer treatment is minimized. From a logistics' viewpoint, machines' utilization rates are increased; there is no waste of time after completing a service (thus avoiding slack and surplus times), fewer resources are needed for scheduling appointments and it is easier to deal with no-shows. The downsides of such a working principle may be the longer waiting times for patients in periods of peak demand and difficulties in planning the capacity of human resources, as working overtime may often be needed. Besides, not all patients are eligible to walk into an imaging facility right after a given examination is prescribed, as other appointments in between may be needed. Therefore, it is advantageous having both scheduled patients and walk-ins, contributing for speeding up the process and, consequently, increased patient satisfaction.

The efficient utilization of the CT-scanners belonging to the RT department of the AVL (RT-AVL) is directly affected by the allocation of its capacity to different patient types. As a physical resource used by several patient types, it has a limited capacity defined by the time that it is available for utilization. The allocation of that capacity means the division of this time to be reserved to each patient type – appointment or walk-in - that needs to use it. This capacity allocation is represented by a schedule where the working hours on each work day are divided in time slots. Each time slot has a patient type associated, meaning that the scanner can be only be booked by the appointment office if the time slot is previously allocated to a patient of that type. In Figure 1 it is represented a possible capacity allocation solution, with the workdays divided in equal time slots, and each of it assigned to Appointments or to Walk-ins (the empty ones).

| | Monday | Tuesday | Wednesday | Thursday | Friday |
|---|---|---|---|---|---|
| *t=1* (7:45-8:10) | Appointment | Appointment | | Appointment | |
| *t=2* (8:10-8:35) | | | | Appointment | |
| *t=3* (8:35-9:00) | Appointment | | Appointment | Appointment | |
| *t=4* (9:00-9:25) | | Appointment | | | Appointment |
| .<br>.<br>. | | | | | |

**Figure 1: Hypothetical example of a capacity allocation solution**

Within this work, we aim to find efficient capacity allocation solutions that are able to guide appointment scheduling combining appointments and walk-ins in the RT department of the AVL, allowing as much walk-in patients as possible. Applying the framework for planning and control in healthcare developed by Hans et al. [3], shown in Figure 2, we conclude that we are operating in the managerial area of resource capacity planning. Besides, since we aim to generate decisions that affect the mid-term operation of the centre and constrain the operational decisions, we can see that we are working at the tactical level of decision-making. In this context, we defined the following specific research objectives:

1. Use a walk-in generator (Kortbeek *et al.*[1]) to obtain a solution for the clinical data gathered in the RT-AVL;
2. Adapt the solution, together with clinicians, taking into account the medical and technological constraints of the RT-AVL;

3. Quantitatively assess the impact of implementing such a solution for the CT-scanners on the RT-AVL through a discrete-event simulation model.

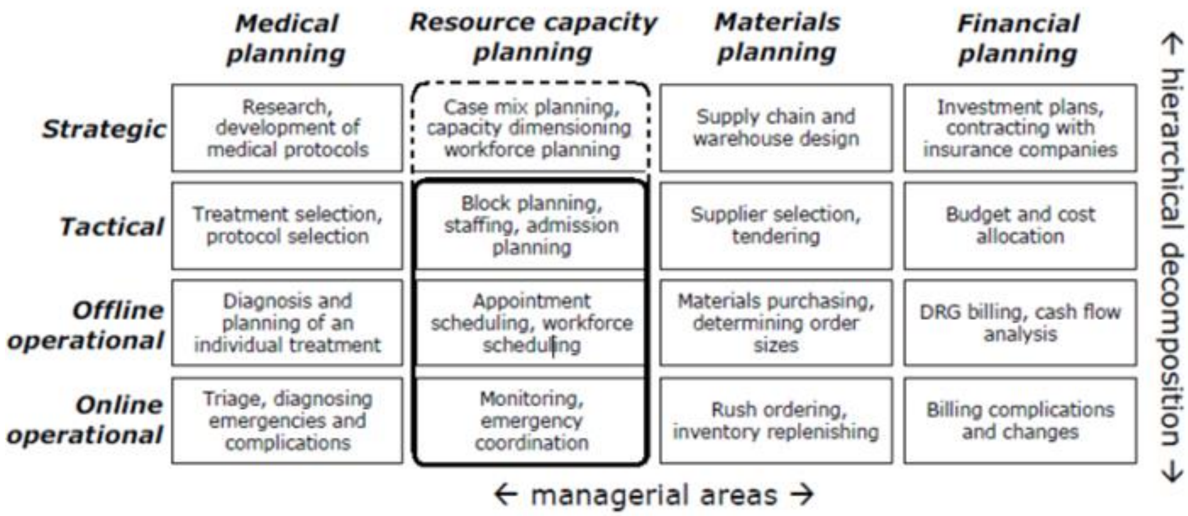



Figure 2: Framework of managerial areas with hierarchical decomposition [4]

The capacity allocation solution obtained in step 1 is similar with the one showed in Figure 1: a simple empty schedule for two patient types. Currently, as in many RT centres, capacity allocation decisions at the RT-AVL are performed in an intuitive way, relying on the expertise of the booking staff, without any clear procedure or decision support system behind. Therefore, the capacity allocation solution developed and used on a daily basis in each of the 2 CT-scanners may be far from optimal when considering the minimization of patients' waiting times. An analysis of the current way of working showed that the CT scanners of the RT-AVL had only between 2 and 3 walk-in patients per day. Given the fact that most patients were eligible to walk-in (60%), this number was considered low by the managers of the department. Thus, the centre was seeking a new solution that could maximize the number of walk-in patients in the clinic. In this work, we aim to find new capacity allocation solutions for the CT scanners of the RT-AVL that maximizes the number of walk-in patients in the clinic without increasing the access times for patients that need an appointment, beneficiating from the latest research works that show that models which combine the two type of patients, appointments and walk-ins, are more successful when it comes to reduce waiting times and increase utilization rate of imaging resources. This work contributes for the improvement of the services in imaging track in RT-AVL centre and is the first one to simulate the Kortbeek *et al.* work in the simplest configuration, allowing to understand the direct consequences of having two patient types, without other disruptive factors.

## Chapter 2 – RT-AVL Case Study

In this chapter, we describe the context of the application of the proposed methodology for the CT scanners of the RT department of the NKI-AVL. Section 2.1 gives an introduction about the preparation stage of RT delivery, focusing on the scanning stage. Section 2.2 describes the current planning and control for the CT scanners at both tactical and operational levels, and Section 2.3 presents the baseline performance measurements that lead to the development of our intervention.

### 2.1 RT chain of operations

A flowchart of the chain of operations in external-beam RT is shown in Figure 3. Without loss of generality, we assume that this procedure is applied to the majority of radiotherapy centres, including that of the AVL. The process starts with the consultation, where an appointment is scheduled. Afterwards, the scanning stage takes place, where one or more imaging exams are done and may include computer tomography (CT), magnetic resonance imaging (MRI), and/or positron-emission computer tomography (PET-CT). For some patient groups, e.g. head-and–neck, a mould is needed to make sure that the patient is always in the same position when being scanned and treated. Once all images have been collected, an image post-processing that combines and optimizes them may be needed. Thereafter, the target area is segmented (contouring). After segmentation, a treatment plan is generated by defining the angles and intensities of the irradiation beams. In the end, the irradiation is delivered in a pre-defined number of fractions. Thereafter, the treatment finished and a follow-up period takes place. This is the description of the whole path of a patient in an imaging track. In this work, we want to optimize the capacity allocation of imaging resources at RT-AVL, therefore we will focus in the time between the end of the consultation and the start of the scanning stage, marked in red in the Figure 3.

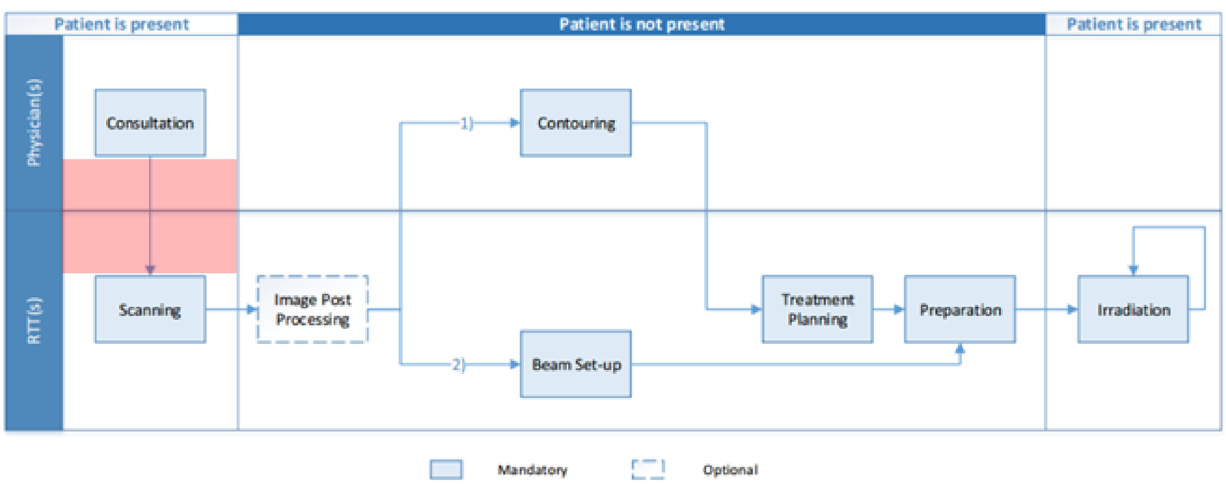



Figure 3: Generalization of the whole RT track

In the RT-AVL the following terms and definitions regarding timeliness are used:

i. Access time: time between the end of one operation and the start of the following. In this work, we refer to access time as the time between the end of consultation and the start of the CT-scan.
ii. Processing time: the time that an operation takes to be completed.
iii. Wait-in-room/ Waiting time: time a patient waits in the waiting room for a given operation. In case of scheduled patients (appointments), this refers to the time between the scheduled time and the actual start of the operation. For walk-in patients this is the time between the time a patient arrives at the department and the actual start of the operation.

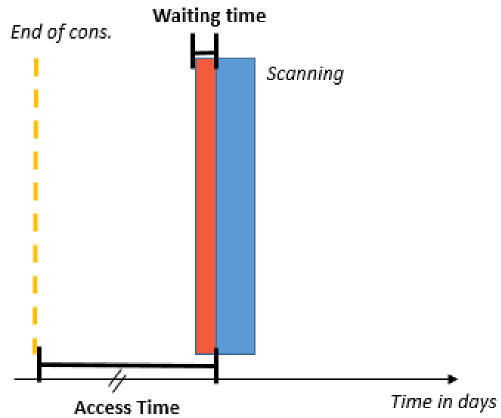



Figure 4: Appointment patient type time frame. 'End of cons.' is end of consultation

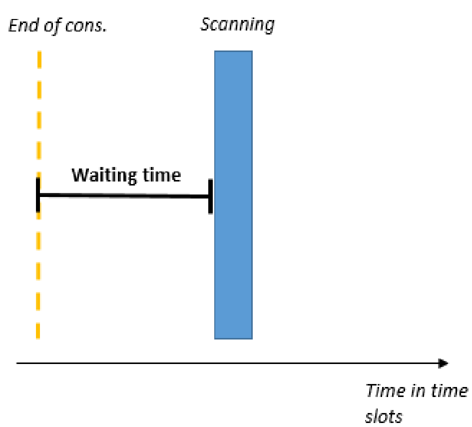



Figure 5: Walk-in patient type time frame

For simplicity, the same terms and definitions are used in this document. Figure 4 depicts the access time for a patient with an appointment, in a day after consultation, please note that besides access time, this type of patient may experience waiting room time. In Figure 5 we can see the terms for a walk-in patient, who waits in the waiting room for the scanning stage, after consultation, in the same day.

### 2.1.1 The imaging track

As we can see in Figure 6, the imaging examinations to be undertaken by a given patient are prescribed at the end of the consultation by the radiation oncologist responsible for that patient. In general, after consultation, the patient is offered an appointment for the CT scanner, usually being forced to come back to the hospital facility in the day of the appointment. While most patients need only a CT-scan, others may need other appointments, such as moulding, dentist or blood analysis, to be performed before the CT. After the CT, other imaging examinations (MRI/PET-CT) may be needed. These are performed in a short time period, preferably in the same day or in consecutive days. Therefore, scan scheduling is affected by procedures, before and after.

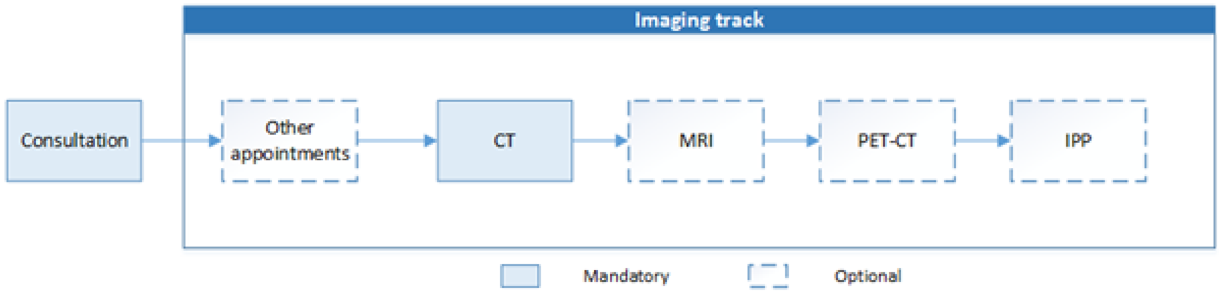



Figure 6: Imaging track generalization

## 2.2. Current planning and control

In this Section we present the capacity allocation system employed in RT-AVL at the tactical level, then in the operational level, in Section 2.2.2, we have a short review over the scheduling process, and in Section 2.2.3 we present the performance measurements available for RT-AVL.

### 2.2.1 Capacity allocation

The RT-AVL has two CT-scanners available for patients. One belongs to the department (CT08), and is available all working day for five days per week. The other one (CT04) is shared with the radiology department and is available half of the working day for 4 days a week.

The capacity of the CT08 is divided in 22 time slots per week day, with a duration of 25 minutes each, opening at 7h45 and closing at 17h05, as shown in Fig. 7. These time slots are restricted to certain patient types. For instance, the first two time slots, at 7h45 and 8h10, are marked as 1* due to the unavailability of RTTs to give an Intravenous (IV) contrast during the CT-scan, so only patients who do not need IV contrast may be scheduled in these time slots. *Mamma* time slots are reserved for breast cancer patients. The reason behind this allocation is that this group represents a large number of cancer patients, and these have fewer medical needs before CT. All these medical and technological constraints, were considered by the managers of the department when this solution was built and are taken into account in the development of our method.

| | Monday | Tuesday | Wednesday | Thursday | Friday |
|---|---|---|---|---|---|
| 7:45 | 1 | 1 | 1 | 1 | 1 |
| 8:10 | 1 | 1 | 1 | 1 | 1 |
| 8:45 | 2 | 2 | 2 | 2 | 2 |
| 9:10 | 2 | 2 | 2 | 2 | 2 |
| 9:35 | 3 | 2 | 2 | 2 | 2 |
| 10:00 | 2 | | | | |
| 10:25 | 3 | 2 | 2 | 2 | 2 |
| 10:50 | 2 | 2 | 2 | 2 | 2 |
| 11:15 | 3 | 3 | 2 | 3 | 3 |
| 11:40 | 2 | 2 | 2 | 2 | 2 |
| 12:05 | 4 | 5 | 5 | 4 | 5 |
| 12:30 | 5 | 2 | 2 | 4 | 2 |
| 12:55 | 2 | 2 | 2 | 2 | 2 |
| 13:20 | 2 | 2 | 2 | 5 | 2 |
| 13:45 | 3 | 3 | 3 | 3 | 3 |
| 14:10 | 3 | 3 | 3 | 3 | 3 |
| 14:35 | 2 | 2 | 2 | 2 | 2 |
| 15:00 | | | | | |
| 15:25 | 2 | 2 | 2 | 2 | 2 |
| 15:50 | 2 | 2 | 2 | 2 | 4 |
| 16:15 | 2 | 2 | 2 | 2 | 2 |
| 16:40 | 5 | 5 | 5 | 5 | 5 |

| | Monday | Tuesday | Wednesday | Thursday | Friday |
|---|---|---|---|---|---|
| 7:45 | | | | | |
| 8:10 | | | | | |
| 8:45 | | 2 | 2 | 2 | 2 |
| 9:10 | | | | | |
| 9:35 | | 3 | | 3 | 3 |
| 10:00 | | | | | |
| 10:25 | | 3 | | 3 | 3 |
| 10:50 | | 2 | 2 | 2 | 2 |

| | |
|---|---|
| | Inloop (walk-in) |
| | Mamma |
| | 1x8/spoed |
| | appointments |
| | appointments without contrast |
| | break |

**Figure 7: Current capacity allocation in RT-AVL, for CT08 (left) and CT04 (right)**

As for the remaining time slots existing in the system, they are described as:

a) *2*: time slots for appointments of any patient type;
b) *1:* time slots for appointments of patients without IV contrast;
c) *3: 1x8*, time slot for sub-acute patients with only one irradiation fraction of 8 Gy;
d) *4: Mamma*, time slot for breast cancer patients;
e) *Pauze*: time slot for break, in which no scans are performed;

### 2.2.1.2 Scheduling (appointment office)

The scheduling of appointments in the CT-scanners at the RT-AVL, as in many other hospitals, is done manually. Requests arrive from radiation oncologists via an internal RT management software – planRT - or by telephone. By looking at the calendar, a booking staff member looks for all the medical needs of the patient in an online platform called iProva, and simultaneously searches within MOSAIQ for suitable time slots available on the required imaging machines, and/or appointments with medical professionals that the patient needs before he/she is scanned. The choice of a suitable slot is then done by combining the patient's attributes, medical needs and preferences (e.g. for a specific day or time).

### 2.2.2 Current baseline performance

For the current baseline performance measurements, we considered the main key performance indicators (KPIs) that are aimed to be optimized with this project: 1) number of walk-in patients; 2) the average access times to CT; 3) the average waiting times to CT; 4) utilization rates of both CT scanners. Besides these KPIs, defined together with the management department of RT-AVL, it was also defined a goal for the access time: having 95% of the appointment-type patients served within 2 days.

The data to measure the average wait-in-room times and the utilization rates of the CT-scanners is not registered in RT-AVL. We got the number of walk-in patients and access times of appointment-type patients, the patients' arrival rate and the patients' group distribution.

### 2.2.2.1 Access times

The average access times for CT scanning in the RT-AVL using data from the year of 2015, which includes a total of 5636 patients, is 3,17 days, with a median of 4,83. We can see through the histogram of Figure 8 that an access time of 4 and 5 days were the most common in the department during 2015. Actually, only about 25% of the patients were scanned within two days, which is far from the goal of 95% of the patients served within 2 days.

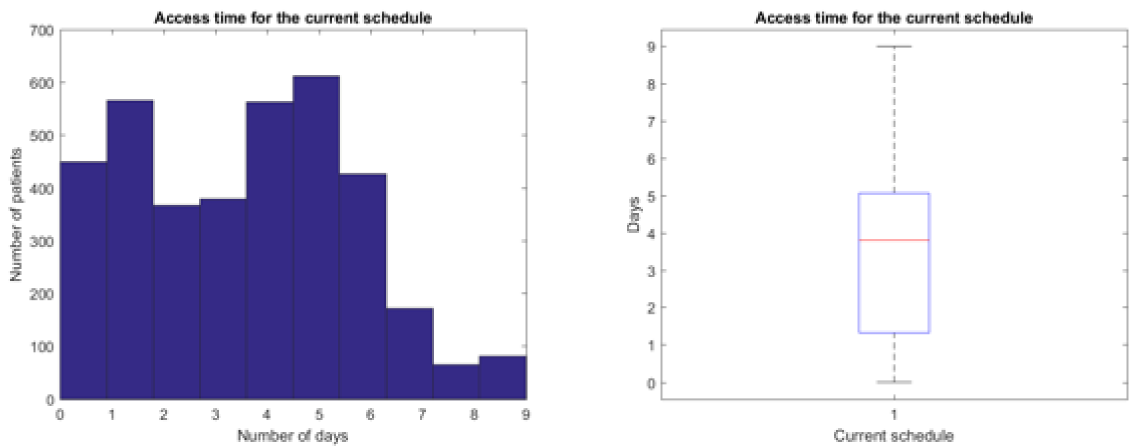



**Figure 8: Access times for CT-scanning verified during the year 2015 in the RT-AVL: histogram (left) and boxplot (right)**

In the current practice we know that the patients wait on average almost a week to get a CT-scanner, this measure is widely spread, which could indicate that some groups are increasing the access time average. Although, in Figure 9, we do not see a special group with more or less deviation from the average. In the measures done for the access time 30% of the population was considered outlier, because the access time was bigger than 10 days.

