

Using Queueing Theory and simulation to lower the access time to NPOs at UMCU RF&S department



Bachelor Thesis – Yuri Hoogendoorn

**UNIVERSITY
OF TWENTE.**



UMC Utrecht

Bachelor thesis

Using Queueing Theory and simulation to lower the access time to NPOs at UMCU
RF&S department.

Author

Yuri Hoogendoorn – s1982699

y.a.hoogendoorn@student.utwente.nl

Study

Bachelor Industrial Engineering and Management at the University of Twente,
Faculty of Behavioural, Management and Social Sciences.

Supervisors

Dr. Sebastian Rachuba

University of Twente

Prof. Dr. Ir. Erwin W. Hans

University of Twente

Janneke Sterk

UMC Utrecht

Management summary

This research is tasked by the rehabilitation, physical therapy science and sports (RF&S) department of UMC Utrecht. The RF&S supports patients with recovery after an accident, disease or medical surgery and they help the patients to live as independently as possible with the consequences of their disease, limitations, or chronic illness. Patients are supported by 8 different specialisms including psychology, physiotherapy, ergo therapy, speech therapy, trauma, social work, oncology, and orthopaedics. Patients that go into rehabilitation at the RF&S receive care that is given by a multidisciplinary team of the different specialisms. The RF&S consists of 120 employees. This research is focused on the psychology department of the RF&S.

The psychology department has a high perceived access time for NPOs. A neuropsychological examination (NPO) is a consult used to examine patients that experience cognitive problems in their daily activities. Starting from the initial problem, a problem cluster is created. From the problem cluster a core problem was defined. The RF&S needs a tool that gives insight into how much capacity is required to meet the access time guideline. To guide the research, we setup a research goal:

To develop a tool that can be used to optimize the capacity planning for NPOs of the RF&S psychology department at UMC Utrecht to realize the access time norm 80% of the time.

The current performance analysis showed that the current level of the access time norm is 20,1%. We used Queueing Theory to create a benchmark against the historical data, which showed that at the current level of capacity the access time norm could be reached 38% of the time.

We found that creating a simulation model that represents the real-world system is the best solution. The simulation model enabled us to test multiple scenarios where we change our input variables. The goal of these scenarios was to find the best solution regarding the access time norm.

Experiment	Avg access time (days)	Utilization	Access time guideline
(1)	50,396 ± 1,065	0,889 ± 0,002	0,237 ± 0,011
(2)	33,686 ± 0,661	0,851 ± 0,003	0,469 ± 0,013
(3)	24,114 ± 0,232	0,705 ± 0,003	0,709 ± 0,007
(4)	20,800 ± 0,172	0,678 ± 0,003	0,818 ± 0,006
(5)	16,784 ± 0,063	0,597 ± 0,003	0,964 ± 0,002
(6)	34,244 ± 0,653	0,919 ± 0,002	0,453 ± 0,012

Table 1: Results from the experiments with the simulation model.

The results in table 1 show that having an extra psychologist for half a year (Experiment (4)) would enable the RF&S to reach the access time guideline 80% of the time. In the conclusion section we discussed that this can also be interpreted as doing 26 extra NPOs per year. We showed that each psychologist needs to do roughly 1 NPO extra per month and that this could be achieved by taking away capacity from other departments that do have a low access time.

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1 Introduction

This chapter describes the rehabilitation, physical therapy science and sports department (RF&S) of the University Medical Centre Utrecht (UMCU) of which this research was tasked by. We start with a company description followed by the problem description. After that we setup a research goal and define research questions for the rest of this research.

1.1 Company description

UMCU is a large academic hospital with more than 11.000 employees. On a yearly basis they take up 32.000 patients for treatment and/or diagnostics. As an academic hospital they strive for high quality care, research, and education. Within UMC Utrecht there are a lot of different departments that each have their own way of treating patients.

The RF&S supports patients with recovery after an accident, disease or medical surgery and they help the patients to live as independently as possible with the consequences of their disease, limitations, or chronic illness. Patients are supported by 8 different specialisms including psychology, physiotherapy, ergo therapy, speech therapy, trauma, social work, oncology, and orthopaedics. Patients that go into rehabilitation at the RF&S receive care that is given by a multidisciplinary team of the different specialisms. The RF&S consists of 120 employees.

The RF&S has two planners for patient appointment planning. The planners plan mostly for patients that need multiple appointments from different care disciplines, they call these complex appointments. The goal is to plan appointments as convenient for patients as possible while also striving to optimally use the available capacity.

1.2 Problem description

A neuropsychological examination (NPO) is a consult used to examine patients that experience cognitive problems in their daily activities. The information acquired from the NPO is used to improve patient treatment and help with diagnosing. For example, when a patient has memory problems, it could be hard for the patient to remember the exercises that he/she got from the physiotherapist. When the healthcare staff knows about the memory problems via an NPO they can take extra measures for the patient to provide him/her with extra help. Therefore, it is important that patients get an NPO in the early stage of their treatment to make sure that the patients' treatment plan fits to his/her needs. However, not every patient that needs an NPO can get it at the start of their treatment due to a perceived lack of capacity. This lowers the quality of care for patients with cognitive problems.

Starting from the initial problem we create a problem cluster depicted in figure 1-1, which shows the relationship between the underlying problems. A bigger version of the problem cluster is depicted in appendix A. We first discuss the relevance of the initial problem (1.2.1). After that we elaborate on the underlying problems that affect the initial problem (1.2.2).

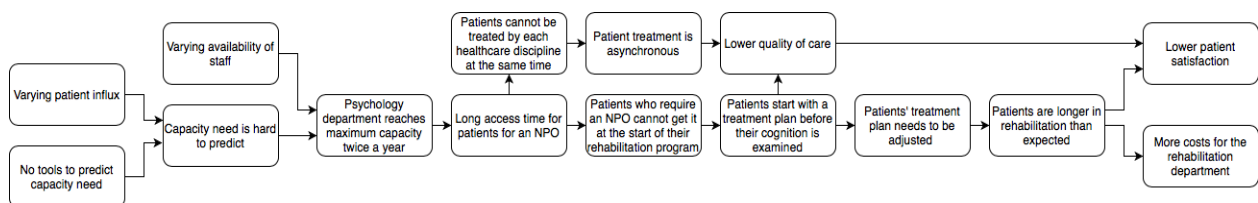


Figure 1-1: Problem cluster

1.2.1 Relevance of the initial problem

When there is a perceived lack of capacity, this causes long access times for patients in need of an NPO. Access time is the time between the day of an appointment request and the actual day of the appointment. Patients that come to the RF&S often need aid from multiple specialisms. What happens when the access time for NPOs increases, is that the care at the other specialisms that do have capacity already starts. This causes the treatment to be asynchronous and not adjusted to the patients' need, which in the end lowers the quality of care. The RF&S has a guideline for the access time, it should not exceed 28 days. Figure 1-2 depicts that the access time guideline has only been met in 20,1% of NPOs over the past five years. The head of the RF&S wants to increase the percentage from 20,1% to 80%.

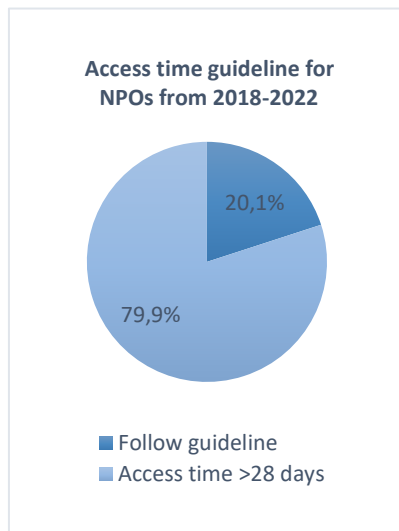


Figure 1-2: Pie chart of the access time guideline. (n=239; data from 2018-2022)

1.2.2 Problems affecting and affected by the initial problem

It is ideal for a patient to get an NPO at the start of their rehabilitation program, however this is not possible when there is no NPO slot available. The problem with that is that the patients' cognition is not examined before the treatment plan is created, which lowers the quality of care that they get. Due to a long access time, the patient receives an NPO during his/her rehabilitation program. The healthcare staff might find out that the current treatment plan does not fit the needs of the patient. The treatment plan then needs to be adjusted causing the patient to be longer in rehabilitation than anticipated. Which increases the costs for the RF&S and lowers the patient satisfaction.

1.2.3 Defining the core problem

When we look at the problem cluster (figure 1-1), there are two problems at the beginning of the chain. These are potential core problem to choose from and are:

- Limited availability of staff.
- No tools to predict capacity need.

One NPO takes a psychologist a full working day. The psychologists at the rehabilitation department often work in multiple places within the hospital, and they have limited time for NPOs. Choosing limited availability of staff as a core problem would be good, however, the rehabilitation department does not always have an NPO capacity problem, therefore, extra availability of staff is not always necessary. It is more beneficial for the rehabilitation department to have tools to predict the capacity need, then they know when more staff is required to meet NPO demand. We identify 'no tools to predict capacity need' as the core problem.

1.2.4 Norm and reality of the core problem

At this moment, the RF&S has no tools or metrics to help them predict the capacity requirement for NPOs. The RF&S currently has a capacity limit of 2 NPOs per week. The RF&S also has an extra psychologist with a zero-hour contract who can be deployed to do one extra NPO per week, increasing the capacity to 3 NPOs per week. They deploy the extra psychologist when they notice that the waiting list is increasing, but this is typically too late. Always deploying this psychologist would completely remove the capacity problems. However, this is too expensive for the RF&S. Therefore, a balance needs to be found between costs and capacity requirements. Besides costs, the extra psychologist cannot be scheduled immediately, it takes about 4 weeks until he/she can be used for scheduling. The reason for this is that patients and the psychologist cannot come on such short notice. When the RF&S has the tools to help them predict the capacity requirement for NPOs, they will be able to know within a 4-week interval whether to schedule the extra psychologist, which then ensures that the maximum capacity is not reached. We conclude that the RF&S needs a tool to know the capacity requirement for NPOs.

1.3 Research goal

We define the following research goal:

To develop a tool that can be used to optimize the capacity planning for NPOs of the RF&S psychology department at UMC Utrecht to realize the access time norm 80% of the time.

1.4 Research questions & research design

In this section, the research questions per chapter, and the steps to solving these questions are given. The research questions have been setup to realize the research goal.

Chapter 2 (Current situation analysis)

In Chapter 2 we describe how appointment planning for NPOs is currently done at the RF&S and analyse the current performance. The chapter is divided into two sections, each section has its own sub research question.

How is appointment planning for NPOs done at the RF&S and what is its current performance to the access time norm?

- *How do patients get an NPO appointment? (2.1)*
- *What is the current performance of the appointment planning? (2.2&2.3)*

The first sub question is answered by observations and an interview. Observations are gathered by sitting next to the planners at the rehabilitation department of UMC Utrecht, watching and asking questions, while they were doing their work. Also attending multidisciplinary discussions (MDO) gives insight into how the rehabilitation department handles their patients. An MDO is a gathering of the healthcare staff where they discuss patients to make sure that the treatment is optimal and that the patient is not forgotten if he/she is long in treatment. The interview is semi-structured, this means that a list of questions is made beforehand, containing the important elements that need to be answered, but the rest of the interview does not have structure. The interview is with one of the psychologists. The interview is used to find out what an NPO is and what it is used for.

A data analysis is done to answer the second sub question. The data consists of NPO related data from years 2018-2022. Three Key performance indicators (KPIs) are defined, the utilization of the NPO slots, the access time of patients to NPOs, and the percentage of cancelled NPOs. In section 2.2, the data analysis on the KPIs is done. In section 2.3 queueing theory is used to calculate the current level to the access time guideline.

Chapter 3 (Systematic literature review)

A systematic literature review is done in chapter 3 where the literature is searched for methods to reduce the access time of patients in outpatient clinics. The following research question is used for the literature search.

