Increasing the number of outpatients treated within the access time norm by implementing a blueprint schedule

Master thesis

Vanja Zomer

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UNIVERSITY OF TWENTE.

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Author
Vanja Zomer

Educational Institution
University of Twente
Faculty of Behavioural Management and Social Sciences
Department of Industrial Engineering and Business Information Systems

Educational program
MS Industrial Engineering and Management
Specialisation: Production and Logistics Management
Research Orientation: Operations Management in Healthcare

Supervisors
dr. ir. A.G. Maan-Leeftink
University of Twente
Centre for Healthcare Operations Improvement and Research

dr. D. Guericke
University of Twente
Centre for Healthcare Operations Improvement and Research

drs. H. Bos
Diakonessenhuis Utrecht
Centre for Healthcare Operations Improvement and Research

Management summary

Problem context

The Medical Psychology department of Diakonessenhuis Utrecht provides mental care for patients who are already in the hospital for other medical reasons. Some patients experience psychological problems during their treatment, caused by the treatment or already caused in the past. To treat these mental health problems, the medical specialist refers such a patient to the Medical Psychology department. The aim of this department is not only to treat patients such that their medical treatment can proceed but also to help patients with their mental health problems during or after treatment.

The project is undertaken to design a blueprint schedule for the Medical Psychology department in Diakonessenhuis. The goal of this research stems from the need to increase the number of patients treated within the access time norm. The access time is the time between the day of the patient referral and the date of the intake. Unplanned inpatient care causes postponing planned outpatient care and therefore results in excessive access times for outpatients. 73% of the outpatients have to wait longer than the national standard of four weeks, with some patients waiting up to twenty weeks.

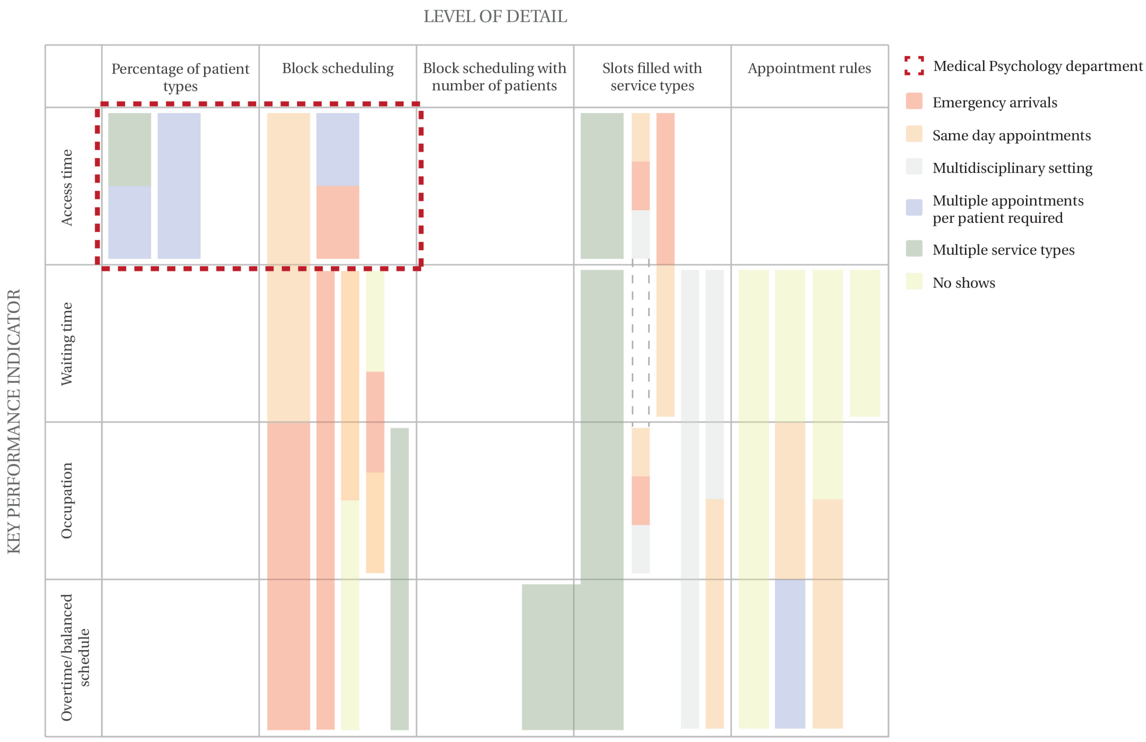

Figure 1: Framework for blueprints with the position of the Medical Psychology department

As blueprints have various goals, levels of detail, and characteristics, we develop a framework in which various types of blueprints are positioned based on the organisations goals, as shown in Figure 1. The positioning of the Medical Psychology department showed that they require a blueprint defining the percentage of time therapists should spend on each patient type, which also includes insight in the amount of time necessary for unplanned care.

Methods

We designed two models to design the blueprint schedule: an exact model and an approximation solution method. The exact model is formulated as a quadratic mathematical programming model, but it is not applicable to solve for large instances within reasonable time. Therefore we designed an approximation solution method, in which we use simulation-based optimisation. The metaheuristic algorithm Simulated Annealing is used as our optimisation approach and the objective values of candidate solutions are determined using a Discrete Event Simulation. Comparing the solution method with our exact model for small instances, the solution approach yields near-optimal solutions with an optimality gap below 25%.

The approximation method allows for experimentation with different configurations. These configurations are based on the baseline input data of the Medical Psychology department. To address managerial questions, we varied the baseline input data. We executed various experiments focusing on adding a therapist to the system, dedicating a therapist to inpatient care, and robustness of the blueprint for changes in arrivals.

Results

Figure 2 and Figure 3 present the results of the designed blueprint according to the access times of inpatients and outpatients respectively. The blueprint significantly increases the number of outpatients treated within the access time norm from 27% to 97%. The number of inpatients increases from 84% to 88%. Besides, the blueprint results in less fluctuation in the access times of individual patients. This means that implementing the blueprint is very promising.

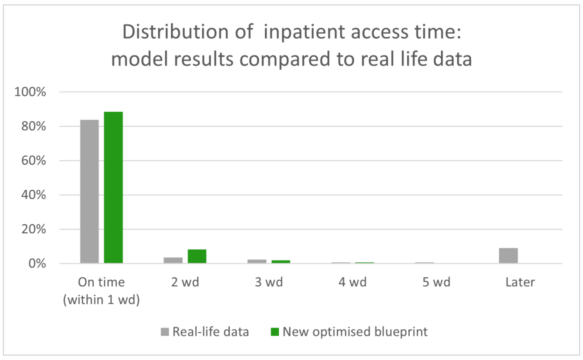

Figure 2: Real life data compared to model results - inpatients (wd = working days)

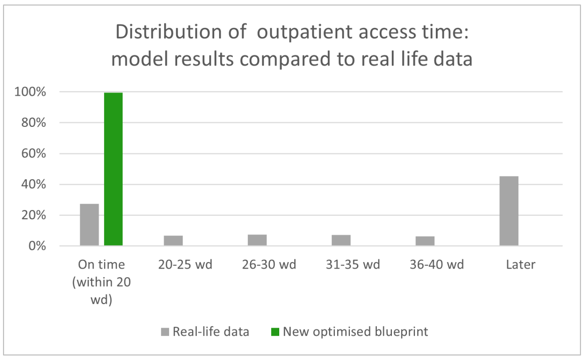

Figure 3: Real life data compared to model results - outpatients (wd = working days)

In additional experiments, we see that child/youth therapists form the bottleneck. Based on the current configuration of the department, the biggest reduction in access time can be achieved by hiring a child/youth therapist, and the smallest reduction in access time is achieved when dedicating a child/youth therapist to inpatient care. If the Medical Psychology department wants to dedicate one therapist to inpatient care, it is best to dedicate the health care neuropsychologist, which is still more profitable than the baseline blueprint. However, dedicating a therapist to inpatient care comes with practical disadvantages. We furthermore observed that the blueprint is sensitive to increasing arrival rates. This means that the blueprint should be revised as soon as an increase in patients of at least 5% occurs at the Medical Psychology department. Finally, we showed that adding a semi-priority group, consisting of 10% of the outpatients having priority over the other 90% of the outpatients, does not deteriorate performance. However, we prefer not to allow such a semi-priority group because it fragments therapist time so much that it becomes very complicated for therapists to adhere to the blueprint and spend the correct amount of time on each group.

Conclusion and discussion

The contribution of this research is threefold. We are the first to design a framework for blueprint types, which can help others to compare various blueprints but also to determine the type of blueprint to design for a specific department. Secondly, we showed that simulation-based optimisation can be used to design a blueprint determining the percentage of time to spend on several patient types including priority for some patient types. These two scientific contributions resulted in a third, practical, contribution: the implementation of an optimised blueprint schedule for the Medical Psychology department can significantly improve the department's access time performance. The percentage of inpatients treated within the norm can increase from 84% to 88% and the percentage of outpatients treated within the access time norm from 27% to 97%. Besides, the use of a blueprint provides insight into the available capacity and helps to determine the expected waiting time of a new patient. Based on that, we are able to recommend implementing a new optimised blueprint in the Medical Psychology department.

Before implementation, however, we recommend the Medical Psychology department to improve their patient registration process. The therapists have their own ways of registering which results in inconsistencies in data interpretation. Besides, therapists can only register fixed times for specific activities. However, often these times do not correspond to reality. According to psychologists, large differences exist between the amount of time that can be registered and the realised used time. For example, indirect patient care for neuro patients requires much more time. This strongly influences the current results, as the results show that neuropsychology forms the smallest bottleneck, which does not correspond to the experience of the Medical Psychology department. Inaccurate registering of patient data causes inaccurate data input. As the blueprint is based on this data input, the blueprints resulting from the experiments in this study are not immediately applicable to the Medical Psychology department and the department should first provide accurate data.

Acknowledgements

My research on "Increasing the number of outpatients treated within the access time norm by implementing a blueprint schedule" is the final step towards finishing my degree in Industrial Engineering and Management.

I am thankful for all support that I have received - from many people in various ways along the road, but in particular from my daily supervisors. I am amazed by the proportion of their time that they have given me. Thanks to them, I could develop myself in critical thinking, systematic problem solving, clear writing and solid argumentation. Their encouragement during harder times and their in-depth, critical feedback has been of crucial significance.

I am also thankful for my family, friends and loved ones. I thank my family who are proud of me no matter what I do. Thanks to my friends, who helped me structure my thoughts or could take my mind of the project for a while. A special thanks to Steven, who has patiently listened to all my struggles, thoughts and ideas. He encouraged and helped me a lot during my graduation project, which was of great value.

I hope you enjoy reading my master thesis as much as I have enjoyed writing it.

Vanja Zomer

Deventer, November 2020

Contents

Chapter 1

Introduction

This research aims to demonstrate the improvement potential of implementing a tactical planning at the Medical Psychology department of Diakonessenhuis Utrecht and Zeist. In doing so, we intend to determine the extent to which the access times of the outpatients at the clinic can be reduced. The research is performed from the department of Integral Capacity Management, which is a department of Diakonessenhuis that aims to improve the planning and scheduling in the hospital.

This chapter introduces the problem. Section 1.1 elaborates on the problem definition, by giving the problem context, motivation for research and the problem statement. Section 1.2 expands on the research design. It gives the research goal, identifies the research questions and methodology, and defines the scope of the research.

1.1 Problem definition

1.1.1 Context

Diakonessenhuis is a medium-sized hospital in Utrecht, with branch locations in Zeist and Doorn. Diakonessenhuis has 500 beds available for patients (Diakonessenhuis, 2022). The hospital has a department for Medical Psychology which provides mental health care for patients who are in the hospital for medical reasons. Some patients require psychological care aside from their medical treatment. This can either be caused by the treatment itself, or by other, unrelated, problems from their past. To treat these patients with mental health problems, the medical specialist refers them to the Medical Psychology department. The aim of the department is not only to help patients such that their medical treatment can proceed but also to help patients with their mental health problems during or after treatment. In a year, about 1200 patients are treated by the department of Medical Psychology at Diakonessenhuis (Diakonessenhuis Utrecht, 2020).

The department of Medical Psychology treats inpatients and outpatients. Inpatients are patients with at least one overnight stay. If an inpatient requires psychological care, the Medical Psychology department aims to treat this patient on the same day, or at the latest the next day (Diakonessenhuis Utrecht, 2020). This means that inpatient care cannot be planned beforehand. On the other hand, outpatient care is plannable care. The access time norm in the Netherlands for outpatients is four weeks (Diakonessenhuis Utrecht, 2020). The access time is the time between the day of the patient referral and the date of the intake.

1.1.2 Motivation for research

Access times in medical health care form a nationwide problem (Vektis, 2022). The Diakonessenhuis forms no exception, as 73% of the outpatients have an access time longer than the national standard of four weeks. Part of this problem is caused by the Medical Psychology department not planning consciously on a tactical level. From various literature we find that implementing a blueprint helps to actively plan on a tactical level (Hulshof et al., 2013, 2013; Bikker et al., 2020; Laan et al., 2018). Some blueprints only determine the percentage of the time that should be allocated to a specific patient type (Hulshof et al., 2013), whereas others are more specific and allocate time slots to patient types (Creemers et al., 2012). Besides, blueprints are designed for a specific context. Therefore, some blueprints incorporate for example emergency patients (Kortbeek et al., 2014; Srinivas & Ravindran, 2020), others are accommodated to a multi-disciplinary setting (Leeftink et al., 2019). Access times are especially long in the clinical setting with a combination of planned and unplanned care (Bikker et al., 2020). This is the case for the Medical Psychology department. A blueprint can help to incorporate the right amount of flexibility into a schedule, such that the planned care and the unplanned care can be given.

1.1.3 Problem statement

This research investigates the potential of developing a blueprint for the Medical Psychology department, in which flexibility will be included for unplanned care. The blueprint has to provide clear guidelines to reserve the appropriate amount of time for inpatient care in each therapist's schedule. The remaining time will be distributed over other activities, which are mainly related to outpatient care but can also be management tasks. The time will be allocated to the activities while optimising the number of patients treated within the access time norm of four weeks. This results in a blueprint schedule with fractions of time assigned to specific activity types.

1.2 Research design

1.2.1 Research goal

The goal of this research is to investigate the improvement potential of implementing an optimised blueprint schedule in the department on the tactical planning level. Since the access times are too long in the department of Medical Psychology, we investigate to what extent a blueprint can influence these access times. Flexibility should be included in this blueprint such that the blueprint is accommodated to unplanned care.

1.2.2 Research questions and methodology

The goal of this research can be summarised by the following main research question:

To what extent can the number of patients treated within the access time norm be increased by implementing a blueprint schedule?

To answer this main question, the following sub-questions are formulated:

1. *How is the Medical Psychology department of Diakonessenhuis currently organised and what is its current performance?*
   Chapter 2 answers this research question. When answering this question, we focus on the Key Performance Indicator (KPI) 'number of patients treated within the access time norm'. To answer the question, we use expert opinion to look into the structure of the organisation. Besides, we perform data analysis and use it for quantitative analysis of the Medical Psychology department. In this process, problems related to the KPI arise. Linking the problems in a problem cluster will identify the core problems. Eventually, this is where the practical goal of the research arises.

2. *What methods are commonly used to design blueprint schedules?*
   To answer this research question, we perform a literature review. The database used for the literature review is Scopus, in which the relevant articles are selected based on the appearance of relevant search terms in the title, abstract and keywords. The literature review provides an overview of the available methods for designing a blueprint schedule, focusing on a hospital setting. The literature review is presented in Chapter 3.

3. *What type of blueprint is most suitable for the Medical Psychology department?*
   We answer this research question at the end of Chapter 3 using the results of the literature review in the previous research question. Together with the expert opinion of the Medical Psychology department, we select the most appropriate blueprint type from the literature review.

4. *How can we create a model for designing a blueprint schedule that maximises the number of patients treated within the access time norms?*
   In Chapter 4, a description of the model will be given as well as the necessary inputs and assumptions. The conclusion of Chapter 3 serves as the basis of the model. Chapter 4 aims to explain the modelling approach of an exact method as well as an approximation model.

5. *What are the effects of the blueprint schedule on the number of patients treated within the access time norm at the Medical Psychology department given several future scenarios, and where is the most improvement potential?*
   This research question is answered in Chapter 5. First, we explain the experimental design. After executing several experiments, the results are analysed. The interesting findings are summarised in this chapter and this is the basis of the conclusions in Chapter 6.

6. *What are barriers to overcome for implementation in practice?*
   In Chapter 2, we investigated how the department of Medical Psychology is organised. Based on this, the main barriers to overcome for implementation are pointed out in Chapter 6.

1.2.3 Scope

When investigating the potential of a blueprint, we need to define the scope of the research. The research questions should fall within this scope. Below, the scope of the research is described.

- The blueprint will be developed for application in the Medical Psychology department in Utrecht and Zeist since the department at those two locations are integrated. A therapist sometimes works at both locations in one week. The Medical Psychology department is not located in Doorn, so the branch location in Doorn is excluded from this research.

- The research will be performed in the Medical Psychology department. The Psychiatry department and the Mental Care department are closely related to the Medical Psychology department. The departments sometimes work together with the Medical Psychology department but have their own planning systems. Therefore, these departments are excluded from this research.
- The funding of the clinic is not regulated by the Medical Psychology department itself. Psychological care is financed by the referring specialism. The Medical Psychology department has to offer the care requested. This means that the department does not have to meet any quota for minimum executed patient treatments. This will therefore not be taken into account in this research.
- We can only use data from a manually entered Excel list and from the Electronic Patients Files[1], HiX. The model that we develop should therefore only require available input data.

[1] In Dutch: Elektronisch Patiënten Dossier

Chapter 2

Background analysis

This chapter aims to answer the first research question: *How is the medical psychology department of Diakonessenhuis currently organised and what is its current performance?* A background analysis is necessary to notice the problems in the current situation, to eventually attain the goal of this research. Section 2.1 gives an extensive description of the Medical Psychology department. Section 2.2 elaborates on the current way of planning on different hierarchical levels. Section 2.3 provides a summary of all problems using a problem cluster and states the core problem of this research. To conclude, Section 2.4 introduces the Key Performance Indicator together with the current performance of the Medical Psychology department.

2.1 Description of the Medical Psychology department

2.1.1 Aim of the department

The Medical Psychology department provides mental health care for patients who are in the hospital for medical reasons. Some patients require psychological care aside from their medical treatment. This can either be caused by the treatment itself, or by other, unrelated, problems from their past. To treat these patients with mental health problems, the medical specialist refers them to the Medical Psychology department. The aim of the department is not only to help patients such that their medical treatment can proceed but also to help patients with their mental health problems during or after treatment.

2.1.2 Patient types

The department distinguishes patient types based on three characteristics. A patient is an inpatient or an outpatient. Inpatients are patients that are in the hospital for at least one overnight stay while outpatients are patients that are in the hospital without requiring a hospital bed. The second characteristic of patients is that the mental health problems are either singular or complex. Patients with singular problems can be treated by therapists with less expertise whereas patients with complex problems require more expertise. The last characteristic for distinguishing patient types is the specialty of the patient. In this research, we distinguish three specialties: child/youth patients, neuro patients who are always adults, and regular adult patients.

If an inpatient needs psychological care, a therapist must visit the patient on the same day, or at the latest on the next day. If necessary, a follow-up appointment is made. The problems of inpatients are often singular rather than complex. Figure 2.1 shows the process of an inpatient.

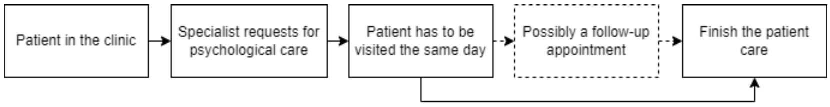

Figure 2.1: The process of inpatients

The process of outpatients is equal for child/youth outpatients and regular adult outpatients. Their process is shown in Figure 2.2. During the triage, outpatients are split into two groups: patients with priority and patients without priority. Patients with priority are mainly patients for whom the medical treatment would otherwise be suspended due to psychological issues, but there can be other causes as well. The department wishes to treat outpatients with priority within two weeks, the outpatients without priority have to wait longer. The national standard for outpatients is a maximum access time of four weeks. (Diakonessenhuis Utrecht, 2020)

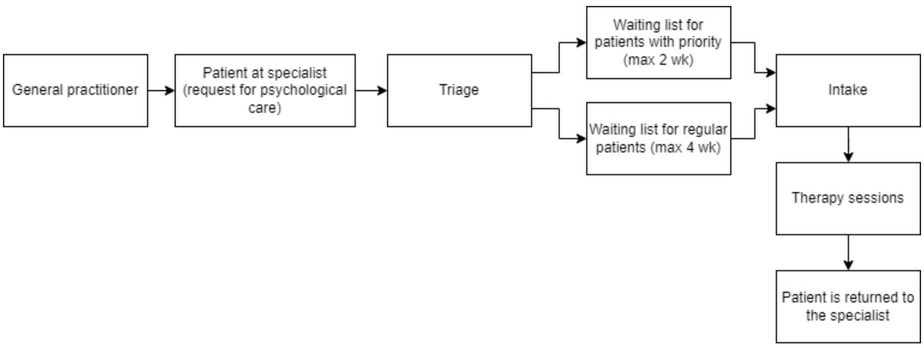

Figure 2.2: The process of child/youth outpatients and regular outpatients

The process for outpatients with the specialty neurology deviates from the process of child/youth outpatients and regular adult patients. Neuro patients are patients with cognitive problems, caused by for example brain injury or dementia. For them, the process is different, as shown in Figure 2.3. These patients have to undergo a neuropsychological assessment in which their cognitive thinking is tested. Based on these tests, the neuropsychologist can make a diagnosis. For neuro patients the national standard for waiting time is also a maximum of four weeks (Diakonessenhuis Utrecht, 2020).

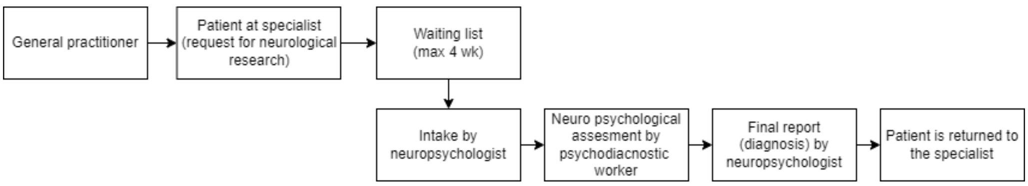

Figure 2.3: The process of neurological outpatients

To provide insight in the department, it is useful to know the patient case mix of the department. Table 2.1 gives an overview.

Table 2.1: Patient case mix at the Medical Psychology department (Source: Patient database Diakonessenhuis, containing 679 patients referred in 2021)

		Percentage of the total
Inpatients	Child/youth	3.8% (26)
	Adults	15.4% (105)
Outpatients	Child/youth	18.8% (128)
	Adults (regular)	45.6% (309)
	Adults (neuro)	16.4% (111)

Table 2.2 summarises the norms for access time per patient type. The access time norms are equal for patients with singular and complex mental health problems. The specialty of the patient also does not influence the norm.

Table 2.2: Patient access norms (Diakonessenhuis Utrecht, 2020)

Patient type	**Access time norm**
Inpatients	1 working day
Outpatients with priority	10 working days
Outpatients without priority	20 working days

2.1.3 Types of therapists

Different patients require different care. Not all therapists are allowed to provide all care. There are three types of therapists within the Medical Psychology department: clinical psychologists, health care psychologists[1] and psycho diagnostic assistants (PDAs). Table 2.3 summarises the availability of these therapists at the Medical Psychology department expressed in full-time equivalent (FTE).