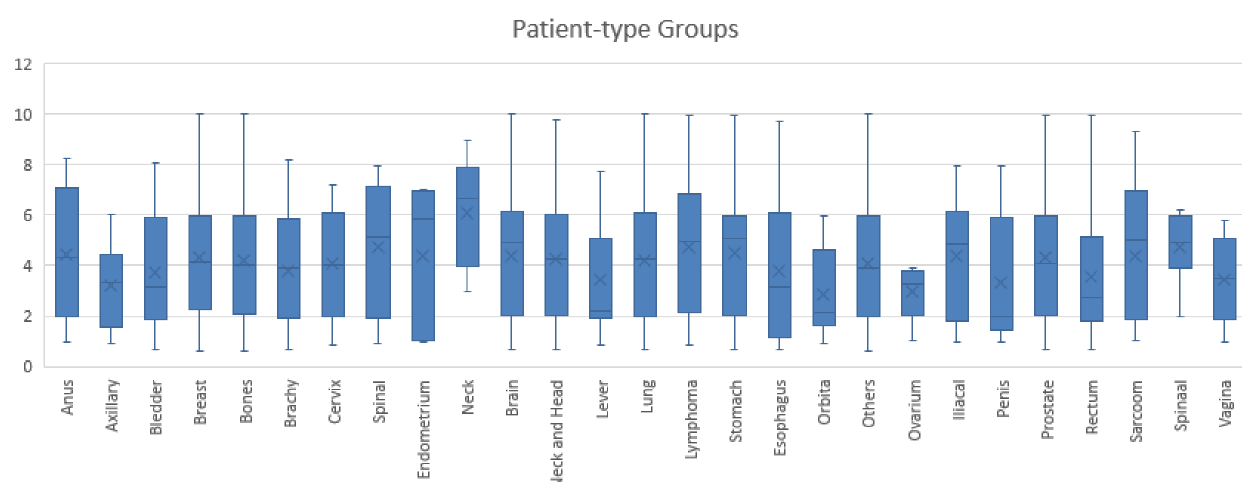



**Figure 9: Boxplot of access time of the different patient-type groups in days**

### 2.2.2.2 Waiting times

The waiting time average in the RT-AVL is 0,2 time slots, i.e. approximately 5 minutes. This is considered a low value for the time a patient waits in the waiting room, on average. However, we must take into account that only 2 to 3 patients per day are scanned in a walk-in fashion, and probably are only admitted as a walk-in, if they do not have to wait much more time than 5 minutes, because there is no systematic way of selecting walk-in patients.

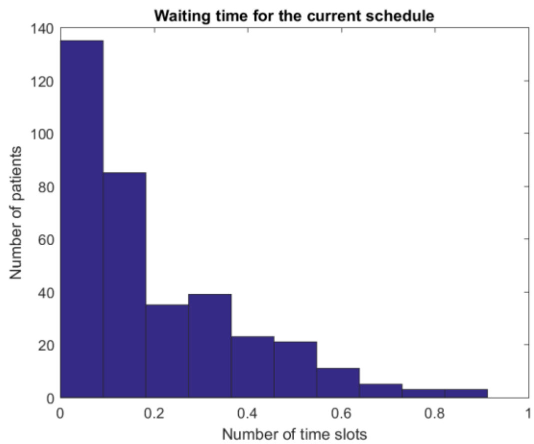



**Figure 10: Waiting time histogram**

## 2.2.2.3 Arrival Rate

In Figure 11we can see the arrival rate for the year of 2015. The values depicted are for the average number of patients within a time slot, according to the schedule in Figure 7, for CT08. This shows the arrival of the patient to the appointment facility, and not to the CT-scanner. We used the division in time slots as the schedule of CT08 to easiness the representation.

From all the working days, Wednesday stands out from the others, however the five days of the working week show similar arrival patterns. The patient is registered after the consultation, because of this the arrival pattern is biased by the end of consultation hours. This can explain the low number of patients in the beginning and the peak in the end.

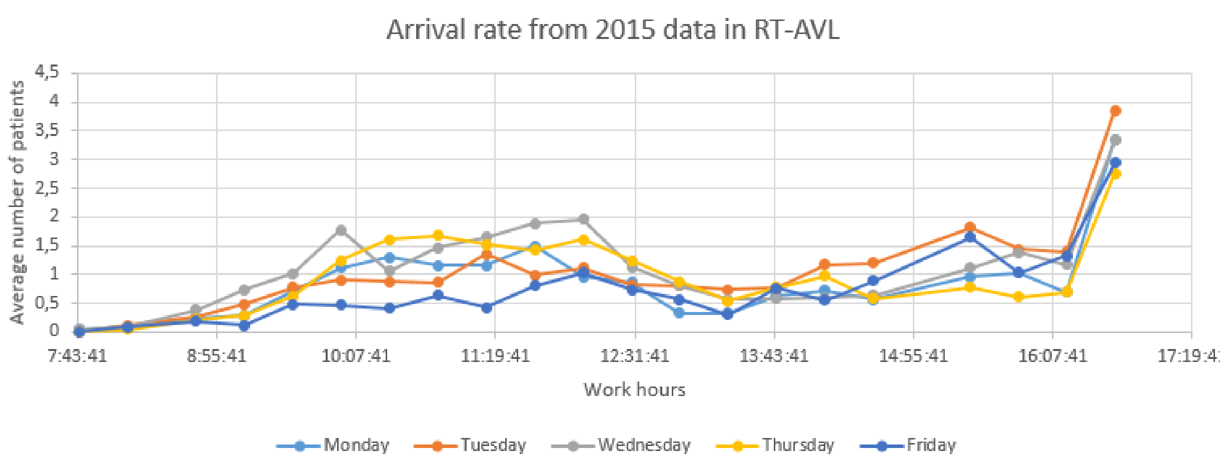



**Figure 11: Arrival rate from 2015 data in RT-AVL, divided by workday**

### 2.2.2.4 Patients' type groups

The Figure 12 shows the current patient population in RT-AVL. The names of the patients' groups are the original names in the Dutch hospital. The major group with 1317 named "*Botmetastasen*" are patients with bone metastasis. Other major groups with 286 and 384 patients are patients with lung cancer and with breast cancer, respectively.

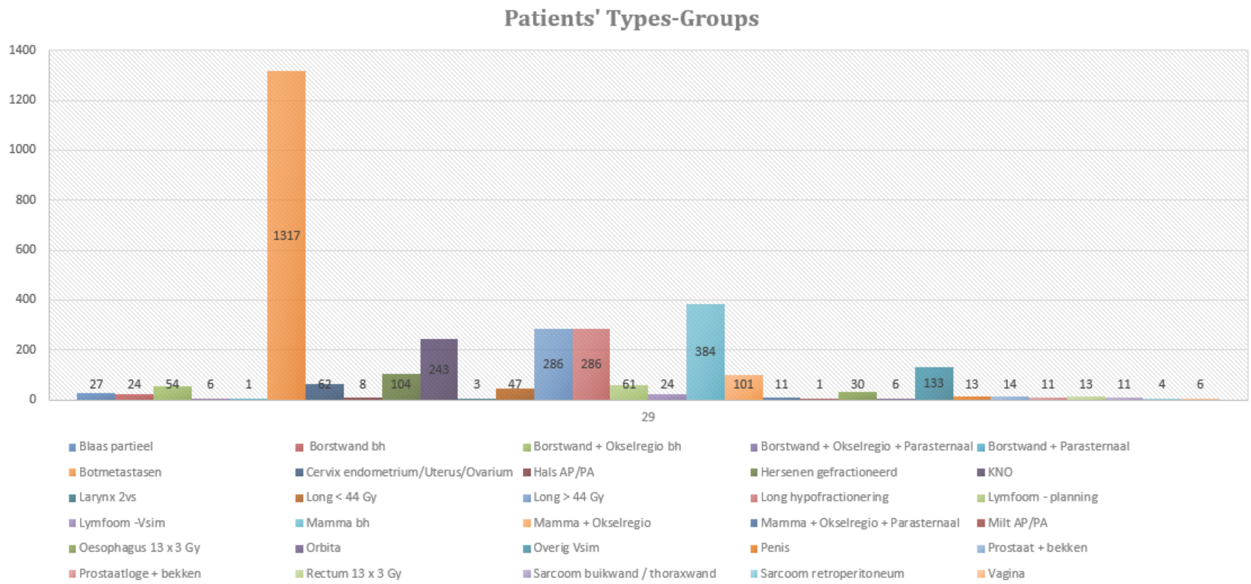



**Figure 12: Patients' type-group in 2015 data at RT-AVL**

**Table 1: Number (#) and percentage (%) of the patient types in practice and percentage of time slots types capacity**

*practice*

| | # patients | % patients | Time slot % |
|---|---|---|---|
| **Walk-ins** | 1590 | 9% | 29% |
| **Appointments** | 1226 | 68% | 23% |
| **Spoed** | 1368 | 19% | 25% |
| **Mamma** | 1223 | 3% | 23% |
| **total** | 5407 | 100% | 100% |

In Table 1, we can see that the percentage of patients for each type in the capacity allocation: walk-ins, appointments, "spoed" (urgent) or "mamma" (breast), with the respective colour they have in the current capacity allocation showed in Figure 7 (CT08 and CT04). Table 1 shows that the fraction of patients belonging to each group in the practice differs from the fraction of time slots for each group. For example, we have the extreme case where the patients belonging to “mamma” group are 3% of the patient population, and in the current schedule 23% of the capacity of both scanners is used for that type.

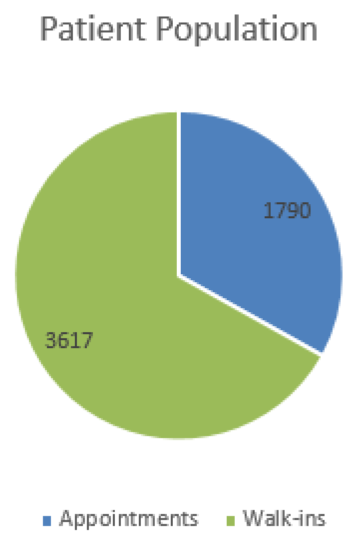



Figure 13: New patient population division

From the 61 patient types, we grouped the patient population into two groups: appointments and walk-ins. From the 61 patient types, 27 were classified as appointments and 34 as walk-ins. In Appendix A we show more information about patient clustering we performed.

### 2.3 Conclusion

The performance measurements in RT-AVL centre were difficult to obtain because the data is not on only one platform, different people manage the different platforms, and some queries are not possible to do. There is no pattern for access times within patient type groups. We see this as an advantage to the implementation of our solution, meaning that somehow the capacity allocation currently implemented, represented by the schedule in Figure 7, is affecting the patients in a similar way. The average access time is almost one week, and only 25% of the patients are served within 2 days, which is superior to the management goal of having 95% of the patients served within 2 days.

The data shows no systematic way of serving walk-in patients, which confirms that there is no walk-in culture in RT-AVL. This is inconsistent with the fact that 63% of the patient population can be served as a walk-in patient, as is showed in Figure 13.

We see space for improvement in this resource capacity allocation, specially concerning access times and patient clustering.

The patients’ arrival rate shows us that the workdays are similar in the number of patients arriving to the imaging facilities. However, we will implement a solution that considers each workday separately, hoping for better results in the simulation, and consequently in the implementation.

The patient population is divided into 61 groups, according to the constrains needed by each group. This division is way too extensive to apply our method. With interviews, visits at the facilities and through discussion with physic doctors, the head of physic doctors and the head of the appointment system, we were able to divide the patient population into two big groups: appointments and walk-ins.

Although the lack of integration in the information system of RT-AVL, we were able to collect enough information to apply our method and after it, compare the performance measurements from the simulation against the current practice.

# Chapter 3 - Literature review

## 3.1 Scope

Appointment systems are very common in many customer facilities. However, an appointment system suitable for all imaging facilities is difficult to develop. Many parameters related to the facilities vary, such as the patient types, staff members that need to be present, arrival rates and service times. This brings to each facility its own characteristics, making the generalization hard to attain. Besides the generalization, when modeling a particular facility, the variability in demand and service times, alongside the different types of patients, increase the complexity of resource planning activities. Because of all these complexities in healthcare processes, existing models from another sectors, although relevant, cannot readily be adapted [5]. Therefore, in this study we focus on relevant literature proposing methods to solve capacity planning problems in healthcare by combining appointments and walk-ins, at both the tactical and operational levels, through the application of operations research methods.

## 3.2 Search strategy

To search for relevant literature within the defined scope, we developed a query that combines a collection of terms for the methods, and a set of terms for the problem. Moreover, in order to cover journals specialized in both the medical and technical fields, the research literature was done in Scopus and PubMed databases. To restrict the number of papers returned by the search, we decided to search in the title and keywords of target papers only. Thus, the final query was the following:

*TITLE-KEY ("simulation" OR “metaheuristics” OR “linear programing” OR “heuristics” OR "queuing theory" OR "stochastic methods" OR "Markov decision process" OR “discrete event simulation”)*
*AND*
*TITLE-KEY ("Capacity allocation" OR "Capacity planning" OR "capacity management" OR "resource allocation" OR "resource planning" OR “walk in” OR "waiting time*" OR "access time*" OR "throughput time*" OR “scheduling” OR “appointment*” OR “no-show*” OR “overtime”) AND ( LIMIT-TO(LANGUAGE,"English" ) )*

As we can see, the words present in the query are divided in two parts, the first field is related with the methods we aim to use and the second with the problem we want to solve. There is an “OR” relationship inside each field and an “AND” relationship between the two parts.

This search returned a total of 200 different papers, which were filtered according to the inclusion and exclusion criteria presented in Table 1. Besides, 2 academic master theses were included. In total, we ended up with 21 papers fully related with our research topic, discussed and categorized in the next section by OR methodology.

**Table 2: Inclusion and exclusion criteria for literature search**

| *Inclusion criteria* | *Exclusion criteria* |
|---|---|
| -Journal paper, conference paper or book chapter | -Paper published before 2000 |
| -Paper uses an OR method or technique | -Paper written in other languages than English |
| -Paper addresses appointments and walk-ins patients | -Paper tackles a medical problem |
| | -Paper focus on macro-planning |
| | -Abstract not available online |

### 3.3 Results

#### 3.3.1 Exact approaches

Exact approaches are mathematical optimization methods that guarantee an optimal solution to a given optimization problem. Although very efficient in terms of solution quality, these methods are usually only able to solve small instances of the problems at hand. In the context of exact approaches, Kolish and Sickinger [4] use a Markov Decision Process (MDP) approach to model two parallel CT-scanners with three patient groups: outpatients, inpatients, and emergency patients. They assumed a random distribution for inpatients and emergency groups, so these are considered as walk-ins. In this walk-in group, they assumed that inpatients were willing to wait, and the emergency patients were served immediately.

Kim and Giachetti [5] use stochastic mathematical modelling to find the optimal number of appointments to maximize profit, introducing a cost for rejected patients. Their model includes both no-shows and walk-ins. It is an example of the use of cost minimization as the objective function.

Timmer and Judith in [6] employ a Bayesian game approach to optimally allocate an MRI scanner capacity, aiming to find if it is really important to have a true demand to obtain a fair capacity allocation of the resource through its users. The system is seen as a “one-resource” type, the MRI, which capacity is distributed through several medical departments. A utility function is used for each user to minimize under and over-estimation of demand. Their work shows that for a small groups of users, 3 or less, the same performance is obtained, no matter how reliable the forecast is. For groups of users bigger than 3, it is then optimal for each user to provide a reliable forecast.

Kortbeek *et al*. [1] propose an exact approach that combines models based on queuing theory and MDP. Their goal is to combine scheduled jobs – appointments - and unscheduled jobs - walk-ins to maximize the fraction of unscheduled jobs served on the day of the arrival, and at the same time satisfy a pre-specified access time norm for scheduled jobs. It is assumed that the unscheduled jobs arrive with a stochastic non-stationary arrival process and have a balking behavior (queue behavior which states that if a queue is too long, further addictions are deferred). Scheduled jobs have priority and a no-show probability is considered. Both unscheduled and scheduled jobs have a cyclic pattern of arrival. To account for this, Kortbeek *et al.* develop a cyclic appointment schedule (CAS) that deals with different time scales. The CAS has a first part that specifies a capacity cycle, the maximum number of patients allocated for each day, with a time scale of days dependent of the cycle length, and a second part that specifies the day schedule, the maximum number of patients to be scheduled per time slot in each day, with a time scale smaller than a day. This analytical evaluation model determines the access time for the first part of CAS and the expected number of deferred unscheduled patients for the second part.

#### 3.3.2 (Meta)Heuristics

Contrary to exact methods, heuristic approaches do not guarantee an optimal solution but they are able to generate good solutions in a reasonable computational time. In this field, Bailey and Welch use a heuristic approach that shows good performance when all time slots are all equal and equally distributed, meaning that the service time is deterministic and equals to the one-time slot. Cayiril et al. [7] construct a universal web-based appointment system that outputs a daily capacity schedule with the following input parameters: target number of patients per session, average service time, the standard deviation of service time, the probability of no-show and walk-in, and the cost ratio. In their constructive heuristic, they develop a dome pattern when service times are stochastic. The intervals increase from the start of the day until a certain time slot has been reached, and thereafter the time slot intervals decrease towards the end of the day.

Klassen and Rohleden [8] show that empty time slots in the beginning of the day, for urgent patients, reduce waiting times, while at the end of the day such time slots can be able to serve a bigger number of patients that are willing to

wait. To obtain both advantages, the time slots for urgent patients should be spread equally during the day. In the same way, Su and Shih [9] show that alternating sequences of appointment schedules with walk-ins works better.
Lin et al. [10] present an approach to reduce the solution space of an MDP-based model, aggregating time slots and applying approximate dynamic programming. It accounts for no-shows and appointment schedules. After aggregation, a myopic heuristic is done (maximize immediate rewards and do not take future information into account) in each of the merged slots. Freville and Plateau [11] also support solution space reduction because of run time performance.
Denton et al. [12] have a Simulated Annealing approach to improve the initial solution by moving appointments back and forth in time. They concluded that this approach shows substantial improvements, but converges slowly.
Petrovic and Morshed in [13] present a multi-objective optimization model using three types of Genetic Algorithm (GA): the standard-GA, the KB-GA and the Weighted-GA. These deal with patients without categorization, with previous knowledge about emergency patients and with patient types with different weights, respectively. They conclude that a previous knowledge about a patient group bring a better performance overall. This type of algorithm, the GA, is relatively easy to implement, however the search space may grow rapidly leading to space and time computing complications.

### 3.3.3 Computer Simulation

Computer simulation is widely used in healthcare planning and control ([14], [15]) and there are some research works related with CT-scanner facilities ([16],[17]). Computer simulation allows to model a real system in order to find bottlenecks, evaluate old and new possible strategies, in a cheaper, faster and safer way than in real world experimentation.
The research applications of computer simulation dealing with combined appointment and walk-in accessibility are only a few. In [18] the authors develop a complete walk-in system for nurse-led NHS waiting center, introducing a delay scheduling. In this approach the patient is warned about the delay time upon his arrival to the facility. The patient can then leave the facility, so the delay is not accountable for wait-in-room time.
Vermeulen [19] uses a Monte Carlo simulation to do an adaptive resource allocation for a CT-scanner in RT-AVL hospital in the Netherlands. It has five types of patients: outpatients with and without IV contrast, urgent, clinic and special. He divided his work in 'Resource Calendar' and 'Scheduling'. The Resource Calendar deals with issues like the time slot type specification (TTS), trying to find which time slot will be allocated to a given patient type. The Scheduling assigns patients to time slots, trying to find how well TTS matches the actual patient arrival. The paper presents two algorithms, the *FlexRes* for scheduling with flexible reservations for urgent patients and the *Dynamic* for adjusting capacity between groups. This paper shows that a flexible approach is better than a static allocation.
Van Lent *et. al.* [16] also used Monte Carlo simulation to reduce throughput times in a CT-scanner imaging track used for a radiology department. They considered the path from the first consultation, then first scanner, and second consultation in the NKI-AVL hospital. They divided the patients in four groups: inpatients, urgent outpatients, short-term outpatients and long term patients, assuming a stable demand for long term patients and finding a distribution for the others. As a simple approach, it shows that imaging track throughput time is more important than CT-scanner access time alone. However more robustness is needed not only to deal with capacity outages and no-shows, but also to attribute different daily demand distributions for each day in the same patient group.
Joustra *et al.* in [20] consider all the radiotherapy care pathway: the first consultation, imaging track, planning stage and the actual treatment. They used discrete event simulation to detect the bottlenecks and quantify the effects of alternative solutions to reduce the throughput times, and queuing theory to give an insight of the impact of variability in improving waiting times. Their results show that a reduction in variability in the outpatient department will lead to substantially lower throughput times and consequently to lower access times and waiting times.