How can outpatient clinics reduce the access time to patient appointments?

Chapter 4 (Solution design)

A solution is designed in chapter 4 based on the outcome of the literature search. A simulation model is built. The input for the simulation model is the outcomes from chapter 2. Chapter 4 has the following research question.

- *How can a simulation model be built that represents the real-world system?*

The research question is answered by the process of building the simulation model. This process consists of multiple steps.

- List the model specifications acquired from the information gathered in chapter 2.
- Describe how the specifications are integrated into the simulation model.
- Give a flow diagram which shows the logic behind the simulation model.
- Determine the output KPIs of the simulation model.
- Determine the optimal run length, warm-up period and number of replications for the experiments.
- Validate the model by comparing the output of the simulation model to the KPIs from chapter 2.

The simulation model that represents the real-world system is used in chapter 5 for experiments.

Chapter 5 (Results)

The simulation model that represents the real-world system is used in chapter 5 for experiments. Chapter 5 is divided into two sections, with their own research question.

- What experiments should be done? (5.1)
- What are the results from the experiments? (5.2)

The experiment selection is described in chapter 5.1. The experiments are determined together with the head of the RF&S. The results and the evaluation of them is given in chapter 5.2.

Chapter 6 (Conclusion)

The final chapter consists of the conclusion, recommendations to the RF&S, and the discussion.

2 Current NPO scheduling and its performance.

This chapter covers the current way the rehabilitation department does its appointment scheduling for NPOs. The chapter is divided into three sub-chapters. First, planning and the patient flow are described. Second, the current performance is analysed by doing a data analysis. Finally, Queueing Theory is used for a more in-depth performance analysis.

2.1 Patient flow

The plan process, the patient flow through the system, and the criteria for NPOs are described in this section. The information described in this section is gathered via observing the planners and asking them questions, and through an interview with one of the psychologists.

2.1.1 Planning

Planning of patients at the RF&S is done by two planners in the electronic environment HiX, which stands for healthcare information exchange. Patients have their own file in HiX which contains all information about their condition and (past) appointments. The planners have multiple lists which they use for planning. The care domain references list contains all patients coming from the general practitioner or other hospitals. The work list of new patients contains all new patients, and the order list consists of all appointments that still need to be planned in. When a patient is referenced to the RF&S, he/she first gets an appointment with a rehabilitation doctor. During this appointment the rehabilitation doctor determines what care the patient needs and sets up a treatment plan. After this the doctor makes an order which is sent to the order list for planning. The order contains all the different care disciplines that the patient needs, for example physiotherapy and occupational therapy. Also, the number of appointments per week is shown. With this information the planners can create a schedule.

2.1.2 General patient flow to NPOs

Figure 2-1 depicts the arrival of a new patient to an NPO. A new patient is referenced to the rehabilitation in three ways. Internally from a different department of UMC Utrecht, or externally from the general practitioner or another hospital. The referenced patients are moved to the 'worklist new patients', where they need to first be triaged by a rehabilitation doctor. Every patient on the worklist has a status indicator which tells the planners what they need to do. The rehabilitation doctor changes the status of the patient to either 'ready for planning' or sends the patient back to the referrer. All patients on the 'worklist new patients' that have the 'ready for planning' status indicator can be scheduled for their first appointment with the rehabilitation doctor. The first appointment takes one hour. During this appointment the rehabilitation doctor determines whether the patient needs to go into outpatient rehabilitation treatment (PRB (poliklinische revalidatie behandeling) or can be treated by primary care. The second option means that the patient is removed from the order list and referenced to primary care. In practice, 20% of new patients will go into PRB and 80% are referenced to primary care. The percentage of patients going into PRB is low because rehabilitation is expensive therefore, only patients that get insufficient treatment by primary care or need treatment by multiple specialisms go into PRB. The rehabilitation doctor also gives the patient a lot of information and in combination with primary care that is most of the time all the care they need to rehabilitate. The rehabilitation doctor also

determines whether the patient needs an NPO. For this he/she use criteria which will be covered in chapter 2.1.3.

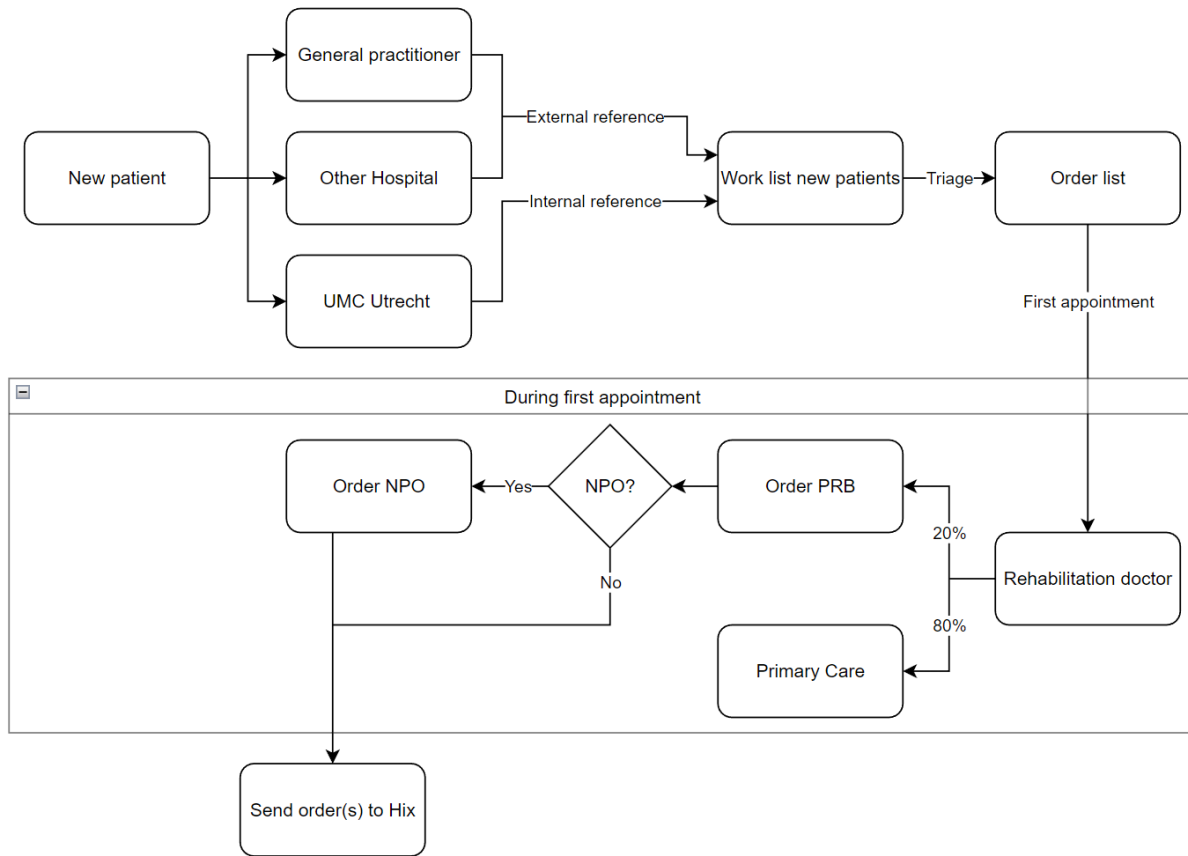


Figure 2-1: Flowchart, arrival of a new patient to NPO order.

2.1.3 NPO criteria

For the rehabilitation doctor to determine whether a patient needs an NPO there are two guidelines. Patients that have acquired brain injury and need to get back into work get an NPO. Also, patients under 60 years old, who do not need to get back into work but do have a household to take care of, get an NPO. These are general guidelines, however the doctor can also give the patient an NPO apart from the guidelines. For example, the patient could tell the doctor that he/she has relational problems since he/she acquired the brain injury. This is a good incentive to find out exactly what is wrong to help the patient in the best possible way. Another example, when the team, who is treating the patient with acquired brain injury, says that the patient is not getting better, the rehabilitation doctor can decide that the patient needs an NPO.

2.2 Current scheduling performance

In this section, we will analyze the current scheduling performance through three KPIs. The utilization of the available NPO slots, the access time of patients to NPOs and the percentage of cancelled NPOs.

2.2.1 Access time

The access time of a patient for an NPO is the time between the NPO order date and the date of the NPO.

$$\text{Access time NPO} = \text{NPO date} - \text{NPO order creation date}$$

A dataset is provided by the RF&S to analyze the current scheduling performance of the RF&S. The data set contains 373 rows which corresponds to the number of NPOs of the past 5 years. The data had some duplicates which have been removed. Next, the access time is calculated for each row. Each row corresponds to a patient. Some rows have an access time of over 100 days which according to the head of the RF&S is impossible. Therefore, these values have been removed from the data. There are now 239 rows of patients left in the dataset. Table 2-1 shows that in the past 5 years, only 20,1% of the patients that had an NPO, had an access time of less than or equal to 28 days. This means that only 20,1% of NPOs follow the guideline.

Access time (days)	Number of NPOs	Percentage of total NPOs
=<28	48	20,1%
>28	191	79,9%
Total	239	100%

Table 2-1: The access time guideline is met 20,1% of the time.

2.2.2 Utilization

The RF&S has a capacity of 2 NPOs per week. This corresponds to 8 NPOs per month and 96 NPOs per year. Table 2-2 shows the utilization over the past 5 years. We observe a low utilization percentage in the years 2020-2022. This is mainly due to COVID-19. This data should therefore be excluded from the queueing analysis in section 2.3. The utilization in 2018 and 2019 is almost at full capacity.

Year	Utilization	# NPOs
2018	91%	87
2019	88%	84
2020	50%	48
2021	55%	53
2022	60%	53

Table 2-2: Utilization over the past 5 years.

2.2.3 NPO cancel analysis

Cancelled appointments have a big impact on the access time and the utilization of the RF&S according to the head of the RF&S. This is because an NPO takes a full working day for a psychologist so when an NPO gets cancelled this causes a big loss of time. A cancelled NPO also means that the patient needs to be rescheduled for another NPO, taking two NPO slots. It is therefore important to analyze whether there are a lot of cancelled NPOs because this could be one of the reasons why the access time guideline is not met. We will now investigate the NPO appointments that were cancelled. The data shows that over the past 5 years, 87 NPO appointments were cancelled. There is a capacity of 96 NPOs per year, 480 per 5 years. Table 2-3 shows that 18,1% of NPOs were cancelled in the last 5 years.

Capacity	Cancelled NPOs	Percentage of NPOs cancelled
480	87	18,1%

Table 2-3: Percentage of NPOs that have been cancelled.

Fortunately, NPO slots that are empty due to a cancel can be refilled with another NPO. 44 out of the 87 were refilled with another NPO. This means that not all NPO cancels caused a loss of an NPO slot. Table 2-4 shows that 8,96% of capacity was lost due to cancelled NPOs. The capacity lost value is used in chapter 4 as input for the simulation model.

Capacity	Non-refilled NPO slots	Capacity lost
480	43	8,96%

Table 2-4: Capacity percentage that was lost due to non-refilled NPO slots.

2.3 Queueing model

In this section, queueing theory is used to create benchmarks against the KPI results from the historical data in chapter 2.2. This is done to show whether it is possible for the RF&S to improve the current system without increasing the capacity. The queueing analysis is also used as input for the simulation model which we will describe in chapter 4. This analysis only uses the data from 2018 and 2019, because 2020 and 2021 are affected too much by Covid-19 as we have seen in section 2.4. 2022 only contains data until November and can therefore also not be used in this analysis. We will first describe the queueing model and after that the analysis is shown.

2.3.1 Model description

The arrival of a patient to an NPO until the NPO is done can be modelled using a M/M/1 queueing model. This model has a single queue where patients arrive with rate λ and are served by one server with service rate μ . Figure 2-2 depicts the model.