Clinical psychologists are allowed to treat patients with complex problems as well as singular problems, health care psychologists can treat patients with singular problems only, and psycho diagnostic assistants (PDAs) are not allowed to treat patients themselves. PDAs assist the psychologists by doing tests with patients, such as neuropsychological assessments.

Health care psychologists and clinical psychologists do have specialties: child/youth, general and neurology. These specialties correspond to the specialties of patient types. The specialty of a therapist is an indication of whether a patient can be treated by the therapist. For example, a neuro patient can only be treated by a therapist specialised in neurology. Table 2.4 gives an overview of which patient types can be treated by which therapist types.

[1] In Dutch: Gezondheidszorg (GZ)-psychologen

Table 2.3: Personnel availability of the Medical Psychology department (Source: Medical Psychology department of Diakonessenhuis, 2022)

Personnel type	**#**	**FTE**	**Task**
Clinical psychologist in training (CP-t)	2	1.78	50% of their time can be used for tasks of a full clinical psychologist, the other 50% of their time is spend on education
Clinical psychologist (CP)	5	4.24	Can treat patients with complex problems, potential specialisation directions are child/youth, general, and neurology
Health care psychologist in training (HCP-t)	2	1.44	50% of their time can be used for tasks of a full health care psychologist, the other 50% of their time is spend on education
Health care psychologist (HCP)	1	0.72	Can treat patients with singular problems, potential specialisation directions are child/youth, general, and neurology
Psycho diagnostic assistant (PDA)	3	1.24	Supportive tasks

Table 2.4: Overview of which patient types can be treated by which therapist types (S = singular problems, C = complex problems)

		CP-child/youth	**CP-neuro**	**CP-general**	**HCP-child/youth**	**HCP-neuro**	**HCP-general**
Inpatients	**Child/youth**	S+C			S		
	Neuro		S+C			S	
	Regular	S+C	S+C	S+C	S	S	S
Outpatients	**Child/youth**	S+C			S		
	Neuro		S+C			S	
	Regular	S+C	S+C	S+C	S	S	S

2.1.4 Requested care

Patients can only enter the department of Medical Psychology when medical specialists refer them. The total yearly demand is about 700 new patients. About 20% of these patients are inpatients and 80% are outpatients (Diakonessenhuis Utrecht, 2020). In this section, the arrival pattern of patients is being considered for both inpatients and outpatients.

Especially the arrival of inpatients is interesting, since their care cannot be planned beforehand. Figure 2.4 shows the frequency of the number of inpatient requests on a day. We can conclude that there is quite some fluctuation in the number of patient requests on a day. Many days there are no requests, but on other days there are three or even more requests. These fluctuations cause planning issues at the department.

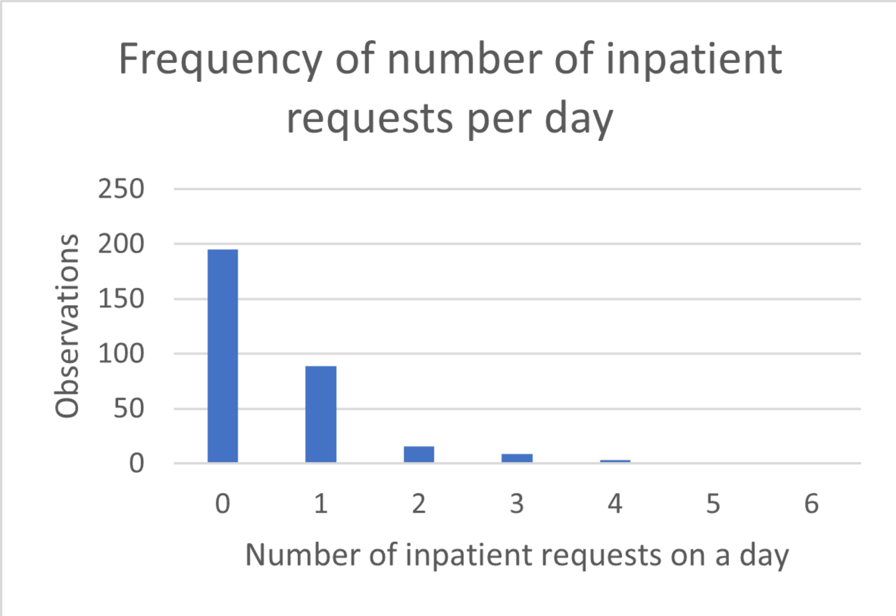

Figure 2.4: Frequency of the number of inpatient requests per working day (Source: Patient database Diakonessenhuis, containing 131 inpatients referred in 2021)

The arrival pattern of the outpatients is investigated on a weekly level. These patients do not have to be treated on the same day, so considering a daily arrival pattern has no added value. In Figure 2.5, the number of outpatient requests are plotted per week. The figure shows that the number of requests fluctuates. However, these fluctuations are not a major problem because outpatients do not have to be treated right away, and therefore outpatient care is plannable care.

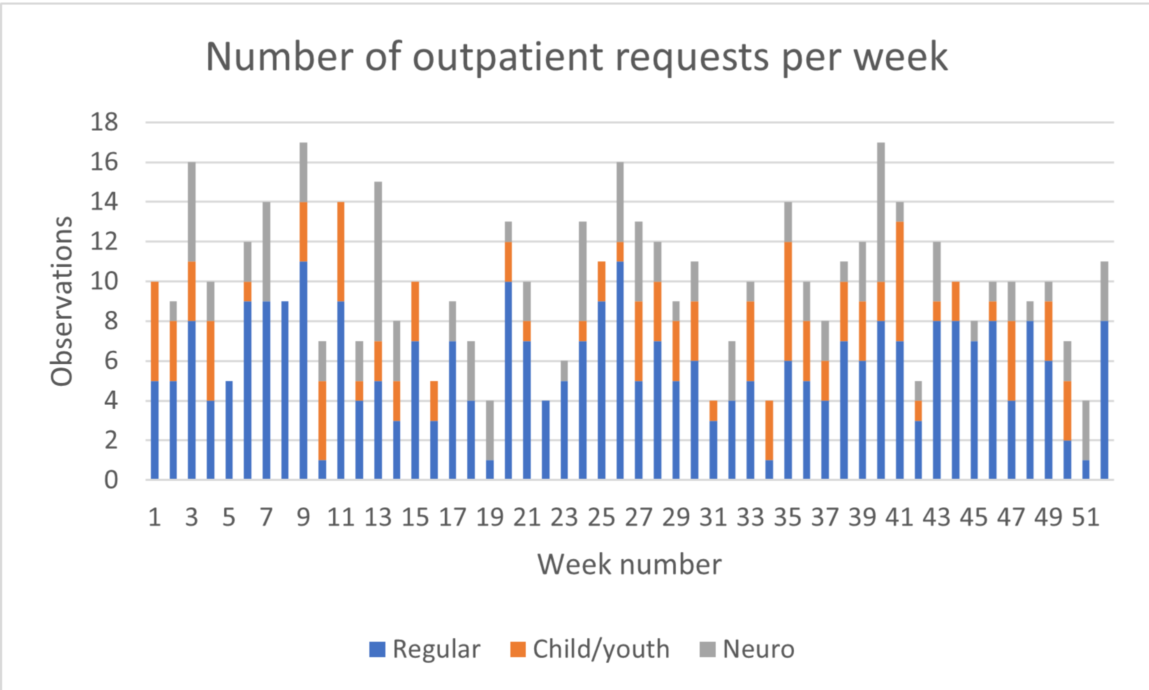

Figure 2.5: Number of outpatient requests per week (Source: Patient database Diakonessenhuis, containing 548 outpatients referred in 2021)

2.1.5 Access times of patients

Table 2.5 summarises the extent to which access time norms are met for each patient type. It becomes clear that the access time norm for inpatients is often achieved. However, for the outpatients this does not apply: only 27% of the outpatients are treated within the access time norm.

Table 2.5: Access times achieved per patient type (Sources: Patient database Diakonessenhuis, containing 679 outpatients referred in 2021, and Patient database Diakonessenhuis 2021/2022)

	Average access time (days)	**Patients treated on time (%)**
Inpatients child/youth	0.90	80.0%
Inpatients regular (adults)	0.69	84.7%
Inpatients total	0.72	83.8%
Outpatients child/youth	83	40.2%
Outpatients regular (adults)	61	31.7%
Outpatients neuro	119	3.1%
Outpatients total	78	27.3%

2.1.6 Access times per therapists

When a patient request comes in, the patient is put on the waiting list. Within a week, triage is done by two therapists of the department. During the triage, it is determined which therapist is going to treat the patient. If the therapist has a delay, this immediately affects all other patients on his/her waiting list. Besides, the waiting times per therapist are unequally distributed. This results in patients that are referred earlier, but treated later than other patients.

Table 2.6 shows the average waiting time at the therapists. The waiting times of therapist F and G are the highest. These therapist are both specialised in neuro psychology and they mainly treat neuro patients. The therapists with the lowest average waiting time are therapist D and E. These therapists are both specialised in child/youth psychology and mainly treat patients younger than 18. Striking is that the average number of sessions is the highest for therapists D and E. This may be explained by the fact that child/youth care requires less indirect patient care compared to neuro psychological care. Two general health care psychologists in training are not included in this table, because they are at the department since 2022.

Table 2.6: Access times per therapist (Sources: Patient database Diakonessenhuis, containing 679 outpatients referred in 2021, and Patient database Diakonessenhuis 2021/2022)

Therapist	**Therapist specialisation**	**Average access time (days)**	**Average number of sessions per patient**
A	CP - general	50	3.21
B	CP - general	66	4,33
C	CP - child/youth (in training)	63	6.50
D	CP - child/youth	39	6.61
E	CP - child/youth	47	7.03
F	CP - neurology (in training)	79	6.57
G	CP - neurology	93	2.81
H	HCP - neurology	48	4.32

2.1.7 Number of therapy sessions per patient

There are various reasons for patients to come to the Medical Psychology department. The different reasons correspond with different treatments and therefore the number of sessions per patient varies. Patients that only come for a screening often need an intake only and no additional sessions. However, a regular patient with complex problems needs many additional sessions. In the histogram in Figure 2.6 the number of treatment sessions necessary for patients is plotted. It shows that most of the patients only need one or two sessions, but there are some patients that need much more sessions. The average number of sessions is 4.5. However, the standard deviation is 4.9, so the dispersion is high.

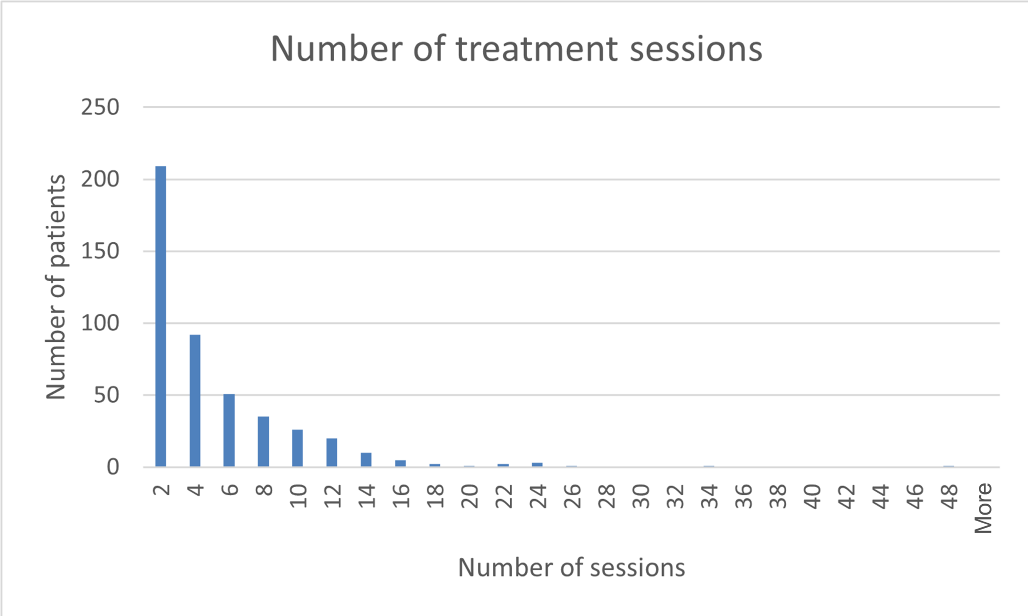

Figure 2.6: Number of treatment sessions per patient (Source: Patient database Diakonessenhuis, 2021/2022, containing 679 patients referred in 2021)

2.2 The current planning method

In this section, the current planning method at the Medical Psychology department is discussed. This is done based on a framework for health care planning and control (Hans et al., 2012). This framework consists of three hierarchical planning levels: strategic, tactical, and operational as discussed in Sections 2.2.2-2.2.4. Section 2.2.1 gives an explanation of these planning levels which can be skipped when familiar with the framework.

2.2.1 Planning levels

The three planning levels differentiate in the degree of flexibility that is remaining. In general this corresponds to the time horizon. Strategic planning decisions are made 1-3 years in advance. Typical examples of strategic decisions in hospital settings can be development of medical protocols, case mix planning, capacity dimensioning and workforce planning. Financial decisions are often strategic decisions as well.

Tactical planning decisions are typically made with a time horizon of several months. Examples of tactical planning decisions in a hospital setting are protocol selection, resource allocation, block planning for staff, admission planning and staffing. A tactical planning can create insight in the available capacity.

Operational planning decisions involves a planning horizon of less than a week. The operational planning level can be divided into two parts: offline and online planning. Offline operational planning in a hospital setting addresses scheduling of specific patients to resources, which is appointment scheduling and workforce scheduling. Online operational planning addresses monitoring and control of the day-to-day activities at the clinic (Hans & Vanberkel, 2012). For example, an incoming emergency patient needs to be treated immediately and thus requires short-term changes to the schedules of therapists.

2.2.2 Strategic planning

The main strategic decisions at the Medical Psychology department are resource dimensioning and workforce planning. The main resource of the Medical Psychology department are therapists. On the strategic level, it is decided how many therapists of each type should be hired. This is therefore also part of workforce planning. Workforce planning also consists of the number of therapists in study. In Table 2.3 in Section 2.1.3, the number of hired therapists are mentioned per function type.

Another strategic decision is the patient case mix, which is the determination of the desired patient type volumes. The department of Medical Psychology is financed by the specialisms that refer the patient, which means that the Medical Psychology department does not fix the patients volumes with the insurer. They treat all patients that are referred by the specialists. However, an estimation of the patient case mix is still important for making a planning. Therefore an estimation is made based on historical data. Table 2.1 in Section 2.1.2 shows the patient case mix of all referrals in the year 2021, which is assumed to be a good estimation.

On the strategic level, the Medical Psychology department also develops medical protocols. At the moment, therapists are trying to standardise the way triage is performed such that it becomes clearer where a patient should be directed. By using protocols, the way therapists work will become more aligned.

2.2.3 Tactical planning

The Medical Psychology department does not consciously plan on a tactical level. The department does not use a clear structure for tactical planning. This results in missing insight in the available capacity and the actual access times of patients. Furthermore, it shows that there are no fixed guidelines for the admission process and the resource decisions made are mainly based on experience.

Admission planning

An important tactical decision is admission planning: the process of accepting a new patient and deciding by whom he or she will be treated. Every week, two therapists perform triage of all newly referred patients. In this triage the two therapists assess whether the new patient is in the right department. If so, the needs of the patient will be evaluated to decide which therapist will treat the patient. Then, the patient is put on the waiting list for access. As soon as an intake spot is available for a new outpatient with therapist X, one of the patients assigned to therapist X receives the intake spot. This can result in long access times for one therapist and relatively short access times for another therapist. This became clear in Table 2.6. Whether there is a new intake spot available is regulated differently per therapist. Some of the therapists decide themselves when there is an intake spot available for a new outpatient. Other therapists have authorised the secretary to manage their agendas. Then, the secretary decides when a new intake can be planned based on how busy the therapist is. Two therapists use a standardised block schedule with fixed intake spots on which the secretary can plan intakes for new patients. The therapist or the secretary will decide which patient will be taken from the waiting list, based on the needs of the patient. It depends on both the priority and the waiting time which patient will be chosen.

Block planning

Standardised block schedules give a better overview of the workload. However, at the Medical Psychology department only two therapists are using one. Besides, all therapist could make their own block schedule, causing mismatched schedules. On the other hand, therapists often block some time slots in their schedule for inpatient care. The requests for inpatient care are fluctuating and by scheduling free time, the therapists are trying to catch this problem. This is a form of block planning. However, the blocked time slots are not attuned to each other. This appears from looking at the blocked time slots. In many time slots nobody blocks time, but in a few time slots multiple therapists block time for inpatients. In addition, therapists often plan other things in the blocked time slots, such as administrative tasks.

Resource allocation

Block planning is closely related to resource allocation. The main resource to allocate at the Medical Psychology department are therapists. At this moment, the decision of how much time will be allocated to certain patient types is made by the therapists. Sometimes this is also based on the current capacity demand. For example, if the access time of neuro patients is getting way too long, a therapist can decide to treat more neuro patients for a while to get rid of the backlog.

Staffing

The last tactical aspect is staffing: How many therapists of each type are working on the various days of the week. A schematic overview of this is given in Table 2.7 below. The number of therapists working on a day is a recurring process, but the amount of work the therapists have to do on those days is not recurring.

Table 2.7: available therapist type per day of the week (Source: Medical Psychology department of Diakonessenhuis, 2022

Personnel type	# therapists	Monday	Tuesday	Wednesday	Thursday	Friday
Clinical psychologist in training (CP-t)	1	2	1	2	1	2
Clinical psychologist (CP)	5	4	4.5	4.5	4	4
Health care psychologist in training (HCP-t)	2	2	2	2	1	1
Health care psychologist (HCP)	1	0	1	1	1	1
Psycho diagnostic assistant (PDA)	3	3	0	0	3	0

2.2.4 Operational planning

The previous section showed that the Medical Psychology department does not use a clear structure for planning. This causes that many problems are solved operationally. Solving problems operationally requires switching time and is therefore at the cost of productivity. Two situations in which operational planning is solving capacity issues are inpatient requests and outpatients with high priority. These are described below.

Inpatient requests
Inpatients need to be treated on the same day. Therefore, every day a therapist is held responsible for inpatient care. When a request comes in, the responsible therapist has to make sure that the patient will be treated on that same day. This does not mean that the responsible therapist will treat the patient, but he or she has to take care that someone is going to treat the patient. As mentioned earlier, some therapists reserve time slots for unscheduled inpatient care. However, it often happens that there is a new inpatient request and none of the therapists has time reserved. Then, there is no designated therapist that treats the inpatient and thus no clear system of how to handle the request; the department solves this operationally. This means having to check email frequently, calling each other to decide who is going to treat the inpatient and having to put down other work. This all requires switching time and this limits the productivity. It especially causes problems because the activities in the schedules of therapists are often planned immediately after each other. There is no time for unexpected additional work.

Outpatients with high priority
Scheduling of outpatients with priority is handled operationally as well. Every week, two therapists check during the triage moment whether there are outpatients to treat with high priority. A patient with high priority needs to get an intake within two weeks. If there is an outpatient with high priority, it is established during a weekly meeting with all therapists of the department, or sometimes via email, which of the therapist has time to treat the patient. In reality, none of the therapists has time for patients with high priority. To make sure that the patient with high priority will be treated, one of the therapists will have to adjust his or her schedule by postponing the scheduled tasks.

2.3 Problem cluster

In the current way of working at the department, described in the previous two sections, multiple problems arose. These problems are summarised in the problem cluster in Figure 2.7 (Heerkens et al., 2021). This problem cluster is used to attain the goal of the research: the core problem.

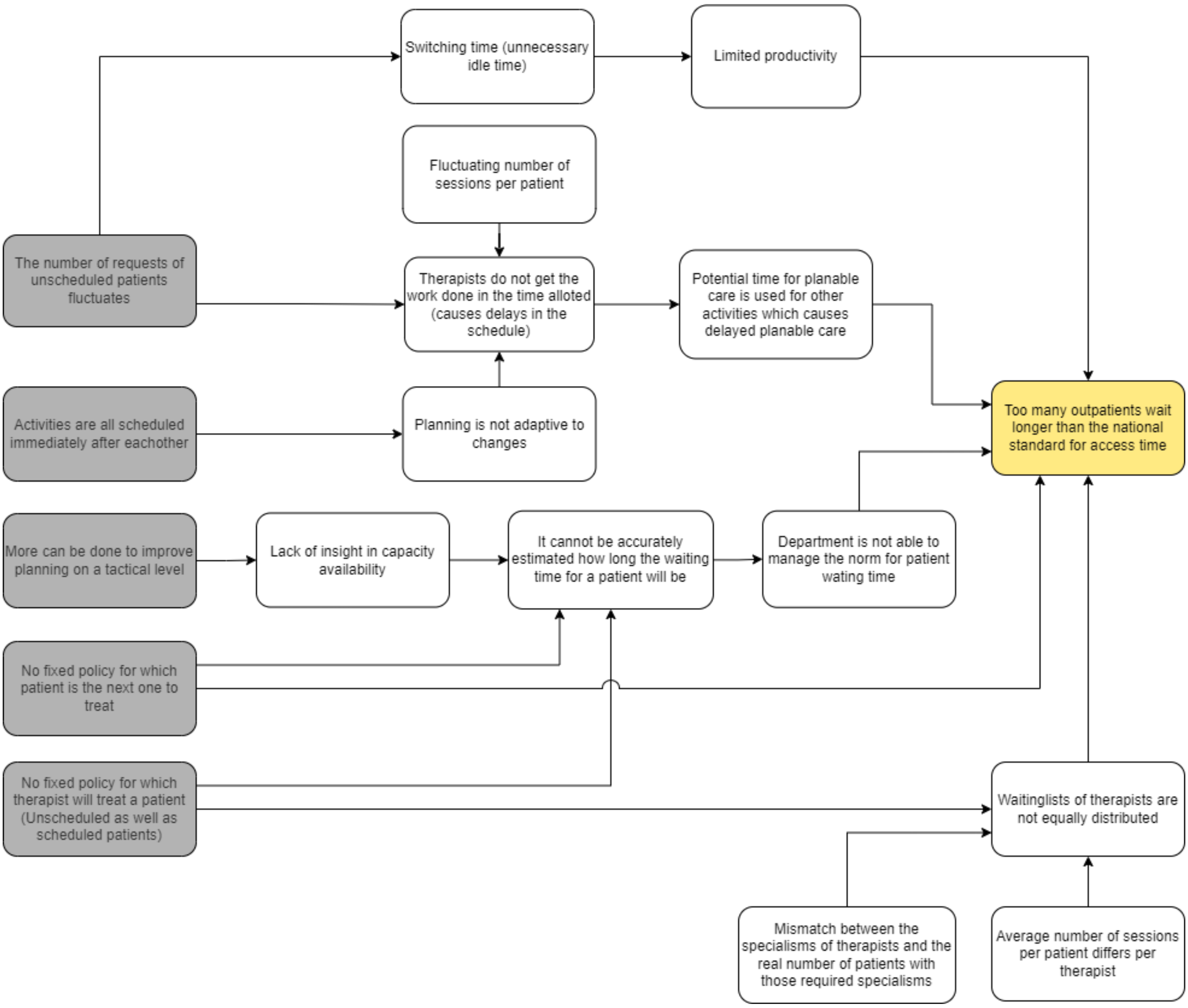

Figure 2.7: Problem cluster

2.3.1 Action problem

At the Medical Psychology department, the access time norm for outpatients is not met. As many as 73% of the outpatients have to wait longer for their treatment than this national standard of four weeks (Diakonessenhuis Utrecht, 2020). Therefore the action problem, also shown in Figure 2.7 in the yellow block, of this research is:

73% of the outpatients wait longer than the national standard for access time.