### 3.4 Discussion

In capacity allocation optimization approaches, we can see that appointment systems are common, although the "one for all" solution is hard to attain. Besides this, adapting systems from other fields is also difficult because of patients' special characteristics, such as the big number of patients' types and the their numerous constrains. Patient categorization and their aggregation in patient-types is a common approach in healthcare planning. This arises from their distinct service requirements and priority levels, which also leads to patient prioritization approaches.

Exact approaches work well for small instances of the problems, but for bigger instances the computational running time is not practical, thus a solution found in a completely mathematical way is not commonly successful in the medical practice. Heuristic approaches do not reach the optimal solution, and can be stuck in a local optimum, however are easier to develop and good solutions are obtained in a faster way than exact approaches. For instance, Littman et al. [21] show that queuing theory works well for small instances, but for large instances it is not solvable in a practical running time. Besides this, exact approaches cause medical acceptance difficulties because it requires dealing with computer-based decision rules [4]. This opens space to explore heuristic approaches [22], namely local and constructive heuristics. All papers report improvement after applying local search on their constructive heuristic method. Computer simulation approaches provide big advantages in finding bottlenecks, visually representing the real system and evaluating solutions generated by other methods. These methods usually verify a better acceptance, and consequently more chances of implementation of new interventions by health care practitioners.

We did this literature search with the goal of finding a method for a two-type patient population, appointments and walk-ins, which increases the number of walk-ins served. We found that the work of Kortbeek *et al.* [1] was the one that combined the biggest number of improvements from previous research works. It uses a combination of exact approaches, as Markov Decision problem, as Kolish and Sickinger [4], and queuing theory as Littman et al. [21], with heuristics in their iteration procedure. Taking the benefit of the quality solution in the exact approaches and the easiness of implementation with the heuristic approach. Besides this, they do not assume a random patient distribution, demarking from the others ([4], [23], [24], [25], [26]) in research, having a stochastic distribution for patients' arrival. When running their method, it is possible to choose an objective function, namely a cost function for rejected patients. This is directly related with our main goal of having the biggest number of walk-in patients served, which is the same of saying the least number of rejected (also defined by deferred) patients.

In the next chapter we explain in detail the work of Kortbeek et al., the way we use it to obtain our first solutions and the RT-AVL input parameters needed. We are the firsts, as far as we know, assessing this method in its simpler way through a simulation model, with the final goal of implementation. This distinguish us from the latest research works because of the direct insights about the appointments and walk-ins combination we can get.

## Chapter 4 – Walk-in schedule generation

In this chapter, we describe the methodology proposed to generate and evaluate new capacity allocation solutions to the two CT scanners used for RT that maximize the number of walk-in patients, minimize the access and wait-in-room times of patients and maximize the utilization rates of both CT-scanners. This methodology follows from the work developed by Kortbeek *et.al.* [1] and it is explained in detail in the following sections. In Section 4.1 it is presented the scope of the problem, followed by its formal description (Section 4.2), and in Section 4.3 the working principle of the methodology is explained in more detail. Finally, in Section 4.4 we present the way we applied the output solutions to the case study of RT-AVL.

### 4.1 Purpose and problem description

The work of Kortbeek *et al*. [1] is used to design schedules combining walk-ins (unscheduled jobs) and appointments (scheduled jobs), with the goal of maximizing the fraction of unscheduled jobs served on the day of the arrival, while satisfying a pre-specified access time norm for scheduled jobs. Scheduled jobs are given priority in case of conflicting access, with the possibility of no-shows. Both unscheduled and scheduled jobs have a cyclic pattern of arrival. Thus. Kortbeek *et al.* develop a method to obtain a cyclic appointment schedule (CAS), i.e. the maximum number of jobs that may be scheduled on each day. The best CAS is attained by employing an iterative algorithm that generates CASs using a First Come First Served (FCFS) principle with two different approaches: complete enumeration, and heuristic, in which the expected fraction of unscheduled jobs served on the day of arrival is maximized, while for scheduled jobs the access time service level is minimized. Each CAS is evaluated with two models in different time scales. The first model -Model 1 - provides an evaluation of the access time for scheduled jobs, having days as the time scale. The second model - Model 2 - evaluates the performance of a single day in the CAS, with a time scale of hours. This analytical methodology gives the best CAS using Model 1 to find the capacity cycle, and the number of time slots for appointments per day, which minimizes the access times. The Model 1 is combined with Model 2, which finds the time of the day for previously defined number of time slots for scheduled jobs, minimizing the number of deferred patients. Deferred patients are patients that were initially walk-in, but because they had to wait above a certain user-defined threshold, they are given an appointment for the next day.

### 4.1.1 Formal problem description

This section presents the formal problem description of Kortbeek *et al.* [3] methodology, defines the cyclic appointment schedule (CAS) and formally states the research goal. This is a generic approach, so it is presented in generic terms: a facility that serves scheduled and unscheduled jobs.

**Assumptions**: The facility has $R$ resources with $T$ time slots available. Each time slot has a time length of $h$. Because of cyclic arrival patterns, the model defines a CAS with a cycle length of $D$, in days. There are two types of jobs, scheduled and unscheduled. Each service takes one-time slot, and a time and date for the service are given immediately after the appointment request. When the facility is congested, unscheduled jobs are offered with an appointment to the earlier time slot of the next day in the cycle (deferred). Unscheduled jobs are willing to wait until $g$ time slots, inclusive. The jobs are allocated in a FCFS fashion. No-shows are allowed with a probability $q$. Scheduled jobs arrive on time and have priority above unscheduled jobs. Overtime of the resources, $R$, is not allowed. It is assumed a non-stationary Poisson process for both unscheduled and scheduled jobs.

The cyclic appointment schedules referred as CAS is defined as an array of arrays.

**Equation 1**

$$\boldsymbol{CAS} = \left(\boldsymbol{C}^{\mathbf{1}}, \dots, \boldsymbol{C}^{\boldsymbol{d}}, \dots, \boldsymbol{C}^{\boldsymbol{d}}\right)$$

**Equation 2**

$$\boldsymbol{C}^{\boldsymbol{d}} = \left(\boldsymbol{c}_{\mathbf{1}}^{\boldsymbol{d}}, \dots, \boldsymbol{c}_{\boldsymbol{t}}^{\boldsymbol{d}}, \dots, \boldsymbol{c}_{\boldsymbol{T}}^{\boldsymbol{d}}\right)$$

In Equation 1, $C^d$ represents the appointment schedule on day *d* of a given cycle, representing the maximum number of appointments slots in that particularly day.
In Equation 2, $c_t^d$ represents the maximum number of jobs that can be scheduled in day *d* in time slot *t*, this has the number of resources available (*R*) as the upper bond. In (1), each $C^d$ has an array of $c_t^d$, as an array of arrays the second equation belongs to the first.

**Table 3: Notation introduced in Section 4.1.1**

| Symbol | Description |
|---|---|
| *R* | Number of resources (CT-scanners) |
| *T* | Number of time slots during a day |
| *t* | Time slot index (t ∈ {1, . . . ,T}) |
| *h* | Length of a time slot |
| *D* | Cycle length in days |
| *d* | Day index (d ∈ {1, . . . ,D}) |
| *g* | Number of time slots an unscheduled patient is willing to wait |
| *q* | ℙ(No-show of a scheduled job) |
| $\boldsymbol{c}_{\boldsymbol{t}}^{\boldsymbol{d}}$ | Maximum number of appointments to schedule in slot *t* on day d |
| $\boldsymbol{C}^{\boldsymbol{d}}$ | Appointment schedule on day d, $C^d = (c_1^d, \dots, c_T^d)$ |

Each CAS is optimized having a maximum pre-defined waiting time of unscheduled jobs, and access time for scheduled jobs. The best CAS is the solution that maximizes the fraction of unscheduled jobs while obeying to these access time norms.

## 4.2 Methods

In sections 4.2.1 to 4.2.3 we describe the methodology to design a cyclic appointment schedule. The best CAS is determined through an iterative procedure that combines the definition of a capacity cycle, with model 1, and day schedule, with model 2. Table 4 provides a summary of the notation used in the following sections.

**Table 4: Notation introduced from Section 4.1.2 to 4.1.4**

| Symbol | Description |
|---|---|
| $\boldsymbol{\phi}^{\boldsymbol{d}}$ | Distribution of the number of deferred jobs on day d |
| $\boldsymbol{\phi}^{\boldsymbol{d}}(\boldsymbol{n})$ | Distribution of the number of deferred jobs on day d in iteration n |

| | |
|---|---|
| $\boldsymbol{\gamma^d}$ | Total appointment request arrival distribution on day d |
| $\boldsymbol{\gamma^d(n)}$ | Total appointment request arrival distribution on day d in iteration n |
| $\boldsymbol{\lambda^d}$ | Initial appointment request arrival rate on day d |
| $\boldsymbol{(y, S^{norm}(y))}$ | Access time service level requirement: fraction of jobs with access time not greater than y is at least S(y) |
| $\boldsymbol{w^d}$ | Access time in day *d* |
| $\boldsymbol{S(y)}$ | Access time service level: fraction of jobs with access time not greater than y |
| $\boldsymbol{k^d}$ | Maximum number of appointments to schedule on day d |
| $\boldsymbol{B^d}$ | Backlog at start of day d |
| $\boldsymbol{\pi_j^d}$ | Stationary backlog probabilities, $\mathbb{P}(B^d = j)$ |
| $\boldsymbol{j}$ | Number of jobs index |
| $\boldsymbol{n}$ | Number of iterations index |
| $\boldsymbol{\mathcal{X}_t^d}$ | Unscheduled job arrival rate on day d during time interval (t −1, t ] |
| $\boldsymbol{e_{t,g}}$ | Number of slots available for unscheduled jobs in the next g intervals after time t |
| $\boldsymbol{p_t^s(s)}$ | $\mathbb{P}$(s scheduled jobs arriving at the start of slot t ) |
| $\boldsymbol{p_u^s(u)}$ | $\mathbb{P}$ (u unscheduled jobs arriving during interval (t −1, t ]) |
| $\boldsymbol{F}$ | $\mathbb{E}$[Fraction of unscheduled jobs served on the day of arrival during one cycle] |
| $\boldsymbol{v^d(n)}$ | Expected number of deferred jobs on day d, in iteration n |

### 4.2.1 Access time and day process evaluation

**Model 1: access time evaluation**

The first model evaluates the performance regarding access times. This model is a discrete-time cyclic queueing model which focuses on backlog, $B^d$ (number of jobs for which a request for an appointment has already been made) to derive, indirectly, the access time distribution. A Lindley-type equation is used to characterize the $B^d$ and a probability generating function to derive its distribution, obtaining $\pi_j^d$: the probability of having a backlog of *j* jobs in the beginning of the day *d*, which means that in the beginning of day *d* there are *j* jobs that have an appointment that have not been set yet. With this probability, it is possible to obtain $P[w^d > y], \mathbb{E}[w^d], S(y)$, i.e. the probability of the access time for a patient arriving in day *d*, $w^d$, be superior to *y*, the expected value of access time for an appointment request arriving on day *d,* $\mathbb{E}[w^d]$, and the access time service level, $S(y)$. In Figure 14 we can see a diagram explaining the working principle of Model 1, which outputs is the capacity cycle that respects the access time service level norm for the distribution of scheduled jobs, $\gamma^d$, taken as input.

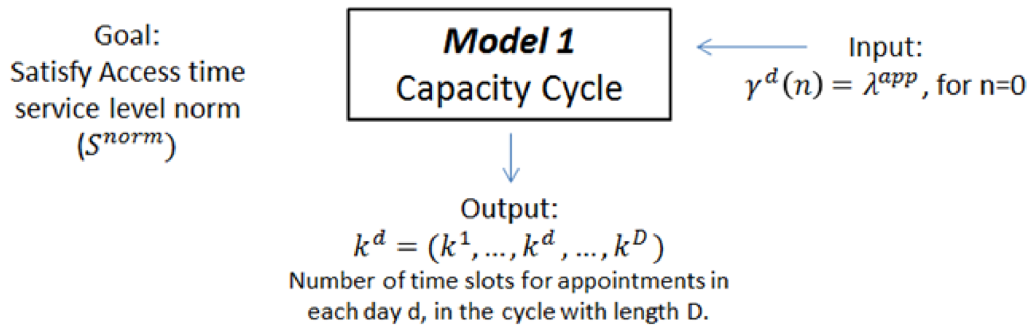


Figure 14: Diagram of model 1

**Model 2: day process evaluation**

The second model evaluates the performance of each CAS through a Markov reward model, concerning the expected number of deferred jobs. The filling of $C^d$, showed in Equation 1, is done according to a FCFS fashion, and unoccupied slots are then reserved for unscheduled jobs. The unscheduled jobs have an inhomogeneous Poisson process with slot-dependent arrival rate, $\mathcal{X}_t^d$. Arriving unscheduled jobs wait until the number of unscheduled jobs already waiting is strictly smaller than the minimum number of service slots during the upcoming *g* intervals that. The number of time slots anticipated to be available for unscheduled jobs during the upcoming *g* intervals is denoted by $e_{t,g}$, as we denoted by equation (3):

Equation 3

$$e_{t,g} = \sum_{j=t}^{\min\{t+g-1,T\}} (R - C_j)$$

Each state of the system is characterized by the tuple *(t,s,u),* referring to the number of scheduled, *s*, and unscheduled, *u*, jobs in the beginning of time slot *t*. Besides this, $p_t^s(s)$ represents the probability of having *s* scheduled jobs at the beginning of time slot *t* and $p_t^u(u)$ represents the probability of having *u* unscheduled jobs in (t-1,t] time interval. Transition probabilities $\mathbb{P}[(s,u)_{t+1}|(v,w)_t]$ define the probability of jumping from state *(t, v, w)* to *(t+1, s, u)* for all possible events. This leads to several performance measurements, starting with $Q_t(s,u)$, the probability that at the start of slot *t* there are *s* scheduled and *u* unscheduled jobs; $v_t$, the expected number of deferred jobs in time interval (0,t]; and finally the main performance measurement of the model, $\phi_t$, the distribution of the number of deferred jobs in time interval (t-1,t]. In Figure 15 a diagram of model 2 is depicted, which has as input the output of model 1, $k^d$, and the arrival rate of unscheduled jobs, $\mathcal{X}_t^d$, and as an output the day schedule with the goal of minimizing the number of deferred patients, $v^d$.

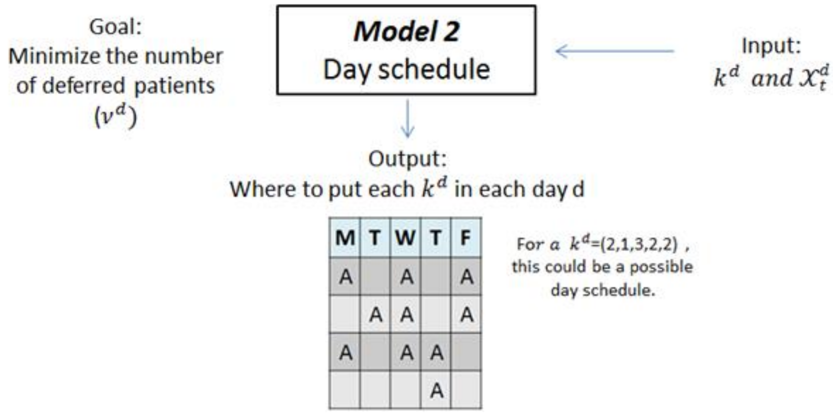



Figure 15: Diagram of model 2

## 4.3 The iterative procedure

The iterative procedure, shown in Figure 17, links access and day processes in order to maximize the unscheduled jobs within the pre-specified access time service level norm established by the user.

As explained in Section 4.2.1, in Model 2 unscheduled jobs are not willing to wait more than $g$ time slots in the day of arrival to the facility. If the time needed to wait is superior to $g$, they are offered an appointment for the next day. Therefore, the number of deferred jobs from CAS is accounted for in the appointment request arrival distribution $\gamma^d$. This is done by recalculating the distribution of the appointment request arrival by adding the deferred jobs from the previous iteration, having as an objective the approximation of the optimal *F*.

There are two ways of doing this iterative procedure, according to Kortbeek *et al.* [1] work: 1) a complete enumeration, with the disadvantage of longer running times; and 2) a heuristic approach, faster and more practical, but not optimal as with the complete enumeration. Both follow the pseudo-code depicted in Figure 16.

| | |
|---|---|
| *Step 1:* *specify input* | *Specify:* $R, T, D, g, q, S^{\text{norm}}(y), \epsilon$; $\forall d : \lambda^d; \forall d, t : \chi_t^d$. |
| *Step 2:* *initialize iterative procedure* | $n := 1; \forall d : \nu^d(1) := 0, \gamma^d(1) := \text{Poisson}(\lambda^d)$. |
| *Step 3:* *find candidate CAS* | *Execute complete enumeration (see Section 6.2) or heuristic procedure (see Section 6.3).* |
| *Step 4:* *assess current solution* | *If* $\forall d : \lvert\nu^d(n) - \nu^d(n-1)\rvert < \epsilon$, *then stop, else proceed to Step 5.* |
| *Step 5:* *adjust deferrals* | $\forall d : \nu^d(n+1) := \nu^d(n), \phi^d(n+1) := \phi^d(n)$, $\gamma^d(n+1) := \text{Poisson}(\lambda^d) * \phi^d(n+1)$; $n := n+1$ *and return to Step 3.* |

Figure 16: Pseudo code of the iterative procedure

Having the specified input data, and starting with zero deferred jobs in the first iteration, a capacity cycle is constructed with Model 1, and a day schedule with Model 2. To consider the deferred jobs, the distribution of appointment request arrival follows the equation in step 5 of Figure 16. The convergence of the algorithm is done on a daily basis, as shown in step 4 of Figure 16.

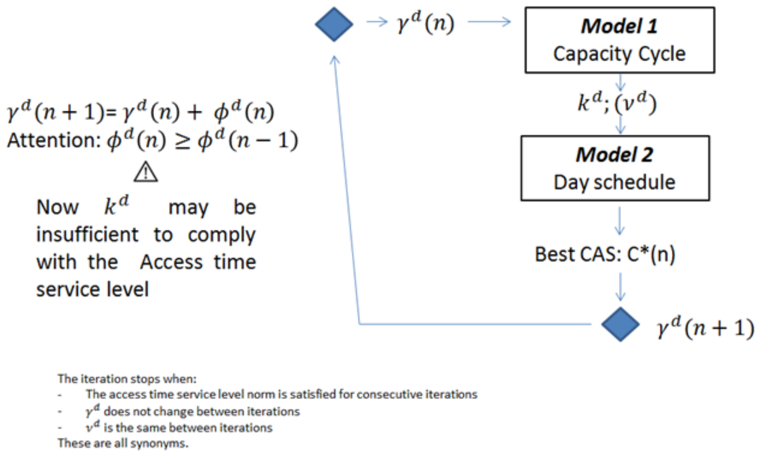



**Figure 17: Diagram of the iterative procedure**

In each iteration the maximum number of appointments to be scheduled, per day, is $R \times T$. To this end,all scheduled jobs are accounted for: appointments and deferred jobs. In each iteration the distribution of the deferred unscheduled jobs, $\phi^d(n)$, where $\phi^d(0) = 0$ , is calculated. In the following iteration, the distribution of the total number of appointments, $\gamma^d(n+1)$ , which is the sum of the Poisson parameter $\lambda^d$ and the distribution $\phi^d(n)$, is then calculated too. In each iteration, and because $\phi^d(n) \geq \phi^d(n-1)$, the number of slots for appointments may be insufficient. So in each iteration, a CAS with more time slots for appointments is obtained. The procedure ends when the distribution of appointment arrivals between iterations does not change substantially. In other words, when the number of expected deferred jobs $\nu^d$ does not change, the algorithm stops and the best CAS is returned. For a deeper understanding of the complete enumeration and heuristic procedures, we address the reader to [1].

## 4.4 Application to the RT-AVL

We used the walk-in schedule generator model explained to obtain capacity allocation solutions for RT-AVL. The Figure 18 is a diagram that shows an overview of this thesis in terms of the methods used. The walk-in generator model gave us the solutions, explained in the next Section 4.4.2. Those are the input for the discrete event simulation build by us and explained in Chapter 5. An executable DELPHI program developed by K. Smid *et al.* [27] was used to generate solutions with the Walk-in Generator methodology explained in the previous sections. We choose this program-model because it does not add new assumptions to the Kortbeek *et. al* method, representing all the theoretical model in its original form, it was done closely with the method's developers and was already used in two case studies for other cancer centers in the Netherlands [26].Through these case studies we were able to choose the best combinations between the heuristics approaches for the itineration part, as it will be explained in Section 4.4.2.