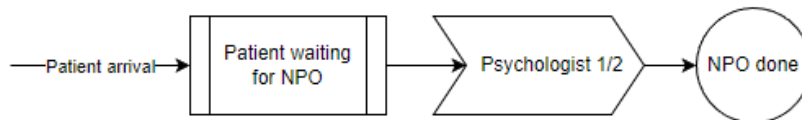


Figure 2-2: Visualization of the queueing model.

The model starts with a patient arrival with rate λ , an arrival is the moment when the NPO-order of a patient is sent to Hix. Next, the patient is waiting for an NPO which is the time between the NPO-order date and the NPO date. During this time the NPO is scheduled to either psychologist 1 or psychologist 2 without any priority. The period for the arrival and the service rate are both in months. To use the M/M/1 queueing model, four things need to hold:

1. Arrivals occur with rate λ according to a Poisson process.
2. The service time is exponentially distributed with parameter μ .
3. The arrival rate and service time are memoryless.
4. There is a single server.

We will also show that from (1.) follows that the interarrival time is exponential with parameter λ .

Arrivals

The Chi-square goodness of fit test was applied to test whether the NPO order data fits a Poisson distribution. The calculation steps are included in Appendix B.1. The Null hypothesis is:

H_0 : the data follows a Poisson distribution.

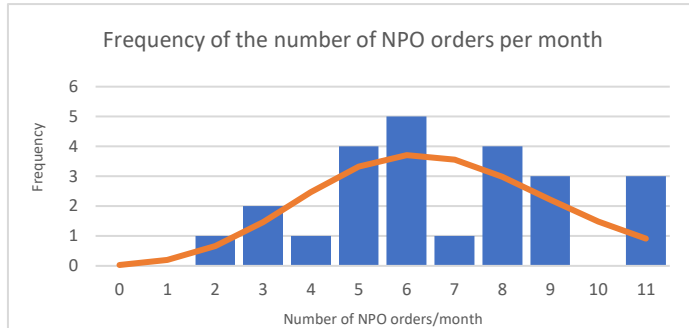


Figure 2-3: Histogram of the number of NPO orders per month.

Distribution	Observed p-value	P-value > $\alpha=0,05$?
Poisson	0,459	Yes

Table 2-5: Observed p-value for the data.

Table 2-5 shows the observed p-value. The p-value for the Poisson distribution is greater than α . We fail to reject the null hypothesis, therefore with 95% confidence we can conclude that the data follows a Poisson distribution. Figure 2-3 depicts the histogram with the fitting Poisson distribution.

Interarrival times

The Chi-square goodness of fit test was used to test whether the interarrival times are exponentially distributed. The calculation steps are included in Appendix B.2. The Null hypothesis is:

H_0 : the interarrival times are exponentially distributed.

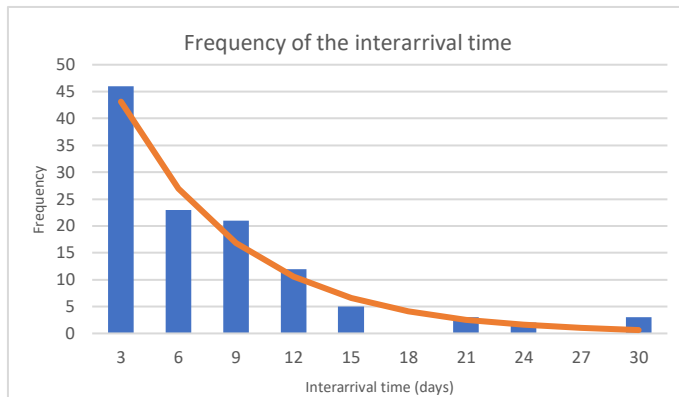


Figure 2-4: Histogram of the interarrival times

Distribution	Observed p-value	P-value > $\alpha=0,05$?
Exponential	0,055	Yes

Table 2-6: Observed p-value for the data.

Table 2-6 shows the observed p-value for the interarrival time data. The p-value is greater than α . We therefore fail to reject the null hypothesis; with 95% confidence we can conclude that the interarrival times follow an exponential distribution. Figure 2-4 depicts the histogram with the expected value of the exponential distribution.

Service times

The Chi-square goodness of fit test was applied to test whether the NPOs that have been carried out fit a Poisson distribution. The Null hypothesis is:

H_0 : the data follows a Poisson distribution.

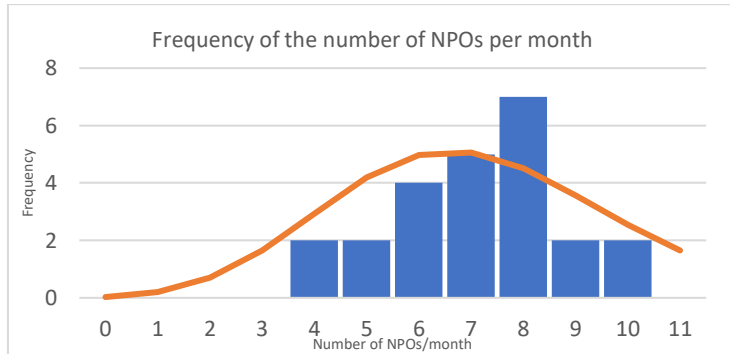


Figure 2-5: Histogram of the number of NPOs per month.

Distribution	Observed p-value	P-value > $\alpha=0,05$?
Poisson	0,782	Yes

Table 2-7: Observed p-value for the data.

Table 2-7 shows the observed p-value. The p-value for the Poisson distribution is greater than α . We fail to reject the null hypothesis, therefore with 95% confidence we can conclude that the NPOs that have been carried out in 2018 and 2019 follow a Poisson distribution. Figure 2-5 depicts the histogram with the fitting Poisson distribution.

Memoryless

For the arrival rate and the service times to be memoryless, the time between the next arrival does not depend on how much time has elapsed since the last arrival. For our system this means that the time between an arrival of a patient does not depend on how much time has elapsed since the last arrival of a patient. This holds for our system because patient come to UMC Utrecht at random points in time and each patient does not know the other patient meaning that arrivals are independent of one another. Therefore, the memoryless property holds for our system.

Number of servers

The RF&S uses two psychologists for their NPOs implicating two servers, but we can also model the system as a queueing system with one server. The service time is in number of NPOs per month. We can add the number of NPOs completed by psychologist 1 to the number of NPOs completed by psychologist 2 to get the service rate of a given month. It is possible to see both psychologist as a single server because there is no priority in which psychologist is chosen for an NPO.

2.3.2 Queueing analysis

We have now shown that arrivals occur according to a Poisson process, implying that the interarrival times are exponentially distributed, the service times are exponentially distributed, the memoryless property holds, and that the number of servers is 1. Therefore, the M/M/1 queueing model can be used to analyze the data. We start by determining the arrival rate and the service rate. Then we analyze the utilization. After that performance measures are calculated. Finally, we determine the current access time guideline percentage.

Arrival rate and service rate

The arrival rate and the service rate of 2018 and 2019 are now calculated. Table 2-8 shows the arrival rate and the service rate per month of 2018 and 2019. The arrival rate data is derived from the number of NPO orders that came in per month. The service rate per month is derived from the number of NPOs that have been carried out per month. The bottom row of table 2-8 shows the average arrival rate and service rate per year.

	Arrival rate (λ) 2018	Service rate (μ) 2018	Arrival rate (λ) 2019	Service rate (μ) 2019
Jan	6	4	7	7
Feb	2	6	11	5
Mar	11	6	9	5
Apr	6	10	8	8
May	11	7	6	8
Jun	8	6	5	7
Jul	3	6	8	9
Aug	5	8	9	4
Sep	5	10	5	8
Oct	9	9	6	8
Nov	3	8	8	8
Dec	6	7	4	7
Average	6,25	7,25	7,17	7,00

Table 2-8: The Arrival rate and the service rate in 2018 and 2019.

Utilization

The utilization (ρ) of the NPO capacity is the arrival rate divided by the service rate.

$$\rho = \frac{\lambda}{\mu} = \frac{\#NPO \text{ orders}}{\#NPOs \text{ done}}$$

Table 2-9 shows the utilization for each month of 2018 and 2019. The average utilization of 2018 and 2019 was 0,942. Out of the 24 months there were 11 months with a utilization higher than 1. A utilization higher than 1 means that there were more NPO orders coming in than there were NPOs being done, meaning that there is a mismatch between supply and demand. This causes the access time to greatly increase during months with a utilization higher than one. To show this figure 2-6 is created which depicts that the access time will go to infinity when the utilization gets close to 1.

ρ	2018	2019
Jan	>=1	>=1
Feb	0,33	>=1
Mar	>=1	>=1
Apr	0,60	>=1
May	>=1	0,75
Jun	>=1	0,71
Jul	0,50	0,89
Aug	0,63	>=1
Sep	0,50	0,63
Oct	>=1	0,75
Nov	0,38	>=1
Dec	0,86	0,57

Table 2-9: Utilization of the NPO capacity per month.

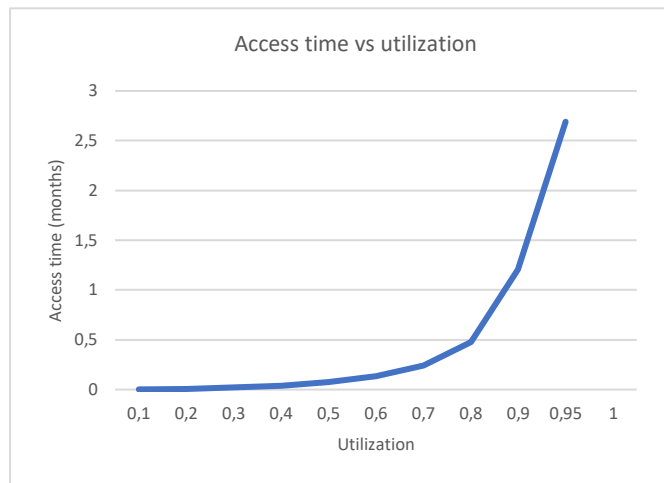


Figure 2-6: Access time vs the utilization. ($\lambda=6,708$; data from 2018-2019).

Performance measures

As previously mentioned, the RF&S has a guideline for the access time which should not exceed 28 days. The performance measures were calculated with the help of basic queueing theory formulas (Appendix B.3). The performance measures are shown in table 2-10. To verify whether on average the guideline is met, the average time in months that a patient waits for his/her NPO is W_q . W_q was 2,260 in 2018 and 2019, this means that the expected access time of a patient to an NPO was 2,260 months. This is more than twice the guideline.

Performance measure	2018 & 2019
λ	6,708
μ	7,125
ρ	0,942
P_0	0,058
L_q	15,158
L	16,100
W_q	2,260
W	2,4

Table 2-10: Performance measures 2018-2019.

Current guideline percentage

The research goal is to comply to the access time guideline 80% of the time. The current % of NPOs that comply to the guideline according to the historical data is 20,1%. We will now compute the current % of NPOs that comply to the guideline with the following formula to create a benchmark:

$$P(W > t) = \rho e^{-\mu(1-\rho)t}$$

This formula computes the probability that the access time of a patient is larger than a value t . To compute the $P(W > t)$ for the guideline, the value for t needs to be 1, because the probability of an access time of 1 month is required. From table 2-8, μ and ρ are 7,125 and 0,942. μ , ρ and the value for t are input for the formula.

$$P(W > 1) = 0,942e^{-7,125(1-0,942)*1} = 0,62$$

We are interested in the probability that the access time is smaller than 1. This is 1 minus the probability that the access time is greater than 1.

$$P(W < 1) = 1 - P(W > 1) = 1 - 0,62 = 0,38$$

This means that the guideline is currently met 38% of the time.

Capacity required to meet the guideline.