2.3.2 Potential core problems

The action problem has multiple causes. The root causes, which do not have a cause in itself are potential core problems for research. These potential core problems can be found in the problem cluster in Figure 2.7 as well. There are five potential core problems that can be solved using planning approaches, which are made grey in the problem cluster.

1. The number of requests of unscheduled patients fluctuates. The current therapist schedule does not adequately accommodate for these unscheduled inpatients. The therapists try to keep some time slots open, but in reality, those slots are filled with other activities. This often causes the daily schedule of the therapists to change on short notice. As a result, therapists have to switch between activities which always requires switching time. This is unnecessary idle time which limits productivity.

2. Activities are all scheduled immediately after each other. This results in a planning that is not adaptive to changes. A planning that is not adaptive to changes will result in more delays than necessary.

3. The Medical Psychology department does not consciously plan on a tactical level. Planning on a tactical level gives insight in the capacity availability of the department, which is especially desirable for the combination of planned and unplanned care. Without planning on a tactical level, the department does not have a clear overview of the capacity availability and the management is unable to steer on the norms for patient access time.

4. There is no fixed policy for which patient will be treated next. Without a good performing admission rule, the access times of some patients will be very high and the access times of other patients will be very low. This results in fewer patients treated within the access time norm.

5. There is no fixed policy for which therapist will treat a patient. Without a good performing allocation rule, some therapists will have longer access times than others. This results in longer access times for patients who are allocated to therapists with longer access times.

2.3.3 Core problem choice

The core problems addressed in this research are problems 1, 3 and 5 from the previous section. This can be accomplished by designing a blueprint schedule. A blueprint can help to incorporate the right amount of flexibility into a schedule, such that the planned care and the unplanned care can be given. This solves problem 1. Blueprints on the tactical level provide structure and insight in the available capacity, solving problem 3. Finally, a blueprint can determine the optimal capacity to spend on different patient types. This helps to assign patients to therapists based on their types, solving problem 5.

2.4 Performance

This section states the current performance of the Medical Psychology department. The first step is to define applicable Key Performance Indicators (KPIs) that suit the goal of this research. The goal of the research is to design a blueprint schedule for the Medical Psychology department while optimising the number of patients treated within the access time norm. Therefore the KPIs that are used in this research are:

- *The percentage of inpatients treated within the access time norm*
- *The percentage of outpatients treated within the access time norm*

We use these KPIs to compare the current situation with a new situation. As described in Section 2.1.5 Table 2.5, the percentages of patients treated within the access time norm differ per patient type. The KPI used for performance aggregates all inpatient types and all outpatient types. It turns out that the current performance of the department, expressed in the KPIs *percentage of inpatients treated within the access time norm* and *percentage of outpatients treated within the access time norm*, are 84% and 27% respectively.

These KPIs provide a good measurement of performance, but one aspect that should not be overlooked is the distribution of the access times. If a small number of patients has to wait extremely long, this also indicates bad performance. Figure 2.8 shows the distribution of the access times of inpatients and outpatients. It shows that especially the outpatients are treated often way outside the access norm.

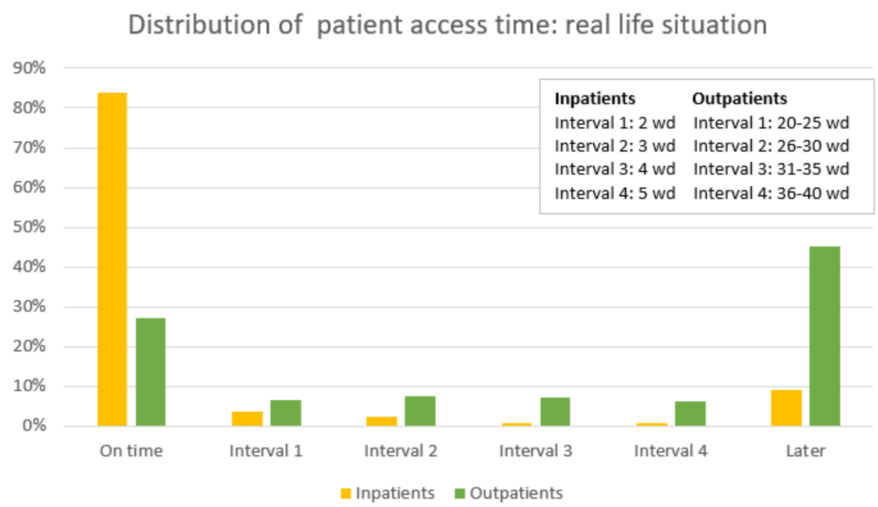

Figure 2.8: Distribution of the access times of inpatients and outpatients in the current situation (Sources: Patient database Diakonessenhuis, containing 679 outpatients referred in 2021, and Patient database Diakonessenhuis 2021/2022)

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2.5 Conclusions

This chapter answers the research question: *How is the Medical Psychology department of Diakonessenhuis currently organised and what is its current performance?* Section 2.1 and Section 2.2 have described the way the department is organised. This has brought us to the main issue for the department of Medical Psychology: 73% of the outpatients wait longer than the national standard for access time. The causes of this are summarised in the problem cluster in Section 2.3 and five potential core problems that occur at the Medical Psychology department arose. From these problems, three problems are chosen to tackle in this research: the fluctuating number of inpatient requests, the fact that the Medical Psychology department does not yet plan consciously on a tactical level and the missing policy for which therapist is treating which patient. In the remainder of this research we focus on tackling these problems by designing a blueprint schedule, focusing on increasing the number of patients treated within the access time norm.

Chapter 3

Theoretical framework

The goal of this chapter is to answer the second and third research questions: *What methods are commonly used to design blueprint schedules?* and *What type of blueprint is most suitable to the Medical Psychology department?* The second research question is answered using a literature review, in which a framework is developed to place various types of blueprints, see Section 3.1 and Section 3.2. The search approach for this literature review can be found in Appendix A. The third research question is answered using the framework and using the expert opinion of employees of the Medical Psychology department in Section 3.3. This section also shows the contribution of this research to science.

3.1 A framework for blueprint classification

To compare several blueprint types, we develop a framework in which the blueprint types can be placed, as shown in Figure 3.1. In this framework, blueprints are distinguished based on how much detail is incorporated in the blueprint, which KPI the approach tries to improve and what characteristics the blueprint type meets. These are three important pillars when deciding on what kind of blueprint to use. In Subsection 3.1.1, we discuss various levels of detail a blueprint can have. In Subsection 3.1.2, we elaborate on the various KPIs that are commonly used for blueprints, and finally, we discuss several characteristics a blueprint can have in Subsection 3.1.3.

3.1.1 Level of detail

The first dimension of the framework is the level of detail. This aspect is important in choosing a blueprint for a department since it has an impact on the way of working. For this framework, five subcategories are formulated in which most of the blueprints in the literature can be placed. These subcategories are stated below.

- **Percentages for patient types:** The blueprint contains only the percentage of the capacity that is assigned to specific patient types. This blueprint type has the lowest level of detail.
- **Block scheduling:** The blueprint consists of blocks with a start and end time. The blocks are assigned to specific patient types.
- **Block scheduling with the number of patients:** The blueprint is a more detailed version of regular block scheduling. In this version, the number of patients to be treated in the block is fixed.

- **Slots filled with patient types:** In this type of blueprint there are fixed slots with a fixed start and end time. Besides, these slots are already assigned to specific patient types.

- **Appointment rules:** Appointment rules form a blueprint in which is determined when to let patients have their appointments. The slots are predefined in this blueprint type and slots can be booked multiple times.

3.1.2 KPIs for blueprints

As the second dimension of the framework, four KPIs are incorporated that are often used in literature for designing blueprints, which we will see in Section 3.2. These four KPIs are access time, waiting time, utilisation and overtime. In Table 3.1, a description of each of the KPIs is given.

Table 3.1: KPIs commonly used for designing blueprints

KPI	**Description**
Access time (long term waiting time)	The time in the queue for patients who are waiting for their appointment date in order to receive treatment (Creemers et al., 2012)
Waiting time (short term waiting time)	The period of time patients are waiting on their appointment on the day of their appointment (Creemers et al., 2012)
Utilisation	The occupancy of the resources
Overtime	The period of time employees (resources) have to work outside the normal scheduled hours

3.1.3 Blueprint characteristics

To categorise the blueprints, the characteristics of the blueprint are used as the third and last dimension in the framework. Six characteristics are commonly used in blueprints in the literature, which are: including emergency arrivals, including same-day appointments, clinics with a multi-disciplinary setting, patients who require multiple appointments, clinics that treat multiple patient types (have multiple service types) and finally including no shows. Below, these six characteristics are described shortly.

- **Emergency arrivals (E):** Emergency arrivals are arriving patients that need to be treated right away. These arrivals can also be seen as walk-in patients, who come to the clinic without an appointment.

- **Same-day appointments (SD):** For same-day appointments, patients call the clinic at the beginning of the day and these patients get an appointment on the same day. Same-day appointments are a more flexible variant of emergency arrivals, since same-day appointments are emergency arrivals with a longer allowed waiting time.

- **Multi-disciplinary setting (MD):** In a multi-disciplinary setting, patients have multiple appointments on the same day with several specialists. Besides, often a sequence of which specialist to see first is involved.

- **Multiple appointments required (MA):** Multiple appointments can be required for a patient. This means that one patient will come back multiple times to see the same specialist.
- **Multiple service types (MS):** Some clinics can offer multiple service types. A service type corresponds to a patient type.
- **No shows (NS):** No shows are patients that do not show up for their appointment. No shows cause unnecessary idle time for the specialists when the appointment schedule is not accommodated to no shows.

3.1.4 Blueprints in the framework

In the literature, various approaches for the design of blueprints are used, resulting in different types of blueprints. The blueprints found in the in the literature study of this review are positioned in the framework in Figure 3.1. In Section 3.2, the blueprint types are discussed in more detail.

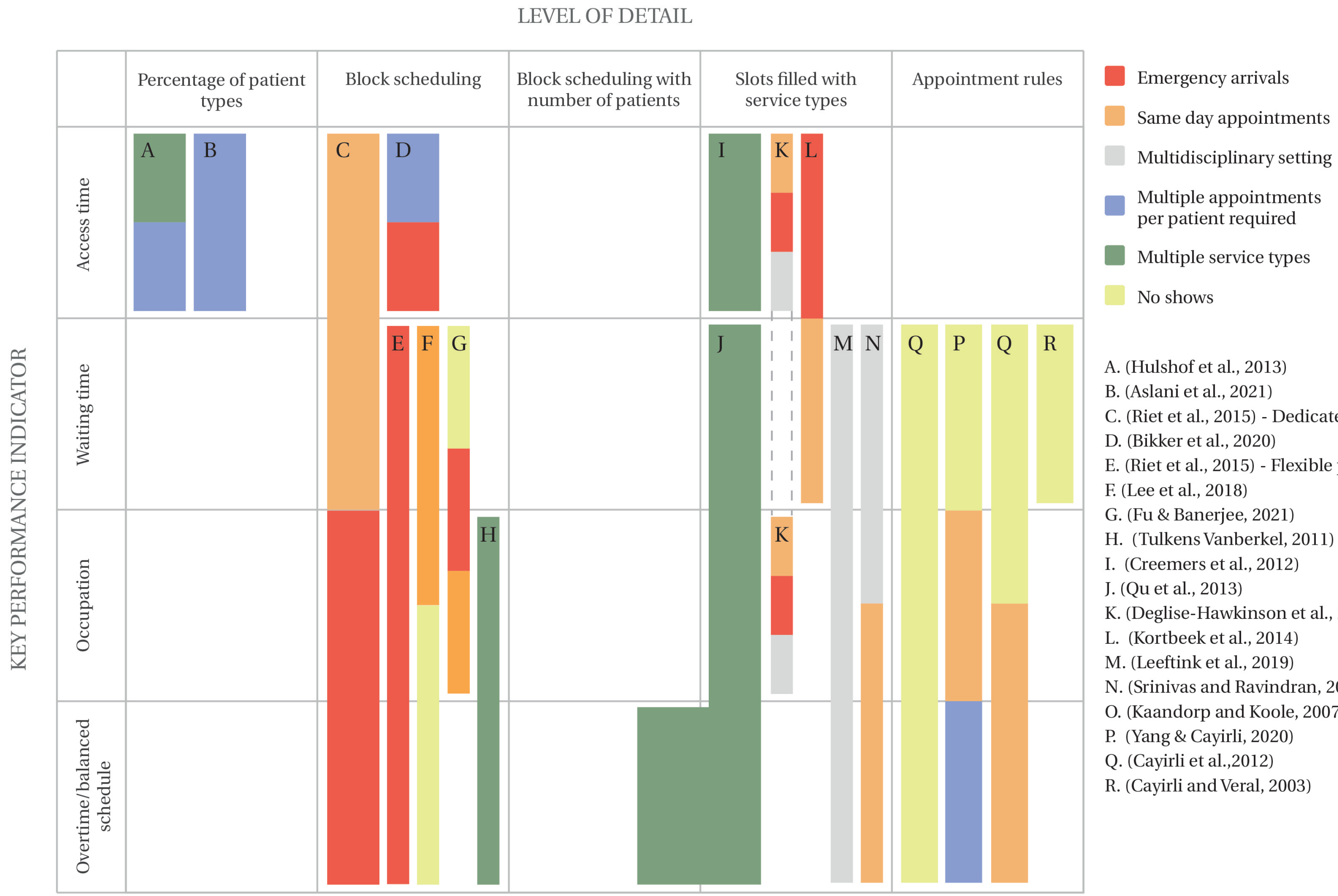
3.2 Blueprint descriptions

In this section, we elaborate on the framework in Figure 3.1. This is done per subcategory in level of detail. The KPIs used in the blueprints are described, together with the characteristics of the blueprints and the methods used for the design.

3.2.1 Percentages for patient types

Blueprints on this level of detail result in fractions of allocated resource capacity to certain service types, which is practically the same as a capacity allocation problem. One of the blueprints for which this holds is developed by Hulshof et al. (2013). This blueprint concerns elective patient admission planning and the intermediate term allocation of resource capacities. The method developed in the paper is a Mixed Integer Linear Programming model. The model results in a blueprint that causes a more equitable distribution of resources and provides control of patient access times and the number of patients served.

On this detail level, the majority of the papers focus on the KPI access time. Nguyen et al. (2015) and Aslani et al. (2021) try to meet access targets for their patients. In both papers, the authors describe an outpatient setting with two appointment types: new patients and follow-up visits. This means that there is dependence between these two patient groups. This setting was first described by (Nguyen et al., 2015), who developed a deterministic model for finding the total required physician time and its allocation to each patient types for meeting the access targets. A capacity allocation for the stochastic variant of this situation is developed by Aslani et al. (2021), where a cardinality-constrained robust optimisation is developed.



A. (Hulshof et al., 2013)
B. (Aslani et al., 2021)
C. (Riet et al., 2015) - Dedicated policy
D. (Bikker et al., 2020)
E. (Riet et al., 2015) - Flexible policy
F. (Lee et al., 2018)
G. (Fu & Banerjee, 2021)
H. (Tulkens Vanberkel, 2011)
I. (Creemers et al., 2012)
J. (Qu et al., 2013)
K. (Deglise-Hawkinson et al., 2018)
L. (Kortbeek et al., 2014)
M. (Leeftink et al., 2019)
N. (Srinivas and Ravindran, 2020)
O. (Kaandorp and Koole, 2007)
P. (Yang & Cayirli, 2020)
Q. (Cayirli et al.,2012)
R. (Cayirli and Veral, 2003)

Figure 3.1: Framework for blueprints

3.2.2 Block scheduling

Fu and Banerjee (2021) address a blueprint in which urgent tasks are handled along with existing schedules. This means that emergency patients or same day patients are incorporated in this type of blueprint. The upcoming urgent tasks are unknown, which causes for uncertainty in demand. There are various other aspects in the healthcare service system, such as no shows, cancellations and punctuality of patients, which cause uncertainty as well. To cope with this uncertainty, the authors propose a stochastic integer programming based aggregated online scheduling method. The method is a block-wise scheduling approach which allocates blocks of capacity to patient types. The objective of the method is to minimise the waiting time cost and idle time.

Blueprints are commonly used in operating theatre planning (Riet et al., 2015). The blueprints in literature use mainly block-wise scheduling. Riet et al. (2015) describe three methods of dealing with emergency arrivals in their blueprints for operating theatres: the dedicated policy, the flexible policy and the hybrid policy. The dedicated policy uses separated operating rooms for elective patients and emergency patients. The purpose of a dedicated operating room is to improve access to care for both elective and non-elective patients (Borgman, 2017; Hans & Vanberkel, 2012). In the flexible policy, all operating theatres can be used by all patient groups. The electives are scheduled in advance and the emergency patients are either inserted through pre-scheduled buffers (break-in-moments) or by deducting an amount of slack from the total capacity. The idea of this flexible policy is to minimise the time that an arriving non-elective patient has to wait before receiving surgery (Borgman, 2017; Hans & Vanberkel, 2012). The last policy suggested by Riet et al. (2015) is the hybrid policy. The hybrid policy consists of a mix of dedicated and flexible resources. This policy tries to obtain a better trade-off between flexibility and access time than the previous two policies. The hybrid policy is not researched often and the authors of the review state that the benefits of the hybrid policy are not yet clear. Therefore the hybrid policy is not included in our framework.

In operating theatre planning, not only emergency scheduling should be taken into account, but also the allocation of the operating time to various specialities is important to consider. The assignment is also known as the master surgery scheduling (MSS) problem (Van Oostrum et al., 2008; Hans & Vanberkel, 2012). A well known approach to design the blueprint of operating theatres is the convolution model by Vanberkel (2011). This model tries to optimally allocate the operating time to various specialities while balancing the the downstream resources (Vanberkel, 2011; Hans & Vanberkel, 2012).

Block scheduling is used to schedule patients with multiple appointments as well (Bikker et al., 2020). The sequential appointments have access time targets that need to be met. Bikker et al. (2020) develop a blueprint in which capacity is allocated to patients at the moment of their arrival, in such a way that the total number of requests booked within their corresponding access time targets is maximised. They formulated this problem as a Markov decision process that takes into account the current patient schedule and future arrivals. The blueprint is developed using an approximate dynamic programming algorithm to obtain approximate optimal capacity allocation policies.

3.2.3 Block scheduling with number of patients

A blueprint can also be a slightly more detailed version of block scheduling (Qu et al., 2013). This is used by Qu et al. (2013). The authors propose a weekly scheduling template for outpatient clinics providing multiple types of services. The blueprint is created in two phases. In the first phase, service categories are assigned to clinic sessions during a week and the optimal number of appointments to reserve for each service type is determined per clinic session. This is achieved by means of a mixed-integer program with the objective to balance the workload and therefore minimises the overtime. The level of detail becomes higher in the second phase, where a stochastic mixed-integer program is used to allocate specific appointment types in each clinic session. The blueprint resulting from the second phase is more of the type 'Slots filled with patient types', discussed in the next section.

3.2.4 Slots filled with patient types

Creemers et al. (2012) describe a blueprint in which server time slots are assigned to different patients classes. Each patient class receives a specific service type. The model presented in the article addresses the access times (long-term waiting) of several patient types and tries to optimise its trade-off with the allocation of hospital resources. A bulk service queuing model is used to obtain the expected waiting time of a patient of a particular class, given a feasible allocation of service time slots. The authors try to find the optimal allocation scheme by using the output of the bulk service queuing models as the input of the step-wise heuristic optimisation procedure.

The blueprint for appointment schedules developed by Kortbeek et al. (2014) prescribes the number of appointments to plan per day and the moment on the day to schedule these appointments. In this way, the slots open for walk-in patients is decided. This means that the blueprint is applicable for outpatient clinics that serve patients on a walk-in basis. The blueprint tries to balance the waiting time at the facility for unscheduled patients and the access time for scheduled patients. The access time evaluation is done by means of a discrete-time cyclic queuing model and the evaluation of the process on a daily level is done using a Markov reward process. The best balanced blueprint is tried to be found by generating many Cyclic Appointment Schedule using an iterative procedure.

Srinivas and Ravindran (2020) develop a comparable blueprint which also determines the number and position of same-day and pre-booking slots reserved for each physician. This is done by minimising the expected total cost consisting of the weighted sum of excessive patient waiting time, the resource idle time, and the resource overtime. However, the blueprint in this paper accommodates for multi-disciplinary patients as well. A stochastic mixed integer programming model that integrates the multi-disciplinary patient flow is proposed. To obtain the schedule configuration, this is evaluated using the sample approximation method.

A blueprint that also accommodates for a multi-disciplinary setting is developed by Leeftink et al. (2019). The authors describe a blueprint for a clinic that serves regular consultations but also multi-disciplinary patients. The second destination of the multi-disciplinary patients is not yet known at the start of the day, but becomes clear after their first consult. The blueprint schedules are designed by optimising the patient waiting time, occupation of the clinicians and clinicians overtime. By optimally allocating the slots to regular patient types or keeping slots open for the multi-disciplinary patients, the blueprint arises. This is modelled by a stochastic integer program and solved with the sample average approximation approach.

Access times also have to be considered when dealing with urgent patients (Deglise-Hawkinson et al., 2018). Deglise-Hawkinson et al. (2018) provide a blueprint in which they determine the total number of slots to assign to patient groups differentiated by urgency, while limiting access delays for initial and downstream appointments. The authors have formulated this problem as a queueing network optimisation and approximate it via deterministic linear optimisation to simultaneously smooth workloads and guarantee access delay targets.

3.2.5 Appointment rules

Appointment rules can improve operational productivity by smoothing demand and reducing the uncertainty in patients arrivals. In this way, capacity and demand can be better matched (Cayirli et al., 2012). An overview of existing appointment rules is given in the review of Cayirli and Veral (2003). The review mentions seven appointment rules, shortly described below. Many sources of variability are present in a clinic. For example service times differ per patients and patients do not show. The appointment rules are used to improve the waiting time of the patients at the clinic.

- Single-block rule, in which all patients are assigned to arrive as a block at the beginning of a clinic session.
- Individual-block/Fixed-interval rule (Yang & Cayirli, 2020), in which patients are assigned to unique appointment times. The appointment times are equally spread throughout the clinic session.
- Individual-block/Fixed-interval rule with an initial block, which is a combination of the previous two rules. In the first block, an initial patient group of size n arrives, like in the single-block rule. The rest of the clinic session is arranged like the Individual-block/Fixed interval rule.
- Multiple-block/Fixed-interval rule is a rule in which patient groups of size m are assigned to each appointment slot with appointment intervals kept constant.
- Multiple-block/Fixed-interval rule with an initial block is a variation of the above system with an initial block of size n > m.
- Variable-block/Fixed interval rule allows different block sizes during the clinic session while keeping appointment intervals constant.
- Individual-block/Variable interval rule (Carreras-García et al., 2020) is a rule in which individual patients are scheduled at varying appointment intervals.