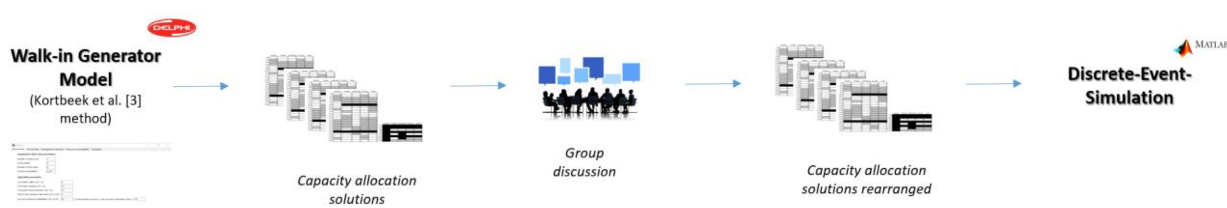



**Figure 18: Overview of the methods used in this research work**

We used this method to develop capacity allocation solutions for both CT-scanners of the RT-AVL, showing filled time slots for appointments and empty time slots for walk-ins. In Section 4.4.1 we provide more details about the input parameters needed, in sections 4.4.2 and 4.4.3 we show the output that is achieved with the algorithm, and the Section 4.5 we explain the modification of the output solutions made by RT-AVL managers.

### 4.4.1 Input parameters

The input parameters of the Walk-in Generator model can be divided in five fields: general data, arrival data, management decisions, resource unavailability and scheduler.

#### *4.4.1.1 General data*

Here we have the following parameters:

- Number of resources:2
- Cycle length: 5
- Number of time slots: 22
- No-show probability: 0

We assigned a no-show probability of zero because there is no accurate data in RT-AVL to asses this number, and it is a known that the probability of no-shows is considerably low, in the rage of 0%-1% according to the managers of the department. The number of time slots per day is 21 on Monday and 22 from Tuesday to Friday, this difference in scanning availability is due to the break time slots for staff. The 'break' slots are defined in the 'Resource Unavailability' data field. Besides these input data, there are also five more parameters associated to the algorithm precision, as you can see in Figure 19.

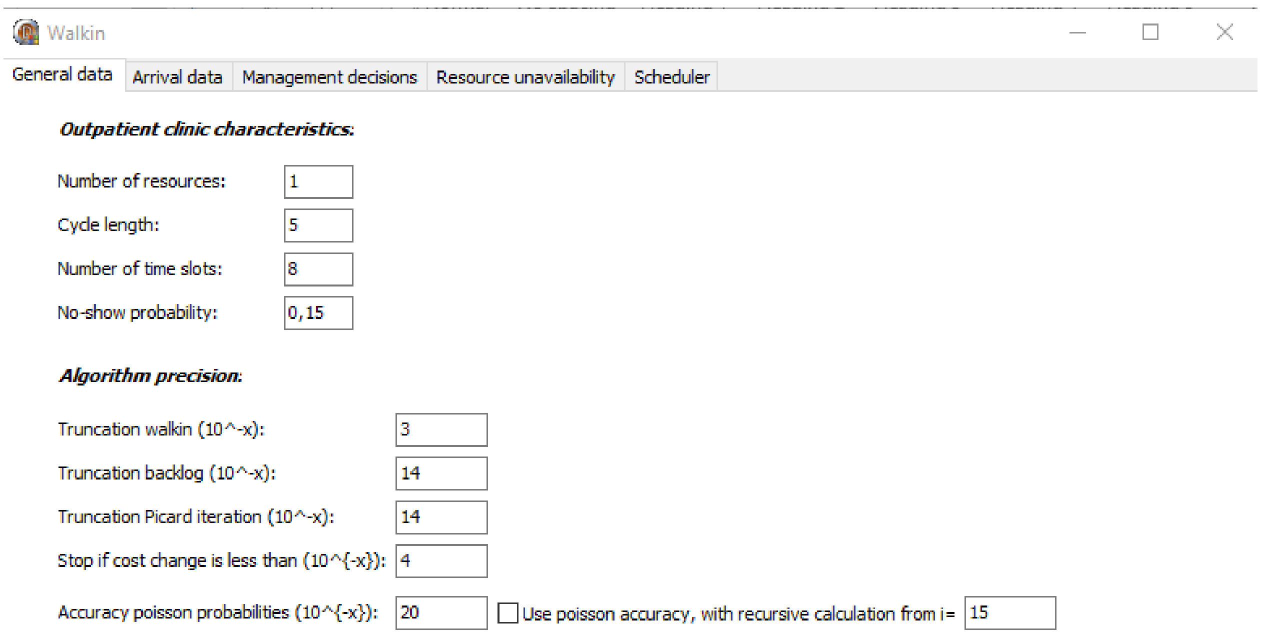



Figure 19: Section of General data in the Walk-in Generator model

#### *4.4.1.2 Arrival data*

The arrival data is divided in arrival rate for appointments, per day, and arrival rate for walk-in patients, per day and per time slot. Both rates are non-stationary Poisson arrival process, being the rate for walk-in patients time slot dependent, as explained in [1]. This rate corresponds to the parameter λ of the Poisson distribution, and the maximum like hood of λ corresponds to the mean.

| | Monday | Tuesday | Wednesday | Thursday | Friday |
|---|---|---|---|---|---|
| 8:10 | 0,0375 | 0,083333 | 0,054167 | 0 | 0,075 |
| 8:45 | 0,120833 | 0,195833 | 0,133333 | 0,1125 | 0,15 |
| 9:10 | 0,245833 | 0,254167 | 0,354167 | 0,172222 | 0,1 |
| 9:35 | 0,469444 | 0,369444 | 0,633333 | 0,493056 | 0,276389 |
| 10:00 | 0,838889 | 0 | 0 | 0 | 0 |
| 10:25 | 0,952778 | 0,715278 | 0,833333 | 0,781944 | 0,318056 |
| 10:50 | 0,858333 | 0,602778 | 1,004167 | 1,002778 | 0,55 |
| 11:15 | 0,661111 | 0,738889 | 1,375 | 0,7 | 0,356944 |
| 11:40 | 1,263889 | 0,681944 | 1,420833 | 0,863889 | 0,598611 |
| 12:05 | 0,544444 | 0,619444 | 1,441667 | 1,004167 | 0,6375 |
| 12:30 | 0,745833 | 0,405556 | 0,866667 | 0,501389 | 0,404167 |
| 12:55 | 0,351389 | 0,495833 | 0,641667 | 0,4625 | 0,540278 |
| 13:20 | 0,229167 | 0,529167 | 0,666667 | 0,419444 | 0,176389 |
| 13:45 | 0,519444 | 0,379167 | 0,379167 | 0,541667 | 0,545833 |
| 14:10 | 0,597222 | 0,634722 | 0,529167 | 0,679167 | 0,366667 |
| 14:35 | 0,483333 | 0,7625 | 0,516667 | 0,373611 | 0,631944 |
| 15:00 | 0 | 0 | 0 | 0 | 0 |
| 15:25 | 0,676389 | 1,016667 | 0,720833 | 0,490278 | 1,108333 |
| 15:50 | 0,706944 | 0,666667 | 0,970833 | 0,398611 | 0,831944 |
| 16:15 | 0,533333 | 0,609722 | 0,970833 | 0,436111 | 0,940278 |
| 16:40 | 2,620833 | 2,423611 | 2,466667 | 2,1875 | 2,106944 |

| | |
|---|---|
| Monday | 5,048611 |
| Tuesday | 6,380556 |
| Wednesday | 9,780556 |
| Thursday | 6,145833 |
| Friday | 7,8625 |

**Figure 20: Arrival rates to be applied in the Walk-in Generator model, for walk-ins (left) and for appointments (right)**

The data in Figure 20 was obtained with 5649 patients records from the year of 2015 in NKI-AVL. In the 2015, 90% of the patients were served as an appointment. To attaining the goal of combining appointments and walk-ins, we performed a patient clustering into those two big groups to obtained the respective arrival rates.

#### *4.4.1.3 Management decisions*

In the section of *Management Decisions* in the model, RT-AVL managers have the following targets for the service level inputs:

- Access time service level norm: 95% patients scanned within 2 days.
- Patience of a walk-in patient (in time slots): test 4 and 6 time slots.

The patience of a walk-in patient corresponds to the g parameter in Section 4.1.1. The Figure 21 shows those inputs in the model. We did not consider a cost for each patient rejected, in this way we attributed a unitary cost, so we could count the patients rejected.

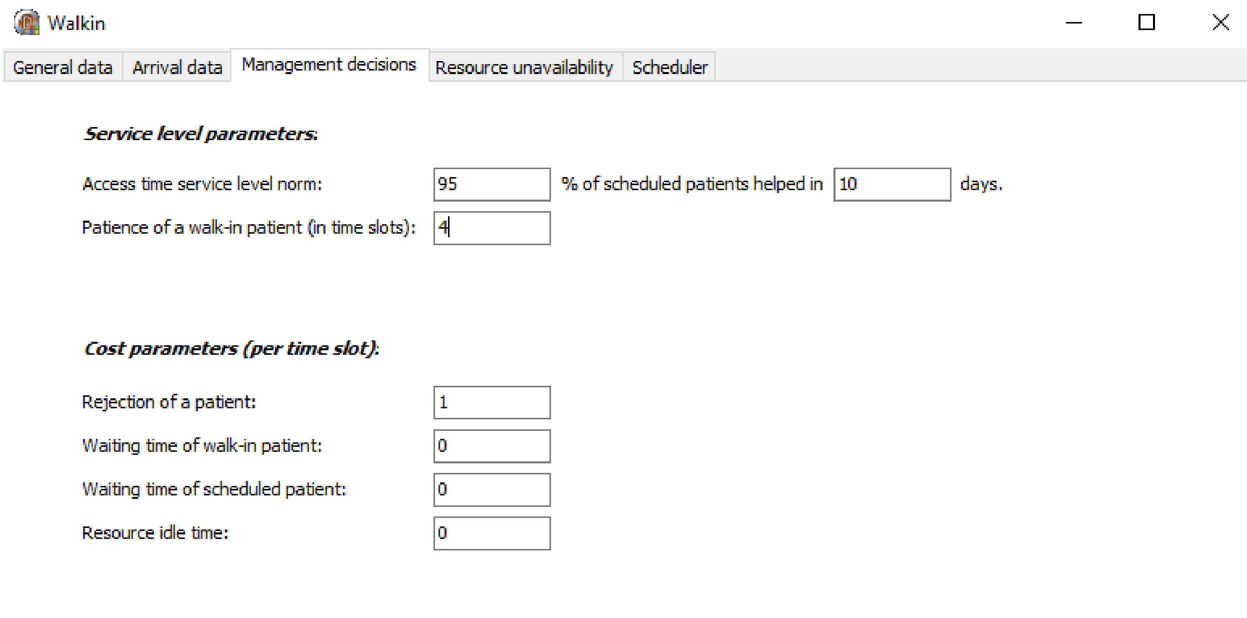
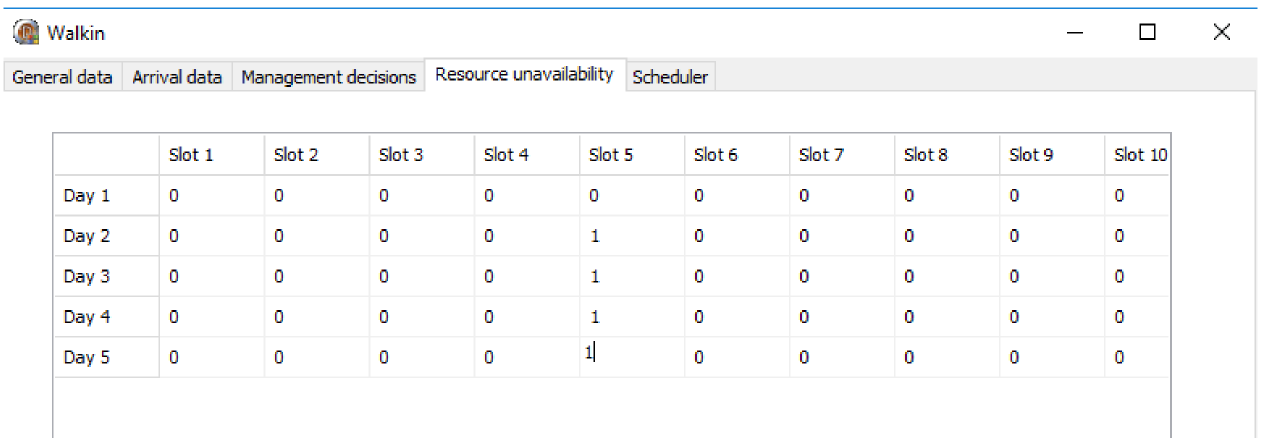



Figure 21: Management decisions section in the Walk-in Generator model

### 4.4.1.4 Resource Unavailability

In this section of the model we can determine the unavailability of the scanner for each time slot, introducing '1' in the unavailable time slot. The Figure 22 shows the CT09 resource unavailability. When comparing this Figure with the Figure 7 in Section 2.2.1, we see that the black time slots will be the '1's in this model section.




| | Slot 1 | Slot 2 | Slot 3 | Slot 4 | Slot 5 | Slot 6 | Slot 7 | Slot 8 | Slot 9 | Slot 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| Day 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Day 2 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 |
| Day 3 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 |
| Day 4 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 |
| Day 5 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 |

Figure 22: Resource unavailability section in the Walk-in Generator model

### *4.4.1.5 Scheduler*

The *Scheduler* section (Figure 23) corresponds to the main view of the program, and allow us to choose the type of heuristics to be applied in the iteration procedure of the methodology. The iteration procedure has the capacity cycle and the day cycle schedule, as explained in the previous Section 4.2.1 with Model 1 and 2, respectively. After choosing one option for the both models, we can choose adding on of the seven local search possibilities. Instead of choosing the day schedule heuristics, we can choose literature benchmarks, signalized as Benchmark 1,2 and 3.

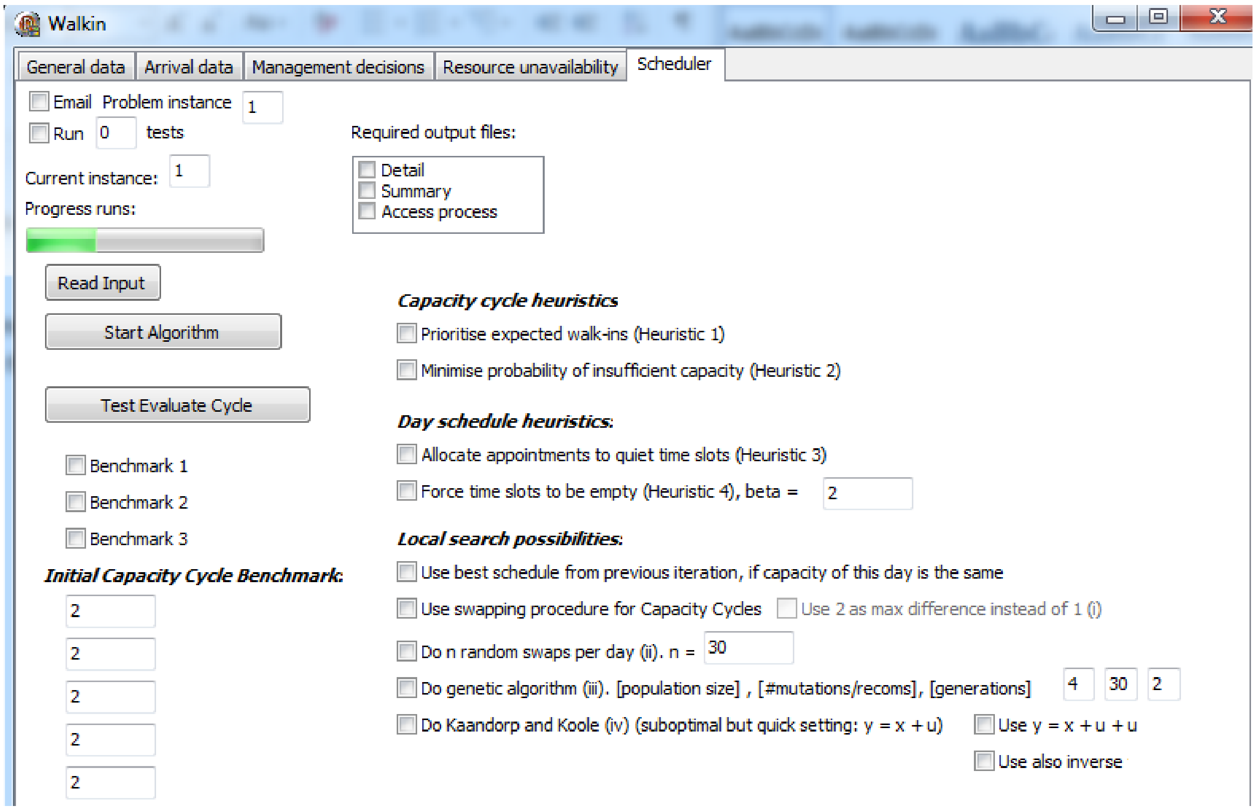



Figure 23: Scheduler section in the Walk-in Generator model

## 4.4.2 Configurations and output solutions

The best results using the Walk-in Generator model in [27] case study were obtained with 'Heuristic 1' for capacity cycle and 'Heuristic 3' for the day schedule. The difference in the fraction of walk-in patients between the solutions created with local search techniques and the ones without local search was 0.001% [27]. Due to this small difference, we did not use local search techniques, helping us to reduce the solution space. Besides the 'Heuristic 1' and 'Heuristic 3', we also used the literature benchmark, 'Benchmark 1', which spread the time slots through the appointment schedule, avoiding concentration of time slots in a certain time frame of the day. Table 5 shows the configurations we had in the Walk-in Generator Model, we analyse the different heuristics and the different values for the g parameter, obtaining eight configurations.

Table 5: Capacity allocation configurations tested

| Number of resources | 1: CT08 | | 2: CT08 and CT04 | |
|---|---|---|---|---|
| **Capacity cycle heuristics** | H1 | H1 | H1 | H1 |
| **Day schedule heuristics** | H3 | Spread | H3 | Spread |
| **g parameter** | 4/6 | 4/6 | 4/6 | 4/6 |
| | 1h | 1b | 2h | 2b |

Table 6: Capacity allocation solutions configurations' results

| | g=4 | | | g=6 | |
|---|---|---|---|---|---|
| | One resource | | | One resource | |
| | 1h | 1b | | 1h | 1b |
| SL | 97,42 | 96,63 | SL | 95,49 | 95,73 |
| AT | 5,72 | 5,87 | AT | 6,01 | 6,17 |
| F | 0,82 | 0,82 | F | 0,85 | 0,85 |
| | Two resources | | | Two resources | |
| | 2h | 2b | | 2h | 2b |
| SL | 97,28 | 95,44 | SL | 95,36 | 95,57 |
| AT | 5,85 | 6,16 | AT | 6,14 | 6,47 |
| F | 0,85 | 0,86 | F | 0,88 | 0,89 |

Table 7: Difference between solutions with g=6 and g=4, for capacity allocation '2b'

| | |
|---|---|
| SL | 0,001 |
| AT | 0,050 |
| F | 0,040 |

SL: Service Level; AT: Access Time; F: Fraction of walk-in patients

From Table 6, considering that the service level of serving 95% of the patients within 2 days is always obtained, we select the best configuration based on the fraction of the walk-in patients served. The solution '2b', for two resources and using the spreading procedure (benchmark -b-) has the biggest value for F. In Table 6 we compare the service level, access time and fraction of walk-in patients for the solution '2b', with g=4 and g=6. The results presented in the table are the difference of each KPI when g goes from 4 to 6. All the KPIs increase, F increases 4%, AT increases 5% and SL increases 0,1%. For an increase of 4% in the fraction of walk-in patients against an increase of one hour in the waiting time in the waiting room, the managers of RT-AVL decided that it would be not worth it. For this reason, we perform the discrete-event-simulation only for the four capacity allocation solutions configurations, with g=4.