The research goal states that the access time guideline needs to be met 80% of the time. We will use this formula to calculate the μ required to achieve the research goal.

$$P(W > t) = \rho e^{-\mu(1-\rho)t}$$

This formula is chosen because we are interested in finding the μ value required to achieve the access time guideline for 80% of the patients. The formula calculates the probability that the mean waiting time of a patient is larger than a value 't', this is exactly what we need to solve our Queueing problem. Our period is in months and the access time guideline is 28 days, therefore the value for 't' should be 1 month. We need to find the μ value for $P(W>1) = 0,20$ (the probability that the mean waiting time is greater than 0,20). The Excel solver function is used to calculate the μ value.

$$0,20 = \frac{6,708}{\mu} e^{-\mu\left(1-\frac{6,708}{\mu}\right)}$$

$$\mu = 8,126$$

According to Queueing Theory, the RF&S needs to do more than 8,126 NPOs per month to reach the access time guideline 80% of the time. The head of the RF&S is interested in a practical solution. Increasing the capacity to 8,126 NPOs per month is not a practical solution. A practical solution is a solution which can be implemented, for example, increasing the capacity in months January and February to overcome a seasonal increase in demand. To give the head of the RF&S a practical solution, we will need knowledge from the literature, because we currently do not know what the best method for meeting the guideline is. We will do the literature search in the next chapter.

3 Theoretical framework

In this chapter, a systematic literature review (SLR) is done to find out how other hospitals have decreased their access time to appointments of their patients. The SLR steps can be viewed at the Systematic Literature Review appendix.

The research question for this systematic literature review is:

- How can outpatient clinics reduce the access time to patient appointments?

Access time is the time between the appointment referral and the appointment itself. This is closely linked to the definition of Van Zyl-Cillie (2023). They state that “access time is the time that a patient waits before being allowed to enter the healthcare habitat to receive service.” They distinguish between waiting time and access time in their paper. This distinguish is also used in this systematic literature review to exclude papers that concern waiting time rather than access time. This systematic literature review shows that there are multiple methods of reducing the access time of patients to appointments. We will discuss the different methods found in the literature and conclude with a decision on which one is most applicable to this research. The found methods are simulation, no show reduction and changing the appointment scheduling.

Simulation

Simulation is mostly used in this field, to show how much capacity is required to fulfill demand. Edward (2008) used computer simulation to test different scenarios to reduce the access time at AMC Amsterdam. They found out that the current capacity level was sufficient to meet demand, however the access time was 5 weeks, so a backlog existed, and they had to increase capacity for a certain amount of time to eliminate it. Elkhuisen (2007) used Queueing Theory in combination with simulation also at AMC Amsterdam. Queueing Theory was used to get insight into the capacity needed to meet their access time norm. Next, they used simulation to do a more detailed analysis to gain insight into how much capacity was needed to meet demand and eliminate backlogs. Joustra (2012) have researched the influence of variances in capacity on the access time. They found that in their situation, the access time could be reduced by 40% when they eliminate variances in capacity. This was done by using Queueing Theory in combination with a discrete event simulation model. (Carreras-Garcia 2020) researched the influence of holidays on the variance in capacity. They found that a mismatch occurs between demand and capacity during holiday weeks which causes an increase of the access time. They also state that managing capacity is a bigger challenge than managing the unpredictability demand.

No shows

The next method is reducing the number of no-shows, patients who do not show up to their appointments. (Babayoff 2022) has improved a hospitals’ outpatient clinic appointment schedule by prediction models. One of the models they considered were the patient no-show prediction models. They state that no shows are not random. The no-show rate of a patient is heterogeneous, patients have different no-show probabilities. The no-show probability of a patient is calculated by several variables (for example, already had a no-show, distance to the hospital). With this knowledge they made a no-show prediction model which was then used to improve the hospitals’ access time. (Carreras-garcia 2020) also uses no-show probabilities per patient to reduce the access time. They propose a scheduling system that maximizes the expected profits of the clinic

while also decreasing the access time by 30%. (Almorsy 2016) states that patients with a longer access time are more likely to not show up to their appointment. They propose that the access time can be reduced when a short list of easily accessed patients is made, whom can be called into an appointment on the same day when a no-show occurs to fill in the gap.

Appointment scheduling

The third method is changing the way of the appointment schedule. (Bikker 2020) formulated a dynamic programming algorithm to obtain the optimal capacity allocation policies for rehabilitation treatments. (Braaksma 2014) used integer linear programming to ensure continuity of the rehabilitation process while also controlling the access time, utilization, and combination appointments. (Kortbeek 2014) designed an appointment system for outpatient clinics. They made two models, one for scheduled patients and one for unscheduled patients.

Conclusion

As we have shown, there are multiple ways to reduce the access time to patient appointments found in the literature. We will now decide which method to use. All papers that design algorithms for appointment schedules seem to be too case specific or too complex to be applicable for this research. The papers about appointment scheduling are also mostly concerning multiple departments within hospitals while our case is specifically covering NPOs at the psychology department. Designing an appointment algorithm will therefore not help in our case. The no-show rate for NPOs at the rehabilitation department is 4,3%. This is a low percentage, it is therefore not beneficial to decrease the no-show rate to lower the access time.

Simulation enables us to test multiple scenarios and change variables to find the optimal solution. The papers from Elkhuisen (2007) and Edward (2008) both had similar problems that they solved by using simulation. In the queueing analysis from chapter 2.3.2 we found that the RF&S had 11 months where the utilization was higher than 1, meaning a mismatch in supply and demand. The RF&S is unable to change the demand side because these are the patients that need an NPO, therefore we need to think of ways to increase the supply side. The supply side is the capacity for NPOs. To increase the supply side, we need to increase the number of NPOs that can be done per month. With simulation we can test multiple scenarios of increased capacity to see which scenario is able to meet the access time guideline. So, together with the head of the RF&S it was decided that building a simulation model that represents the real-world system is the best way to move forward.

4 Solution design

This chapter covers the simulation model. We start by giving the model specifications according to chapter 2. Then we show the interface of the simulation model. Next, a flow diagram which describes the logic behind the simulation model is shown. We then explain how the specifications are integrated into the model. This is followed by describing the output of the model and the experiment set-up. We will end this chapter by validating the simulation model.

4.1 Model specifications

We create a simulation model from the queueing model showed in figure 2-4. To make the simulation model as close to reality as possible, a list of specifications is created from the information from chapter 2. In chapter 2, we explained how patients flow through the hospital and how planning is done at the RF&S.

- (1) The system has a planner who plans the NPOs, a waiting list with infinite capacity, and two NPO slots per week. There are two psychologists, each psychologist does one NPO per week.
- (2) New patients arrive during working hours, Monday to Friday from 8:00-17:00. The number of NPO requests per week follow a Poisson distribution with $\lambda=1,677$. The lambda is acquired from the data analysis in chapter 2 where we observed that the lambda per month in 2018 and 2019 was 6,708. We simplify by saying that a month consists of 4 weeks.
- (3) Scheduling is done on a first come first serve basis.
- (4) Planners can plan 14 weeks ahead.
- (5) The time it takes to complete an NPO is deterministic and is set to 6 hours.
- (6) The access time of a patient is counted from the moment that the patient is added to the waiting list until the start of the NPO.
- (7) Patients that have received an NPO leave the system.
- (8) Patients have a no-show probability of 0,09. When a no-show occurs, the patient is re-added to the waiting list for rescheduling. In chapter 2.4.4 we analyzed the NPO cancels, we found that 9% of the cancelled NPOs is non-refilled, that is why the no-show probability of the system is set to 0.09.
- (9) Each psychologist has 5 holiday weeks per year, so there is a total of 10 holiday weeks per year. Holiday weeks do not overlap, this means that there is one NPO slot per week during holiday weeks.

4.2 Simulation flow diagram

The simulation model is created in Plant Simulation. This is a discrete event simulation program, where time passes only when certain events take place. An overview of the simulation model is depicted in figure 4-1. An enlarged version of figure 4-1 is shown in appendix C.

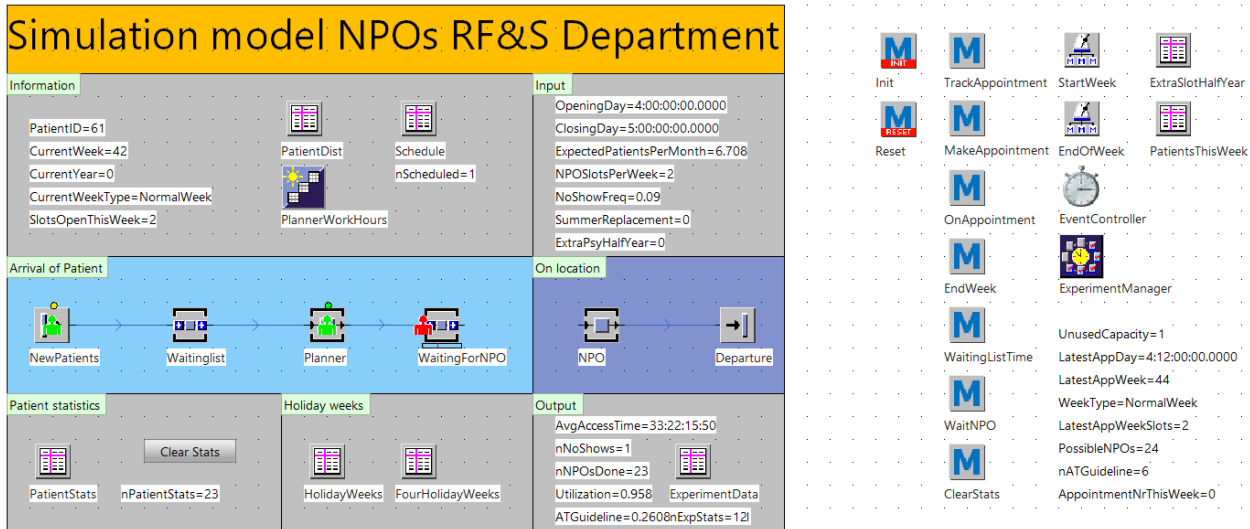


Figure 4-1: Overview simulation model

A flow diagram is created to show the logic behind the simulation model. Figure 4-2 depicts the flow diagram. The simulation starts by generating new patients according to a Poisson process with rate λ . The system generates either a normal patient with probability p or a no-show patient with probability $1-p$. These patients are then added to the waiting list. Each patient gets a waiting list time once they enter the waiting list. Then the planner schedules the patient to the earliest free slot in the schedule. The number of NPO slots available on the schedule is limited. When there is no free NPO slot available, the patient is re-added to the front of the waiting list. Each scheduled patient receives an appointment day and is moved to 'Patient waiting for NPO'.

On the appointment day of the first patient on the schedule, the system checks the patient type. A normal patient is moved to 'NPO' and after the NPO, the patient leaves the system. A no-show patient is re-added to the waiting list on the appointment day. A no-show in this system means that the NPO is cancelled in such short notice that the planners are unable to re-fill the appointment slot with a different patient. A no-show therefore causes a loss of an appointment slot. After a no-show patient is re-added to the waiting list on the appointment day, the attribute 'Missed NPO' is set to one and the patient moves through the system as if it were a normal patient.