There exists variations on these appointment rules. For example, Kaandorp and Koole (2007) design a blueprint taking cancellations into account. No shows are often only known on short term. The authors use a local search procedure to decide which slots can be double booked and which slots should not be double booked. The resulting schedule is optimised based on the waiting time of patients and the idle time and overtime of doctors.

Cayirli et al. (2012) formulated a universal appointment rule: The Dome rule. This is a universal appointment rule that can be parameterised through a planning constant for different clinics. The planning constant is dependent on the environmental factors of the clinic. Environmental factors taken into account are the occurrence of no-shows and walk-ins, number of appointments per session, variability of service times, and cost of doctor's time to patient's time.

3.3 Positioning the Medical Psychology department

In this section, we will position the desired blueprint type for the Medical Psychology department in the framework from Section 3.1. Besides, we will point out the practical relevance as well as the scientific relevance of this research.

The blueprint for the Medical Psychology department should focus on the KPI access time, since this is identified as the action problem in 2. The department desires a blueprint in which there is a lot of flexibility to schedule themselves, especially for outpatient scheduling, which constitutes the majority of the total patients to schedule. Therefore, the Medical Psychology department is positioned on the detail level *Percentages for patient types.* However, for the inpatients who should be treated on the same day, the department wishes to have a clear system with blocks reserved for inpatients. This is on the detail level *Block scheduling.* Figure 3.2 shows the position of the Medical Psychology department in the framework.

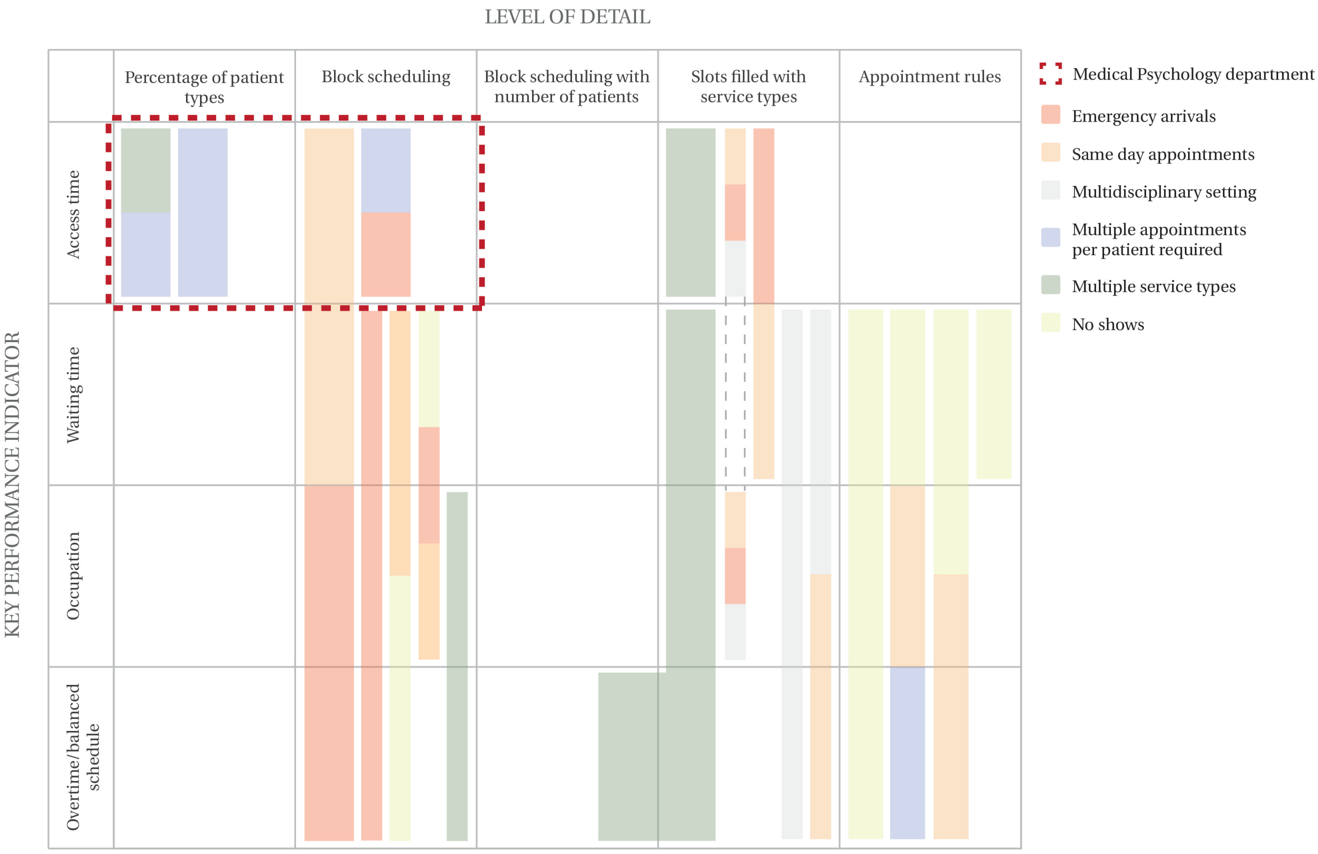


Figure 3.2: Framework with position of the Medical Psychology department

The most important characteristics that should be incorporated at the Medical Psychology are *Same day appointments* and *Multiple service types.* The inpatients should be treated on the same day, so they should be prioritised. On the other hand, the group of outpatients consists of multiple types of patients who need various services and these services can only be performed by a selection of the therapists. These service types should be included in the blueprint for making it suitable for the Medical Psychology department.

Figure 3.2 shows that there are a few papers in which blueprints are developed for the position. However, none of these blueprints include the same characteristics as desired for the Medical Psychology department. The work of Hulshof et al. (2013) comes closest to the desired blueprint for the outpatients. The authors used a Mixed Integer Linear Programming model to develop a blueprint for a hospital network in which multiple patient groups with various treatments are served, while trying to achieve equitable access for patients. The situation for our blueprint is comparable but also accounts for urgent patients.

The division of inpatients in blocks on the day is most comparable with the work of Riet et al. (2015). The purpose of a dedicated operating room is to improve access to care for both elective and urgent patients. The dedicated policy keeps whole servers free for emergency patients. Therapists are more flexible in changing from purpose than equipped operating rooms. Besides, our same day patients do not necessarily need to be served immediately, like emergency patients. Therefore, it is interesting for us to extend the research of Riet et al. (2015) by determining on which servers to put these blocks and when.

3.4 Conclusions

This chapter answers the second and third research question. We answer the second research question, *What methods are commonly used to design blueprint schedules?*, by providing a framework for blueprint types. A literature study is performed to identify commonly methods for designing blueprint scheduled and these blueprints are placed in the framework. The framework could be used to answer the third research question: *What type of blueprint is most suitable to the Medical Psychology department?* The blueprint for the Medical Psychology department should focus on the KPI access time, since this resulted from the problem analysis in 2. The department wants a blueprint in which they still have as much flexibility as possible, except for inpatient. The department desires clear insight in when to schedule free time blocks for these urgent patients. Therefore, the level of detail should be partly *Percentages for patient types* and partly *Block scheduling*. Finally, the characteristics that should be included in the blueprint are *Same day appointments* and *Multiple service types*. In the next chapter, a blueprint at this position in the framework will be developed.

Chapter 4

Model

In this chapter we develop a model resulting in a blueprint of the most suitable type for the Medical Psychology, determined in the previous chapter. This means that we answer the fourth research question: *How can we create a model for designing a blueprint schedule that maximises the number of patients treated within the access time norms?* This is done by first formulating the problem theoretically in Section 4.1. Section 4.2 introduces the solution approach. We finish with a translation of the model results into the blueprint in Section 4.3.

4.1 Theoretical problem formulation

4.1.1 System description

This section gives a systematic overview of the system modelled in this chapter, as summarised Figure 4.1. Various patient types p with various priorities arrive at the Medical Psychology department according to Poisson distributions, with arrival rates λ_p. These patient types p have exponentially distributed service times with mean $1/\mu_p$. These patients must be divided over the queues of the therapists t, such that the waiting times for patients waiting for each of the therapists are more equitable. To do so, we have to determine x_{pt}: the fraction of the arrival rate λ_p to assign to therapist *t*. The goal of our model is to optimise the values of x_{pt}, such that a blueprint can be constructed. If we know how many patients of each type a therapist should treat, we can calculate the amount of time a therapist should spend on each patient type. This will result in a blueprint.

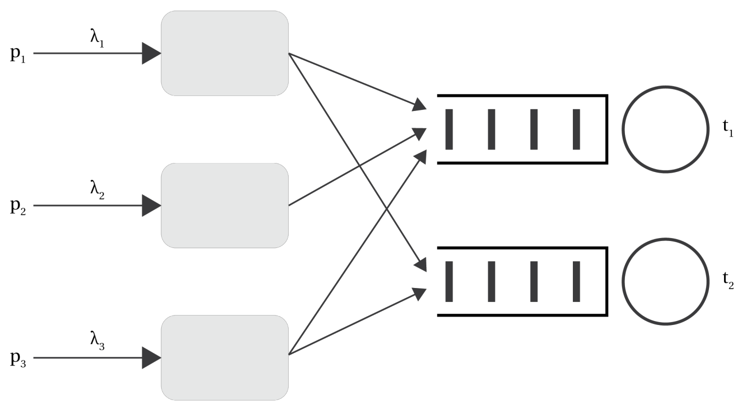


Figure 4.1: Visualisation of the system

When the patients are divided over queues per therapist, these queues can be modelled as individual single server queues. Poisson distributed arrival rates can be split and merged and still be Poisson distributed (Winston, 2004), which means that the total arrival rate at the queue of a therapist t is still Poisson distributed. Let λsub_{pt} be the the arrival rate of patient type p at therapist t. With known fractions x_{pt}, the values for λsub_{pt} can easily be calculated by Equation 4.1.

$$\lambda sub_{pt} = x_p t \cdot \lambda_p \qquad for p \in P \tag{4.1}$$

The patients arriving at the queue of a therapist t are from multiple patient types p, which corresponds to service times from exponential distributions with various means $1/\mu_p$ and probably different priorities j, where j = *1, 2, .., J*. The lower the value of j, the higher the priority of the patient. If a patient with a higher priority is waiting in the queue, this patient will be treated first. However, the treatment of the patient in service will not be interrupted.

4.1.2 M/H/1 queue with a non-preemptive priority policy

The M/H/1 queue is a single-server queue in which the arrivals are distributed according to a Poisson process and the service times of the patients are hyperexponentially distributed. A priority policy models a queue in which some patients should be served before other patients. For the non-preemptive policy, patients may not interrupt the service time of a lower priority customer, but they have to wait till the service time of the low priority patients has been completed. This reflects the situation at the Medical Psychology department and therefore we use the M/H/1 queue with a non-preemptive priority policy.

Patient types correspond to a priority, which means that all patients of type p have priority j. However, it is possible that patients of different patient types p have the same priority j. Therefore, we introduce the concept of priority groups G_j. Priority groups G_j are sets consisting of the patient types p with priority j. Since every patient type p has a priority j, the union of all priority groups G_j should contain all patient types p.

A priority group G_j containing multiple patient types must deal with the fact that patient types have different mean service times. This can be modelled as a hyperexponential distribution. A random variable X is hyperexponentially distributed if X is with probability p_i, $i = 1, 2, ..., k$ an exponential random variable X_i with mean $1/mu_i$ (Adan & Resing, 2015). For this random variable we use the notation $H_k(p_1, ..., p_k; \mu_1, ..., \mu_k)$.

As mentioned in the previous section, a queue of a therapist t can be modelled as an M/H/1 queue if the arrival rates of all patient types p at the therapist are known. Figure 4.2 shows the part of the system that can be modelled as an M/H/1 queue. In this small example, there are three patient types and two therapists. Patients of type p_1 are in priority group G_1 and have priority over patients in priority group $G_2 = \{p_2, p_3\}$.

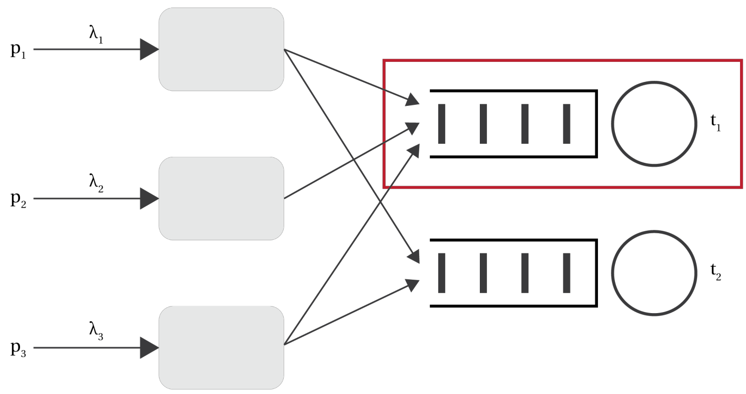


Figure 4.2: Single M/H/1 queue with non-preemptive priority policy

Equations 4.2-4.5 calculate the expected values for waiting time, $E(W_j)$, for the M/H/1 queue with a non-preemptive priority policy. These calculations hold for all therapists t. The equations are based on the M/G/1 non-preemptive priority policy equations of Adan and Resing (2015) in which we use a hyperexponential distribution for the service times. Table 4.1 gives a summary of the notation for the M/H/1 queue with a non-preemptive priority policy.

Table 4.1: Summary of notation for M/H/1 queue with a non-preemptive priority policy

Notation	**Description**
λsub_{pt}	Arrival rate of patient type $p \in P$ at therapist $t \in T$
μ_p	Service rate of patient type $p \in P$
G_j	Set of patient types with priority $j \in J$
$E(B_j)$	Expected service time of group group G_j
$E(R_j)$	Expected residual service time of group G_j
ρ_j	The proportion of time the server is occupied by a patient from group G_j
$E(W_j)$	The expected waiting time for patients from group G_j

$$E(B_j) = \sum_{p\in G_j} \frac{1}{\mu_p} \cdot \frac{\lambda sub_{pt}}{\sum_{p\in G_j} \lambda sub_{pt}} \qquad for j = 1,...,J \qquad (4.2)$$

$$E(R_j) = \frac{\sum_{p\in G_j} \frac{2}{\mu_p^2} \cdot \frac{\lambda sub_{pt}}{\sum_{p\in G_j} \lambda sub_{pt}}}{2 \cdot E(B_j)} \qquad for j \in 1,...,J \qquad (4.3)$$

$$\rho_j = E(B_j) \cdot \sum_{p\in G_j} \lambda sub_{pt} \qquad for j = 1,...,J \qquad (4.4)$$

$$E(W_j) = \frac{\sum_{i\in J} \rho_i \cdot E(R_i)}{(1-(\rho_1+...+\rho_j))(1-(\rho_1+...+\rho_{j-1})} \qquad for j = 1,...,J \qquad (4.5)$$

4.1.3 Quadratic mixed integer nonlinear mathematical programming model for division of patients over therapists

To define the blueprint, it is necessary to determine the arrival rates of patient types p at the queues of therapists t: λsub_{pt}. When the arrival rates are known, the expected waiting times of the queues can be calculated according to the approach described in Section 4.1.2. This means that the fractions x_{pt} need to be determined, since we can immediately calculate λsub_{pt} with these values. Figure 4.3, gives a visualisation of the fractions x_{pt}.

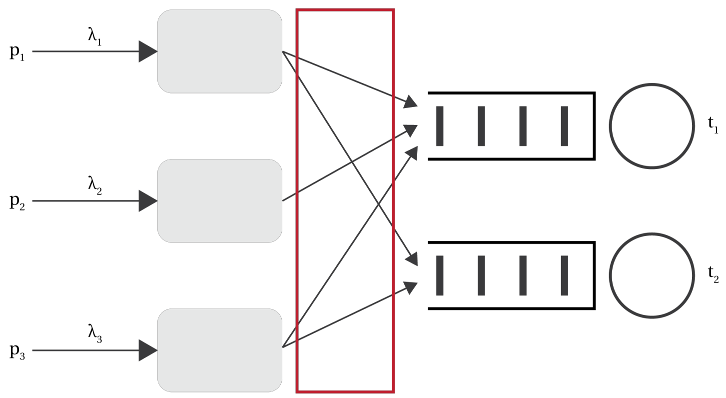


Figure 4.3: Visualisation of fractions x_{pt}

The fractions x_{pt} should be assigned to the therapists optimally. The mathematical programming model that describes this situation is formulated below. First, the sets and parameters are given. Second, the decision variables and model variables are stated. Then, the objective value is formulated and described and finally, the constraints of the model are formulated.

Sets and parameters
Table 4.2 gives an overview of the sets and Table 4.3 gives an overview of the parameters used in the mathematical programming model.

Table 4.2: Sets used in the quadratic mixed integer nonlinear mathematical programming model

Set	Element	Description
P	p	Unique service types
T	t	Unique therapists
J	j	Unique priorities
G_j	p	Group j containing patient types p with priority j
K	k	k^{th} interval bound

Decision variables
The goal of this mathematical program is to determine the optimal assignment of patient types p to therapists t. This assignment is equivalent to the fractions x_{pt}, which means that x_{pt} is the decision variable in this model. We let the set $x*$ be the solution of the mathematical program, containing the fractions x_{pt}, see Equation 4.6.

Table 4.3: Parameters used in the quadratic mixed integer nonlinear mathematical programming model

Parameter	**Description**
λ_p	Arrival rate of patient type p at the system
μ_p	Service rate of patient type p
F_{pt}	Matrix containing whether a therapist is allowed ($F_{pt} = 1$) to treat patient type p or not ($F_{pt} = 0$).
I_{jk}	Interval bounds k for penalising model variable $\overline{W_{jt}}$ where $k \in K$

$$x* = \{x_{pt} : p \in P, t \in T\} \tag{4.6}$$

Model variables
The model variables' values are calculated during execution of the model and are related to the objective function. The model variables are summarised in Table 4.4.

Table 4.4: Model variables used in the quadratic mixed integer nonlinear mathematical programming model

Model variable	**Description**
x_{pt}	Fraction of the arrival rate λ_p, $p \in P$, to assign to therapist $t \in T$
λsub_{pt}	Arrival rate of patient type $p \in P$ at therapist $t \in T$
B_{jt}	Estimation of the service time of group $j \in J$ at therapist $t \in T$
R_{jt}	Estimation of the residual service time of group $j \in J$ at therapist $t \in T$
ρ_{jt}	Proportion of time therapist $t \in T$ is occupied by patient group $j \in J$
$\overline{W_j t}$	Estimation of the waiting time of group $j \in J$ at therapist $t \in T$
a_{jkt}	Binary variable which is 1 if $\overline{W_{jt}}$ is in interval between interval bounds k and $k-1$ ($k = 1, 2, ..., K$), and 0 otherwise
ϕ_{jkt}	Auxiliary variable to determine the values of a_{jkt}, with $k \in K$

Objective function
The objective function should minimise the average waiting time exceeding the norm. In this objective function, a small exceedance of the norm is penalised less severe than a large exceedance of the norm. The penalty depends on what the interval the mean waiting time is in. To determine the interval of the mean waiting time of therapist t, a_{jkt}, we use piece-wise linear function functions (Winston, 2004), see Constraints 4.16-4.19. The formulation of the objective function is given in Equation 4.7.

$$\min z = \sum_{j \in J} \sum_{t \in T} \sum_{k=1}^{K} (k-1)^2 \cdot a_{jkt} \tag{4.7}$$

Constraints
The mathematical program should satisfy several constraints. These constraints are given in

Equations 4.8-4.21. Constraints 4.8-4.12 represent the calculation of the mean waiting times per group *j* for every therapist *t*, similar to the single M/H/1 queue.

$$\lambda sub_{pt} = x_{pt} \cdot \lambda_p \qquad \forall p \in P, \forall t \in T \tag{4.8}$$

$$\overline{B_{jt}} = \sum_{p \in G_j} \frac{1}{\mu_p} \cdot \frac{\lambda sub_{pt}}{\sum_{p \in G_j} \lambda sub_{pt}} \qquad \forall j \in J, \forall t \in T \tag{4.9}$$

$$\overline{R_{jt}} = \frac{\sum_{p \in G_j} \frac{2}{\mu_p^2} \cdot \frac{\lambda sub_{pt}}{\sum_{p \in G_j} \lambda sub_{pt}}}{2 \cdot \overline{B_{jt}}} \qquad \forall j \in J, \forall t \in T \tag{4.10}$$

$$\rho_{jt} = \overline{B_{jt}} \cdot \sum_{p \in G_j} \lambda sub_{pt} \qquad \forall j \in J, \forall t \in T \tag{4.11}$$

$$\overline{W_{jt}} = \frac{\sum_{i \in J} \rho_{it} \cdot \overline{R_{it}}}{(1 - (\rho_{1t} + \ldots + \rho_{jt}))(1 - (\rho_{1t} + \ldots + \rho_{j-1,t})} \qquad \forall j \in J, \forall t \in T \tag{4.12}$$

Constraints 4.13-4.15 describe the requirements of the system. Constraint 4.13 ensures that the chosen proportions x_{pt} do not result in servers with exploding queues. Constraint 4.14 ensures that all arriving patients are assigned to a therapist. With constraint 4.15, the qualifications of therapists are modelled, as some patient types cannot be treated by specific therapists, indicated by $F_{pt} = 0$ (1 otherwise). If a therapist t cannot treat a patient type p, the proportion x_{pt} will be set to zero.

$$\sum_{j \in J} \rho_{jt} \leq 1 \qquad \forall t \in T \tag{4.13}$$

$$\sum_{t \in T} x_{pt} = 1 \qquad \forall p \in P \tag{4.14}$$

$$x_{pt} \leq F_{pt} \qquad \forall p \in P, \forall t \in T \tag{4.15}$$

Constraints 4.16-4.19 determine the interval that contains the mean waiting time of group j. This is done using piece-wise linear functions. Figure 4.4 illustrates the variables used for the piece-wise linear functions.

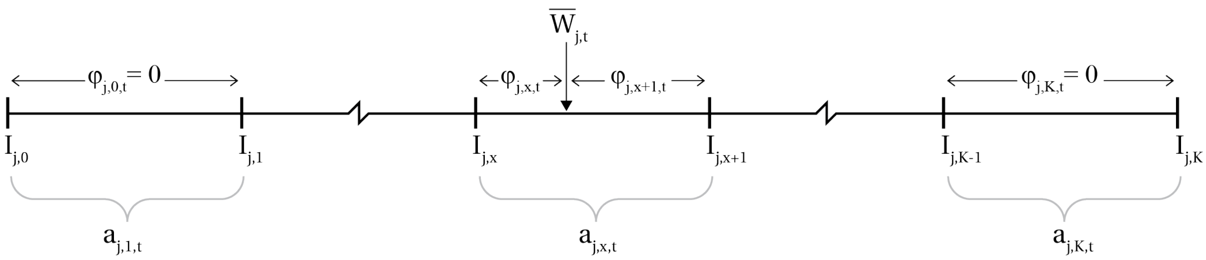


Figure 4.4: Illustration of the variables used for the piece-wise linear functions

$$\overline{W_{jt}} = \sum_{k=0}^{K} I_{jk} \cdot \phi_{jkt} \qquad \forall j \in J, \forall t \in T \tag{4.16}$$

$$\sum_{k=0}^{K} \phi_{jkt} = 1 \qquad \forall j \in J, \forall t \in T \tag{4.17}$$

$$\phi_{j,0,t} \leq a_{j,1,t} \tag{4.18a}$$

$$\phi_{jkt} \leq a_{jkt} + a_{j,k+1,t} \qquad \forall k = 1, ..., K-1 \tag{4.18b}$$

$$\phi_{j,K,t} \leq a_{j,K,t} \tag{4.18c}$$

$$\sum_{k=1}^{K} a_{jkt} = 1 \qquad \forall j \in J, \forall t \in T \tag{4.19}$$

Finally, Equations 4.20 and 4.21 give the dimensions of the decision and model variables.

$$x_{pt}, \lambda sub_{pt}, \overline{B_{jt}}, \overline{R_{jt}}, \rho_{jt}, \phi_{jkt} \geq 0 \qquad \forall j \in J, \forall k \in K, \forall p \in P, \forall t \in T \tag{4.20}$$

$$a_{jkt} \in \{0, 1\} \qquad \forall j \in J, \forall k = 1, .., K, \forall t \in T \tag{4.21}$$

4.2 Solution approach

In Section 4.1, we gave the theoretical formulation of our problem. However, this quadratic mixed integer nonlinear mathematical programming model is only solvable for very small instances. Therefore, we need a heuristic to find a good solution. Besides, the mathematical programming model only optimises the average waiting time per therapist, which means that the variance of the individual waiting times of patients is not taken into account. Therefore, we use a simulation model to be able to use a more relevant KPI as objective function. This section describes the solution approach we will use in this research. We programmed the solution approach in Python 3.8. The pseudo code can be found in Appendix B.