These four solutions are shown in the following pictures.

| | Monday | Tuesday | Wednesday | Thursday | Friday |
|---|---|---|---|---|---|
| 7:45 | 0 | 0 | 0 | 0 | 0 |
| 8:10 | 0 | 5 | 0 | 5 | 5 |
| 8:45 | 1 | 1 | 1 | 1 | 1 |
| 9:10 | 1 | 1 | 1 | 1 | 1 |
| 9:35 | 1 | 1 | 1 | 1 | 1 |
| 10:00 | 0 | | | | |
| 10:25 | 0 | 0 | 0 | 0 | 1 |
| 10:50 | 0 | 1 | 0 | 0 | 1 |
| 11:15 | 1 | 1 | 0 | 0 | 1 |
| 11:40 | 0 | 0 | 0 | 0 | 0 |
| 12:05 | 0 | 0 | 0 | 0 | 0 |
| 12:30 | 1 | 1 | 0 | 1 | 1 |
| 12:55 | 1 | 1 | 0 | 1 | 1 |
| 13:20 | 1 | 1 | 1 | 1 | 1 |
| 13:45 | 1 | 1 | 1 | 1 | 1 |
| 14:10 | 1 | 1 | 1 | 1 | 1 |
| 14:35 | 1 | 0 | 1 | 1 | 1 |
| 15:00 | | | | | |
| 15:25 | 0 | 0 | 1 | 0 | 0 |
| 15:50 | 0 | 0 | 0 | 1 | 0 |
| 16:15 | 1 | 1 | 0 | 1 | 0 |
| 16:40 | 0 | 0 | 0 | 0 | 0 |

**Figure 24: Capacity allocation solution '1h'**

| | Monday | Tuesday | Wednesday | Thursday | Friday |
|---|---|---|---|---|---|
| 7:45 | 0 | 0 | 0 | 0 | 0 |
| 8:10 | 5 | 0 | 0 | 5 | 0 |
| 8:45 | 1 | 1 | 1 | 1 | 1 |
| 9:10 | 1 | 1 | 1 | 1 | 1 |
| 9:35 | 0 | 1 | 1 | 1 | 1 |
| 10:00 | 0 | | | | |
| 10:25 | 0 | 0 | 0 | 0 | 1 |
| 10:50 | 1 | 0 | 0 | 0 | 1 |
| 11:15 | 0 | 1 | 0 | 0 | 1 |
| 11:40 | 0 | 0 | 0 | 0 | 0 |
| 12:05 | 0 | 1 | 0 | 0 | 0 |
| 12:30 | 0 | 1 | 0 | 1 | 1 |
| 12:55 | 1 | 1 | 0 | 1 | 1 |
| 13:20 | 1 | 1 | 0 | 1 | 1 |
| 13:45 | 1 | 1 | 0 | 1 | 1 |
| 14:10 | 1 | 1 | 1 | 1 | 1 |
| 14:35 | 1 | 0 | 1 | 1 | 1 |
| 15:00 | | | | | |
| 15:25 | 0 | 0 | 1 | 0 | 0 |
| 15:50 | 0 | 0 | 0 | 1 | 0 |
| 16:15 | 1 | 0 | 0 | 1 | 0 |
| 16:40 | 0 | 0 | 0 | 0 | 0 |

| | Monday | Tuesday | Wednesday | Thursday | Friday |
|---|---|---|---|---|---|
| 7:45 | | | | | |
| 8:10 | | | | | |
| 8:45 | | 0 | 0 | 0 | 0 |
| 9:10 | | | | | |
| 9:35 | | 0 | | 0 | 0 |
| 10:00 | | | | | |
| 10:25 | | 0 | | 1 | 1 |
| 10:50 | | 1 | 1 | 1 | 1 |

**Figure 25: Capacity allocation solution '2h', CT08 (left) and CT04 (right)**

| | Monday | Tuesday | Wednesday | Thursday | Friday |
|---|---|---|---|---|---|
| 7:45 | 5 | 5 | 5 | 5 | 5 |
| 8:10 | 0 | 0 | 0 | 0 | 0 |
| 8:45 | 1 | 1 | 1 | 1 | 1 |
| 9:10 | 1 | 1 | 1 | 1 | 1 |
| 9:35 | 1 | 1 | 1 | 1 | 1 |
| 10:00 | 0 | | | | |
| 10:25 | 1 | 1 | 1 | 1 | 1 |
| 10:50 | 0 | 1 | 0 | 0 | 1 |
| 11:15 | 1 | 1 | 1 | 1 | 1 |
| 11:40 | 0 | 0 | 0 | 0 | 0 |
| 12:05 | 1 | 1 | 0 | 1 | 1 |
| 12:30 | 0 | 0 | 0 | 0 | 0 |
| 12:55 | 1 | 1 | 0 | 1 | 1 |
| 13:20 | 1 | 1 | 0 | 0 | 1 |
| 13:45 | 1 | 1 | 0 | 1 | 1 |
| 14:10 | 1 | 1 | 0 | 1 | 1 |
| 14:35 | 0 | 0 | 1 | 1 | 1 |
| 15:00 | | | | | |
| 15:25 | 0 | 0 | 0 | 0 | 0 |
| 15:50 | 0 | 0 | 0 | 0 | 0 |
| 16:15 | 0 | 0 | 0 | 1 | 0 |
| 16:40 | 0 | 0 | 0 | 0 | 0 |

Figure 26: Capacity allocation solution '1b'

| | Monday | Tuesday | Wednesday | Thursday | Friday |
|---|---|---|---|---|---|
| 7:45 | 5 | 5 | 5 | 5 | 5 |
| 8:10 | 0 | 0 | 0 | 0 | 0 |
| 8:45 | 1 | 1 | 1 | 1 | 1 |
| 9:10 | 1 | 1 | 1 | 1 | 1 |
| 9:35 | 1 | 1 | 1 | 1 | 1 |
| 10:00 | 0 | | | | |
| 10:25 | 1 | 1 | 1 | 1 | 1 |
| 10:50 | 0 | 0 | 0 | 0 | 1 |
| 11:15 | 1 | 1 | 1 | 0 | 1 |
| 11:40 | 0 | 0 | 0 | 0 | 0 |
| 12:05 | 1 | 1 | 1 | 0 | 1 |
| 12:30 | 0 | 0 | 0 | 0 | 0 |
| 12:55 | 1 | 1 | 1 | 0 | 1 |
| 13:20 | 1 | 1 | 0 | 0 | 1 |
| 13:45 | 1 | 1 | 0 | 1 | 1 |
| 14:10 | 1 | 0 | 0 | 0 | 1 |
| 14:35 | 0 | 0 | 1 | 0 | 0 |
| 15:00 | | | | | |
| 15:25 | 0 | 0 | 0 | 0 | 0 |
| 15:50 | 0 | 0 | 0 | 0 | 0 |
| 16:15 | 0 | 0 | 0 | 1 | 0 |
| 16:40 | 0 | 0 | 0 | 0 | 0 |

| | Monday | Tuesday | Wednesday | Thursday | Friday |
|---|---|---|---|---|---|
| 7:45 | | | | | |
| 8:10 | | | | | |
| 8:45 | | 1 | 1 | 1 | 1 |
| 9:10 | | | | | |
| 9:35 | | 0 | | 0 | 0 |
| 10:00 | | | | | |
| 10:25 | | 0 | | 1 | 1 |
| 10:50 | | 0 | 0 | 0 | 0 |

Figure 27: Capacity allocation solution '2b', CT08 (left) and CT04 (right)

### 4.5 Repairing of solutions to be evaluated

To the four capacity allocation solutions, the team of experts performed some rearrangements having in mind the specific RT-AVL constraints. These rearrangements consisted in changing some time slots for walk-ins in the morning to appointment type time slots. The reason for this to happen was the constrains related with the staff availability and with the consultations hours.

#### 4.5.1 Staff availability

A CT-scan may require that an IV contrast is administered to a patient before the scan. In these situations, there must be a physician to administrate the contrast to the patient. In NKI-AVL, the physicians are only available after 8h45 AM, and thus every time slot for appointments before 8h45 A.M in the new appointment schedule as to be a non-IV-contrast time slot, following the current doctors' schedule in the hospital.

#### 4.5.2 Consultation hours

The walk-in patients, as well as the appointment patients, are referred to the CT-scanner after consultation. Because walk-in patients can have the CT-scan done in the same day of consultation, before the end of the first consultation there are no walk-in patients available for the scanner. Knowing that the first consultation of a work day ends at 9h40 A.M, every slot for walk-in patients before that hour will never be fulfilled, and represent a waste of capacity. Thus, in the output solutions, every time slot for walk-in before 9h40 A.M was adapted to an appointment-type time slot. All changes have been performed maintaining the number of time slots for appointments (capacity cycle), and only changing the order of certain time slots, as it can be noticed in the following Figures.

| | Monday | Tuesday | Wednesday | Thursday | Friday |
|---|---|---|---|---|---|
| 7:45 | 5 | 5 | 5 | 5 | 5 |
| 8:10 | 5 | 5 | 5 | 5 | 5 |
| 8:45 | 1 | 1 | 1 | 1 | 1 |
| 9:10 | 1 | 1 | 1 | 1 | 1 |
| 9:35 | 1 | 1 | 1 | 1 | 1 |
| 10:00 | 0 | | | | |
| 10:25 | 0 | 0 | 0 | 0 | 0 |
| 10:50 | 0 | 1 | 0 | 0 | 1 |
| 11:15 | 0 | 1 | 0 | 0 | 0 |
| 11:40 | 0 | 0 | 0 | 0 | 0 |
| 12:05 | 0 | 0 | 0 | 0 | 0 |
| 12:30 | 1 | 1 | 0 | 1 | 1 |
| 12:55 | 1 | 1 | 0 | 1 | 1 |
| 13:20 | 1 | 1 | 1 | 1 | 1 |
| 13:45 | 1 | 1 | 1 | 1 | 1 |
| 14:10 | 1 | 1 | 1 | 1 | 1 |
| 14:35 | 1 | 0 | 0 | 1 | 1 |
| 15:00 | | | | | |
| 15:25 | 0 | 0 | 0 | 0 | 0 |
| 15:50 | 0 | 0 | 0 | 1 | 0 |
| 16:15 | 0 | 0 | 0 | 0 | 0 |
| 16:40 | 0 | 0 | 0 | 0 | 0 |

Figure 28: Capacity allocation solution '1hr' (rearranged)

| | Monday | Tuesday | Wednesday | Thursday | Friday |
|---|---|---|---|---|---|
| 7:45 | 5 | 5 | 5 | 5 | 5 |
| 8:10 | 5 | 5 | 5 | 5 | 5 |
| 8:45 | 1 | 1 | 1 | 1 | 1 |
| 9:10 | 1 | 1 | 1 | 1 | 1 |
| 9:35 | 1 | 1 | 1 | 1 | 1 |
| 10:00 | 0 | | | | |
| 10:25 | 0 | 0 | 0 | 0 | 0 |
| 10:50 | 0 | 0 | 0 | 0 | 0 |
| 11:15 | 0 | 0 | 0 | 0 | 1 |
| 11:40 | 0 | 0 | 0 | 0 | 0 |
| 12:05 | 0 | 0 | 0 | 0 | 0 |
| 12:30 | 1 | 1 | 0 | 1 | 1 |
| 12:55 | 1 | 1 | 0 | 1 | 1 |
| 13:20 | 1 | 1 | 0 | 1 | 1 |
| 13:45 | 1 | 1 | 0 | 1 | 1 |
| 14:10 | 1 | 1 | 1 | 1 | 1 |
| 14:35 | 0 | 0 | 0 | 1 | 1 |
| 15:00 | | | | | |
| 15:25 | 0 | 0 | 0 | 0 | 0 |
| 15:50 | 0 | 0 | 0 | 1 | 0 |
| 16:15 | 0 | 0 | 0 | 0 | 0 |
| 16:40 | 0 | 0 | 0 | 0 | 0 |

| | Monday | Tuesday | Wednesday | Thursday | Friday |
|---|---|---|---|---|---|
| 7:45 | | | | | |
| 8:10 | | | | | |
| 8:45 | | 1 | 1 | 1 | 1 |
| 9:10 | | | | | |
| 9:35 | | 0 | | 0 | 0 |
| 10:00 | | | | | |
| 10:25 | | 0 | | 1 | 1 |
| 10:50 | | 1 | 1 | 1 | 1 |

Figure 29: Capacity allocation solution '2r' (rearranged), CT08 (left) and CT04 (right)

| | Monday | Tuesday | Wednesday | Thursday | Friday |
|---|---|---|---|---|---|
| 7:45 | 5 | 5 | 5 | 5 | 5 |
| 8:10 | 5 | 5 | 5 | 5 | 5 |
| 8:45 | 1 | 1 | 1 | 1 | 1 |
| 9:10 | 1 | 1 | 1 | 1 | 1 |
| 9:35 | 1 | 1 | 1 | 1 | 1 |
| 10:00 | 0 | | | | |
| 10:25 | 0 | 0 | 0 | 0 | 0 |
| 10:50 | 0 | 1 | 0 | 0 | 1 |
| 11:15 | 1 | 1 | 1 | 1 | 1 |
| 11:40 | 0 | 0 | 0 | 0 | 0 |
| 12:05 | 1 | 1 | 0 | 1 | 1 |
| 12:30 | 0 | 0 | 0 | 0 | 0 |
| 12:55 | 1 | 1 | 0 | 1 | 1 |
| 13:20 | 1 | 1 | 0 | 0 | 1 |
| 13:45 | 1 | 1 | 0 | 1 | 1 |
| 14:10 | 1 | 1 | 0 | 1 | 1 |
| 14:35 | 0 | 0 | 1 | 1 | 1 |
| 15:00 | | | | | |
| 15:25 | 0 | 0 | 0 | 0 | 0 |
| 15:50 | 0 | 0 | 0 | 0 | 0 |
| 16:15 | 0 | 0 | 0 | 1 | 0 |
| 16:40 | 0 | 0 | 0 | 0 | 0 |

Figure 30: Capacity allocation solution '1br' (rearranged)

| | Monday | Tuesday | Wednesday | Thursday | Friday |
|---|---|---|---|---|---|
| 7:45 | 5 | 5 | 5 | 5 | 5 |
| 8:10 | 5 | 5 | 5 | 5 | 5 |
| 8:45 | 1 | 1 | 1 | 1 | 1 |
| 9:10 | 1 | 1 | 1 | 1 | 1 |
| 9:35 | 1 | 1 | 1 | 1 | 1 |
| 10:00 | 0 | | | | |
| 10:25 | 0 | 0 | 0 | 0 | 0 |
| 10:50 | 0 | 0 | 0 | 0 | 1 |
| 11:15 | 1 | 1 | 1 | 0 | 1 |
| 11:40 | 0 | 0 | 0 | 0 | 0 |
| 12:05 | 1 | 1 | 1 | 0 | 1 |
| 12:30 | 0 | 0 | 0 | 0 | 0 |
| 12:55 | 1 | 1 | 1 | 0 | 1 |
| 13:20 | 1 | 1 | 0 | 0 | 1 |
| 13:45 | 1 | 1 | 0 | 1 | 1 |
| 14:10 | 1 | 0 | 0 | 0 | 1 |
| 14:35 | 0 | 0 | 1 | 0 | 0 |
| 15:00 | | | | | |
| 15:25 | 0 | 0 | 0 | 0 | 0 |
| 15:50 | 0 | 0 | 0 | 0 | 0 |
| 16:15 | 0 | 0 | 0 | 1 | 0 |
| 16:40 | 0 | 0 | 0 | 0 | 0 |

**Figure 31: Capacity allocation solution '2br' (rearranged)**

In this new capacity allocation solutions, there are time slots with the number 5, referring to the appointment time slots without IV contrast needed.

The rearrangement performed for the RT-AVL include the insights from the expert team in the cancer center with the concern of keeping the system simple and similar to the original Kortbeek *et al.* model. As referred in Section 3.4, it is an objective of this thesis the simulation, and later implementation, of a capacity allocation solution made by the method with the least assumptions as possible, so the conclusions taken could be directly related with the combination of the two patient's type, and not about other factors.

To the easiness of reading the tables, all the results presented from now on are for the solutions: '2h', '2hr' and '2b','2br', counting for both CT scanners, weighting the results for each performance measurement with 0.113 for CT04 and 0.887 for CT08.

## Chapter 5 – Simulation Model

In this chapter, we present the development of our simulation model using a 10-step framework for the scope explained in Chapter 2 for the case study of RT-AVL. We start by describing the 10 steps, and present the model following each of these steps, starting with the formulation of the problem (Section 5.1), the data needed (Section 5.2), the model development (Section 5.3), validation (Section 5.4), and conclusions (Section 5.5).

### 5.1 Conceptual scope

A simulation model has the main objective of mimicking the behavior of a real system. This allows the evaluation of different possible configurations of the real system, with the possibility of evaluating the current system and compare the performance with new proposed configurations. The 10-steps scheme for a simulation model are present in the Figure 32.

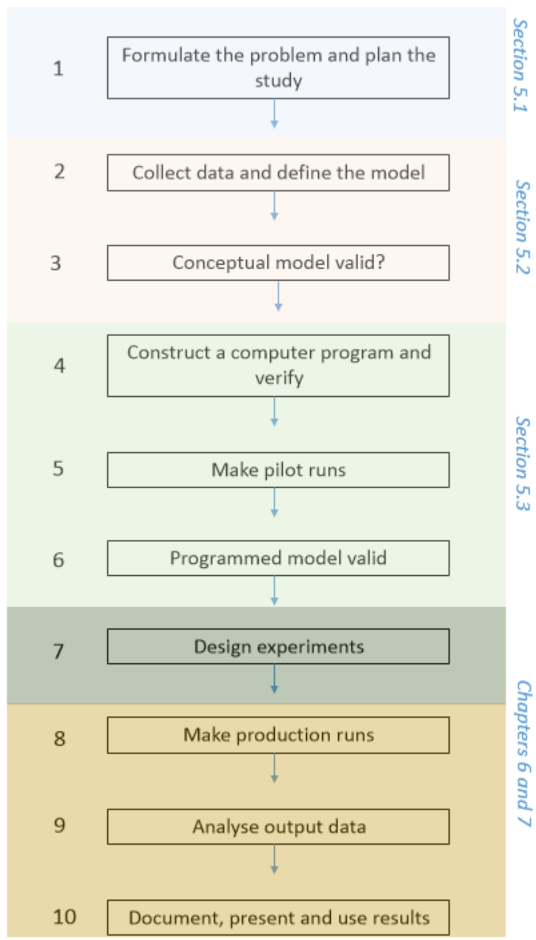



Figure 32: 10-steps scheme for a simulation model

The first step focus on a certain managerial problem of interest to the manager, including the definition of objectives, performance measurements, and scope, as explained in Section 5.1.1.

### 5.1.1 Scope

The scope of the research is the capacity allocation of imaging devices in a radiotherapy department combining appointments and walk-ins. We study the case of the RT-AVL, with 2 CT-scanners and a patient population divided in 61 care plans. A capacity allocation solution is represented by an appointment system for each machine. This appointment system has time slots allocated for a patients' groups.

The conceptual model can be generally represented by the Figure 33. Upon the patient's arrival, an evaluation whether he/she is eligible for walk-in takes place. If the patient is of appointment type, then he goes to the planner, if not, he can walk into the server right away.

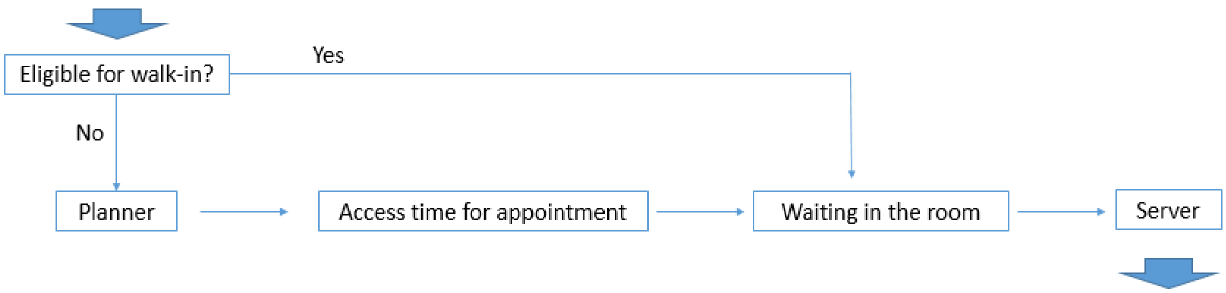



Figure 33: Overview of the simulation model

In a more detailed view of the system four components can be identified: tests, preparations, planner and servers. There are two components which are common for every patient: the initial test, identified as 'Test0', and the destination , identified as 'Server' in Figure 33. Only appointment-type patients pass by the 'Planner'. In the destination, independently of the care plan assigned to the patient, she/he will be assigned to one of the three types of time slots: walk-in time slot, appointments time slot (with or without contrast) and no-contrast time slot.