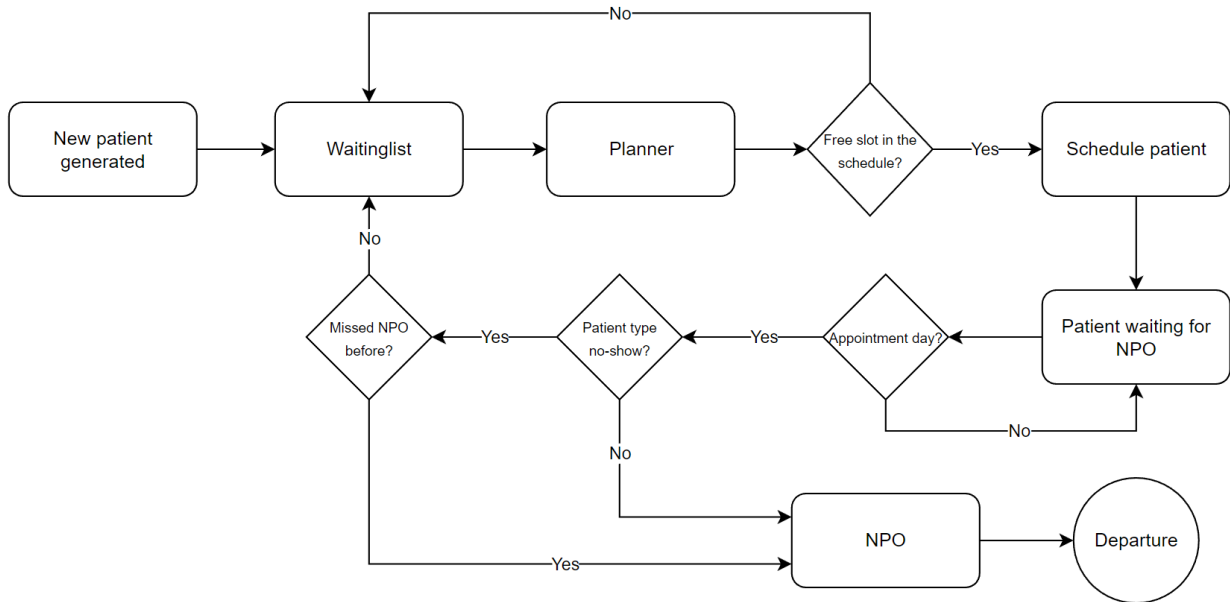


Figure 4-2: Simulation flow diagram

4.3 Integration of model specifications

Chapter 4.2.1 listed the model specifications; we will now describe, from (1) to (9), how the specifications are integrated into the simulation model. Assumed is basic knowledge of Plant Simulation.

Specification (1)

The system has a planner who plans the NPOs, a waiting list with infinite capacity, and two NPO slots per week. There are two psychologists, each psychologist does one NPO per week.

Two workstations are added and named 'Planner' and 'NPO'. The model does not need two separate workstations for each psychologist because NPO appointments do not overlap. A buffer is added and named 'WaitingList'. The number of NPO slots is given by a global variable named 'NPOSlotsPerWeek' in the input section of the simulation model interface. This variable also represents the number of psychologists available for NPOs.

Specification (2)

New patients arrive ($\lambda=6,708$ per month) during working hours, Monday to Friday from 8:00-17:00.

A source module is added to the model and named 'NewPatients'. The arrival interval of $\lambda=6,708$ is added in the settings of 'NewPatients'. A Shift Calendar module is added to the simulation model to comply to the working hours. A shift from 8:00-17:00, Monday to Friday, is put into the Shift Calendar. The 'Planner' and the 'NewPatients' modules both use the Shift Calendar. This means that they only operate during the shift.

Specification (3)

Scheduling is done on a first come first serve basis.

The 'WaitingList' module is connected to the 'Planner' module. Plant Simulation uses first come first serve by default, by connecting the modules by an arrow, this principle is automatically used.

Specification (4)

Planners can plan 14 weeks ahead.

With two NPO slots per week a total of 28 NPOs can be scheduled. To implement this into the simulation, a maximum of 28 patients can be present at 'WaitingForNPO'.

Specification (5)

The time it takes to complete an NPO is deterministic and is set to 6 hours.

The processing time at the 'NPO' module is set to 6 hours.

Specification (6)

The access time of a patient is counted from the moment that the patient is added to the waiting list until the start of the NPO.

Once a patient is generated by the 'NewPatients' source, it is automatically moved to the 'WaitingList' module. The method 'WaitinglistTime' is activated on entrance of a patient. Within the method there is code which gives the patient a 'WaitingListTime'. Once the patient arrives at the 'NPO' module, the method 'TrackAppointment' is activated. The patient receives a 'ArrivalAtNPO' time. The access time of a patient in the simulation model is calculated once the patient leaves the model. The access time is the 'ArrivalAtNPO' – 'WaitingListTime'.

Specification (7)

Patients that have received an NPO leave the system.

The module 'NPO' is connected to the 'Departure' module. Once the processing time of an NPO is finished, the patient automatically leaves the system.

Specification (8)

Patients have a no-show probability of 0,09. When a no-show occurs, the patient is re-added to the waiting list for rescheduling.

The 'NewPatients' source generates two patient types: a normal patient, and a no-show patient. The selection of a patient type is done via a distribution table. Within the distribution table the normal patient frequency is set to 0,91 and the no-show patient frequency is set to 0,09. Once a no-show patient arrives at the 'NPO' module it is moved to the 'WaitingList' module. Once this happens, the 'MissedNPO' attribute of the patient is set to 1 and the model now treats the patient as a normal patient.

Specification (9)

Each psychologist has 5 holiday weeks per year, so there is a total of 10 holiday weeks per year.

A table called 'HolidayWeeks' is added to the model. A screenshot of the table is shown in figure 4-3. Inside the table there are 10 rows in which the holiday week numbers can be put in. The model checks when making an appointment whether the appointment week, in which it wants to schedule the patient, is a holiday week. If the appointment week is a holiday week, the model knows that it can only schedule the number of 'NPOSlotsPerWeek' – 1.

	integer 1
string	Holidays
1	12
2	16
3	23
4	24
5	25
6	26
7	27
8	28
9	43
10	50

Figure 4-3: 'HolidayWeeks' table from the simulation model.

4.4 Key performance indicators simulation model

KPIs are added to the simulation model to validate-and evaluate experiments with the model. The KPIs are displayed under output on the simulation overview in figure 4-1. The KPIs are updated either when a patient departs the system or at the end of a week.

Average access time

The access time of a normal patient in the model is calculated by subtracting the waiting list time of the patient from the appointment day. The access time of a no-show patient is calculated differently. A no-show patient has two appointment days, the original NPO day and the actual appointment day. A no-show patient also has two waiting list times. Therefore, a no-show patient also has two access times. The access time of a no-show patient is calculated by taking the average of the 2 access times. The average access time of the current simulation run is calculated with the following equation where 'n' is the number of NPOs that have been carried out.

$$\text{Average access time} = \frac{n - 1}{n} * \text{AvgAccessTime} + \frac{1}{n} * \text{access time of the patient}$$

Utilization

The utilization of the model is the fraction of available NPO slots that have been used for NPOs and is updated at the end of every week in the simulation. The utilization is calculated with the following equation where 'n' is the number of NPOs that have been carried out and 'n*' the total number of NPOs that could have been carried out in the current time frame.

$$Utilization = \frac{n}{n^*}$$

The 'n*' parameter is updated at the end of every week by adding the 'SlotsOpenThisWeek' value, under information on the simulation overview in figure 4-1, to the 'n*' value. 'SlotsOpen-ThisWeek' changes depending on whether the current week is a holiday week or a regular week.

Access time guideline

To later being able to see if the research goal is achieved, a KPI for the access time guideline of 28 days needed to be created. The KPI is called 'ATguideline' in the model, this is short for access time guideline. This KPI displays the fraction of patients that followed the access time guideline. The access time of a patient is calculated when the patient departs the system, after that the model checks whether the access time is less than 28 days. 'Atguideline' is set to 1 when the access time is lower than 28 days and set to 0 when it is greater than 28 days. The access time guideline KPI is calculated by the following equation where 'n' is the number of NPOs that have been carried out and 'Atguideline' is the number of patients that followed the access time guideline.

$$Access\ time\ guideline = \frac{AT\ guideline}{n}$$

4.5 Simulation experiment setup

A proper warm-up period, simulation run length and the number of replications per experiment is now determined. A proper setup is necessary for the experiments in chapter 5 because we want the results of the experiments to be as close to reality as possible.

4.5.1 Warm-up period

The simulation model starts with an empty waiting list, therefore the access time of the first patients is significantly lower than the access time later into the simulation run. The waiting list in the real world does not start empty, it is an already running system. Thus, to get representative results we need to determine a warm-up period for the simulation model. The time-series inspection method proposed by (Robinson, 2014, p. 176) is used to determine the warm-up period. We choose this method because it is a simple and effective method for determining the warm-up period. We have three KPIs in our model, utilization, access time and access time guideline. A time-series for each KPI needs to be created. After that we inspect each time-series and see where there is initialization bias. Finally, the time-series with the longest initialization bias is the warm-up period. The warm-up period is then the week number where the initialization bias has ended. Robinson mentioned in his book that the data of the time-series can be very noisy, which makes it difficult to spot any initialization bias. He recommends doing multiple replications for each time-series because outliers are then subsumed into the calculation of the mean for each period which

smoothens the graph for easier inspection. We therefore decide to do 20 replications for each time-series. Each KPI can have a different warm-up period, it is therefore necessary to split the time-series up in three graphs. Figure 4-4 to 4-6 show the time-series of the three KPIs. A red line is added to each graph to show where we observed the warm-up period of the KPIs. Table 4-1 shows the warm-up period per KPI. The utilizations' warm-up period is the longest at 30 weeks. According to Robinson, we need to take the longest warm-up period to ensure that all initialization bias of each KPI has been removed. Therefore, the warm-up period for the simulation model is 30 weeks.

Time-series	Warm-up period (weeks)
Access time	5
Utilization	30
Access time guideline	3

Table 4-1: Warm-up period per time-series

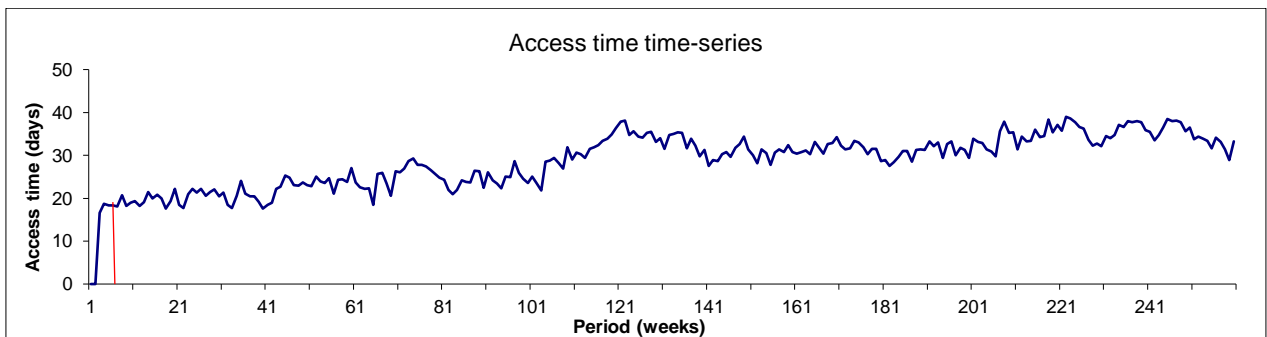


Figure 4-4: Time-series of the access time over a period of 5 years.

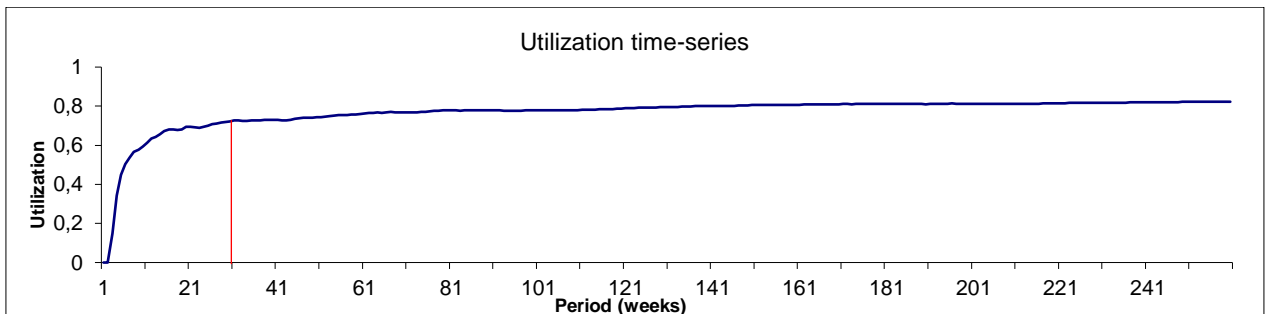


Figure 4-5: Time-series of the utilization over a period of 5 years.