4.2.1 Simulation-based optimisation

We use simulation-based optimisation to find a good solution for our problem. This approach is, among others, successfully used by Soykan and Rabadi (2022) and by Hsu et al. (2022). We use a metaheuristic as optimisation approach, while the performance measures of candidate solutions follow from a simulation model. Figure 4.5 summarises our solution approach. In the following sections, this framework will be discussed in more detail.

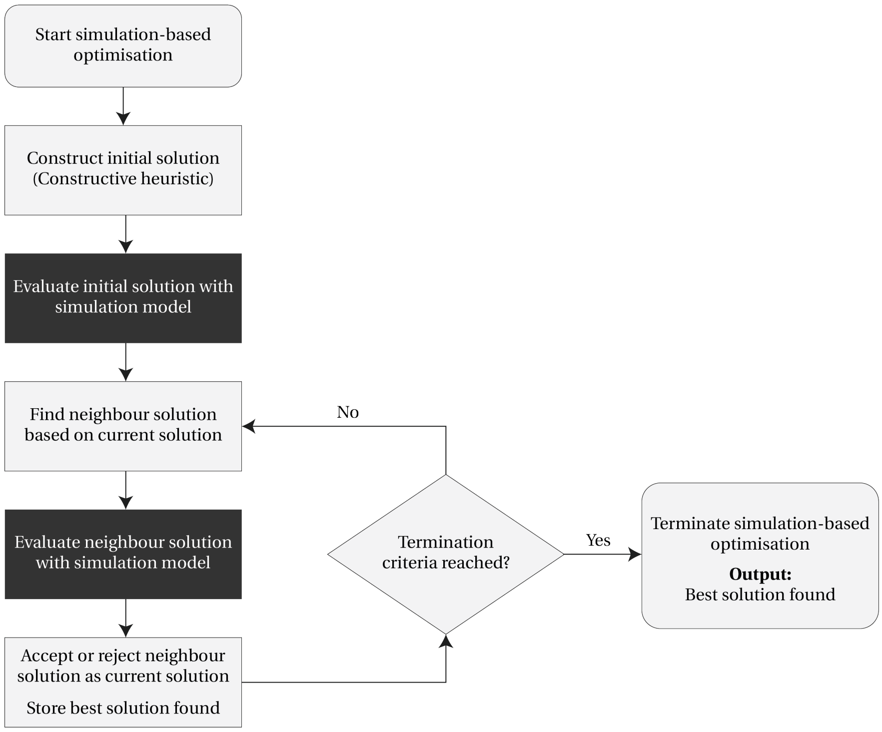


Figure 4.5: Framework for simulation-based optimisation

4.2.2 Constructive heuristic

To start with the simulation-based optimisation approach, we need an initial solution that we can improve. This initial solution should be feasible, which means that the solution should satisfy the following three restrictions:

1. The occupation of the queue cannot be more than 100%. This would result in exploding queues. This corresponds to Constraint 4.13 in our mathematical programming model.
2. All patients should be treated. This corresponds to Constraint 4.14 in our mathematical programming model.
3. The therapists can only treat patients they are allowed to treat based on their qualifications. This corresponds to Constraint 4.15 in our mathematical programming model.

The initial solution is constructed by dividing the fraction of each patient type to assign equally over all therapists that are qualified to treat that particular patient type. For the fractions x_{pt} then hold:

$$x_{pt} = \begin{cases} 0 & \text{if } F_{pt} = 0 \\ \frac{1}{\sum_{t \in T} F_{pt}} & \text{otherwise} \end{cases} \tag{4.22}$$

This not necessarily results in a feasible solution, since the queues of the therapists might explode. If this is the case for one or more of the queues, we check for which therapists the queue is exploding and for which therapists the queues do not explode. All therapists with exploding queues are randomly assigned one of the therapists with a not exploding queue.

Then we select a patient type which both therapists are allowed to treat. We remove a part of the assigned fraction for the selected patient type from the therapist with the exploding queue and add this fraction to the therapist with the not exploding queue. This approach is repeated until none of the queues is exploding, which means that a feasible solution is found. In the case that all queues are exploding, it means that there is additional capacity is needed and that no initial solution can be constructed.

4.2.3 Evaluation with simulation model

The goal of the simulation model used in the simulation-based optimisation approach is to evaluate potential solutions. This means that the input for the simulation model is a potential solution and the output is the objective value of that potential solution. In this section, we describe the simulation model.

Objective function
The mathematical programming model, formulated in Section 4.1.3, bases the optimisation only on the average waiting time per therapist. This has two disadvantages that can be solved using simulation. First, the average waiting time can still be widely spread. Some patients might have to wait very short, while others might wait very long. Besides, the objective function in the mathematical programming model does not weight a queue based on its number of patients. A simulation overcomes these issues, because it allows the optimisation criterion to take into account the waiting time of every patient. We determine the probability that a patient is treated within the norm. However, similar to the objective used in the mathematical programming model, we want to penalise a small exceedance of the waiting time norm less severely than a large one. The objective function we use in the solution approach is given in Equation 4.23.

$$\min z = \sum_{j \in J} \sum_{k=1}^{K} (k-1)^2 \cdot \frac{\text{\# patients from group j with waiting time in interval k}}{\text{total \# patients from group j}} \tag{4.23}$$

Discrete Event Simulation (DES) model
For the simulation model, we use Discrete Event Simulation (DES), as often used to simulate queueing systems (Christos & Lafortune, 2008; Canonaco et al., 2008). The DES model simulates the single M/H/1 queue of a therapist with a non-preemptive priority policy. The queues of all therapists can be evaluated independently of each other, as was the case in the mathematical programming model.

The model starts by generating the patients arriving at the queue of a therapist. The patients are given several attributes; a patient number, a patient type, an arrival time, a service time and a priority. Depending on these attributes, events take place in the model.

There are two different event types in our DES; patient arrivals and patient departures. The two events in the simulation both trigger a sequence of actions. The flowchart in Figure 4.6 illustrates the sequence of actions that follows from these events. If the event is a patient arrival, the patient can be put in service if the therapist is available. Otherwise, the patient will be put in the queue. If the event is a patient departure, this means that the therapist has become available. This means that a patient from the queue can be put in service. This will be the longest waiting patient from the highest priority patient group in the queue. This whole process will be executed as long as the simulation termination criteria are not reached.

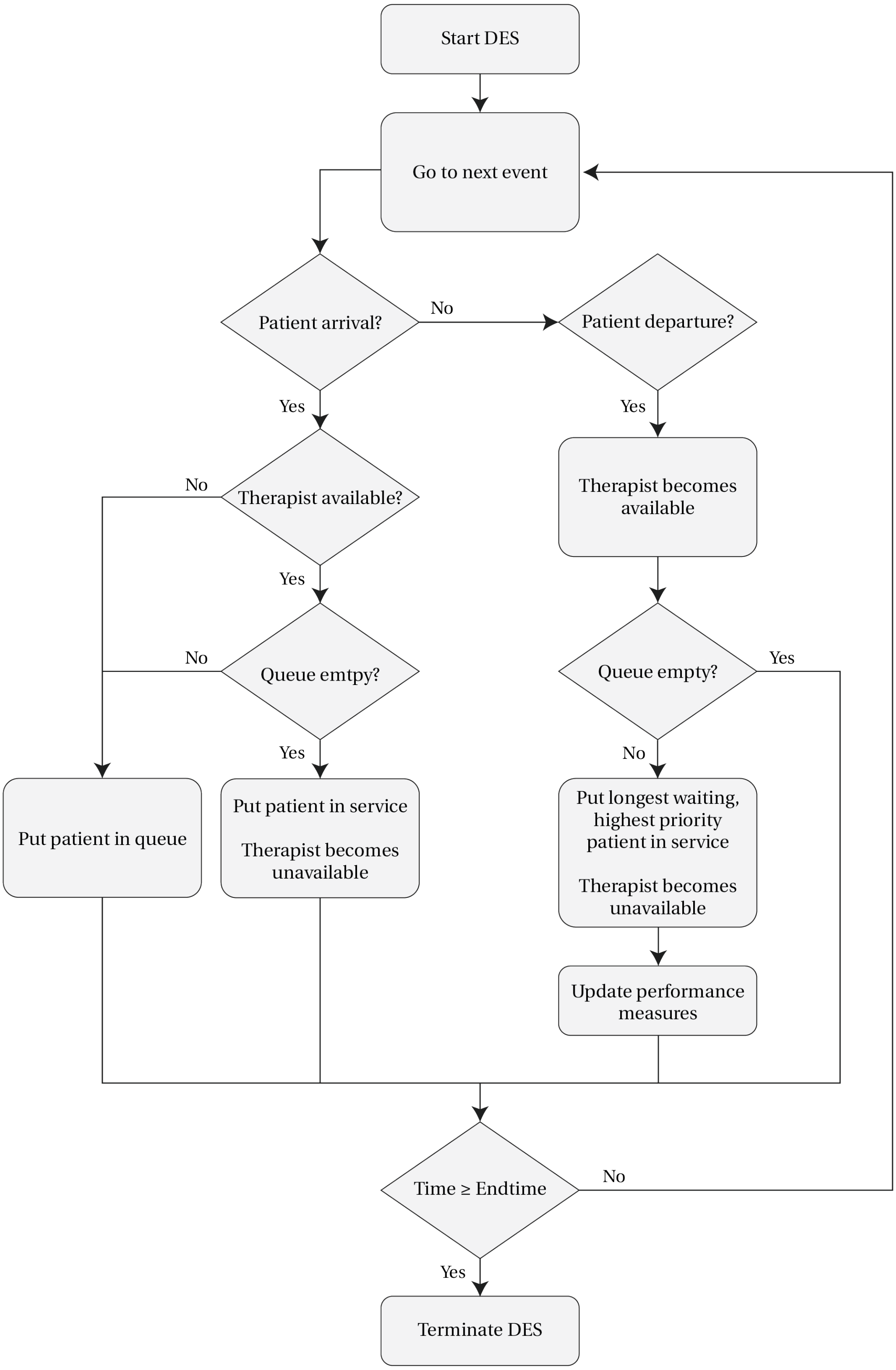


Figure 4.6: Flowchart Discrete Event Simulation (DES)

4.2.4 Neighbour solutions

To find potential solutions we slightly change an already found feasible solution, called our current solution. A solution that is based on our current solution but is changed a little bit is called a neighbour solution. In this subsection, we discuss the operator we use with the corresponding neighbourhood. We also elaborate on delta computations, to minimise the running time of our solution approach.

Neighbourhood

To find potential solutions we use the operator *Move*. This means that we move a part of the fraction of patient type p^*, with corresponding priority j^*, assigned to therapist t_a to another therapist t_b. To make sure that therapists only treat patient types of their speciality, the patient type p^* should be a patient type that both therapist t_a and therapist t_b are allowed to treat. The size of this part, s_{move}, is the minimum of three aspects: the amount x_{pt_a} already assigned to therapist t_a, the maximum therapist t_b can receive without ending up with an exploding queue, r, and the step size z. Using this structure for s_{move}, we ensure that all solutions we obtain are feasible. Equations 4.24-4.27 show the formulas that together form the *Move* operator.

$$r = \frac{\mu_{p^*} \cdot (\rho_{j^*t_b} + 1 - \sum_{j \in J} \rho_{jt_b} - \sum_{p \in G_{j^*} \setminus \{p*\}} \frac{\lambda sub_{pt_b}}{\mu_p}) - \lambda sub_{p^*t_b}}{\lambda_{p^*}} \tag{4.24}$$

$$s_{move} = max\{x_{pt_a}, r, z\} \tag{4.25}$$

$$x_{pt_a} = x_{pt_a} - s_{move} \tag{4.26}$$

$$x_{pt_b} = x_{pt_b} + s_{move} \tag{4.27}$$

To ensure that our neighbourhood is connected, we will vary the step size z during the simulation-based optimisation. In the beginning, we use a high value for z to reach the right region in the solution space. During the process, we decrease z to become more and more specific. At the end of the optimisation approach, z has become very small. We expect that we already are in the right region and only very small changes can improve the objective value. This means that we can reach every possible feasible solution by consecutively executing the described *Move* operator. Using the small step size in the end, we ensure that the optimal solution can be reached via the *Move* operator.

Delta computations

The recalculation of neighbour solutions can be very time consuming. The concept *delta computations* only recalculates the changed parts in the new solution. In our neighbourhood structure, we change fractions of only two therapists: therapist t_a and t_b. Since the queues of the therapists are evaluated independently of each other, we only need to reevaluate the queues of these two therapists. This saves computation time. To be able to use this, we keep track of the changed therapists and the previous solution per therapist in the simulation.

4.2.5 Acceptance

We use the metaheuristic Simulated Annealing for optimisation, as also successfully used by Scollen and Hargraves (2018) and by Sibalija (2018). If the neighbour solution is better than the current solution, we always accept that neighbour solution as new current solution. However, by only accepting better neighbour solutions, we can get stuck in a local optimum. The large advantage of simulated annealing is that it enables the program to escape from local optima. This is done by sometimes accepting worse neighbour solutions as current solutions. Therefore, in the beginning of the simulation-based optimisation, we often accept worse solutions as current solution. However, when the solution approach progresses, we accept worse solutions less and less often. This means that the program does a lot of exploration of the solution space in the beginning, and more exploitation towards the end. This exploration-exploitation balance is managed by the temperature of the metaheuristic, which is decreasing during the simulation-based optimisation. In Table 4.5, we summarise our acceptance criteria.

Table 4.5: Acceptance of a neighbour solution

Situation	**Accept neighbour as current solution**	**Don't accept neighbour as current solution**
Neighbour better than current	Always	Never
Neighbour worse than current	$r < e^{\frac{Current-Neighbour}{Temperature}}$	$r \geq e^{\frac{Current-Neighbour}{Temperature}}$
	$r \in \mathbb{R}, r \in [0,1]$	$r \in \mathbb{R}, r \in [0,1]$

4.3 Translation to a blueprint

Our goal was to make a blueprint which shows the percentage of time each therapist t should spend on each patient type p. We can obtain this by translating the fractions x_{pt}. Let v_{pt} represent the percentage of time therapist t has to spend on patient type p. The translation from x_{pt} to v_{pt} can be done by applying the formula in Equation 4.28. The set of all variables v_{pt} represent the blueprint v, shown in Equation 4.29.

$$v_{pt} = \frac{\lambda sub_{pt} \cdot \frac{1}{\mu_p}}{\sum_{p \in P} \lambda sub_{pt} \cdot \frac{1}{\mu_p}} \qquad \forall p \in P, \forall t \in T \tag{4.28}$$

$$v = \{v_{pt} : p \in P, t \in T\} \tag{4.29}$$

4.4 Conclusions

This chapter answers the fourth research question: *How can we create a model for designing a blueprint schedule that maximises the number of patients treated within the access time norms?* First, we formulate an exact approach. However, the possibilities of this exact approach are minimal and besides the calculation time turns out to be too long. Therefore, we develop an approximation method: simulation-based optimisation. This solution approach is able to determine a blueprint for the Medical Psychology department. In the next chapter, we will dive into the performance of this method by executing several experiments.

Chapter 5

Experimental design and results

In the previous chapter, we developed a model to design a blueprint schedule for the Medical Psychology department. In this chapter, we test our developed method in two ways. First, we compare our heuristic approach to our exact model for small instances. Secondly, we test the real-life instances from the Medical Psychology department. We execute several experiments based on the input data of the Medical Psychology department.

5.1 Experimental design

5.1.1 Model input

In this subsection, we summarise the input for the baseline instance. This reflects the current situation at the Medical Psychology department. The input data necessary to design a blueprint with our solution approach are given in Table 5.1, Table 5.2 and Table 5.3.

Table 5.1 shows the patient types, with their arrival rates, service time parameters, and priority group, of the Medical Psychology department. Patients arrive according to a Poisson process with rate λ_p, and service times are exponentially distributed with rate $\frac{1}{\mu_p}$. Table 5.2 lists the therapists available to the Medical Psychology department and the amount of Full Time Equivalent (FTE) per therapist. For therapists in training, we work with 50% of the FTE since we can only use 50% of their time for patient care. Note that the therapists of the Medical Psychology department can spend 60% of their time on direct patient care. The other 40% is indirect patient care and is not included in the service time. Therefore, we only schedule 60% of every therapist's FTE. Finally, in Table 5.3, we summarise which patient types each therapist type is allowed treat. Therapists in training are allowed to treat the same patient types as therapists who are not in training. For a substantiation of our input variables, we refer to Appendix C.

The last input variable specific for the medical psychology department are the access time norms: one working day for inpatients and 20 working days for outpatients. We assume that a working day is equal to 8 hours.

Table 5.1: Summary of the input for the baseline measurement - patients ([U] = Utrecht, [Z] = Zeist)

Patient type	**Arrival rate (week)**	**Service rate (week)**	**Priority group j**
Inpatients - adults [U] (singular)	2.14	8.55	1
Inpatients - adults [Z] (singular)	0.16	12.31	1
Inpatients - child/youth [U] (singular)	0.63	4.96	1
Inpatients - adults [U] (complex)	0.27	4.81	1
Neuro patients [U] (singular)	1.63	7.76	2
Neuro patients [Z] (singular)	1.06	10.04	2
Neuro patients [U] (complex)	0.04	4.45	2
Remaining outpatients - adults [U] (singular)	4.40	7.36	2
Remaining outpatients - adults [Z] (singular)	0.59	8.20	2
Remaining outpatients - child/youth [U+Z] (singular)	3.08	4.92	2
Remaining outpatients - adults [U] (complex)	2.63	6.04	2
Remaining outpatients - child/youth [U] (complex)	0.06	6.96	2

Table 5.2: Summary of the input for the baseline measurement - therapists

Therapist type	**FTE**
Clinical psychologist - general 1	0.792
Clinical psychologist - general 2	0.889
Clinical psychologist - child/youth 1	0.847
Clinical psychologist - child/youth 2	0.847
Clinical psychologist - neuro psychology	0.864
Clinical psychologist in training - child/youth	0.889 * 0.5
Clinical psychologist in training - neuro psychology	0.889 * 0.5
Health care psychologist - neuro psychology	0.722
Health care psychologist in training - general 1	0.722 * 0.5
Health care psychologist in training - general 2	0.722 * 0.5

Table 5.3: Summary of the input for the baseline measurement - allowed treatments

Patient type	**CP-general**	**CP-child/youth**	**CP-neuro**	**HCP-general**	**HCP-neuro**
Inpatients adults [U] (singular)	1	1	1	1	1
Inpatients adults [Z] (singular)	1	1	1	1	1
Inpatients child/youth [U] (singular)	0	1	0	0	0
Inpatients adults [U] (complex)	1	1	1	0	0
Neuro patients [U] (singular)	0	0	1	0	1
Neuro patients [Z] (singular)	0	0	1	0	1
Neuro patients [U] (complex)	0	0	1	0	0
Remaining outpatients adults [U] (singular)	1	1	1	1	1
Remaining outpatients adults [Z] (singular)	1	1	1	1	1
Remaining outpatients child/youth [U+Z] (singular)	0	1	0	0	0
Remaining outpatients adults [U] (complex)	1	1	1	0	0
Remaining outpatients child/youth [U] (complex)	0	1	0	0	0

Based on the baseline instance, the model parameters are determined. The warm up period and the run length of the Discrete Event Simulation are respectively 10 years and 100 years. In Appendix D, details about the determination of the warm-up period and run length are given. Furthermore, the cooling scheme of the Simulated Annealing algorithm is determined in Appendix E. A summary of our cooling scheme is given in Table 5.4.

Table 5.4: Cooling scheme Simulated Annealing

Parameter	**Value**
Start temperature	50
End temperature	0.005
Markov chain length m	250
Decrease factor α	0.8

5.1.2 Model validation

We validated the evaluation model used in our simulation-based optimisation by expert opinion. The background analysis discussed in Chapter 2 provided good insights to how it should be modelled and serves as a basis for our modelling approach. One aspect of the real life situation that was simplified in our evaluation model is that of recurring appointments. Because modelling these as recurring appointments would complicate the model to an extent that would make it perform slowly, they were modelled to be one appointment. This is reasonable to assume given the level of detail of the model: It only schedules the percentage of time spent on patient types, not the actual operational planning of those patients. Experiment section 5.2.2 will elaborate on this, affirming that it has been a valid approach.
Unfortunately our model could not be compared with the current situation for evaluation. Currently, Diakonessenhuis does not yet have clear policies for assigning patients to therapists to compare. An evaluation also requires more data of the treated patients to be available.

5.1.3 Experiments

We execute two types of experiments. First, we investigate the performance of our solution approach by comparing it to our mathematical model. This can only be done for small instances, because for large instances the mathematical model does not find a solution within reasonable time. These experiments will be referred to as the theoretical experiments. Secondly, we execute several experiments for the Medical Psychology department. The instances for these experiments are too large for the exact model, so these will only be executed for our simulation-based optimisation model. Below, we describe the experiments we investigate.

- **Theoretical experiments - Performance of the solution approach:** We will investigate the gap between our simulation-based optimisation approach and our mathematical programming model. This is only possible for small instances, since the mathematical programming model cannot be solved for large instances within reasonable time. We expect a small gap, since this would imply that our solution model performs well. We will keep track of the computation time, since this tells us when we should use our exact model and when it becomes interesting to use the approximation method.

- **Practical experiments - Baseline measurement**: The baseline measurement will be the first practical experiment, since the baseline measurement reflects the current situation at the Medical Psychology department. The input values for the baseline measurement are described in the previous section. To address managerial questions, we vary the baseline input data in the successive experiments.

- **Practical experiments - Additional therapist type:** The first variation of our practical experiments investigates a typical strategic question: Which therapist type should be most profitable to hire as an addition to the current set of therapists at the Medical Psychology department? This potential future scenario is relevant to the Medical Psychology if there is budget to hire a new therapist. It also provides insight in which therapist type is the largest bottleneck in the baseline measurement.
- **Practical experiments - Dedicated therapist for inpatients:** The Medical Psychology department tries to cope with unplanned inpatients care. We are interested in the potential of having a therapist dedicated to the inpatients.
- **Practical experiments - Sensitivity for increase in arrivals:** In the future, the demand at the Medical Psychology department can change. With this scenario, we want to investigate the impact of changes in the arrival rates on the performance of the baseline blueprint. We also investigate what the performance would be if we design a new blueprint which includes the changes. This can give an indication about when the baseline blueprint should be revised.
- **Practical experiments - Additional priority group:** The Medical Psychology department distinguishes an additional group of semi-priority outpatients. The department estimates that the semi-priority patients account for 10% of all outpatients. These should be treated with higher priority than regular outpatients, but with a lower priority than inpatients. The department desires to treat these patients within 10 working days. In this experiment, we investigate the impact of having this third priority group.