### 5.1.2 Model Assumptions

The model replicates a part of the real system of RT-AVL, which is, as any other simulation model, bounded by a set of assumptions/simplifications while simultaneously keeping the system realistic and controllable. In this section, we present the list of assumptions made when building the simulation model that mimics the track for CT-scanning at the RT-AVL:

- Operating overtime is not allowed;
- Breakdown probability is set to zero due to the insignificant breakdown probability value verified in practice;
- Queue dodging it is not taking into account, patients will always wait until they are served under the waiting time they are willing to wait;
- Once an appointment is made, it cannot be changed;
- Arrival of patients happen according to a non-stationary Poisson process;
- When scheduling for two servers, the choice of the server is based on the first available server;.
- The servers can only serve one patient at once;
- Appointments are only made for servers, not for test and preparation components;
- There is no distinction between inpatients and outpatients, all the patients are served in the same way;
- Servers share the same waiting room;
- There are no waiting rooms for Test 1 or for procedures;
- Servers are considered to be the last stop in the system;
- Patient type is determined at the arrival and does not change during the pathway;

- Patients can only be at one component at a time - the process in the model is sequential, there are no parallel processes;
- Patients only visit the facility once, if in reality they come to the hospital more than once they are counted as another patient;
- Seasonal trends are not included in the arrival rates. We use the same arrival rates for the whole year;
- Holidays during the work days are not taken into account, during the whole year a week has always five work days;
- Patients' preferences are not taken into account, they are scheduled in the time slot with the smallest waiting time/ access time;
- All patients are considered punctual, no delays;
- The no-show probability is set to zero.
- Brachytherapy patients were excluded, because they represent 0.5% of the patients population and have several restrictions

These assumptions were verified and approved by the head of medical physicists, a medical physicist, the head of the appointment office and the team leader of Imaging Process.

### 5.1.3 Scheduling process

#### *Patient Creation*

Based on data extracted from the internal medical information system – MOSAIQ – and, the intranet RT planning tool - PLANRT, we gathered information about the patient population during the years of 2014, 2015 and 2016. We analysed this information and found 61 care plans (Appendix A), per the following parameters:

- Walk-in eligibility;
- Test 1 result (breath and hold, Dentist consultation, PET-CT);
- Procedures needed (P1, P2);
- Contrast needed.

The patients' data to be input into the simulation is then divided in the following parameters:

- Patient ID;
- Patient care pathway ID;
- Walk-in eligible (true/false);
- Contrast needed (y/n);
- Test 1 type ID (1/2/3);
- Test 1 result (y/n/n.a);
- Procedure 1 (y/n);
- Procedure 2 (y/n);
- Arrival data:
  - Time slot;
  - Weekday;
  - Year week.

All patients are clustered in three patient types, corresponding to the three time slot types to which they are assigned: walk-ins; appointments with IV contrast; appointments without IV contrast.

An appointment patient type is defined by his eligibility to walk into the server as a result of Test 1. These patients receive an appointment in the first available time slot of the next day, if the server is available. If the patient is a walk-in, then he can walk into the server in the same day of the consultation. If the expected waiting time is bigger than a pre-defined maximum time for the time a patient is willing to wait, is offered an appointment for the next day. By definition, this is a deferred patient, i.e. a walk-in patient transformed into an appointment patient due to the rather long waiting time he would have to wait to be served in the same day.

### *Patient route*

The route a patient follows in the simulation model depends on the care plan of the patient, i.e. depends on the medical needs of the patient. Figure 29 and 30 represent all the possible routes a patient may experience in the model.

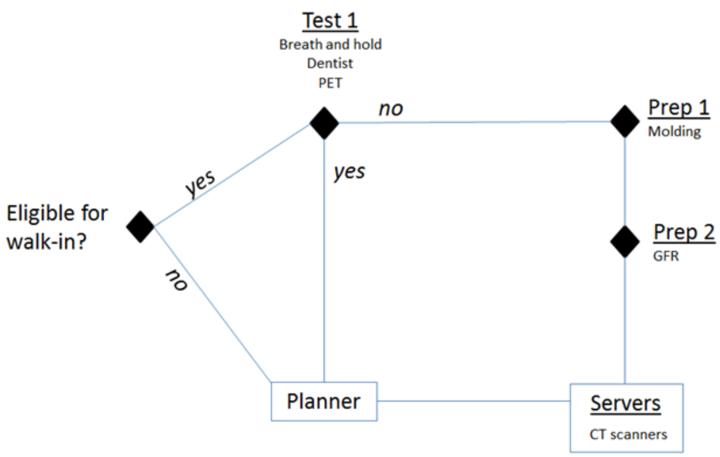



**Figure 34: Simulation model routes**

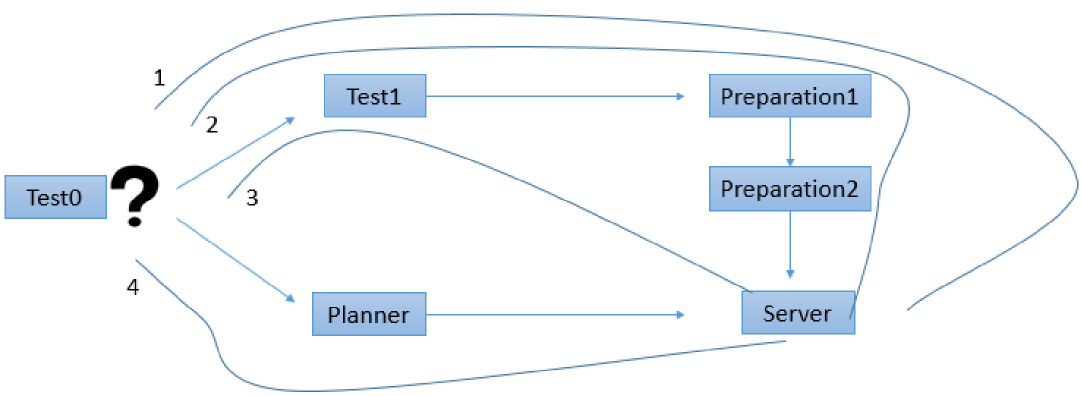



**Figure 35: Simulation model routes detailed**

Each patient is attributed with a care plan, corresponding to a care pathway, following a distribution based on the data analysed. If the patient is eligible for walk-in follows the route to the Test 1, if not, follows the route to the planner.

In the planner, the model needs to know if the patient needs IV contrast, to search an appointment time slot suitable for the patient. This route end in the server after finding the time slot.

In the route to the Test 1, the patient has three binary tests to perform. Only if the three results are negative, the patient follows the route as a walk-in, ending in the server without passing by the planner. After Test 1 the walk-in patient may need one procedure, two or none. The number of procedures needed does not change his or hers final destination to the server as a walk-in patient. If one of the tests is positive, the patient goes to the planner as an appointment patient type.

### *Test 1 and Preparation procedures*

Within the same care plan exist patients of appointment type and walk-in type. To distinguish them we perform the Test 1. According to each care plan, patients can perform one, two or all the test components. The test is modelled by a binomial distribution, with a success probability (p) and number of samples (n) for each component:

**Table 8: Components' distribution parameters**

| | **n** | **p** |
|---|---|---|
| **1- Breathe and Hold** | 1356 | 0,346 |
| **2- Dentist Consultation** | 346 | 0,287 |
| **3- PET-CT** | 543 | 0,178 |

The test is assumed to have a zero-processing time and an infinity capacity, it serves the patients in a First Come First Served (FCFS) fashion. For a positive result the patient goes to the planner as an appointment type of patient, if the result is negative he/she goes to the walk-in route.

The result of the Test 1 does not change only the route, but also the planning horizon. For instance, if the Test 1 is positive for the type breathe–and-hold technique (ID equal to 1), the patient has a planning horizon greater or equal than one day, this way the patient can practice the technique at home. If the Test 1 is positive with an ID equal to 2 (dentist consultation), the patient has a planning horizon greater or equal than 8 days (one week and a half), to align with the dentist's schedule. If the Test 1 is positive with an ID equal to 3 (PET-CT needed), the planning horizon is extended until the next Monday or Friday, so the PET-CT scan be performed in the same day the MRI scan is performed. This shift in the plan horizon does not count for access time, just the days after this shift count.

Besides Test 1, the model incorporates two preparation procedures. These procedures are the moulding and GFR (blood analysis). If both procedures are needed, they always happen in sequence, as shown in Figure 29. According to the care plan of the patient, it can happen that both procedures are needed, only one of them is needed, or none. The processing times for preparation procedures are deterministic and equal to one time slot. Besides, it is assumed that there is sufficient capacity to get zero waiting times for these procedures. If only one procedure is needed, the patient is counted as able to walk into the server after one time slot from the time of his arrival. If both procedures are needed, he is only counted after two time slots. This way, the time spent to undertake these procedures are not counted for the waiting time of the patient.

*Patient allocation*

The simulation model receives as input a capacity allocation solution: an empty schedule to allocate the patients while they arrive to the facility. Each patient, according to his care plan, is assign to one of the three types of time slots in a FCFS way. The three time slots are: appointment; walk-ins and appointments with no contrast. All with the same time length of 25 minutes.

*Servers*

There are two servers with different capacity. We assume that there is no preference of one over another, i.e. the patient is allocated to the one that is available with the smallest access time or waiting time. If there are slots available in both servers, with the same access time or waiting time, the choice between the servers is randomly chosen.

## 5.2 Data and information collection

In this section we explain in detail the information and data collected run the simulation model.

### 5.2.1 Patient-type parameters

Almost the entire data related with the patient type was collected through the use of queries built specifically to the software MOSAIQ  of the department. The division in 61 care plans was done according to each patients' care plans currently used in the clinic.

The information about which patient care plans classify as walk-in or appointment type, and information about the tests and the procedures needed by each care plans was collected during interviews held with experts of the radiotherapy department.

### 5.2.2 Test 1 and procedures parameters

The concept of a test for deciding the route of some care plans was a representation of the real system approved by the hospital experts. We fitted the data into these tests and estimated their distribution.

The procedures' processing times are not recorded by the hospital, however it was agreed that these processing times would equal one time slot. With the help of several interviews and after some site visits we were able to define a patient route for each care pathway.

### 5.2.3 Organizational parameters

The number of time slots per resource/per day, and the number of working days were assumed to be equal to the current capacity allocation for the CT-scanners in RT department of the -AVL currently have.

*Arrival process*

Our arrival rate of patients is a considered a stochastic process, it takes the uncertainty into account, which is very important, specially in healthcare, due to the high variability verified in the system.

Theoretically, the patients' arrival rate holds the property of "lack of memory", i.e. the arrival of a patient at a certain time slot is independent from the arrival of the next patient, and so on. This can be represented by means exponential distribution, with the mean inter-arrival time being $E[X] = \frac{1}{\lambda}$, where $\lambda$ is the mean arrival rate per time unit (time slot of 25 minutes) in a Poisson distribution.

The arrival rate of all patients was calculated with data recorded from 1 of January 2015 to 31 of December 2015, i.e. for the whole year 2015.

A Chi-squared test was done to compare the observed data with the expected data generated using the Poisson distribution. We used a *p > 0,05* to accept the hypothesis that the arrival rate fits a Poisson distribution.

## 5.3 Verification and validation of the model

### 5.3.1 Warm-up and cool-down period

Our simulation model finds its performance measurements when it reaches a steady state, not when a natural event ends the simulation. This kind of simulation is called 'non-terminating simulation'. To reach the steady state, the model needs to pass a period where the model has a transient behaviour. To do this we will calculate the so called "warm-up" period. In this period the model does not represent the real system, because the schedule is originally empty, so the performance measurement including data from this transient period of the cycle will not be accurate.

To calculate the warm up period we will use the performance indicator utilization that influences the two major indicators: access times and waiting times. To smooth out variations in data, we calculate a moving average:

**Equation 4**

$$Y_i(w) = \frac{1}{2w+1} \sum_{s=-w}^{w} Y_{i+s}$$

With the window $w \leq |\frac{1}{4}m|$, where $m$ is the amount of observations and $w = i - 1 \; if \; i \leq w$. Using a run length of 1 year, resulting of 5688 observations, the maximum window is 1422. Additionally, we removed the same amount of data at the end of each run, in this way we do not count the patients who have an appointment but have not yet been served. We define this period as the "cool-down" period.

### 5.3.2 Run Length

With the warm-up and the cool-down period deleted, each replication can be considered to be a terminating simulation. This means that we can use the confidence interval (CI) half width to determine the minimum number of replications required. With a relative error ($\gamma$) of 2% and a confidence level ($\alpha$) of 95%, using the following formulas:

**Equation 5**

$$X_n = \frac{1}{n} \sum_{i=1}^{n} X_i$$

**Equation 6**

$$S_n^2 = \frac{1}{n-1} \sum_{i=1}^{n} (X_i - X)^2$$

Equation 7

$$\delta(n,a) = t_{n-1,1-\alpha/2}\sqrt{\frac{S_n^2}{n}}$$

Equation 8

$$\frac{\delta(n,a)}{|X_n|} \le \gamma'$$

Equation 9

$$\gamma' = \frac{\gamma}{\gamma+1}$$

Equation 10

$$n = n+1$$

Equation 11

$$n*(\gamma) = min\left\{ i \le n\colon \frac{t_{n-1,1-\alpha/2}\sqrt{\frac{S_n^2}{n}}}{|X_n|} \le \frac{\gamma}{\gamma+1} \right\}$$

We found that n*=43 for the experimental setting. We performed 50 runs since the run time is not an issue in our computational experiments.

We performed these simulations in a personal computer with a dual core processor i7 1.2 GHz, 8GB of RAM and using Matlab software. Each replication required, on average, 48 minutes and 12 seconds to be completed.

### 5.3.3 Verification and validation

The verification of the model ensures the technical functioning of the programmed model. Typically, the verification involves 8 steps: write and debug in components or sub methods; let more than one person review the computer program; use different parameters; trace the state of the simulated system; run the model under simplified assumptions; compute the sample mean and sample variance and compare to desired values; use a commercial simulation package; observe animations.

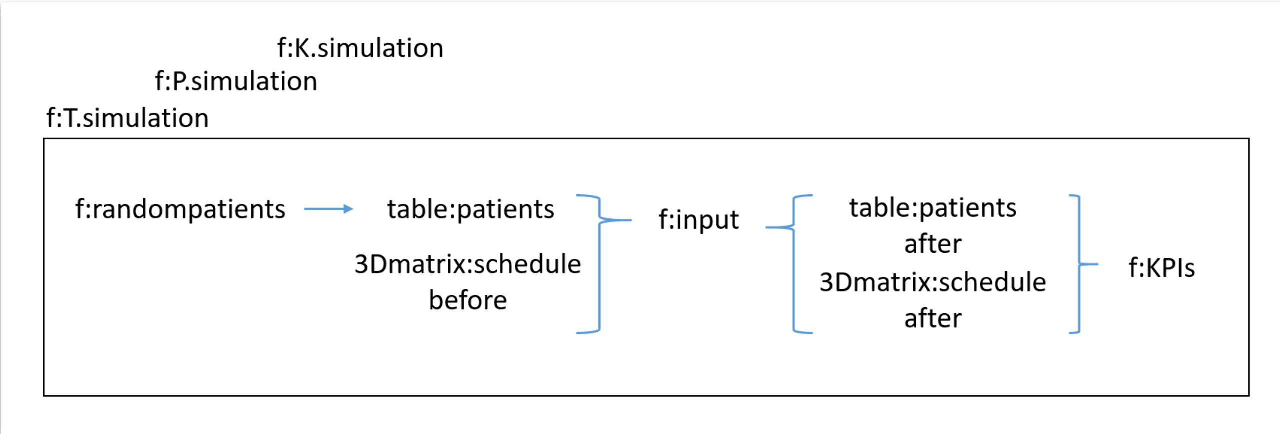



**Figure 36: Modules of the discrete-event-simulation model**

The program is divided into three big functions: *randompartients*, *input* and *KPIs*. The *randompatients* function creates the patients, with their characteristics and arrival time, creating the table patients, with all the information needed for each patient, see Section 5.1.3. According to the capacity allocation solution being tested, which is a 3D matrix named *schedulebefore*, each patient is allocated to a time slot. The capacity solution is one, if only one resource is being tested, or two if we are counting with the two CT-scanners. It is a 3D matrix representing in YY axis the time slots, in XX axis the work days and in the ZZ axis the weeks in a working year, typically 52 weeks. The input function will attribute a time slot in the *schedulebefore* to each patient, creating the table *patientsafter*, all the patients already allocated, and the *scheduleafter*, the time slots already referred to a specific patient. The function KPIs will compare the patients and schedules before and after, outputting the performance measurements needed. This module, represented in Figure 36 inside the rectangle, is managed by the function *X.simulation*, where X. can be T. when the traditional capacity allocation is being tested, P when the table patients is based on real data and not on the probabilistic distributions (for model validation) and K. for the capacity allocation solutions found with the Walk-in Generator model. Therefore, we write and debug the simulation into components, which were revised by one of the supervisors, Bruno Vieira. Due to the different configurations, showed in the X. types in the *X.simulation* function, we were able to test different parameters, starting with the simplest configuration. The *KPIs* function compare the desired values, which was really useful for debug and later for validation.

Concluding, we performed all these steps except for the last one, because the language we used is not straightforward when using animation to see what is happening in the running.

### *Access time*

After running the simulation model with mentioned data, we verified that the average access time is around 3 days for the simulated experiments, whilst we measured around 4 days in practice. The confidence interval for 95% of this performance measurement is [1,27;1,30]. As the zero does not belong to this interval, the null hypothesis is rejected. The difference in the results for the access time are statistically relevant, and not due to some randomness. We believe that this discrepancy can be explained by the fact that patient's preferences are being considered in the clinic, which goes against the first come first served assumption used in both Kortbeek *et al.* method and the simulation model.

### *Waiting time*

Only patients that were available in a time slot next to the walk-in time slot were served, leading to a low waiting time. Due to the low number of patients assumed as walk-in population in RT-AVL, 360 patients (8% of the patient population), and the inexistence of a time to limit the waiting time, we can say that there is no walk-in culture in the department. Because of this, we do not attribute a big relevance to this performance measurement.

The waiting time we obtained was 2,3 time slots and in practice was 1,98. In Table 9, the number of patients for the simulation model is an average number for the 200 runs performed, and for practice it is the number of patients served in the year of 2015.

**Table 9: Access time (AT) and waiting time (WT) parameters for simulation model and for practice**

| | Simulation model | Practice |
|---|---|---|
| **AT** | 2,880759 | 4,173526 |
| **WT** | 2,344007 | 1,981986 |
| **#patients** | 4537 | 4391 |

## Chapter 6 – Computational experiments

In this chapter, we explore which experiments are useful for the implementation of the combined system in RT-AVL. In Section 6.1 we give a detailed view about the inputs needed for the simulation model and in Section 6.2 we do an extensive sensitivity analysis.

### 6.1 Input parameters

As explained in Section 5.2, the input parameters can be divided in four fields: patients-type; Test1; Procedures and Organizational parameters. In the Table 10 you can see in more detailed the parameters in each field.

**Table 10: Patients-type, Test1, Procedures and Organizational parameters**

| Patients-type parameters | |
|---|---|
| N | Total number of patients |
| $n_i$ | Fraction of patients with care pathway *i* |
| $np_i$ | Number of preparations the care pathway needs |
| $t_i$ | If the patient care pathway *i* needs Test1 |
| $nh_i$ | Number of days in the planning horizon for care pathway *i* |
| cpID | Care pathway ID |
| bcont | Boolean for contrast |
| WI | Boolean for eligibility for walk-in |
| Test 1 parameters per patient type | |
| $t_1$ =(n,p) | Distribution of the first component of Test 1 |
| $t_2$=(n,p) | Distribution of the second component of Test 1 |
| $t_3$=(n,p) | Distribution of the third component of Test 1 |
| tID | Test ID (1,2,3) |
| Procedures parameters | |
| $p_1$ | Processing time of procedure 1 |
| $p_2$ | Processing time of procedure 2 |
| $r_i$ | Route of care pathway *i* |
| Organizational parameters | |
| $Nts_{d,s}$ | Number of time slots for day *d* in resource *s* |
| L | Cycle length |
| Wd | Number of working days in one cycle |
| $ts_n$ | Time slot of arrival of patient ID *n* |
| $wd_n$ | Weekday of arrival of patient ID *n* |
| $yd_n$ | Year week of arrival of patient ID *n* |
| R | Number of replicated planning cycles |

Besides these parameters, we should also include the set of capacity allocation solutions presented in Section 4.5.2 as input of the simulation model.

## 6.2 Sensitivity analysis

In order to understand which factors influence the performance of the system, we also perform a sensitivity analysis. In Section 6.2.1 we explain the analysis we did for the different scheduling scenarios and in Section 6.2.2 we demonstrate how we vary the workload in order to understand the robustness of the solutions to the variability of some input parameters.