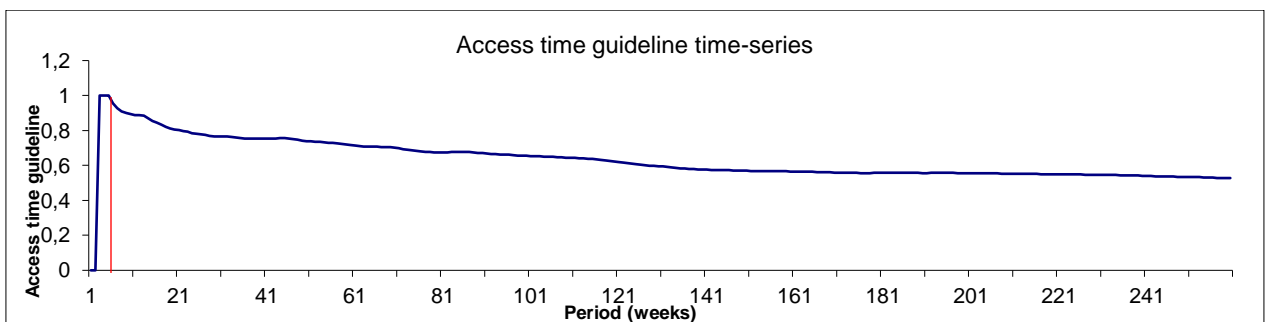


Figure 4-6: Time-series of the access time guideline over a period of 5 years.

4.5.2 Run length

We want to compare the real-world data from 2018 and 2019 to the simulation model. In chapter 2.2 we found that the years 2020-2022 were affected too much by COVID-19 and that the data should therefore be removed from the analysis. This is why we use the data from older years because these years can be seen as 'normal' years according to the head of the RF&S. Therefore, the run length is set to 2 years, this is equal to 730 days.

4.5.3 Number of replications per experiment

We will now find out how many replications we should perform. A replication is a run of a simulation that uses specific streams of random numbers (Robinson, 2014, p. 182). According to Robinson, we need to do multiple replications to get a better estimate of the mean performance of the simulation model. Robinson describes three methods for determining the number of replications. The first method is the rule of thumb method by Law and McComas (1990). This method says that at least three to five replications need to be performed. The second method is the graphical method where the cumulative mean of the KPI is plotted from a series of replications. The third method is the confidence interval method which (Robinson, 2014, p. 184) describes as the best method for determining the number of replications, this is therefore also the method we will be using.

The output of the simulation model is given in confidence intervals, the model gives the cumulative mean of the KPI and a lower-and upper interval. The deviation %, of the lower-and upper interval from the cumulative mean, decreases as the number of replications increases. The goal is to find the replication number of the 95% confidence interval where the deviation % is smaller than 5%. 5% is according to Robinson an acceptable deviation % and that is why we will also be using it. The deviation % is calculated according to the following formula where X is the cumulative mean, LI the lower interval and UI the upper interval.

$$Deviation \% = \left(1 - \frac{\frac{LI + X}{2}}{UI}\right) * 100$$

We need to determine the number of replications for each KPI, the utilization, the access time, and the access time guideline. The highest number of replications will be used for the experiments, the same as we did for the warm-up period. Table 4-2 shows the 95% confidence intervals for the utilization for 20 replications where the model is run for 730 days (the previously determined run length). For each replication we noted down the cumulative mean, the standard deviation, the lower-and upper interval, and the deviation %. From table 4-2 we see that the deviation % is below 5% for the first time at 10 replications. The same process is done for the access time guideline and the access time. Table 4-3 shows the 95% confidence intervals for the access time guideline. We found that 20 replications were not nearly enough to get a deviation % of 5%. We therefore increased our replication steps significantly. The table shows that we need a minimum of 1500 replications to reach the 5% deviation. For the access time we found that a minimum of 300 replications is required shown in table 4-4. The number of replications for the access time guideline is the highest at 1500. This will therefore be the number of replications per experiment.

Replication	Cumulative mean	Standard deviation	95% Confidence interval		
			Lower interval	Upper interval	% deviation
1	0,840	n/a	n/a	n/a	n/a
2	0,894	0,075	0,218	1,569	59,34%
3	0,856	0,084	0,649	1,064	21,87%
4	0,863	0,070	0,752	0,974	12,13%
5	0,841	0,077	0,746	0,937	10,77%
6	0,853	0,074	0,775	0,931	8,76%
7	0,852	0,068	0,789	0,915	7,14%
8	0,850	0,063	0,797	0,903	6,05%
9	0,853	0,060	0,807	0,899	5,25%
10	0,847	0,060	0,804	0,889	4,90%
11	0,852	0,059	0,812	0,891	4,54%
12	0,850	0,056	0,814	0,885	4,10%
13	0,853	0,055	0,820	0,886	3,80%
14	0,855	0,054	0,825	0,886	3,50%
15	0,860	0,055	0,830	0,890	3,43%
16	0,858	0,053	0,830	0,887	3,27%
17	0,862	0,054	0,834	0,890	3,20%
18	0,863	0,053	0,836	0,889	3,03%
19	0,861	0,051	0,837	0,886	2,80%
20	0,863	0,050	0,839	0,886	2,69%

Table 4-2: Confidence interval method, results from 20 replications on the utilization with the simulation model.

Replication	Cumulative mean	Standard deviation	95% Confidence interval		
			Lower interval	Upper interval	% deviation
1	0,456	n/a	n/a	n/a	n/a
2	0,228	0,322	0	3,123	681%
3	0,308	0,267	0	0,972	142%
4	0,370	0,25	0	0,768	80%
5	0,454	0,287	0,098	0,809	61%
20	0,339	0,222	0,235	0,443	27%
30	0,297	0,215	0,217	0,378	24%
100	0,226	0,224	0,182	0,270	18%
1000	0,241	0,228	0,226	0,255	6%
1250	0,239	0,227	0,226	0,251	5,1%
1500	0,237	0,225	0,225	0,248	4,7%

Table 4-3: Confidence interval method, results from 1500 replications on the access time guideline with the simulation model.

Replication	Cumulative mean	Standard deviation	95% Confidence interval		
			Lower interval	Upper interval	% deviation
1	29,120	n/a	n/a	n/a	n/a
2	45,861	23,674	0	258,570	273,04%
10	33,985	11,963	25,426	42,543	22,65%
100	50,740	21,166	46,540	54,939	7,96%
150	48,771	20,588	45,449	52,093	6,59%
250	49,910	21,113	47,280	52,540	5,14%
300	49,457	20,727	47,102	51,811	4,7%

Table 4-4: Confidence interval method, results from 300 replications on the access time with the simulation model.

4.5.4 Simulation model validation

We want to give the RF&S useful and valid recommendations from the simulation model. This can only be achieved when the model reflects the real-world system. That is why we will now validate the simulation model. The results from the data analysis in chapter 2 showed that the access time guideline is met 20,1% of the time and the utilization was 0,895. To validate the simulation model, we will now run the model with the warm-up period of 210 days, a run length of 730 days, and 1500 replications. Table 4-5 shows the results of the simulation run, the real-world data and the difference between them. The difference between the values of the real-world data and the simulation model is small. We can therefore say that the model represents the real-world system.

	Utilization	Access time guideline
Real-world data	0,895	0,201
Simulation model	0,889 ± 0,002	0,237 ± 0,011
Difference	0,006 ± 0,002	0,036 ± 0,011

Table 4-5: Comparison between the real-world data and the results from the simulation mode

5 Experiments & results

This chapter covers the experiments that are done with the simulation model and the results from the experiments. The optimal warm-up period, number of observations and the run length found in chapter 4 are used for the experiments.

5.1 Experiments

Two sets of experiments are done with the simulation model. The first set of experiments is done while using the experiment-manager (section 5.1.1). The second set of experiments is done with a dataset generated by the simulation model (section 5.1.2).

5.1.1 First set of experiments

The first set of experiments consists of 6 experiments with the experiment-manager. The first 5 experiments were developed together with the head of the RF&S. The last experiment is made to test whether the 'NoShowFreq' has a big impact on the access time guideline. In chapter 2.2.3 we found that the capacity lost due to cancelled NPOs is 9%. The last experiment is the current system without any NPO cancels.

Experiments with experiment-manager

Plant Simulation has a build-in experiment-manager which is used to do experiments with the simulation model. Figure 5-1 depicts the input variables of the simulation model, 4 of the input variables are used for the experiments. The experiments each have different values for 'NPOSlotsPerWeek' (w), 'SummerReplacement' (x), 'ExtraPsyHalfYear' (y), and 'NoShowFreq' (z) and are shown, in order, between the brackets (w; x; y; z) in the list below.

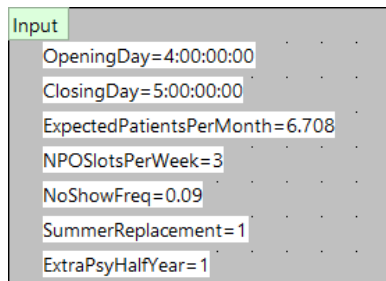


Figure 5-1: Input variables of the simulation model.

'NPOSlotsPerWeek' (w) is the number of psychologists available for NPOs. 'SummerReplacement' (x) is a variable in the model that can either be 1 or 0 depending on whether there is an extra psychologist during the summer holiday weeks (weeks 23-28) or not. 'ExtraPsyHalfYear' (y) is a variable that can either be 1 or 0 depending on whether there is an extra psychologist for half a year or not. 'NoShowFreq' (z) is the frequency of no-shows occurring in the simulation model. By varying these variables, the KPIs change when the model is run.

- (1) The model with two psychologists. (2; 0; 0; 0,09) (current situation)
- (2) The model with two psychologists and an extra psychologist during the summer holiday period. (2; 1; 0; 0,09)
- (3) The model with two psychologists and an extra psychologist for half a year not during the summer holiday period. (2; 0; 1; 0,09)

- (4) The model with two psychologists and an extra psychologist for half a year during the summer holiday period. (2; 1; 1; 0,09)
- (5) The model with three psychologists. (3; 0; 0; 0,09)
- (6) The model with two psychologists and 0 no-shows. (2; 0; 0; 0)

The output of the experiments are the KPIs defined in chapter 4.4, the average access time, the utilization, and the access time guideline.

5.1.2 Second set of experiments

The second set of experiments consists of experiments (1), (2) and (4) from section 5.1.1, where the simulation run length is increased from 2 years to 5 years.

Long-term experiments

The second set of experiments consists of long-term experiments. We will analyze the long-term effect per experiment on the access time per week. A table called 'ExperimentData' is created in the simulation model. This table stores the average access time per week. Figure 5-2 shows a screenshot of the 'ExperimentData' table. The data from the 'ExperimentData' table is exported to Excel for further analysis in section 5.2.2.

	integer 1	time 2	integer 3	integer 4
string	WeekNr	AccessTime	Experiment	Run
1	31	39:04:00:00.0000	5	1
2	32	45:04:00:00.0000	5	1
3	33	46:04:00:00.0000	5	1
4	34	41:13:00:00.0000	5	1
5	35	40:16:00:00.0000	5	1
6	36	38:16:00:00.0000	5	1
7	37	37:13:21:57.1925	5	1
8	38	33:04:00:00.0000	5	1

Figure 5-2: Screenshot of the 'ExperimentData' table from the simulation model

5.2 Results

We will now show and evaluate the results from the experiments. The KPI output from the simulation model is given in confidence intervals, this means that there is uncertainty in the output. To tighten the confidence intervals the number of replications is very high, a 1000 replications per experiment. The results per KPI per experiment consists of averages across the 1000 simulation runs (replications) that are done per experiment.