The results of these experiments are given in the next section, Section 5.2.

5.2 Results

This section elaborates on the results of the experiments. We programmed the quadratic mixed integer nonlinear mathematical programming model as well as the simulation-based optimisation model in Python 3.8 executed on a computer with an i7 processor and 16GB random access memory. For the mathematical programming model, we used the optimisation software Gurobi.

5.2.1 Theoretical experiments - Performance of the solution approach

In this set of experiments, we investigate the performance of our solution approach by comparing it with our exact approach. We do this by executing our exact approach and determining the objective value it yields. Then we execute the solution approach with the same input as our exact approach and obtain the solution setting. The objective value of this solution setting, using the objective function of our exact model, is calculated and compared with the obtained objective value from our exact approach.

We want to compare the largest instances possible. However, our exact approach needs too much computation time for three therapists and two patient types already. Therefore, we can only compare instances with two therapists and at most four patient types. For two therapists and five patient types, the computation time is over 12 hours which is considered too long. In order to test various instances increasing in size, we compare the exact approach and the solution approach for instances with two therapists and two, three, and four patient types. These experiments are executed for therapists that are allowed to treat all patient types. To eliminate setting differences, we keep the total occupation to 0.8 for all three experiments. The results are given in Table 5.5

Table 5.5: Results: Theoretical experiments - Performance of the solution approach (perf = performance, comp. time = computation time)

Experiment	**Exact approach**	**Solution approach**	**Gap**
2 therapists, 2 patient types	perf: 200 comp. time: 3.2 s	perf: 249 comp. time: 3717 s	49 (24.5%)
2 therapists, 3 patient types	perf: 201 comp. time: 338 s	perf: 236 comp. time: 3843 s	35 (17.4%)
2 therapists, 4 patient types	perf: 209 comp. time: 2947 s	perf: 261 comp. time: 3935 s	52 (24.9%)

The performances given in the table are both based on the objective function of our exact approach, in which a small exceedance of the access time norm is penalised less severe than a large one. This is realised by using a quadratic function for the penalty. A gap of 52 is therefore relatively small. Besides, the gap is not only caused by approximation. The solution method is designed to optimise a slightly different objective function, to compare our two models, we tested the solution gained from the approximation model on the objective function of our exact model. This has a negative influence on the gap between objective of the solution obtained from the exact approach and the solution obtained from the solution approach. Therefore, we think that our solution method performs well.

We can see that the computation time of our solution approach remains constant with increasing instance size. This is because the computation time of or solution approach is strongly dependent on the number of patients that go through the system. Since we are keeping the total occupation to 0.8, the number of patients going through the system does not deviate strongly from run to run. However, the computation time of the mathematical model rapidly increases with the instance size. We advise to use the solution approach from an instance size of two therapists and five patient types or larger. Then, the additional computation time does not outweigh the optimality gap. For larger instances, the optimality gap will probably increase slightly since we use the same number of iterations for a larger solution space. However, we expect that the solution obtained by our solution approach will stay near-optimal, because we explore and exploit a large part of the solution space.

When looking at the blueprints itself, the solutions are very different. This implies that there are many promising solutions in different regions of the solution space. This makes it hard to find the global optimum, but it makes it easier to find a good performing solution. This also brings opportunities for optimisation based on other criteria, because if there are many good performing solutions according to access time in different regions of the solution space, some of these solutions might perform fairly good based on other criteria as well. Especially because the solutions are so different from each other, the solutions might score different on the new criteria. This increases the chance of having good solutions based on other criteria as well.

5.2.2 Practical experiments - Baseline measurement

In the first practical experiment, we determine the blueprint for the baseline situation at the Medical Psychology department. Figure 5.1 shows the resulting blueprint. The average penalty for patients treated outside the access time norm is 0.90. Figure 5.2 and Figure 5.3 show the distribution of patients' access time over the intervals. These figures also shows the current performance at the Medical Psychology department obtained from the available data. It turns out that 66% of the inpatients and 97% of the outpatients can be treated within the access time norm.

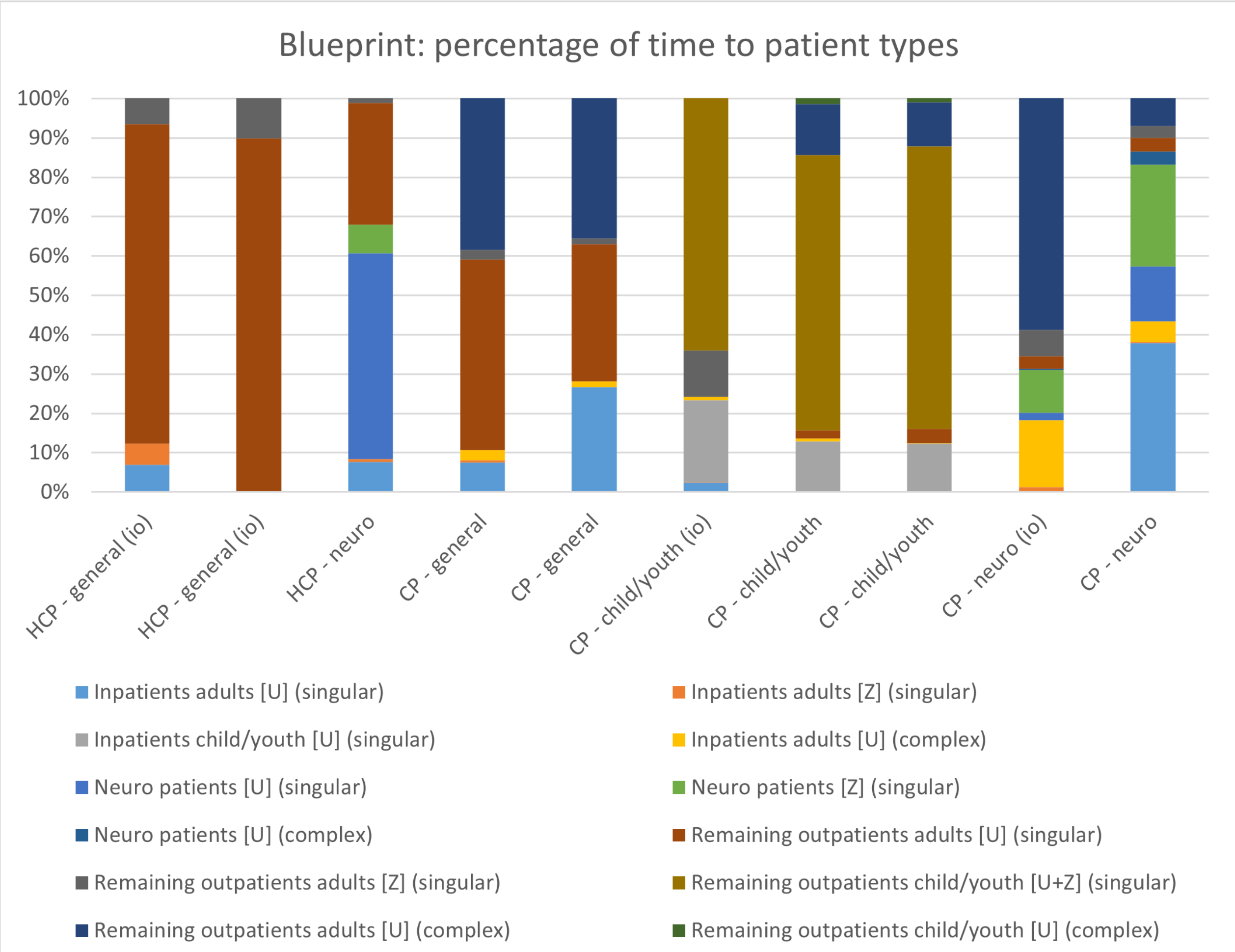


Figure 5.1: Blueprint base measurement

The number of outpatients treated within the access time norm is close to 100%, which was the main goal of our research. Especially compared to the current situation, in which 40% of the outpatients have an access time longer than 40 working days. Furthermore, the blueprint results in less fluctuation in access times of individual patients.

The number of inpatients treated within the access time norm, however, is relatively low. Especially since the inpatients treated within the access time norm are much higher in the real-life situation at the Medical Psychology department. A reason for this is that the service time is modelled as one service, while in reality the patients have multiple recurring appointments. It is chosen to model this as one service time because the goal of the blueprint is to obtain the percentage of time therapist should spend on each patient type. However, since we cannot interrupt a service, a long service time of an outpatient can cause that an inpatient is waiting that whole service time of the outpatient. In reality, the appointment of the outpatient is only one hour and the inpatient can be treated after that. This means that our model overestimates the access time of inpatients.

To show the difference in performance when modelling the service time of patients multiple separated service times, we calculated the performance of the original baseline blueprint based on higher arrival and service rates. We assume that the appointments at the Medical Psychology department take one hour, so we increased the access rates and service rates by 40/old service rate. In this way, we created all appointments of one hour. This is not realistic as well, since some of the service time of patients is processing time by therapists, for example writing reports about the diagnosis or consultations with doctors and other therapists. However, it gives an indication of the real performance. In this way of modelling we assume Poisson arrivals as well, but the arrivals of recurring appointments of one patient are not independent. We assume that in the long run, this mediates.

Figure 5.2 shows that the number of inpatients treated within the access time norm does increase a lot. The percentage of patients treated within the access time norm becomes even higher than the real-life performance. The percentage of outpatients treated within the access time norm stays the same compared to the baseline blueprint, see Figure 5.3. We showed that the original baseline blueprint performs well for the case with separated service times, so in our simulation based optimisation, we keep using one longer service time. The calculation of the performance with the Discrete Event Simulation is more time consuming when simulating the service times as separate service times because many more events take place.

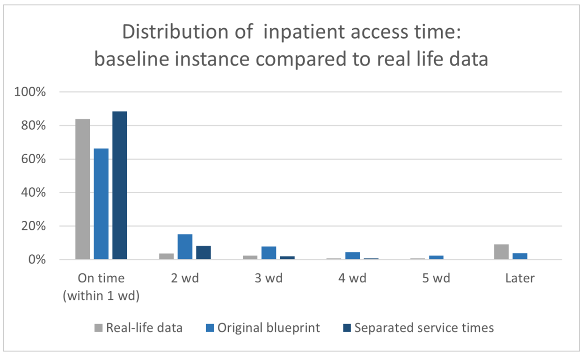


Figure 5.2: Distribution base measurement inpatients (wd = working days)

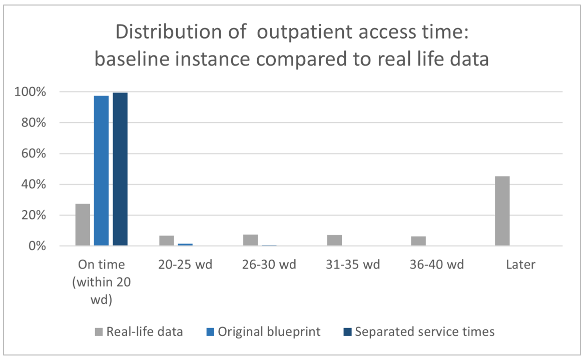


Figure 5.3: Distribution base measurement outpatients (wd = working days)

5.2.3 Practical experiments - Additional capacity

In this experiment, we determine the performance when adding a therapist of a certain type to the base model. The results are shown in Figure 5.4. The performance reflects the average penalty, which means that the lower the value for the performance the better. This means that the child/youth psychologists are most profitable to add. The clinical psychologist is most profitable, but clinical psychologists are more specialised and thus more expensive than health care psychologists. Therefore, based on these results we would advise to hire a health care psychologist for child/youth when there is budget to hire additional personnel.

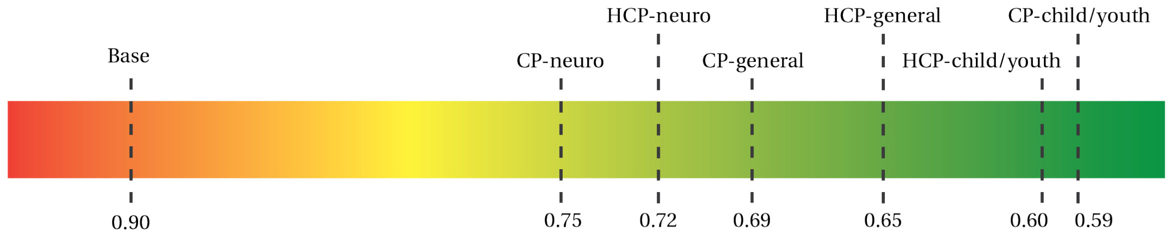


Figure 5.4: Results of the experiments when adding a therapist type

For the child/youth psychologists, adding a clinical psychologist is more profitable. For the clinical general and clinical neuro psychologists however are outperformed by the health care psychologists of the same type. However, we would expect a higher performance for the clinical psychologists, since the clinical psychologists are allowed to do the same tasks and more as health care psychologists. Clinical psychologists are therefore more expensive, but these costs are not included in the model. Therefore, we expect that the solutions are not optimal, which makes sense because the solution approach is an approximation. To get an idea of the uncertainty of the performances, we execute our solution method ten times for our advise, which is adding a health care psychologist specialised in child/youth. This results in values between 0.53 and 0.77. The performances of all other experiments with an additional therapists are in this interval, which means that we cannot conclude that adding a health care psychologist for child/youth is absolutely the best decision. This is an indication that our used run length for the Discrete Event Simulation might be too short. To make a more informed decision, we advise to do more replications of the experiments.

Adding a health care psychologist for child/youth does improve the systems performance compared to the baseline measurement. More inpatients are treated on time and the percentage of outpatients treated on time also slightly improves. However, we do not think the costs of an additional therapist outweigh the small improvement in performance. Figure 5.5 and Figure 5.6 show the improvement potential of the distribution of patient access time when adding a health care psychologist for child/youth to the current situation.

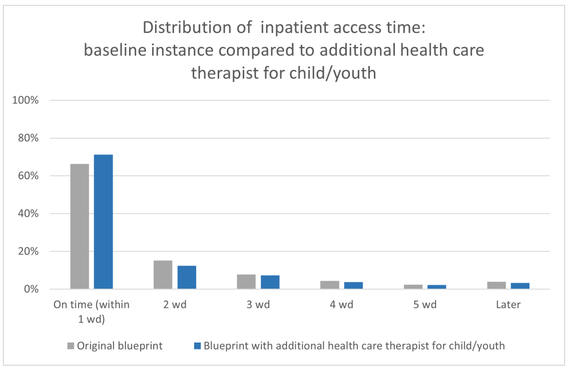


Figure 5.5: Distribution inpatient when adding an additional child/youth health care psychologist (wd = working days)

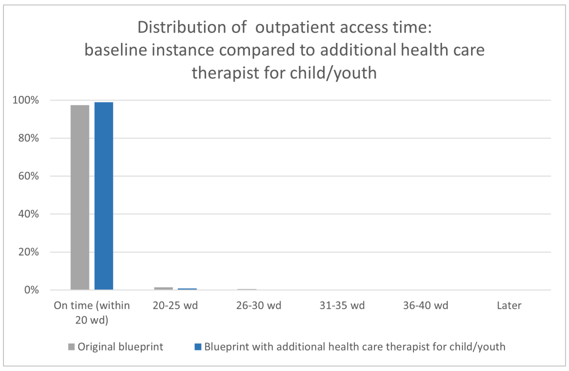


Figure 5.6: Distribution outpatient when adding an additional child/youth health care psychologist (wd = working days)

5.2.4 Practical experiments - Dedicated therapist for inpatients

The department is interested in the potential of one therapist dedicated to inpatient care. Therefore we test instances in which one therapist is dedicated to inpatient care. We allow other therapists to treat inpatients as well, since otherwise the queue of the dedicated therapist would explode. We executed four experiments in which one type of therapist is dedicated to inpatient care. We decided to not dedicate therapist in training, since they have to do a diverse set of tasks to learn the specialism. The results are shown in Table 5.6.

Table 5.6: Results of the experiments when dedicating a therapist to inpatient care

Therapist type dedicated	Performance
Clinical psychologist - general	0.94
Clinical psychologist - child/youth	1.32
Clinical psychologist - neuro psychology	0.87
Health care psychologist - neuro psychology	0.81

The lower the performance, the better, so dedicating a health care psychologist for neuro psychology to inpatient care is most profitable. This is an indication that neuro psychologists are the least restrictive resource. This corresponds to our findings in Subsection 5.2.3, where an additional neuro psychologists was the least profitable. The performance is even better than the baseline measurement, which yields a performance of 0.90. However, this difference is not significant.

Based on the performance, it seems to be profitable to add a therapist dedicated to inpatient care. However, it is not necessarily desirable to do this. The dedicated therapist always has to do inpatient care, which does not contribute to motivation and personal development. Besides, the dedicated therapist does probably not work every day, which means that the other therapists who got inpatient care assigned should work on the days the dedicated therapist is not available. Otherwise, inpatients request care at days no therapist is available for inpatient care and the patients have to wait for therapists coming to work, which is an even bigger problem in holiday periods.

5.2.5 Practical experiments - Sensitivity for increase in arrivals

The experiments in this section are done to investigate the sensitivity of the model to changes in arrival rate. We investigated 6 scenarios: changes in arrival rates between -15% and +15% with steps of 5%. For every scenario, we investigate what the performance would be if the blueprint is not revised. This gives an idea of the robustness of our blueprint. We also investigate what the performance would be if the blueprint is revised. The larger the gap between these two, the more revising the blueprint yields. The results of the experiments are given in Figure 5.7.

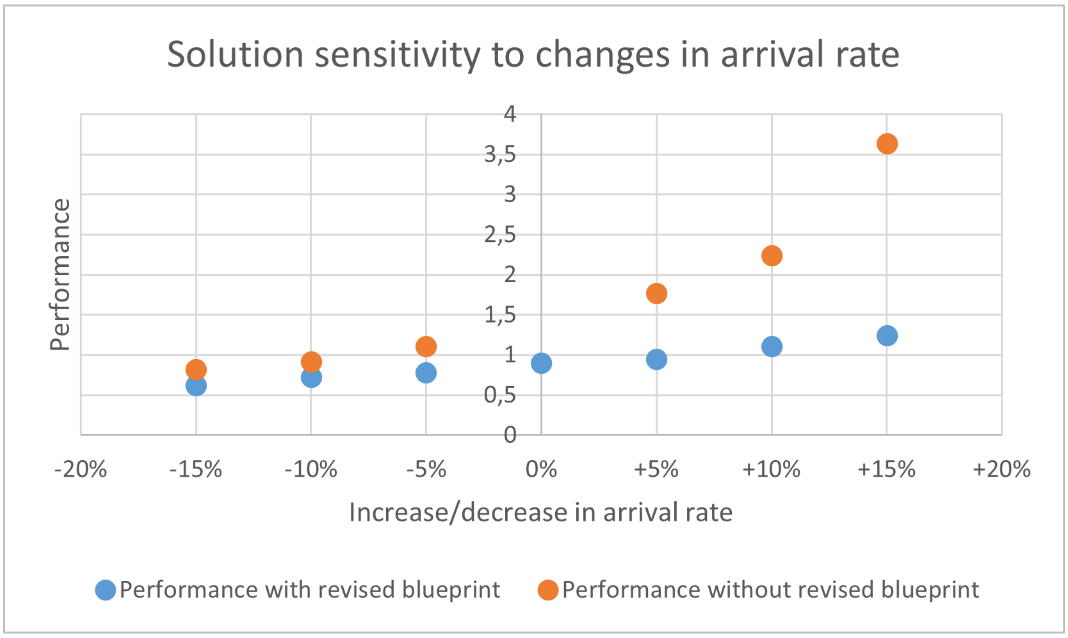


Figure 5.7: Sensitivity of the model to changes in arrival rate

The results show that the blueprint is not very sensitive to changes when the arrival rates decrease. The performance of the baseline blueprint is slightly worse than the performance of a revised blueprint based on lower arrival rates. However, for increasing arrival rates this does not hold. The performance of the baseline blueprint increases fast when the arrival rate increases, and the performance deteriorates more rapidly when the increase is in arrival rate larger. This could be due to the quadratic element in the objective function. We see that, for the scenario with +5% increase in arrival rate, the performance of the the unrevised blueprint is 85% higher than the revised blueprint. For the scenario with +15% increase in arrival rate, this gap became 200%. Figure 5.8 and Figure 5.9 show that, when a 5% increase in arrival rate occurs, revising the blueprint is profitable for both the percentage of inpatients treated on time as the percentage of outpatients treated on time. Therefore, we advise to revise the blueprint when the arrival rates increase with 5% or more.

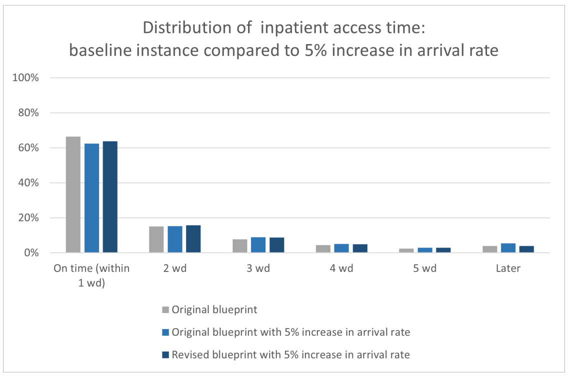


Figure 5.8: Distribution inpatient access time with 5% increase in arrival rate (wd = working days)

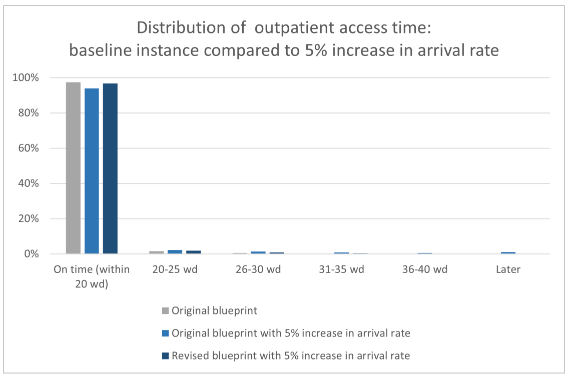


Figure 5.9: Distribution outpatient access time with 5% increase in arrival rate (wd = working days)

5.2.6 Practical experiments - Additional priority group

In the previous experiments, we gave all outpatients the same priority. However, at the Medical Psychology department some outpatients get priority over other outpatients: semi-priority patients. These patients have an access time norm of 10 working days and do not have priority over inpatients. We did not include the semi-priority group in the previous experiments, because there is no available data on the number of outpatients belonging in this category. Employees of the Medical Psychology department estimate the percentage of outpatient with semi-priority to be 10% of the outpatients. In this last experiment, we test the influence of this additional priority group.

We model this by splitting the semi-priority outpatients and the regular outpatients, which means that we get 8 additional patient types. The standard 8 outpatient types and an additional 8 outpatient types with semi-priority. The arrival rates of the standard outpatients are 90% of the baseline instance and the arrival rates of the semi-priority outpatients becomes 10% of the baseline instance. The service times stay the same for the corresponding types, since we assume that the semi-priority does not influence the required service time.