### 6.2.1 Factors' response

We performed computational experiments for two scenarios: the best solution using the heuristic method(h), and the best solution using the best benchmark in literature(b), as referred in Section 4.4.1. For each of these scenarios we analysed the combination of these two factors:

- number of resources available: for one (1:CT08) or two (2:CT08 and CT04)
- rearrangement with managers' opinions: performed (r) or not performed

This lead us to test 8 capacity allocation solutions, as stated in Table 11:

Table 11: Capacity allocation solutions evaluated

| | |
|---|---|
| 1h, 2h | Schedule appointments generated by the Walk-in Generator model, for one and for two CT-scanners, respectively |
| 1hr, 2hr | The same schedule appointments as 1 and 2 but with the rearrangements by the managers |
| 1b, 2b | Schedule appointments generated according the literature benchmark, for one and for two CT-scanners, respectively |
| 1br, 2br | The same schedule appointments as 3 and 4 but with the rearrangements by the managers |

### 6.2.2 Variability in workload

Patient inflow for RT is increasing over the years. Besides, due to the optimization of the appointment schedule, an improvement in accessibility and patient service is expected, and therefore with a system that combines walk-ins and appointments we can expect an increase in the demand. Thus, we decided to run two types of experiments with the arrival rates. We increase the workload by 20%, multiplying the arrival rate per day, per time slot, by a factor of 1.20, and also for an extreme case of an increase of 40%. Besides the constant increase of the workload, we run the model with arrival rates which vary during the day, with a 20% increase just in the morning (until 11h40 AM), and the same amount of increase but just in the afternoon, after 13h45.

The patterns for the four experiments with the arrival rate are shown in the following figures.

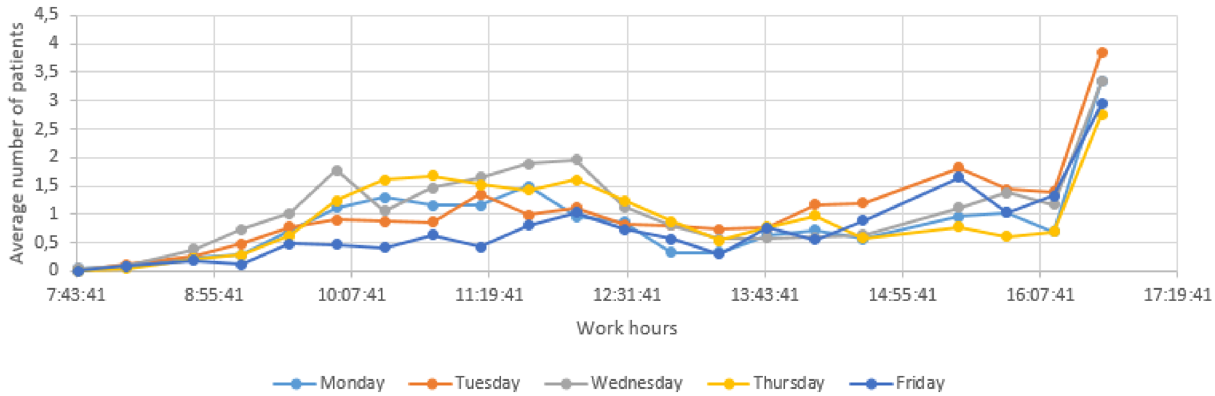



**Figure 37: Arrival rate from 2015 in RT-AVL**

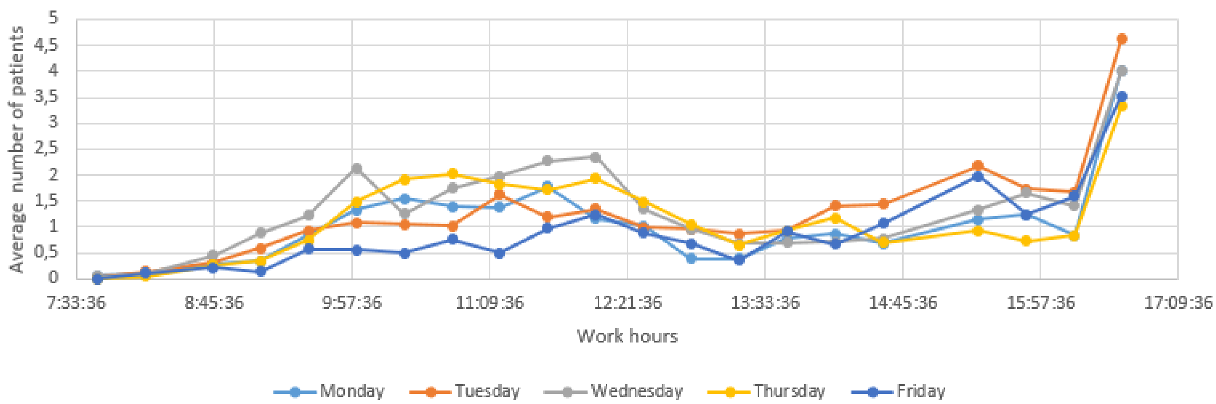



**Figure 38: Arrival rate from 2015 in RT-AVL with a 20% of increase**

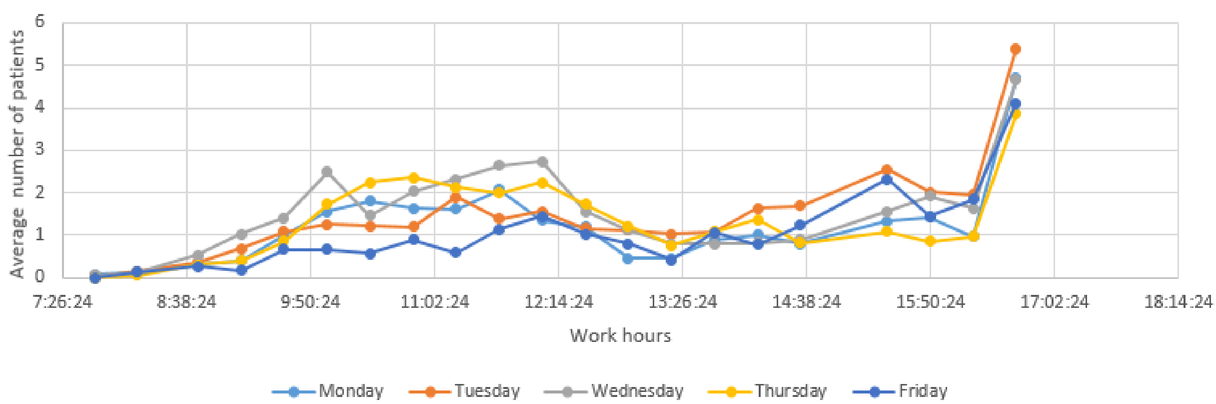



**Figure 39: Arrival rate from 2015 in RT-AVL with a 40% of increase**

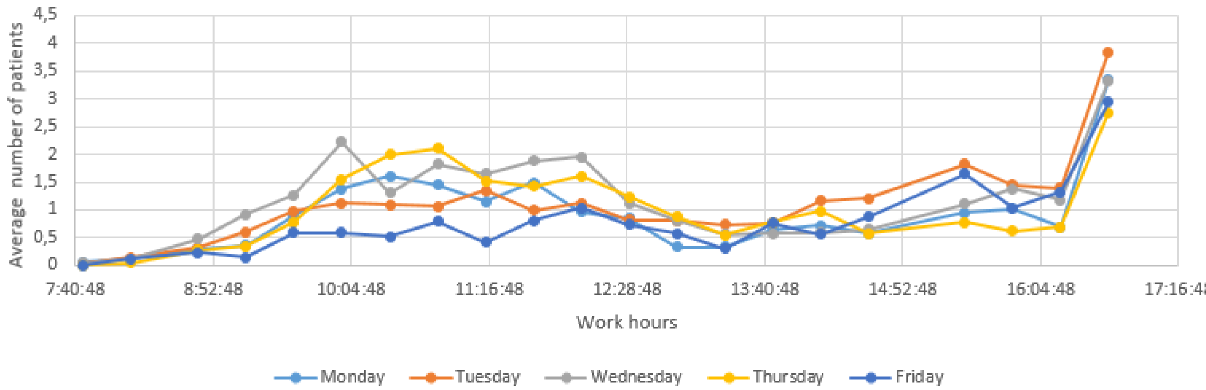



**Figure 40: Arrival rate from 2015 in RT-AVL with a 20% of increase in the morning**

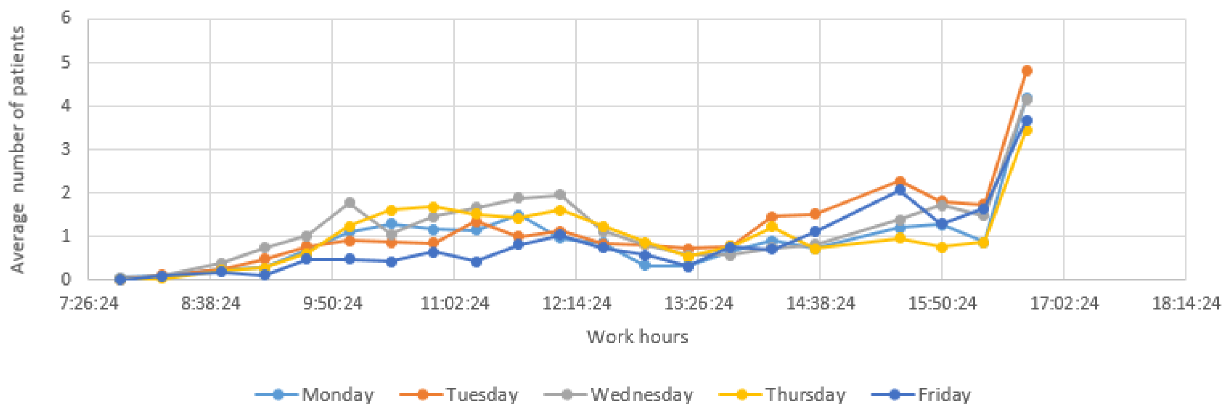



**Figure 41: Arrival rate from 2015 in RT-AVL with a 20% of increase in the afternoon**

## 6.3 Results

We divided the results into 4 categories: for one resource (CT) in Section 6.3.1; for two resources (CTs) in Section 6.3.2; the solution chosen versus the traditional solution in Section 6.3.3; the solutions with the managers 'modifications in 6.3.4; and the results for the different arrival rates in Section 6.3.5.

The access time (AT) referred in the tables 11 to 17, is the access time for 95% of the patient population. This way we know that when this value exceeds the 2 days, the service level norm of having 95% of the patients served within 2 days is not fulfilled anymore. The waiting time (WT) in these tables has an upper bound of 4 time slots, 1hour and 40minutes, we can analyse its behaviour due to the increase in workload, however it is not a decisive performance measurement.

### *6.3.1 One resource*

In these experiments, the performance measurements were done considering only one CT scanner, analysing the best capacity allocation solution obtained with Walk-in Generator model ('1h') and with the literature benchmark with the spreading procedure ('1b'). In both cases, we analyse the difference between having the time slots rearranged or not, according to the RT-AVL managers' recommendations.

**Table 12: Results of the one resource capacity allocation solutions**

| | 1h | 1hr | 1b | 1br |
|---|---|---|---|---|
| **AT (95%)** | 1,606054 | 2,645021 | 1,624851 | 1,918818 |
| **WT** | 2,778001 | 2,711051 | 3,40749 | 3,020713 |
| **FWI** | 0,605206 | 0,69122 | 0,651725 | 0,704645 |
| **UT** | 0,388101 | 0,434978 | 0,414547 | 0,443108 |

In this set of solutions, we chose the one with the lowest waiting time (WT) and access time (AT), a higher utilization rate (UT) and fraction of walk-in patients (FWI). The solution '1br' has 70% of fraction of walk-in patients and 44% of utilization rate, being the solution with the highest values in these performance measurements in Table 12.

### *6.3.2 Two resources*

We also performed the analysis having two CT-scanners, closer to the real situation in RT-AVL centre. Solution '2br' has 76% of FWI and 62% of UT, being the one with the highest values in these performance measurements from the Table 13.

**Table 13: Results of the two resources capacity allocation solutions**

| | 2h | 2hr | 2b | 2br |
|---|---|---|---|---|
| **AT (95%)** | 2,189792 | 1,480905 | 1,460386 | 1,547265 |
| **WT** | 0,352261 | 2,37398 | 2,839733 | 2,562651 |
| **FWI** | 0,647739 | 0,729378 | 0,713114 | 0,761848 |
| **UT** | 0,62758 | 0,635664 | 0,623228 | 0,623156 |

Choosing the solution with best performance from Section 6.3.1 and Section 6.3.2, we can compare the solution '1br' and '2br', to see the effect of having one or more resources in RT-AVL department in Table 14

**Table 14: Comparison between capacity allocation solution '1br' and '2br'**

| | 1br | 2br | Difference |
|---|---|---|---|
| **WT** | 3,020713 | 2,562651 | -0,458062 |
| **FWI** | 0,704645 | 0,761848 | 0,057203 |
| **UT** | 0,743108 | 0,623156 | -0,119952 |

With the second CT-scanner, the RT-AVL has less 15% (half day) in waiting time (WT), more 6% in the fraction of walk-in patients, and a decrease of 12% in the utilization rate (UT).

### *6.3.3 The managers' modifications*

As shown in Table 15, there is no statistical significance, with p>0.05, in the values of access time (AT) and utilization rate (UT) for the solutions '2b' and '2br'. There is a difference in the waiting time values, however as explained in the beginning of this section, this is a bounded value. The fraction of walk-in patients served with '2br' is 5% bigger than with '2b', with 76% of the walk-.in patients served as a walk-in.

**Table 15: Comparison between capacity allocation solutions '2b' and '2br'**

| | 2b | 2br | Statistical difference (p>0.05) |
|---|---|---|---|
| **AT (95%)** | 1,460386 | 1,547265 | No |
| **WT** | 2,839733 | 2,562651 | Yes |
| **FWI** | 0,713114 | 0,761848 | yes |
| **UT** | 0,623228 | 0,623156 | No |

The solution '2br' shows the biggest values for the performance measurements FWI and UT, indicated in Table 14 and 15, the analysis performed in the next section will be with this capacity allocation solution.

### *6.3.4 The traditional versos the new solution*

Concluding that the capacity allocation solution marked as '2br' is the one with the best overall performance, we compared it with the current practice capacity allocation solution being used at the RT-AVL.

**Table 16: Comparison between capacity allocation solution in practice and '2br'**

| | Practice | 2br | Gains |
|---|---|---|---|
| **AT (95%)** | 2,880759 | 1,547265 | 1,5 days |
| **WT** | 2,344007 | 2,562651 | |
| **FWI** | 27% | 76% | 49% |
| **UT** | 0,73684 | 0,623156 | |

As shown in Table 16, we have less 1,5 days in access time for 95% of the patient population, fulfilling the service level norm with half day of margin. The capacity allocation solution '2br' includes the combination of appointments and walk-ins, serving 76% of the walk-in patient population, with an increase of 49% of the fraction of walk-in patients served.

In Figure 42, the orange boxplot representing the '2br' solution has 62% of utilization rate against 74% in the current practice in RT-AVL. These results do not overlap and are significantly different. Their meaning is explaining in discussion, Section 6.4.

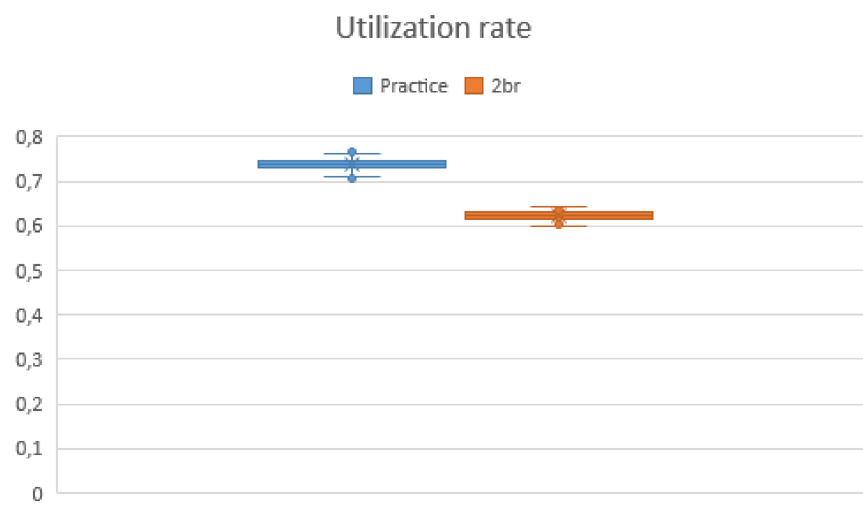



**Figure 42: Practice and capacity allocation solution '2br' utilization rate (UT)**

The Figure 43 shows the values for fraction of walk-ins patients for the practice and for the solution '2br'. The solution '2br' has 76% of FWI and the practice has 27%. The are no outliers for these performance measurements and the standard deviation for practice is 0,13 and for the '2br' solution is 0,32.

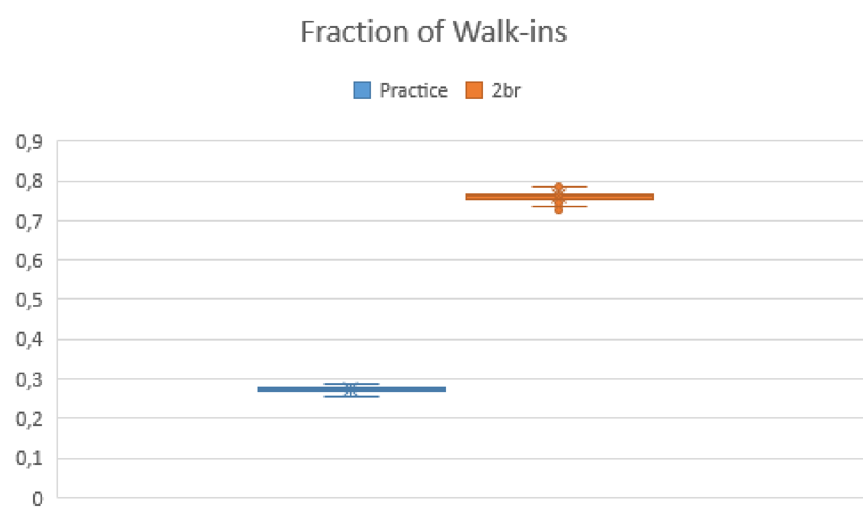



**Figure 43: Practice and capacity allocation solution '2br' fraction of walk-in patients (FWI)**

The access time for the practice is currently 2,8 days and for the '2br' solution is 1,5 days. The practice shows a 0,56 standard deviation and the solution '2br' a 0,73 standard deviation. As shown in Figure 44, the access time for the solution '2br' has outliers, 15 in 200 runs, which represents 7,5% of the runs.

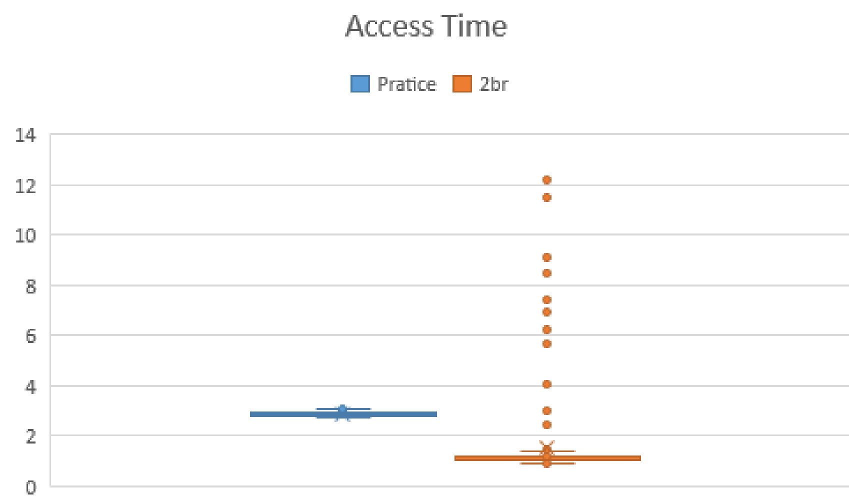



**Figure 44: Practice and capacity allocation solution '2br' access time (AT) in days**

The waiting time in RT-AVL is currently 2,3 time slots, about an hour, and for the solution ‘2br’ is 2,6 time slots, about an hour and 5 minutes. The standard deviation for the practice values is 6,12 and for the solution ‘2br’ is 0,71. Although the mean value for waiting time for the two solution has a difference of 5 minutes, in Figure 45 you can visualize the difference in the standard deviation and the outlier in the practice values.