5.2.1 Results first set of experiments

Table 5-1 shows the results from the experiments. Each row in the table represents one of the experiments. The columns consist of the 3 KPIs, average access time, the utilization, and the access time guideline. We will now evaluate the results. The experiments are listed here again for easier reading.

- (1) The model with two psychologists. (Current situation)
- (2) The model with two psychologists and an extra psychologist during the summer holiday period.
- (3) The model with two psychologists and an extra psychologist for half a year not during the summer holiday period.
- (4) The model with two psychologists and an extra psychologist for half a year during the summer holiday period.
- (5) The model with three psychologists.
- (6) The model with two psychologists and 0 no-shows.

The utilization difference between experiment (1) and (2) are small while the access time guideline for experiment (2) is almost twice the access time guideline of experiment (1). The difference between the average access time is also very large while there is only an extra psychologist during the summer holiday.

Experiment	Avg access time (days)	Utilization	Access time guideline
(1)	50,396 ± 1,065	0,889 ± 0,002	0,237 ± 0,011
(2)	33,686 ± 0,661	0,851 ± 0,003	0,469 ± 0,013
(3)	24,114 ± 0,232	0,705 ± 0,003	0,709 ± 0,007
(4)	20,800 ± 0,172	0,678 ± 0,003	0,818 ± 0,006
(5)	16,784 ± 0,063	0,597 ± 0,003	0,964 ± 0,002
(6)	34,244 ± 0,653	0,919 ± 0,002	0,453 ± 0,012

Table 5-1: Results from the experiment-manager for the 5 experiments.

Experiment (3) and (4) are both experiments with an extra psychologist for half a year. The difference is that (4) is during the summer holiday and (3) is not. There is a significant difference between the access time guideline of (3) and (4). The same is seen between (1) and (2). There seems to be a big impact on the KPIs when there is an extra psychologist during the holiday weeks.

(3) and (4) have a low utilization compared to (1) and (2). Experiment (4) and (5) meet the access time guideline of 80%.

In chapter 2.3 we showed with Queueing Theory that when the utilization approaches 1, the access time will exponentially increase. The same effect is seen by looking at the output of the utilization and the access time from the experiments in table 5-1. We plot the utilization and the access time in figure 5-3. To highlight the effect arrows are added to figure 5-3. The black arrow shows the difference between the utilization and the orange arrow shows the difference between the access time. We compare the difference between the results from experiment (1) and (2) and the results from experiment (3) and (4). The black arrow between (1) and (2) is very small compared to the black arrow between (2) and (3). While the orange arrow between (1) and (2) is a lot longer than the orange arrow between (2) and (3), indicating that once the utilization approaches 1, a small increase in utilization has a big effect on the access time.

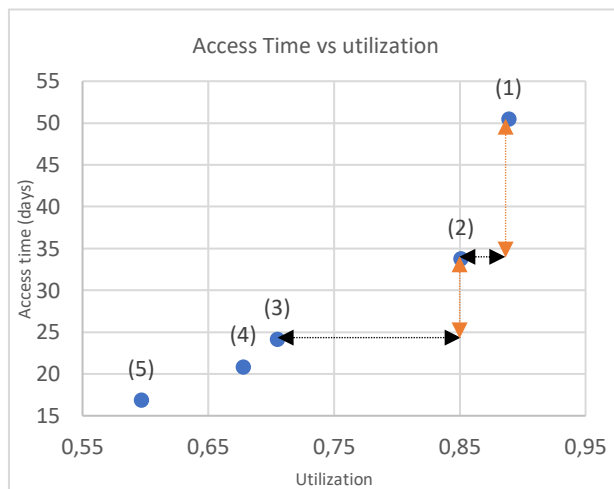


Figure 5-3: Access time vs the utilization. (Data from the simulation model results).

Experiment (1) and (6) are both experiments that represent the current system. The only difference is that (6) has a 'NoShowFreq' of 0. The average access time of (6) is 16 days lower than (1) and the access time guideline is almost twice the access time guideline of (1), while the utilization of (6) is 0,03 higher than (1). According to figure 2-6 this is not what we would expect. We would expect a much higher access time instead of a lower access time. The reason that the utilization can be higher is because there is less variability with 0 no-shows. The only part of variability in the system is the patients that arrive at random points in time when we take away no-shows.

5.2.2 Results second set of experiments

For the long-term analysis of the access time, the run length was increased from 2 to 5 years. Figure 5-5 depicts the average access time per week over a period of 5 years for the three experiments, the full graph can be found in Appendix D. The yellow line is the current situation (1), the grey line is the current situation with an extra psychologist during the summer period (2), and the blue line is the current situation with an extra psychologist for half a year during the summer period (4). The average access time per week for the yellow line will on the long run keep increasing meaning that there is not enough capacity available to meet the NPO demand. The blue line remains relatively straight throughout the 5 years, indicating that there is sufficient capacity. The average access time per week for the grey line also increases throughout the 5 years but is also able to recover and follow the blue line again.

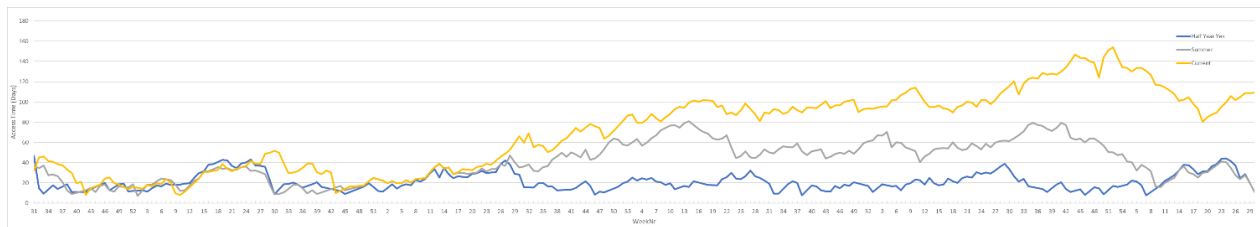


Figure 5-4: Long-term effect on the access time for experiments (1), (2) and (4).

Both the grey and blue line have an extra psychologist during the summer holiday weeks (week 23-28). Figure 5-6 depicts the effect on the access time during the holiday weeks. A few weeks after the holiday weeks the access time for the yellow line increases while the other two decrease.

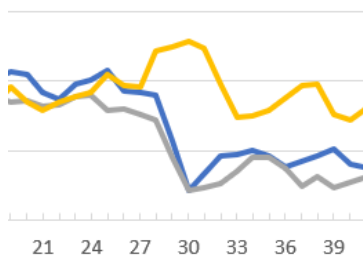


Figure 5-5: Holiday effect on the access time

6 Conclusion, recommendations and discussion

This chapter concludes the research and shows how the research goal is achieved. Recommendations to the RF&S are also given in this chapter. We end the chapter with a discussion.

The objective of this research is to lower the access time for patients to NPOs of the UMC Utrecht RF&S psychology department and with that increasing the number patients that meet the access time guideline. The research goal is formulated as:

“To develop a tool that can be used to optimize the capacity planning for NPOs of the RF&S psychology department to realize the access time norm 80% of the time.”

6.1 Conclusion

The results from the simulation model, given in table 5-1, show that to meet the access time norm 80% of the time, experiment (4) and (5) suffice. (4) meets the access time norm 82% of the time while (5) meets it 96% of the time. However, the utilization of (5) is below 60% which means that a lot of capacity will be unused. Therefore, the best solution to achieve the research goal is setup (4). Setup (4) is the current system with an extra psychologist for 6 months during the summer holiday weeks. We also did an experiment (6) where the no-show rate is 0. This experiment showed that by decreasing the variability in the system, the utilization can be higher while not causing a big increase in the access time.

6.2 Recommendations

The conclusion described that hiring an extra psychologist for 6 months, during the summer holiday period, is the best solution that meets the research goal. However, hiring an extra psychologist for 6 months is very expensive and will lower the utilization from 88% (currently) to about 68%. This means that there will be a lot of unused NPO slots which also costs money. Instead of hiring an extra psychologist the RF&S should investigate other departments that already have a low access time and take away from their capacity and use it to do extra NPOs. Having an extra psychologist for half a year means that the capacity is increased by 26 NPOs per year, the extra psychologist does 1 extra NPO for 26 weeks. We can also interpret the 26 extra NPOs differently. If we divide the 26 extra NPOs over the 2 current active psychologists this would be 13 extra NPOs per psychologist per year, which is equal to roughly 1 NPO extra per month. The RF&S should find a way to take away capacity from other departments to enable each psychologist to do one extra NPO per month. This would then according to the simulation model reach the access time guideline 80% of the time.

6.3 Discussion

In chapter 2 we analyzed the current performance. We found that the data from 2020-2023 were unusable due to the influence of COVID-19. This unfortunately meant that only data from 2018 and 2019 were available for analysis. There is only a maximum capacity of 8 NPOs per month which means that over a course of two years the amount of data is limited. We found that the current access time guideline is met 20,1% of the time. The goal is to increase this percentage to 80%. If the data from the past 3 years would have been usable too, we might have found more patterns in the data that could lead to more solutions.

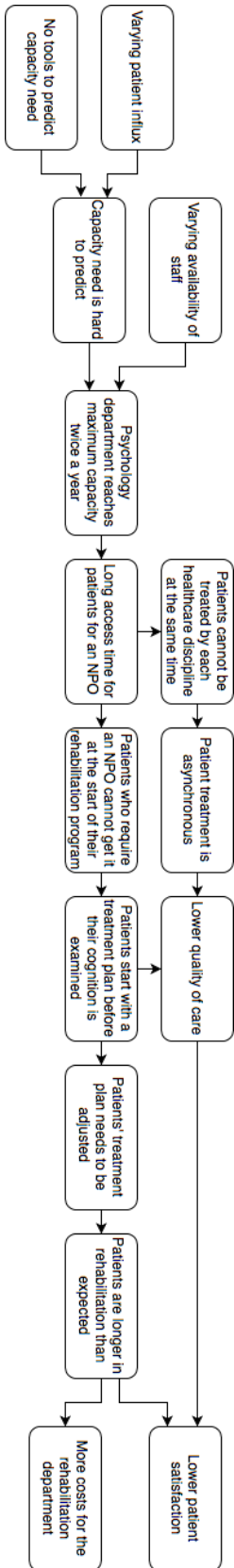
We created a simulation model that was used to do 6 experiments with. The results showed that having an extra psychologist for half a year would enable the RF&S to reach the access time guideline 80% of the time. In the conclusion section we discussed that this can be interpreted as doing 26 extra NPOs per year. We showed that each psychologist needs to do roughly 1 NPO extra per month and that this could be achieved by taking away capacity from other departments that do have a low access time. There might be other departments that meet their access time guideline and could even achieve the guideline with less appointments for example. These extra appointments could then be used at the psychology department to do more NPOs. Due to time restrictions, we were unable to analyze the access time for other departments of the RF&S to analyze where capacity can be taken away. This is a good objective for future research.

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Appendix A



Appendix B

B.1 Arrival calculation

Historical data of UMC Utrecht database from years 2018 and 2019 are used for this analysis as these years have not been affected by COVID-19. The data is an excel file which shows all NPOs that have been carried out from January 2018 until January 2020. The pseudoID, NPO date, NPO time, OrderID, Order date, NPO duration are all included. The data contained a lot of duplicates and empty columns which have been removed when the pseudoID and Order date were the same. All pseudoIDs and Order dates were extracted from the data and put into a new excel tab. The order date is used to make a new table where the rows are the months and the columns the years. Table B-1 shows the number of NPO orders during a month of a year. For example, row 1 and column 1 has a value of 6, this means that in January 2018 there were 6 NPO orders.