The performance deteriorates slightly when adding a semi-priority group of 10% of the outpatients: from 0.90 in the baseline measurement, to 0.92 in the situation with the semi-priority group. This is only a small difference and is not significant. The small difference implies that it is not a problem to have a semi-priority group of 10% of the outpatients in terms of performance. An explanation could be that the access times of most regular outpatients were short and only increased slightly, not exceeding the access time norm. A larger semi-priority group is likely to cause more deterioration in performance. In Figure 5.10, the distribution of the access times of the patients is given per priority group. The distribution of patient access time is approximately equal to the distribution of the baseline measurement. Here 97% of the semi-priority outpatients and 97% of the regular outpatients are treated on time, where in the baseline 97% of all outpatients are treated on time. 63% of the inpatients were treated on time after adding the semi-priority group; a slightly worse result compared to the baseline measurement in which 66% of the inpatients were treated on time. Unfortunately, we cannot compare this to the current situation, since there is no quantitative data available about which patients belong in the semi-priority group and thus whether they were treated within their access time norm of 10 working days.

The influence of adding a semi-priority group of 10% of the outpatients does not have a large influence on the system in terms of performance. However, there are two other disadvantages of modelling the semi-priority group. First, the solution space becomes much larger. This will result in a larger gap between the optimal solution and the best found solution. Secondly, it can be difficult for therapists to work with a high number of patient types. The blueprint gives information about what percentage of the time should be spend on each patient type. The more patient types, the more fragmented the blueprint gets, making it harder to adhere by the therapists. Therefore, it is preferred to have the fewest number of priority groups possible.

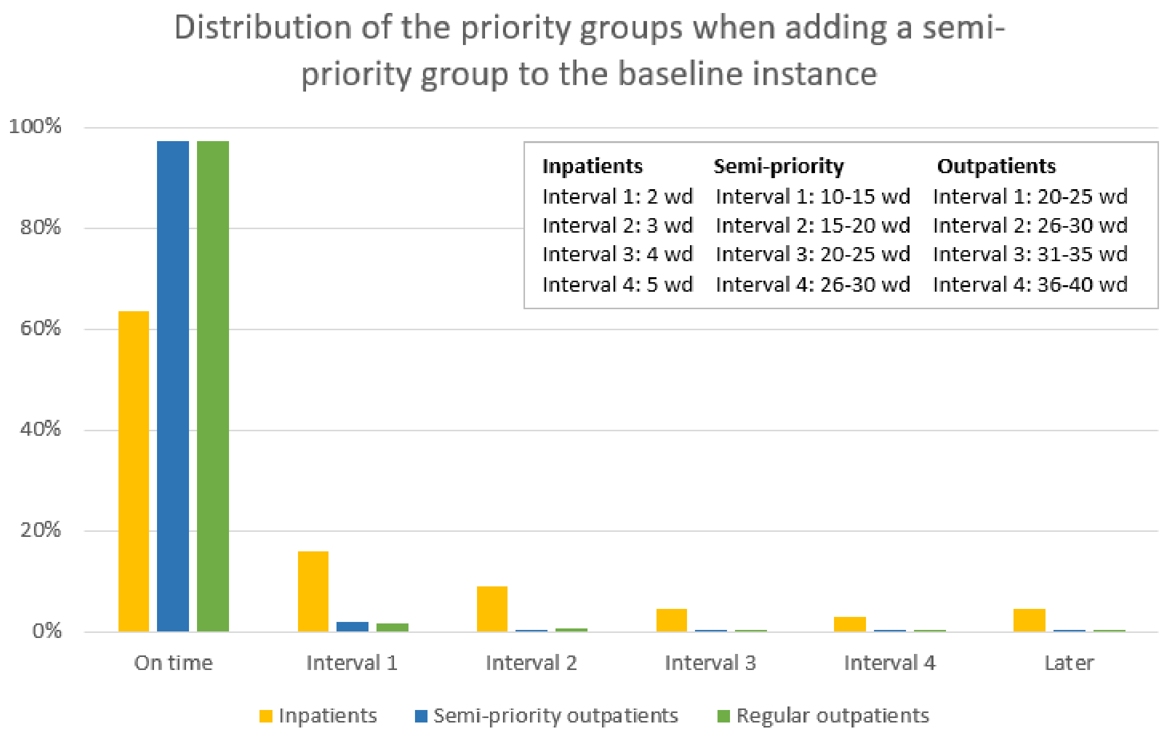


Figure 5.10: Distribution of patient access times per priority group, including semi-priority outpatients

5.3 Conclusions

This chapter answers the fifth research question: *What are the effects of the blueprint schedule on the number of patients treated within the access time norm at the Medical Psychology department given several future scenarios, and where is the most improvement potential?* We show that the blueprint significantly increases the number of outpatients treated within the access time norm from 27% to 97%. The number of inpatients increases from 84% to 88% when modelling the service times as separated appointments. This means that implementing the blueprint is very promising.

In additional experiments, we see that child/youth therapists form the biggest bottleneck. Adding a child/youth therapist to the baseline instance ensures the largest improvement in performance. If the Medical psychology department wants to dedicate one therapist to inpatient care, they should choose to dedicate the health care neuro psychologist. This did not yield a significant change in performance compared to the baseline blueprint. However, we do not advise to do this, since it comes with practical disadvantages. By doing experiments on changes in arrival rate, we found that the blueprint is sensitive to increasing arrival rates. This means that the blueprint should be revised as soon as an increase of 5% or higher occurs at the Medical Psychology. Our final experiment was adding a semi-priority group, which consists 10% of the outpatients. Despite the performance not deteriorating much, we prefer not to allow such a semi-priority group because of the increasing problem size.

Chapter 6

Conclusion

This chapter contains the conclusion of the research, in Section 6.1, answering the research questions stated in Chapter 1. Section 6.2 provides a discussion of the research. We state the necessary steps for implementation in Section 6.3 and we finish in Section 6.4 with opportunities for further research.

6.1 Conclusion

This project aimed to design a blueprint schedule for the Medical Psychology department in Diakonessenhuis to optimise the number of patients treated within the access time norm. For this, we designed a blueprint using simulation-based optimisation. We found that implementing this can increase the number of inpatients and outpatients treated within the access time with respectively 4 and 70 percentage points, compared to the current situation.

As blueprints have various goals, levels of detail, and characteristics, we developed a framework in which various types of blueprints are positioned based on the organisations goals. The positioning of the Medical Psychology department showed that they require a blueprint defining the percentage of time therapists should spend on each patient type, which also includes insight in the amount of time necessary for unplanned care.

We designed two models to design the blueprint schedule: an exact model and an approximation solution method. The exact model is formulated as a quadratic mixed integer nonlinear mathematical programming model, but it performed too slow for large instances. Therefore, we designed a simulation-based optimisation heuristic using Simulated Annealing. When comparing the heuristic with our exact model, it showed that the approximation approach yields a near-optimal solution.

The approximation method allows for experimentation with different configurations. These configurations are based on the baseline input data of the Medical Psychology department. To obtain some managerial insight, we varied the baseline input by executing various experiments. First, we focused on adding a therapist to the system. This analysis showed that adding a child/youth therapist ensures the largest improvement in performance. Then, we analysed the effect of dedicating one therapist to inpatient care. This did not yield a significant change in performance. However, we advise against this as it comes with practical disadvantages. The final experiment showed that the blueprint is sensitive to increasing arrival rates. The results indicate that the blueprint should be revised from a 5% increase in patients.

Ultimately, the results of the research provide quantitative data on the improvement potential of implementing a blueprint schedule at the Medical Psychology department. The percentage of inpatients treated within the norm increased from 84% to 88% and the percentage of outpatients treated within the access time norm increased from 27% to 97%. Moreover, the use of a blueprint provides insight into the available capacity and helps to determine the expected waiting time of a new patient. We believe that these are major improvements and therefore we recommend implementing the blueprint in the Medical Psychology department.

6.2 Discussion

The first limitation is the limited patient data. The registration in the patient database is not managed accurately at the moment. The therapists approach the of the patient registration process differently, resulting in inconsistencies in data interpretation. Inconsistencies in registration cause large differences in arrival rates for various patient types and thus in the blueprint. This means that our blueprint is not directly applicable to the Medical Psychology department.

The second limitation is that therapists can only register fixed times for specific activities. Often, these times do not correspond to reality. We modelled this remaining time as indirect patient care, but it would be more accurate if the duration of indirect patient care was registered as well. According to psychologists, large differences exist between the amount of required indirect patient care per patient type. For example, indirect patient care requires much more time for neuro patients than for other types. Excluding this from the model has influenced the results, as the results of the model show that neuropsychology forms the smallest bottleneck. In reality only 3.1% of the neuro patients are treated within the access time norm.

The third limitation we want to point out is the comparison of the model to the real-life situation. Compared to the real-life situation, our modelling approach shows major improvements, especially for the access time of the outpatients. However, a reason for this can be that there is a backlog in the department. A backlog negatively influences performance. In our model, we did not take a backlog into account.

The last limitation to discuss is the uncertainty in the resulting performances. This was especially apparent in the experiments for additional capacity. The performance values were very close, so there was no clear configuration that performed better. This could be because the run length of the Discrete Event Simulation is more sensitive for various situations than expected and that the run length should be longer than assumed. A longer run length would be disadvantageous for the computation time of our solution method. Especially because the simulation-based optimisation has to evaluate many candidate solutions with the Discrete Event Simulation.

6.3 Implementation plan

The blueprint designed in this research is not directly implementable in the Medical Psychology department. As already mentioned in the discussion, the registration of patients in the database is not up to date. However, we used these data as input for the blueprint of our research. The department should manage the registration in the patient database more accurately. Only then, more accurate input data can be retrieved and used for the model, which is necessary to make the blueprint relevant for the Medical Psychology department. However, there are also some other changes needed.

The therapists need to keep track of the available time for each patient type. An integrated system is best since it gives therapists insight in the amount of work they do. It also allows the management to check whether the blueprint is adhered by the therapists. However, an integrated system is not yet available, so the therapists should monitor this themselves. Also, the patient type of a patient should be determined immediately at the referral. The patient should then immediately be assigned to the therapist with the most time available for that patient type according to the blueprint and his or her agenda. A therapist should treat the assigned outpatients in a first-come-first-serve order and must not deviate from this if not really necessary.

When the department is using the blueprint, it should be revised frequently since the blueprint is sensitive to changes. Two changes that are a reason for revision are changes to the configuration of the department and increase in yearly average patient arrival rate. A revised blueprint can result in a totally different distribution of patients among therapists. Because patients who have already started treatment must finish their treatment at the same therapist, the revision is not a quick adaptation, but a gradual transition. If changes happen often, the department is often in the transition phase, meaning that the potential of using the blueprint is not fully utilised.

6.4 Further research opportunities

The results presented in this thesis provide new research opportunities for both the blueprint framework and the model. The framework we designed for positioning blueprints does not cover all common key performance indicators and characteristics imaginable. Expanding the framework in this way also requires more literature research to be done on these topics. Moreover, exploring the literature from several data bases will improve the framework as well, since we only used the Scopus database.

The model is not highly adaptive to changes. If input parameters change, the current version of the blueprint would require an update for optimal performance. Since temporary changes in input parameters are not uncommon, this means a frequent revision of the blueprint. Each revision of the blueprint requires a transition phase in the department which is at the cost of efficiency. Therefore, a more robust blueprint would be an improvement.

The Discrete Event Simulation comes with a lot of uncertainty. We could increase the run length to solve this, but it could also be interesting to use robust optimisation. For every iteration, a confidence interval could be constructed and the upper bound of the confidence interval could be used as an objective value. In this way, accidental low performances due to randomness are not influencing the optimisation approach. These are relatively simple adjustments of the model. However, the computation time of the model will increase rapidly and the experiments should be executed with more powerful hardware.

Our exact model and our solution model include symmetry, which is currently unused. This results in the same therapist types having several patient mixes, while the same therapists should get the same mix of tasks. Including symmetry brings the benefit of a smaller solution space. This decreases the computation times of the exact model and gives a better solution in the same computation time of the approximation solution method.

Additional requirements can be included to make the model even more applicable to the Medical psychology department. For example, a diverse patient case mix for therapists in training, and disallowing very small assigned percentages that make it harder to apply the blueprint in practice. It is also interesting to use the model outside the Medical Psychology department. Additional requirements can be used to make the model applicable to other areas in which access times are a problem. These can be other departments in a hospital, or examples outside the health care field, such as the production of various products with a specific delivery time, or court trials in which some have priority over others.

The blueprint we designed only defines the percentage of time to spend on each patient type. The department desired to have a blueprint on this level of detail, but planning the inpatient capacity can benefit from specifying the moment of capacity usage. For example, when three therapists have inpatient time assigned, but none of them is working on Wednesdays, inpatients referred on Wednesdays always have to wait till Thursday for treatment. Our blueprint can serve as a basis for a model that divides the inpatient capacity over the weekdays. The new model could use our results as input, or, if the computation time allows, it could extend the Discrete Event Simulation with the working days of therapists.

References

Adan, I., & Resing, J. (2015). *Queueing Systems* (Tech. Rep.). Eindhoven: Eindhoven University of Technology.

Aslani, N., Kuzgunkaya, O., Vidyarthi, N., & Terekhov, D. (2021, 3). A robust optimization model for tactical capacity planning in an outpatient setting. *Health Care Management Science*, *24*(1), 26–40. doi: 10.1007/s10729-020-09528-y

Bikker, I. A., Mes, M. R., Sauré, A., & Boucherie, R. J. (2020, 7). Online Capacity Planning for rehabilitation Treatments: an Approximate Dynamic Programming Approach. *Probability in the Engineering and Informational Sciences*, *34*(3), 381–405. doi: 10.1017/S0269964818000402

Borgman, N. (2017). *Managing urgent care in hospitals* (Doctoral dissertation, University of Twente, Enschede, The Netherlands). doi: 10.3990/1.9789036543606

Canonaco, P., Legato, P., Mazza, R. M., & Roberto Musmanno. (2008, 8). A queuing network model for the management of berth crane operations. *Computers and Operations Research*, *35*(8), 2432–2446. doi: 10.1016/j.cor.2006.12.001

Carreras-García, D., Delgado-Gómez, D., Baca-García, E., & Artés-Rodriguez, A. (2020). A Probabilistic Patient Scheduling Model with Time Variable Slots. *Computational and Mathematical Methods in Medicine*, *2020*. doi: 10.1155/2020/9727096

Cayirli, T., & Veral, E. (2003). *Outpatient Scheduling In Health Care: A Review Of Literature* (Vol. 12; Tech. Rep.). New York: Hofstra University.

Cayirli, T., Yang, K. K., & Quek, S. A. (2012, 7). A Universal Appointment Rule in the Presence of No-Shows and Walk-Ins. *Production and Operations Management*, *21*(4), 682–697. doi: 10.1111/j.1937-5956.2011.01297.x

Christos, C. G., & Lafortune, S. (2008). *Discrete Event Systems Second Edition.*

Creemers, S., Beliën, J., & Lambrecht, M. (2012, 6). The optimal allocation of server time slots over different classes of patients. *European Journal of Operational Research*, *219*(3), 508–521. doi: 10.1016/j.ejor.2011.10.045

Deglise-Hawkinson, J., Helm, J. E., Huschka, T., Kaufman, D. L., & Van Oyen, M. P. (2018, 12). A Capacity Allocation Planning Model for Integrated Care and Access Management. *Production and Operations Management*, *27*(12), 2270–2290. doi: 10.1111/poms.12941

Delahaye, D., Chaimatanan, S., & Mongeau, M. (2019). Simulated Annealing: From Basics to Applications. In M. Gendreau & J.-Y. Potvin (Eds.), *Handbook of metaheuristics* (pp. 1–35). Cham: Springer International Publishing. doi: 10.1007/978-3-319-91086-4

Diakonessenhuis. (2022). *Diakonessenhuis.* Retrieved 20/03/2022, from `https://www.diakonessenhuis.nl/over-ons#:~:text=We%20hebben%20in%20ons%20ziekenhuis,500%20bedden`

Diakonessenhuis Utrecht. (2020). *Jaarverslag 2020 Medische psychologie Diakonessenhuis* (Tech. Rep.). Utrecht: Diakonessenhuis.

Fu, Y., & Banerjee, A. (2021, 9). A Stochastic Programming Model for Service Scheduling with Uncertain Demand: an Application in Open-Access Clinic Scheduling. *Operations Re-*

search Forum, *2*(3). doi: 10.1007/s43069-021-00089-6

Hans, E. W., & Vanberkel, P. T. (2012). *Chapter 5 Operating Theatre Planning and Scheduling* (Tech. Rep.). Enschede: Center for Healthcare Operations Improvement & Research.

Hans, E. W., Van Houdenhoven, M., & Hulshof, P. J. (2012). A framework for healthcare planning and control. In *International series in operations research and management science* (Vol. 168, pp. 303–320). Springer New York LLC. doi: 10.1007/978-1-4614-1734-7{_}12

Heerkens, H., Winden, A. v., & Tjooitink, J.-W. (2021). *Solving managerial problems systematically* (1st ed.). Groningen/Houten: Noordhoff Uitgevers bv.

Hsu, H.-P., Chou, C.-C., & Wang, C.-N. (2022, 6). Heuristic/Metaheuristic-Based Simulation Optimization Approaches for Integrated Scheduling of Yard Crane, Yard Truck, and Quay Crane Considering Import and Export Containers. *IEEE Access*, *10*, 64650–64670. doi: 10.1109/access.2022.3180752

Hulshof, P. J., Boucherie, R. J., Hans, E. W., & Hurink, J. L. (2013, 6). Tactical resource allocation and elective patient admission planning in care processes. *Health Care Management Science*, *16*(2), 152–166. doi: 10.1007/s10729-012-9219-6

Kaandorp, G. C., & Koole, G. (2007, 9). Optimal outpatient appointment scheduling. *Health Care Management Science*, *10*(3), 217–229. doi: 10.1007/s10729-007-9015-x

Kortbeek, N., Zonderland, M. E., Braaksma, A., Vliegen, I. M., Boucherie, R. J., Litvak, N., & Hans, E. W. (2014, 10). Designing cyclic appointment schedules for outpatient clinics with scheduled and unscheduled patient arrivals. *Performance Evaluation*, *80*(C), 5–26. doi: 10.1016/j.peva.2014.06.003

Laan, C., van de Vrugt, M., Olsman, J., & Boucherie, R. J. (2018, 5). Static and dynamic appointment scheduling to improve patient access time. *Health Systems*, *7*(2), 148–159. doi: 10.1080/20476965.2017.1403675

Leeftink, A. G., Vliegen, I. M., & Hans, E. W. (2019, 3). Stochastic integer programming for multi-disciplinary outpatient clinic planning. *Health Care Management Science*, *22*(1), 53–67. doi: 10.1007/s10729-017-9422-6

Nguyen, T. B. T., Sivakumar, A. I., & Graves, S. C. (2015, 6). A network flow approach for tactical resource planning in outpatient clinics. *Health Care Management Science*, *18*(2), 124–136. doi: 10.1007/s10729-014-9284-0

Qu, X., Peng, Y., Kong, N., & Shi, J. (2013, 9). A two-phase approach to scheduling multi-category outpatient appointments - A case study of a women's clinic. *Health Care Management Science*, *16*(3), 197–216. doi: 10.1007/s10729-013-9223-5

Riet, V. C., Van Riet, C., & Demeulemeester, E. (2015). *Trade-offs in operating room planning for electives and emergencies: a review* (Tech. Rep.). Retrieved from `http://ssrn.com/abstract=2553849https://ssrn.com/abstract=2553849Electroniccopyavailableat:http://ssrn.com/abstract=2553849Electroniccopyavailableat:https://ssrn.com/abstract=2553849`

Scollen, A., & Hargraves, T. (2018). *Simulated annealing: Introduction, applications and theory.*

Sibalija, T. V. (2018). *Application of simulated annealing in process optimization: A review.*

Soykan, B., & Rabadi, G. (2022). A simulation-based optimization approach for multi-objective runway operations scheduling. *Simulation*. doi: 10.1177/00375497221099544

Srinivas, S., & Ravindran, A. R. (2020, 9). Designing schedule configuration of a hybrid appointment system for a two-stage outpatient clinic with multiple servers. *Health Care Management Science*, *23*(3), 360–386. doi: 10.1007/s10729-019-09501-4

Vanberkel, P. T. (2011). *Interacting Hospital Departments and Uncertain Patient Flows* (Tech. Rep.). Enschede: Research School for Operations Management and Logistics.

Van Oostrum, J. M., Van Houdenhoven, M., Hurink, J. L., Hans, E. W., Wullink, G., & Kazemier, G. (2008, 4). A master surgical scheduling approach for cyclic scheduling in operating room departments. *OR Spectrum*, *30*(2), 355–374. doi: 10.1007/s00291-006-0068-x

Vektis. (2022, 2). *Factsheet wachttijdinformatie ggz.* Retrieved 27/03/2022, from `https://www.vektis.nl/intelligence/publicaties/factsheet-wachttijdinformatie-ggz#:~:text=De%20aanmeldwachttijd%20is%20de%20tijd,wachttijd%20is%20daarmee%2014%20weken.`

Winston, J. B., Wayne L.; Goldberg. (2004). *Operations Research APPLICATIONS AND ALGORITHMS.*

Yang, K. K., & Cayirli, T. (2020, 1). Managing clinic variability with same-day scheduling, intervention for no-shows, and seasonal capacity adjustments. *Journal of the Operational Research Society*, *71*(1), 133–152. doi: 10.1080/01605682.2018.1557023

Appendix A

Literature review approach

This appendix presents the systematic approach of search for literature. We present the approach used for finding the articles. The objective and scope of the literature are described in order to define relevant search terms. By doing so, the useful articles are identified. The database used for this literature review is the Scopus database, as provided by the University of Twente.

Search for articles
The aim of the literature review is to determine the type of blueprint most suitable for the Medical Psychology department. To achieve this goal we design a framework in which the blueprint found in literature can be placed. This framework distinguishes the key performance indicators, level of detail and included characteristics. The focus of the literature review is on blueprints incorporating unplanned care and optimising the KPI access time. We only investigate blueprints types and their methods, other solutions are out of scope.

The search string used was:

("*blueprint*" OR "*block plan**" OR "*block schedul**" OR "*optimal schedul**" OR "*capacity allocation*" OR "*capacity planning*" OR "*resource planning*" OR ("*schedul**" AND "*template*") OR "*appointment schedul**" OR "*appointment system**" OR "*patient scheduling*")

AND

("*hybrid appointment*" OR "*open access schedule**" OR "*open access requirement**" OR "*open-access schedul**" OR "*open access plan**" OR "*advanced access*" OR "*same day schedul**" OR "*same day patient**" OR "*same-day requests*" OR "*urgent access*" OR "*same-day schedul**" OR "*same-day patient**" OR "*short-notice schedul**" OR "*walk-in schedul**" OR "*access time*" OR "*access management*" OR "*emergency planning**" OR "*emergency schedul**" OR "*emergency surgery*")

In total, these keywords provided a collection of 182 sources from the Scopus library. The sources were then filtered based on several exclusion criteria. The exclusion criteria used can be found in Table A.1 together with the number of sources this yields for.