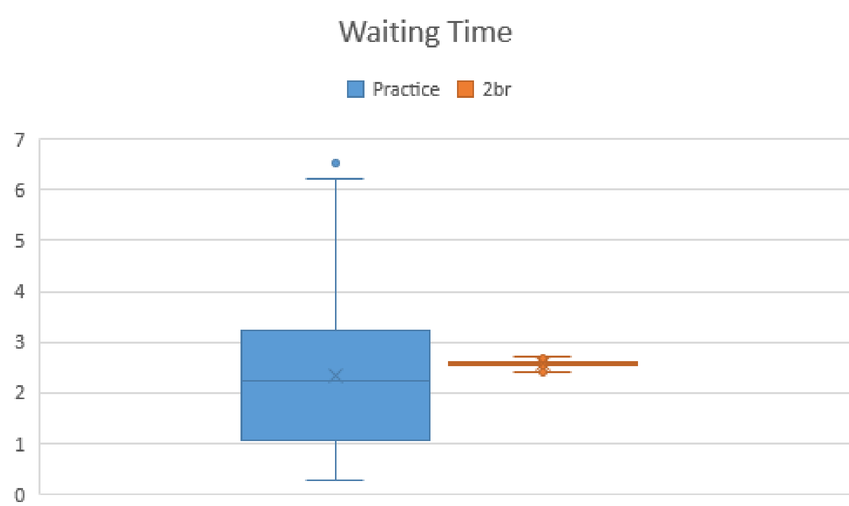



**Figure 45: Practice and capacity allocation solution '2br' waiting time (WT) in time slots units**

### *6.3.5 The increased workload*

The improved accessibility and patient service may occur into an increase of patient’s arrival. This way, we obtained the results for the performance measurements of capacity solution 2br with several increases in the workload.

In Table 17, we can compare the performance measurements of the base case, with the normal arrival rate expected for RT-AVL, with an increase of 20%. The capacity allocation solution shows an increase in the fraction of walk-in patients (FWI) from 76% to 91% and in the utilization rate from 62% to 75%, keeping the service level norm. Due to these good results, we also perform an extreme case with an increase of 40% in the workload. Comparing with the 20% increase scenario, in this case the utilization rate has an increase of 2%, but the fraction of walk-in patients goes to 67%, with a decrease of 24%, and the service level norm is not fulfilled, although it only has a small increase of 0.2 days.

We perform an itineration in the simulation runs to find the critical increment in the workload in terms of fulfilling the service level norm. That value founded is shown in Table 17 as 'Critical increase of 29%'. This value of 29% represent the biggest increment in the workload supported by the capacity allocation while preserving the service level norm. Comparing the performance measurements of the critical situation with the base situation, the capacity allocation solution shows a decrease of 7% in the fraction of walk-in patients and an increase of 18% in the utilization rate.

The capacity allocation solution 2br shows a top performance of 91% in the fraction of walk-in patients served and a utilization rate of 74%, when the workload is increased by 20%, having the flexibility of fulfilling the service level norm until the incensement of 29% in the workload.

**Table 17: Different workloads increments (base, 20%,40%,critical) for capacity allocation solution '2br'**

| | Base arrival rate | Increase of 20% | Increase of 40% | Critical increase of 29% |
|---|---|---|---|---|
| **AT (95%)** | 1,547 | 1,857 | 2,166 | 1,996 |
| **WT** | 2,563 | 3,075 | 3,588 | 3,306 |
| **FWI** | 0,762 | 0,914 | 0,673 | 0,690 |
| **UT** | 0,623 | 0,748 | 0,772 | 0,804 |

In Table 18 we show the results of incrementing the workload just in the morning period, until 11h40 AM. Comparing the values with an increase of 20% between Table 16 and Table 17, where the increment is equal to all time slots during the day versus only in the morning time slots, respectively, the fraction of walk-in patients has a difference of 2% and the utilization rate is 10% bigger when the increase is just in the morning. The critical value for the increment in the utilization rate is bigger when the increment is just in the morning than when it is during all day. The critical increment founded for this situation was 33%, with a difference of 4% between Table 17 and 16.

**Table 18: Different workloads morning increments (20%, 29%, critical) for capacity allocation solution '2br'**

| | Increase of 20% | Increase of 29% | Critical increase of 33% |
|---|---|---|---|
| **AT (95%)** | 1,779 | 1,934 | 1,988 |
| **WT** | 2,947 | 3,203 | 3,408 |
| **FWI** | 0,740 | 0,777 | 0,744 |
| **UT** | 0,717 | 0,733 | 0,855 |

When the increment in workload is just in the morning we obtain better results, referred above, than when it is during the whole day. To check if this was due to the fact that the total daily increment is lower if it is just in the morning than in the all day, we also analyse afternoon increments in Table 19.

In Table 19 for an increase of 20% in the workload in the afternoon, the fraction of walk-in patients is 70%, when for the same increase but for the whole day (Table 16), the fraction is 91%. The utilization rate is 78%, when for the same increase but for the whole day (Table 15), is 75%. The critical value for increment in the workload was 23%, 10% smaller than for the same amount of increment but in the morning (Table 18), and 6% smaller than for the same amount of increment but for the whole day (Table 16).

**Table 19: Different workloads afternoon increments (20%,29% and critical) for capacity allocation solution '2br'**

| | Increase of 20% | Critical increase of 23% |
|---|---|---|
| **AT (95%)** | 1,934 | 1,994 |
| **WT** | 3,203 | 3,331 |
| **FWI** | 0,702 | 0,699 |
| **UT** | 0,779 | 0,810 |

## 6.4 Discussion

This Section is divided in four sub sections, sub section 6.4.1 reflects about the number of resources needed by the RT-AVL center, the sub section 6.4.2 about the effect of the rearrangements, sub section 6.4.3 compares our solution with the current one and sub section 6.4.4 analyses the effect of having different workloads.

### *6.4.1 Number of resources*

With the capacity allocation solution '1br', counting only with one resource and using the 'b' algorithm (time slots spread during the day with the benchmark number one in Walk-in Generator Model) the performance measurements show satisfactory results. These results are 74% for the utilization rate and 70% for the fraction of walk-in patients, with the service level norm fulfilled. This tell us that only one CT-scanner would fulfill the managers' requirements for RT-AVL. However, when comparing these values with the ones from '2br' solution, for both CT-scanners, we realize that just by adding scanner 'CT04' with four work days and only eight time slots per working day, there is a bigger space for improvement and the facility can serve more patients. We conclude this by looking to the difference in the utilization rate, 12% of the capacity in the scanner becomes available for new patients. Because of the increase in capacity, the fraction of walk-in patients also increases by 6%.

After the analysis made considering the number of resources, we chose the capacity allocation solution '2br' as the one to perform following analyses.

### *6.4.2 Managers' rearrangements*

In Table 15 we compared the performance measurements for the solution '2b' with ('2br') and without ('2b') rearrangements. There is no statistical difference between the results for access time and utilization rate, for the solution with and without rearrangements. This is an optimistic result for the implementation of the solution, once the constrains we had to add do not cause loss of performance.

There is an increase in the fraction of walk-in patients served of 5%, from 71% without rearrangements to 76% with the rearrangements. The improvement in this performance measurement is expected because the rearrangement done was the shifting of appointment time slots to the early morning walk-in time slots, where do not exist walk-in patients yet. In the Walk-in Generator Model was not possible to input this type of constrain, therefore we did the rearrangements afterwards, and the results were positive.

### 6.4.3 Traditional versus the new solution

Because the solution '2br' has the higher FWI and UT, we compare it with the traditional solution, the one in current practice at RT-AVL. The combination of walk-in and appointment time slots in the capacity allocation solution showed a reduction of access times of one and half day, 46% reduction, and a reduction of 11% in the utilization rate. This lead to more time slots available to new patients, and show that a new capacity allocation solution could optimize the scanners capacity.

The outliers found in the access time results, shown in Figure 44, represent 7,5% of the runs in the simulation model. Because they are less than 10%, they do not influence our results. The waiting time showed in Figure 45 for the practice has a standard deviation of 6.12, this value reflects the lack of a walk-in culture in RT-AVL, and for this reason is not a god performance measurement to compare.

### 6.4.4 Increase of the workload

As stated in the previous paragraphs, the utilization rate reduced when we applied the '2br' capacity allocation solution. This optimization in capacity allowed to receive more patients, and because of that when the arrival rate is increased by 20% the results for the performance measurements still under the managers' requirements. As it is shown in Table 17, 18 and 19, the higher utilization rate and fraction of walk-in patient is attained when the arrival rate is increased by 20%, obtaining 75% in UT and 91% in FWI. We can conclude that with the implementation of the '2br' solution the RT-AVL CT-scanners could serve 20% more patients, which would be 5444 patients instead of 4537, more 907 patients per year. This would be, in average, more 18 patients per week.

From Table 17 we can observe that the '2br' solution is flexible in terms of keeping the performance measurements with the increasing arrival rate. The solution can get an 80% in UT and a 69% in FWI with a 30% increase in workload. This means that the resources can serve until 5853 patients per year, which means 1326 more patients per year or 25more patients per week.

We analyze the flexibility during the work day, comparing between an increase in the morning, until 11h40, and in the afternoon, after 13h45. The capacity allocation solution is more flexible during the morning, with a maximum value of increase in the workload, fulfilling the service level norm, of 33% against a maximum value of 23% in the afternoon. This shows the importance of the CT04 in the capacity management of the scanners. With CT04 available in the morning slots, the system became more responsive to an increase in the workload in the morning.

## Chapter 7 – Conclusions and future research

In the final chapter we look at the work done in this thesis and its contribute for literature and for the cancer center, next we explore some limitations and possible improvements and lastly we give some ideas for future research in literature and in the cancer center.

We started this research with the following objective: optimization of capacity allocation of the imaging resources in diagnostic facilities, combining walk-in and appointment patients, in the cancer center of NKI-AVL, with the main goal of increasing the fraction of walk-in patients. To reach this goal we divided the work in two parts. The first one was the search for a state-of-the-art model, theoretical consistent and case study tested, to produce capacity allocation solutions. The second part was the development of a simulation model, to evaluate those solutions in RT-AVL. We started with an extensive review of theory, which gave us the concepts, definitions and terminology that we needed to develop a simulation model that can be used to analyze the combination of walk-in and appointments. Through a process analysis of the CT- scan casus of the RT-AVL and by studying the processes described by research conducted at other diagnostic facilities we identified the elements we need to simulate the service process of diagnostic facilities.

By combining the theory and the process analysis we developed the discrete event simulation model, which has of four elements: (i) the initial decision about a patient being eligible to walk-in to the CT-scanner, (ii) a planner for appointments, (iii) a test component and (iv) preparation components (see Figure 36). All these elements can be combined to match real world systems, such as that of the radiotherapy department of the AVL. By adding design choices corresponding to when walk-in is possible, how appointments are scheduled and how many time patients are willing to wait in the waiting room, there is a broad range of functionalities to experiment with.

The CT-scans at the AMC are currently organized through a 100% appointment system. Strictly speaking only 10% of all patients can get an appointment on the same day, being a walk-in patient. The relatively small number of time slots in a CT-scan for walk-ins is not aligned with the patient population type, where 63% can be served as a walk-in. In the current situation is an indication that the CT-scans could be organized through a combined walk-in and appointment system. We used the discrete-event-simulation model to simulate this new situation and the results show that:

- Most walk-in patients can be served on the day of the request;
- Access time of appointments decreases compared to the current situation;
- More patients incur waiting time than in the current situation;
- Number of served patients increase.

The patient clustering was decisive to attain the research goal. Because of this we attribute a major importance to the part where we study the RT-AVL system. Interviews to hospital's experts and visits on site were crucial. The two-patient cluster used in Walk-in Generator model was a good simplification to start the patient population study. We ended with three clusters of patients after the modifications by the managers, which was still a low number. We consider this an advantage to simplify the capacity allocation solution. If there are some patients that do not fit in any of the three groups, the staff in the planner have the ability, and resources, to choose the best time slot for those patients. These kinds of patients should represent 5% of the whole patient population.

Furthermore, we experimented with the patient's patience factor, allowing the decision makers to make trade-offs between the performance indicators:

-Increasing the allowed waiting time for walk-in patients reduces the fraction of walk-in patients who is deferred, but also leads to higher waiting time for walk-in patients;

The sensitivity analysis showed that the system remains stable with an increased patient arrival rate, by workload during all day, or just during the morning or in the afternoon, being more robust to increased workloads in the morning.

Some of the results, such as the response to the increased workload, can be used to give practical advice. However, there is not a best practice that can be advised. The power of the simulation model is that all effects can be mapped to aid the decision makers. To make full use of this power we suggest a method in which the main effects from the simulation are used to start a discussion between members of the project group, and that the interaction effects between different factors are used as catalyst to come to a consensus. We also note that the experimental factors in the model are only one side of the decisions corresponding to a combined walk-in and appointment system. There are also internal and external organizational changes, such as changes in information requirements and responsibilities. These changes need to be mapped if a department decides to implement a combined walk-in and appointment system. Based on this research the radiotherapy department of the AVL decided to continue with the analysis of these internal and external organizational changes, with the goal to implement a combined walk- in and appointment system for the CT-scans.

In our work we used some improvements stated in the literature and build upon that. Bailey and Welch, through their research work, showed that heuristic approaches work better for capacity allocation solutions with a deterministic service time, consequently a defined time slot length, equal through all the schedule/solution. Although Cayiril et al. [7] have work with a dome pattern for time slots, the approach of Bailey and Welch is sill the most used and sucefull in the latest research works( [28], [29]). Both Lin et al. [10] and Freville and Plateau [11], support solution space reduction through dynamic programming and myopic heuristic, respectively. We also did solution space reduction, but with a simpler way: we did not apply local search to the heuristics used, because we considered we had already too much entropy in our solutions. In other way, Denton et al. [12] used simulated annealing to improve the initial solution, we did not do this once we got good results with the initial solutions we got.

Klassen and Rohleden [8] show that empty time slots in the beginning of the day, for urgent patients, reduce waiting times, while at the end of the day such time slots can be able to serve a bigger number of patients that are willing to wait. To obtain both advantages, the time slots for urgent patients should be spread equally during the day. In the same way, Su and Shih [9] show that alternating sequences of appointment schedules with walk-ins works better. This supports that the best results we obtained were with the '2br' solution that spreads the time slots through the day. Therefore, some of our results were validated by the literature, while others add new insights from which future research works can build upon that, namely the relationship between the decrease of access time and increase of utilization rate when combining appointments and walk-in patients, through the almost direct application of the Kortbeek *et al*. model.

### 7.1 Discussion and future research

In this section we will discuss three topics that relate to the development of the simulation model and its further use: (i) generalizability of results, (ii) validation through more extensive cases, and (iii) the link between theory and practice.

For the first topic we look at the possible implications of attaining the same improvements of combining walk-ins and appointments, increasing to the maximum the fraction of walk-in patients, for other diagnostic facilities. The results for the CT-case of the RT-AVL are promising, however we have also seen that case-dependent factors were very determining for the performance of the system, for example the effect of having the first time slots adjusted to the staff availability. To avoid erroneous conclusions, it is important to note that the model only allows the user to understand the direct effect of having walk-ins in the optimization of the capacity allocation. A future user would have to translate the new real system to the components in the model, tests and procedures, and to do the process analysis, data collection and input preparation. Even more so, this simulation model is really simple, meaning that there are few assumptions, which could be too restrictive for some cases.

The second topic is closely related to this issue. The model was validated by simulating the current situation of the CT-scans at the RT-AVL, a system with only appointments. This validation does not in any way ensure that this model can be used for experiments on other cases that also have an appointment system. It is a limitation of the research that we only reviewed one case extensively. We think that the model can be used for a broad range of cases, but cannot claim that the model is truly generic.

The last discussion topic is related to the development of the model and the discrepancy between theory and practice. Two suggestions we distilled from the theory review were:

- Define independent components, this allows other modelers to work in a flexible manner. A model to which extra components/elements can easily be added/removed has the most potential when it comes to component based simulation.

- Complete model reuse is so complex that it is considered the holy grail of simulation modeling.

Taking a component based perspective was very useful to think of a workable structure that allows reuse. However, we found that it was not possible to develop independent components that are easily combined to form a model that was useable for experimentation with a specific purpose. In other words, some of the components we defined are dependent on the general structure of the model and the availability of information provided by other components. The result is that we developed a model that can be completely reused, is very flexible, but only within the defined limits. The consequence is that if a case requires additional functionalities these can be added, but for most functionalities this will mean that the structure of related components will have to be adapted to this change.

The ideas for future research concern the analytical model used, the simulation that was build and possibility of implementation. When using the Walk-in Generator model for two resources, the total arrival rate is split for each resource and the model runs independently for each one. This goes against what happens in practice since the RT department verifies a single arrival rate for both scanners, and the patients walk into one of the available resources.

For the discrete event simulation model, we took some simplifications and assumptions into account, that could be improved in a future work. The day and time of the breaks in the new capacity allocation solutions were assumed to be the same that existed in practice. A study about the best time slots for the breaks in each of the scanners, as well as the length of those time slots, could be an interesting line for further research. In terms of implementation, we believe that a valuable contribution would be a deeper study in the field of health sciences about the patient population and possible clusters based on care content, which is crucial for research works in resource allocation problems.

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### Appendix A – Patients care plans clustered into appointments and walk-ins

| Care plan name | Number of patients | Type | Test/procedure1/procedure2 |
|---|---|---|---|
| Anus +/- liezen | 29 | APP | |
| Blaas partieel | 27 | APP | |
| Blaas | 53 | APP | |
| Borstwand bh | 24 | APP | t |
| Borstwand | 44 | WI | |
| Borstwand + Okselregio bh | 54 | APP | |
| Borstwand + Okselregio | 74 | WI | |
| Borstwand + Okselregio + Parasternaal | 6 | WI | |
| Borstwand + Okselregio + Parasternaal bh | 10 | APP | t |
| Borstwand + Parasternaal | 1 | APP | |
| Borstwand AP/PA | 4 | WI | |
| Botmetastasen | 1317 | WI | |
| Botmetastasen Stereotaxie | 51 | WI | p2 |
| Cervix endometrium/Uterus/Ovarium | 62 | APP | |
| Dwarslaesie/Myelum | 20 | WI | |
| Hals AP/PA | 8 | WI | p1 |
| Hersenen 1 fractie | 138 | APP | |
| Hersenen gefractioneerd | 104 | APP | |
| Hersenen WBRT | 231 | WI | p1 |
| KNO | 243 | APP | |
| KNO 6x6 Gy | 7 | WI | p2 |
| Larynx 2vs | 3 | WI | p2 |
| Lever | 21 | APP | |
| Long < 44 Gy | 47 | WI | p2 |
| Long > 44 Gy pet-ct | 41 | APP | t+p2 |
| Long > 44 Gy | 286 | WI | p2 |
| Long AP/PA | 81 | WI | p2 |
| Long hypofractionering | 286 | WI | |
| Lymfoom - planning dent | 11 | APP | t+p1p2 |
| Lymfoom - planning | 61 | WI | p1p2 |
| Lymfoom -Vsim dent | 1 | APP | t+p1p2 |
| Lymfoom -Vsim | 24 | WI | p1p2 |
| Maag | 29 | WI | p2 |
| Mamma bh | 384 | APP | t |
| Mamma | 414 | WI | |

| | | | |
|---|---|---|---|
| Mamma + Okselregio | 101 | WI | |
| Mamma + Okselregio bh | 91 | APP | t |
| Mamma + Okselregio + Parasternaal | 11 | WI | |
| Mamma + Parasternaal | 5 | WI | |
| Milt AP/PA | 1 | WI | p2 |
| Oesophagus | 59 | WI | p2 |
| Oesophagus 13 x 3 Gy | 30 | WI | p2 |
| Okselregio (virtueel) | 14 | WI | |
| Orbita | 6 | WI | p1 |
| Overig planning | 168 | WI | p2 |
| Overig Vsim | 133 | WI | p2 |
| PAO (+/- iliacaal enkelzijdig) | 13 | WI | |
| Penis | 13 | APP | |
| Prostaat | 215 | APP | |
| Prostaat + bekken | 14 | APP | |
| Prostaatloge | 57 | WI | |
| Prostaatloge + bekken | 11 | WI | |
| Rectum / sigmoid | 94 | APP | |
| Rectum 13 x 3 Gy | 13 | APP | |
| Rectum 5 x 5 Gy | 87 | APP | |
| Sarcoom buikwand / thoraxwand | 11 | WI | |
| Sarcoom extremiteit | 33 | APP | |
| Sarcoom retroperitoneum | 4 | WI | |
| Spinaal | 10 | APP | p2 |
| Vagina | 6 | APP | |
| Vulva +/- liezen | 11 | APP | |
| | 5407 | | |