	2018	2019
1	6	7
2	2	11
3	11	9
4	6	8
5	11	6
6	8	5
7	3	8
8	5	9
9	5	5
10	9	6
11	3	8
12	6	4

Table B-1: Number of NPO orders per month

Bin	Frequency
0	0
1	0
2	1
3	2
4	1
5	4
6	5
7	1
8	4
9	3
10	0
11	3

Table B-2: frequency table of the NPO orders per month

Table B-2 depicts the frequency table made from table B-1. Figure 2-6 depicts the histogram created from table B-2.

For each bin 0 to 11 an expected value according to the Poisson distribution is calculated using the excel formula:

=POISSON.VERD(F2;\$B\$15;ONWAAR)*24

The outcome is multiplied by 24 because we have n=24 data points. Table B-3 depicts the expected value according to the Poisson distribution.

Data	Poisson
0	0,029
1	0,197
2	0,659
3	1,474
4	2,472
5	3,317
6	3,708
7	3,554
8	2,980
9	2,221
10	1,490
11	0,909

Table B-3: expected Poisson distribution value for each bin.

The data is tested to the Poisson distribution using the following formula:

=CHIKW.TEST(K2:K13;L2:L13)

B.2 Interarrival time calculation

The data used in appendix B.1 is also used to calculate the interarrival time. A new Excel tab was created where the pseudoIDs and order dates are copied to. The data is sorted on order date. There are 115 data rows in total for 2018 and 2019. The interarrival time is the number of days between each NPO order. The second order date minus the first order date gives the interarrival time of the second NPO order. This is done for each order date. Table B-4 gives an example of what the data looks like.

PseudoID	ORDER_DATE	Interarrival time
37603977	12-12-2017	
47803733	20-12-2017	8
25872810	9-1-2018	20
34504054	16-1-2018	7
46912747	25-1-2018	9
34734624	26-1-2018	1
26477914	23-2-2018	28
45194644	7-3-2018	12
34202255	9-3-2018	2
34502655	20-3-2018	11
45194644	21-3-2018	1
30302943	27-3-2018	6

Table B-4: example of the interarrival data.

Table B-5 depicts the frequency table created from the interarrival times. We want to find out whether the data follows an exponential distribution. For each bin the expected value is calculated for the Exponential distribution with $\lambda=0,157$. The column on the right of table B-5 depicts the expected value per bin. The following Excel formula is used to calculate the value:

`=EXPON.VERD(L9;M6;WAAR)*115`

Bins	Frequency	P(X)	Cumulative	Expected value
3	46	0,3750	0,3750	43,127
6	23	0,6094	0,2344	26,954
9	21	0,7559	0,1465	16,846
12	12	0,8474	0,0915	10,528
15	5	0,9046	0,0572	6,580
18	0	0,9404	0,0358	4,112
21	3	0,9628	0,0223	2,570
24	2	0,9767	0,0140	1,606
27	0	0,9855	0,0087	1,004
30	3	0,9909	0,0055	0,627

Table B-5: frequency table of the data, expected value for the exponential distribution.

The p-value for the Chi-square goodness of fit test is calculated using the Excel formula:

`=CHIKW.TEST(M9:M18;P9:P18)`

B.3 Queueing Theory formulas

Utilization:

$$\rho = \frac{\lambda}{\mu}$$

Probability that there are 0 patients in the system:

$$P_0 = 1 - \frac{\lambda}{\mu}$$

Average number of patients in the queue:

$$L_q = \frac{\lambda^2}{\mu(\mu - \lambda)}$$

Average number of patients in the system:

$$L = \frac{\lambda}{\mu - \lambda}$$

Average time a patient spends in queue (access time):

$$W_q = \frac{\lambda}{\mu(\mu - \lambda)}$$

Average time a patient spends in the system:

$$W = \frac{1}{\mu - \lambda}$$

Systematic literature review

Introduction

The aim of this bachelor assignment is to find out how the rehabilitation department of UMC Utrecht can decrease the number of times the access time of patients for a neuropsychological examination (NPO) exceeds the set guideline of 28 days. The rehabilitation department is an outpatient clinic, patients only come to the hospital for their appointment and go home afterwards. The access time of an NPO is the time between the NPO order and the appointment itself. A systematic literature review (SLR) is done to find out how other hospitals have decreased their access time to appointments of their patients.

The research question for this systematic literature review is:

- How can outpatient clinics reduce the access time to patient appointments?

Databases

In this SLR the included databases are Pubmed, Scopus and web of science. Pubmed is a database which is specialized in the medical field and has its own index terms called MeSH, this helps finding synonyms for the search terms. Web of science and scopus are also used as both are multi-disciplinary databases and contain a large amount of peer reviewed scientific articles from all scientific domains.

Inclusion and exclusion criteria

Inclusion and exclusion criteria need to be defined before an SLR. The inclusion and exclusion criteria determine whether an article found during the literature search is relevant for answering my research question and helps with the transparency. It is therefore important that these criteria are written down and are consistently used when searching for literature. Table 1a shows the inclusion criteria and 1b shows the exclusion criteria used for this systematic literature review.

Inclusion criteria		Justification
Setting	Healthcare	The focus is on the medical field.
Language	English	Most used language in scientific research.
Sorted on	Relevance	
Population characteristics	Patients, Medical staff	

Table 1a

Exclusion criteria		
Clinics where patients are present during their entire treatment.		Patients at the rehabilitation department of UMCU only come in for their appointments.
Papers about optimizing the waiting time while the patient is in the hospital.		I am interested in reducing the access time not the waiting time.

Table 1b

Describing the search strategy

The search strategy consists of three stages. The first stage is a preliminary search to find synonyms for the key concepts and to find out how much is out there. After the first stage the inclusion and exclusion might need to be updated. In the second stage the updated criteria are used to do another search and narrow the search field down. The used search strings are put into a search term table. Out of every search from each stage of the search process, the relevant papers are added to the Endnote library. In the third stage, we will go through each paper in Endnote removing duplicates and/or irrelevant papers. This will leave only relevant papers used for the theory section of this report. From these papers a conceptual matrix is constructed which shows the selected articles for review and the concepts they address.

Preliminary search

For the first stage, the research question is broken down into key concepts. The key concepts are outpatient clinic, access time, patient, and appointment. All key concepts of the research question are listed in table 2. The next step is finding synonyms or related terms to the key concepts. The-saurus is used for synonyms and google scholar to find related terms. The concepts in Table 2 have ' * ', ' "" ', these are used for the search string in the databases. For example, patient can be patient and patients, a '*' is used to indicate that the database may use both patient and patients when searching for results. "Waiting time" was added as a related term to "access time" despite it being an exclusion criterion. Waiting time is often used interchangeably with access time in literature.

Key concepts	Related terms / synonyms	Broader terms	Narrower terms
"Outpatient clinic*"	Hospital*	Healthcare	"Psychology department*"
"Access time*"	"Waiting time", "Queue time"		
Patient*			
Appointment*	Consultation*	Session*	
Reduce*			

Table 2

Main search

The second stage consists of the main search. The key concepts and their related terms/synonyms (table 2) are put together into a search string. When a key concept has one or more related terms or synonyms an 'OR' is put between them, after that the entire concept is put between brackets followed by an 'AND' for the next key concept. Or in other words, moving horizontally in table 2 means adding an 'OR' and moving vertically means adding an 'AND'. Multiple searches are done using different search strings to either broaden or narrow the search field. The entire search process is shown in table 3. The relevancy of a paper is determined by using the predetermined inclusion and exclusion criteria (table 1a, 1b) and by first reading the title, keywords and abstract of the paper. All relevant papers are added to Endnote for later use in the conceptual matrix.

Where did I search?	Search string	Number of hits	Relevancy
Web of science	("outpatient clinic*" OR hospital* OR Healthcare OR "Health care") AND ("Access time" OR "Waiting time" OR "Queue time") AND patient* AND Appointment*	488	Out of the first 50 hits, 48 were about minimizing the waiting time before an appointment. I am interested in the access time and therefore "waiting time" should be removed from the search string.
Web of science	("outpatient clinic*" OR hospital* OR Healthcare OR "Health care") AND "Access time" AND patient* AND Appointment*	17	10 papers were added to the Endnote library. All these papers seem to be very relevant for answering the research question. I noticed that Access time is also often used in plural. The search is done again with "Access time*".
Web of science	("outpatient clinic*" OR hospital* OR Healthcare OR "Health care") AND "Access time*" AND patient* AND Appointment*	20	The number of hits increased by 3 but these papers were not relevant.
Scopus	("outpatient clinic*" OR hospital* OR Healthcare OR "Health care") AND "Access time*" AND patient* AND Appointment*	40	The same search was now done in Scopus. 2 relevant papers were added to the Endnote library.
Pubmed	("outpatient clinic*" OR hospital* OR Healthcare OR "Health care") AND "Access time*" AND patient* AND Appointment*	25	The same search is done in Pubmed. No new relevant papers were found.

Table 3

Creating the concept matrix

There were 5 duplicate papers in the Endnote library which have been removed. There are currently 13 relevant papers in the Endnote library. After reading all the abstracts, this seems to be enough to answer the research question. A concept matrix is now created to show all relevant papers and the concepts they address. Table 4 shows the concept matrix, almost all papers are about appointment scheduling, this is due to the concept ‘appointment*’ which was used in all the search strings. This might have caused a lot of papers to be excluded from the literature search. Therefore, we need to go back to the second stage to do another literature search without the key concept ‘appointment*’ to verify whether there are more relevant papers. Table 5 contains the new search strings with its results. It turned out that appointment is an important key concept for this research question and should not be left out. The newly added paper was added to table 4 and is colored.

Reference ▽/ Concept ▷	Access time	Queueing theory	Simulation	No shows	Appointment scheduling	Methodology	Literature review
Elkhuizen et al. (2007)	X	X	X		X	X	
Edward et al. (2008)	X		X		X		
Van Sambeek et al. (2011)	X		X		X	X	
Joustra et al. (2012)	X	X	X			X	
Braaksma et al. (2014)	X				X	X	
Kortbeek et al. (2014)	X				X	X	
Almorsy and Khalifa (2016)	X			X	X	X	
Laan et al. (2018)	X				X	X	
Van Bussel et al. (2018)	X					X	
Bikker et al. (2020)	X		X		X	X	
Carreras-garcia et al. (2020)	X			X	X	X	X
Aslani et al. (2021)	X					X	
Babayoff et al. (2022)				X	X	X	
Van Zyl-Cillie et al. (2023)	X						X

Table 4

Where did I search?	Search string	Number of hits	Relevancy
Web of science	("outpatient clinic*" OR hospital* OR Healthcare OR "Health care") AND "Access time*" AND patient* AND Appointment*	176	Out of the first 50 hits there were no new relevant hits. The search string is now too broad. ‘Reduce’ seems to be a good keyword so it is added to table 2 and used for the next search.
Web of science	("outpatient clinic*" OR hospital* OR Healthcare OR "Health care") AND "Access time" AND patient* AND reduce	52	1 new paper is added to Endnote. The most relevant papers are now all in the Endnote library.

Table 5

Simulation model NPOs RF&S Department

Information PatientID=61 CurrentWeek=42 CurrentYear=0 CurrentWeekType=NormalWeek SlotsOpenThisWeek=2		Input OpeningDay=4:00:00:00.0000 ClosingDay=5:00:00:00.0000 ExpectedPatientsPerMonth=6,708 NPOSlotsPerWeek=2 NoShowFreq=0.09 SummerReplacement=0 ExtraPsyHalfYear=0	
Arrival of Patient 		On location 	
Patient statistics PatientStats nPatientStats=23 Clear Stats		Output AvgAccessTime=33:22:15:50 nNoShows=1 nNPOsDone=23 Utilization=0.958 ATGuideline=0.2608nExpStats=121 ExperimentData	
Holiday weeks HolidayWeeks FourHolidayWeeks			

Appendix D