Table A.1: Overview of the literature search approach

	Number of sources
Sources after search string	182
Exclusion criteria	
Language: Dutch or English	-4
Only use Article, Book, or Review	-18
Full article not available	-33
Article data before the year 2000	-18
Did not discuss a relevant blueprint type	-91
Sources selected for this literature review	**18**

Appendix B

Pseudo code

Algorithm 1 Main loop: Simulated Annealing algorithm with delta computations

```
CurrentSolution ← ConstructiveHeuristic
CurrentOutcomes, CurrentObjective ← EvaluateStartSolution(CurrentSolution)
CurrentBestSolution ← CurrentSolution
CurrentBestObjective ← CurrentObjective
CurrentBestOutcomes ← CurrentOutcomes
Temperature ← StartTemperature
stepsize ← StartStepSize
while Temperature > EndTemperature do
  for m = 1:MarkovChainLength do
    NeighbourSolution, ChangedTherapists ← FindNeighbour(CurrentSolution, stepsize)
    NeighbourOutcomes, NeighbourObjective ← EvaluateNeighbourSolution(NeighbourSolution, ChangedTherapists, CurrentOutcomes)
    if NeighbourObjective < CurrentObjective then
      if NeighbourObjective < CurrentBestObjective then
        CurrentBestSolution ← NeighbourSolution
        CurrentBestObjective ← NeighbourObjective
        CurrentBestOutcomes ← NeighbourOutcomes
      end if
      CurrentSolution ← NeighbourSolution
      CurrentObjective ← NeighbourObjective
      CurrentOutcomes ← NeighbourOutcomes
    else
      if RandomValue < e^((CurrentObjective - NeighbourObjective)/Temperature) then
        CurrentSolution ← NeighbourSolution
        CurrentObjective ← NeighbourObjective
        CurrentOutcomes ← NeighbourOutcomes
      end if
  end for
  Temperature ← α· Temperature
  stepsize ← stepsize - decrease_stepsize
end while
```

Appendix C

Modelling assumptions

To use our model for the Medical Psychology department, assumptions had to be made. In this appendix, we describe these assumptions.

Arrival process
We assume that patients arrive according to a Poisson distribution. This means that the inter arrival times of the patients are assumed to be exponentially distributed. To check whether this assumption is reasonable, we tested this with the data. The results can be found in Figure C.1. We see that the distribution of the inter arrival times is comparable to the exponential distribution. Only the value for one day between arrivals is lower than expected for an exponential distribution. This can also be caused by the lack of data at the Medical Psychology department. The plot is based on only 679 data points. Besides, this assumption is often used in the literature for arrival processes (Winston, 2004). Therefore, we think assuming Poisson distributed arrivals for the patients at the Medical Psychology department is reasonable.

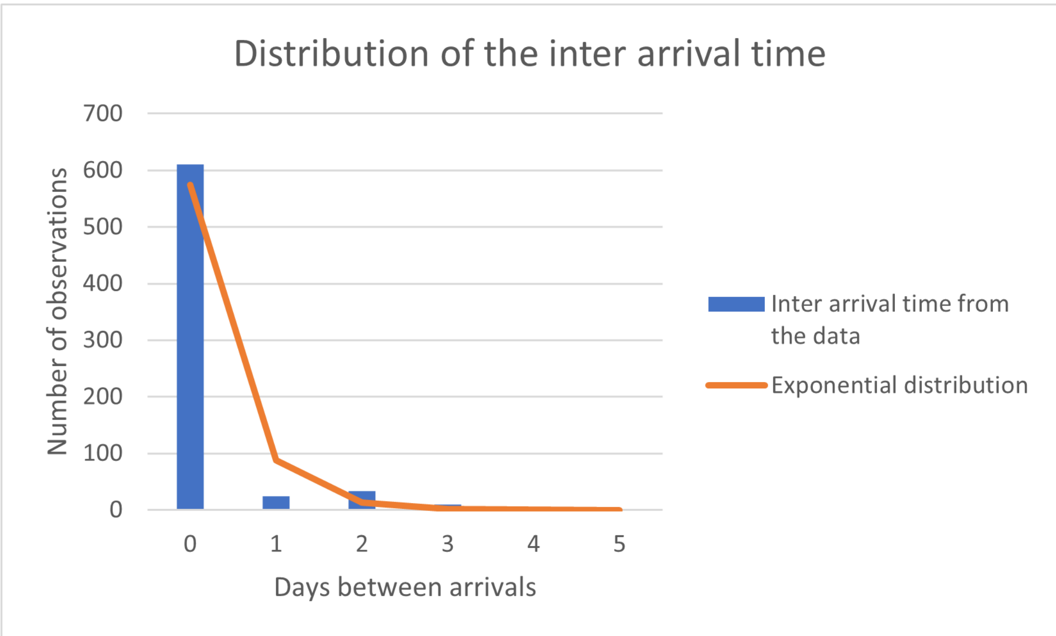


Figure C.1: Distribution of the inter arrival time (Source: Patient database Diakonessenhuis, 2021, containing 679 patients

Service times
Patients at the Medical Psychology department often has multiple recurring appointments. However, in the mathematical model and the solution approach, we model the service time of patients as one long service time. This means that patients have to wait for the whole service to end before a new patient can enter service. In the real-life situation, the new patient can enter service earlier but the previous patient will come back after a few weeks. This means that by approaching the recurring services as one long service time, we will overestimate the waiting time. However, our goal is only to determine the percentage of time therapists should spend on each patient type. For this cause it is not necessary to model the recurring treatments of patients separately.

We assume that the long service times of the patient types are exponentially distributed. We substantiate this assumption by showing the distribution of the service times of regular outpatients, since this patient group is the largest one and we have therefore the most data points available. Figure C.2 shows the distribution of these patients.

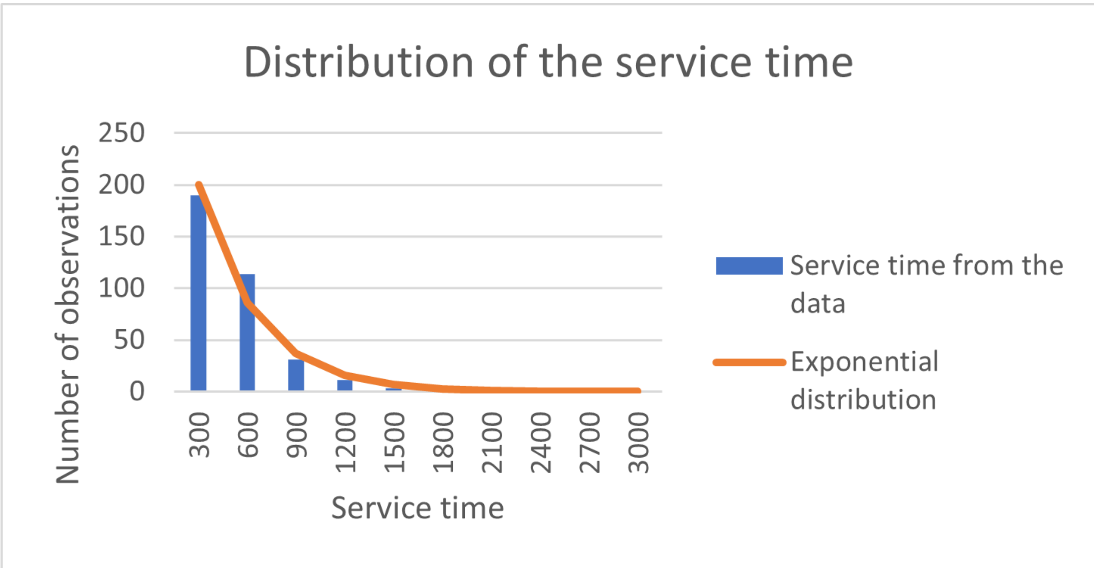


Figure C.2: Distribution of the service time of the regular outpatients (Source: Patient database Diakonessenhuis, 2021/2022, containing 350 patients)

We assumed that the service time of the patient types does not depend on the therapists. Theoretically this should be the case, but not necessarily; different therapist can have different working methods. These differences are not quantified and we are therefore unable to add them to the model.

We can only use 60% of the time to schedule, because therapists use the other 40% for indirect patient care. The exact time spend on the patients is therefore unknown, we only know the ratio of 60:40. We model this by pretending that therapists work slower, by increasing the service time and therefore decreasing the service rate. The disadvantage of this approach is that the service rates of all patient types are reduced proportionally. However, probably some patient types require more indirect patient care than other patient types. We cannot change this because there is no data available about the indirect patient care.

A comparable approach is used to model the differences between therapists in the amount of FTE they work. We pretend that part time therapists work slower than therapists that work full time. This results in an incorrect estimation of the waiting time, since in the real-life situation therapists do not simply work slower, but they work only a few days of the week. In the case that inpatients are assigned to such a part time therapist, the inpatient can request care on a day the therapist is not working. On the day the part time therapist is working, he does not work slower. It would result in a more accurate access time if we model system day by day, but this would result in much longer computation times. We are designing a blueprint on the tactical planning level and we only need to determine the percentage of time a therapist should spend on several patients types. Therefore, we assume that it is not necessary to model the access time more accurately.

Appendix D

Warm-up period and run length

In this appendix, we determine the warm-up period and the run length of the Discrete Event Simulation (DES). First we describe the experiments on which the warm-up period and run length are based, then we determine the warm-up period, and we finish with the determination of the run length.

Experiments for warm-up period and run length determination
The warm-up period and run length are based on several experiments, which are expected to need the longest warm-up period and run length. The DES evaluates one therapist at the time. We decided to use the therapist who can treat the most patient types and test experiments in which a few of all these patient types are assigned to this therapist. The clinical psychologist specialised in child and youth turned out to be the therapist who can treat the most patient types, namely nine out of twelve. We expect this to be the most unstable situation, since these patient types arrive with various service times.

We also expect differences in warm-up period and run length for very full systems compared to less full systems. Therefore, we decided to test five different values for the occupation ρ: 0.975, 0.8, 0.6, 0.4 and 0.2. In the five experiments, we let the arrival rate at the therapist be a percentage of the total input arrival time of the base instance of the Medical Psychology department, such that the total occupation ρ gets the right values. In this way, all allowed patient types arrive at the therapist in all five experiments.

In Table D.1, we show the sub arrival rates calculation of the patient types at the therapist for the experiments. The fractions corresponding to the five experiments are given in Table D.2.

Table D.1: Arrival rates at therapist for the experiments to determine the warm-up period and run length of the DES

Patient type	Arrival rate (week)	Arrival rate experiments
Inpatients - adults [U] (singular)	2.14	2.14 * fraction
Inpatients - adults [Z] (singular)	0.16	0.16 * fraction
Inpatients - child/youth [U] (singular)	0.63	0.63 * fraction
Inpatients - adults [U] (complex)	0.27	0.27 * fraction
Neuro patients [U] (singular)	1.63	1.63 * fraction
Neuro patients [Z] (singular)	1.06	1.06 * fraction
Neuro patients [U] (complex)	0.04	0.04 * fraction
Remaining outpatients - adults [U] (singular)	4.40	4.40 * fraction
Remaining outpatients - adults [Z] (singular)	0.59	0.59 * fraction
Remaining outpatients - child/youth [U+Z] (singular)	3.08	3.08 * fraction
Remaining outpatients - adults [U] (complex)	2.63	2.69 * fraction
Remaining outpatients - child/youth [U] (complex)	0.06	0.06 * fraction

Table D.2: Fractions for the five experiments to determine to determine the warm-up period and run length of the DES

Experiment	Value
ρ = 0.975	0.25
ρ = 0.8	0.21
ρ = 0.6	0.16
ρ = 0.4	0.11
ρ = 0.2	0.05

Warm-up period

A commonly used method to determine the warm-up period is the Welch's graphical procedure. 10 independent runs of 100 years are executed for each experiment and the waiting time of each observation is determined. Then the moving averages for the windows 100, 1000, 2000 and 2500 are calculated and they are plotted over time, shown in Figure D.1 for ρ = 0.975. Each data point represents the waiting time of one patient. The larger the window, the more smooth the graph becomes. As soon as the graph is smooth enough, we can determine when the system becomes stable. Here, this is the case for a window of 2500. Figure D.2 shows only Welch's procedure for a window of 2500. From this figure, it can be seen that the line stabilises after approximately 1200 patients. Converted, this comes down to a warm-up period of 7 years. This is calculated for all five experiments and the results are given in Table D.3. We want to use a warm-up period large enough for all situations, so to be save, we use a warm-up period of 10 years.

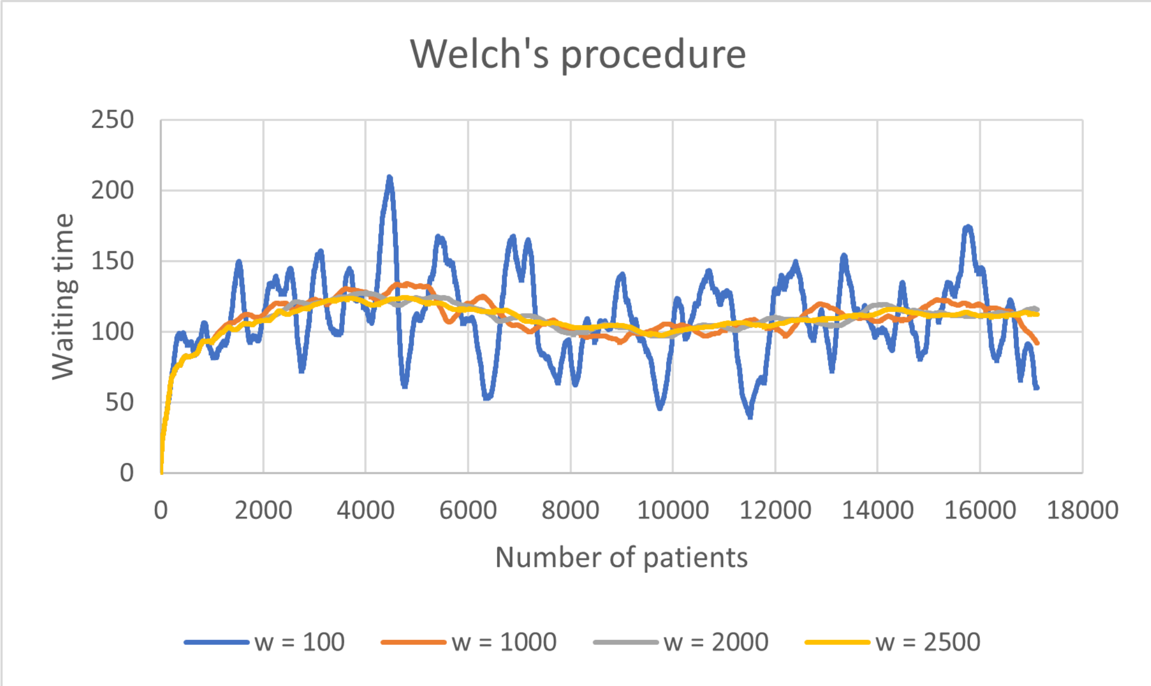


Figure D.1: Welch's graphical procedure for windows 100, 1000, 2000 and 2500 for the experiment $\rho = 0.975$

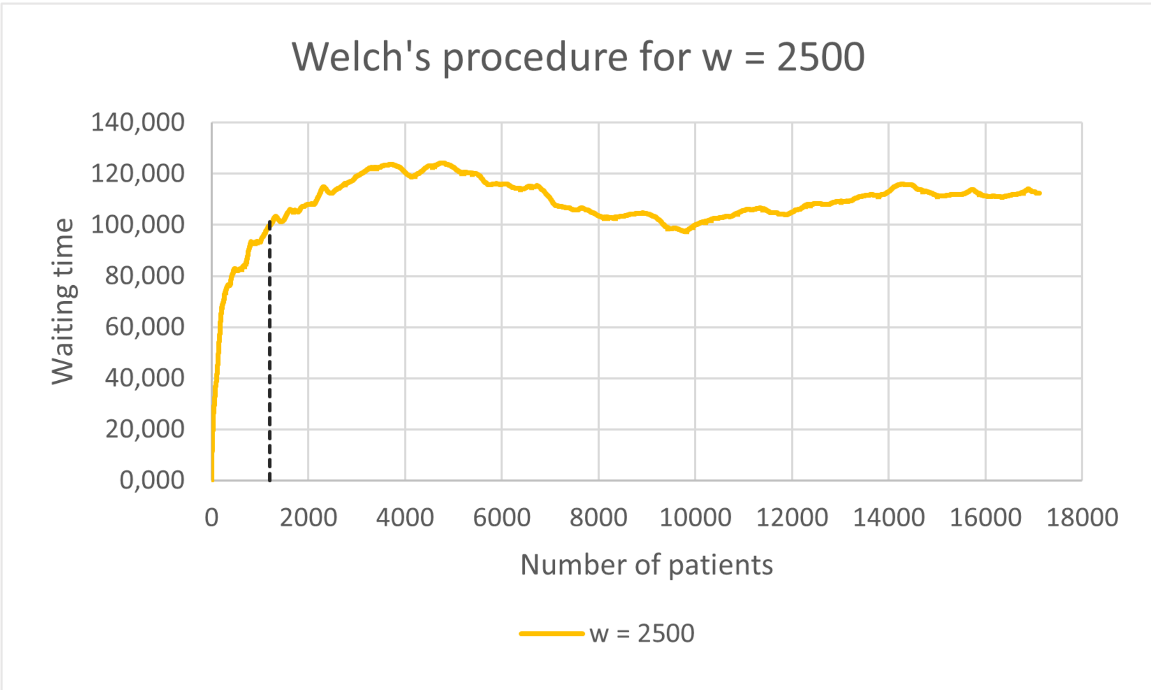


Figure D.2: Welch's graphical procedure with window 2500 showing that the waiting time of patients stabilises after approximately 1200 patients

Table D.3: Minimum warm-up period for the five experiments

Experiment	Warm-up period
$\rho = 0.975$	7 years
$\rho = 0.8$	6.5 years
$\rho = 0.6$	5.7 years
$\rho = 0.4$	4.2 years
$\rho = 0.2$	3.5 years

Run length

For the run length, we use an alternative procedure. We want to use a run length such that we only need one replication, because of our simulation-based optimisation approach. Therefore, we use the Confidence Interval Half Width approach in which we see every patient as a replication. Then, we determine the number of replications necessary, which is actually the number of patients the run should contain to be sure enough of the average waiting time. The average waiting time is not our KPI, since we work with intervals for the waiting time and work with the average penalty. The average waiting time is more specific and we expect this to need a longer run length then our situation. Therefore, this is a more strict approach and should therefore be sufficient.

We want to obtain the average waiting time with a maximum relative error of at most 0.05. When aiming for a relative error of 0.05, the actual relative error of the model is $\frac{1}{1+0.05} = 0.048$. The results of the Confidence Interval Half Width approach for all five experiments are given in Table D.4. It turned out that the minimum run length should be 84.5 years. To be save, we use a run length of 100 years.

Table D.4: Minimum run length for the five experiments

Experiment	Run length
$\rho = 0.975$	11.2 years
$\rho = 0.8$	23.2 years
$\rho = 0.6$	41.0 years
$\rho = 0.4$	72.5 years
$\rho = 0.2$	84.5 years

Appendix E

Cooling scheme Simulated Annealing

In this appendix, we determine the cooling scheme of our simulated annealing approach. The cooling scheme consists of four parameters: start temperature and end temperature, the Markov chain length m and the decrease factor α. (Delahaye et al., 2019) All parameters will be based on the base case of the Medical Psychology department.

The start and end temperature are determined based on the acceptance ratio plot in Figure E.1. This plot is made based the model of our solution approach. The acceptance ratio is the ratio of accepted worse solutions compared to total number of proposed worse solutions. At the start of the simulation, we want to accept almost all proposed worse solutions, so the acceptance ratio should be close to 100% in the beginning. The acceptance ratio plot shows that this corresponds to a start temperature of 50. Here, the acceptance ratio is 99%. At the end of the simulation, we should not accept worse solutions anymore, so the acceptance ratio should be close to 0%. This is the case for an end temperature of 0.005, since then the acceptance ratio is only 0.2%.

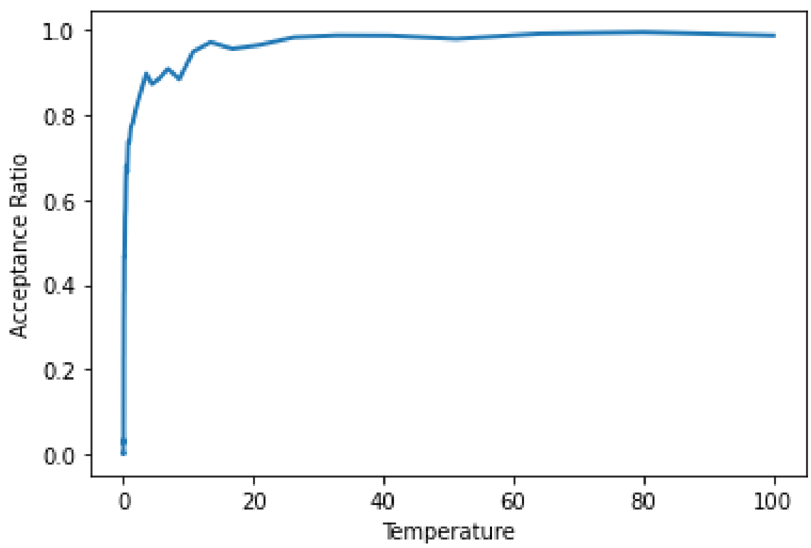


Figure E.1: Acceptance ratio for various temperatures

The third component of the cooling scheme is the Markov chain length m: the number of neighbours to evaluate for the same temperature. The Markov chain length m should be about the size of the neighbourhood. The neighbourhood allows to move a part of patient type p from therapist t_a to therapist t_b, but only if both therapist t_a and therapist t_b are allowed to treat patient type p. This means that the size of the neighbourhood can be calculated by the formula in Equation E.1. For the base case of the Medical Psychology department, the size of the neighbourhood is about 500. To keep the total run time low, we assume a Markov chain length of $m = 250$ should be sufficient.

$$\text{neighbourhood size} = \sum_{p \in P} \#\,\text{therapists}_p \cdot (\#\,\text{therapist}_p - 1) \tag{E.1}$$

The last parameter to determine is the decrease factor α. This parameter is always smaller than 1 and decreases the temperature after the evaluation of m candidate neighbour solutions by a factor α. The smaller α, the faster the temperature decreases and thus the smaller the total run time. On average, it takes 0.85 seconds to find a candidate neighbour solution, evaluate this solution and decide to accept or reject the solution. For every temperature, this needs to be done 250 times, because of the Markov chain length. We find a run time of 150 minutes reasonable, so this means that we can evaluate $\frac{150 \cdot 60}{0.85 \cdot 250} \approx 42$ temperatures. This corresponds to an α of 0.8.

The cooling scheme for our simulation is summarised in Table E.1 below.

Table E.1: Cooling scheme Simulated Annealing

Parameter	**Value**
Start temperature	50
End temperature	0.005
Markov chain length m	250
Decrease factor α	0.8

In the theoretical experiments in Section 5.2, we compare our exact mathematical model with our solution approach. To do so, we should compare instances that can be solved by the mathematical model as well as by the solution approach. The mathematical model becomes very slow already for small instances. Therefore, the cooling scheme of the simulated annealing is changed a bit for the theoretical experiments, since the neighbourhood size is smaller in these experiments. The number of therapists is only 2, and the number of patient types is at max 7. Therefore, we decreased our Markov chain length to 50 for the theoretical experiments. The rest of the cooling scheme is kept the same.