Defining and improving congruence between treatment plans and realization in rehabilitation care

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Sint Maartenskliniek

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Management summary

Introduction

This study focuses on measurement and improvement of the degree of accordance between treatment protocols, individualized treatment plans and realized care in the rehabilitation centre of the Sint Maartenskliniek (SMK), Nijmegen. Congruence is defined as the extent to which plans or protocols are in accordance with realized care. SMK's management perceives that congruence between treatment plans are often not congruent with realization. However, they have no management information on congruence, and are thus unable to measure and ultimately improve congruence. In this research we define how to measure congruence, and propose and evaluate interventions to improve congruence.

Problem description

Rehabilitation care typically concerns multidisciplinary treatment and is characterized by repetitive therapy patterns. When a patient is admitted to the rehabilitation centre, the physician first draws a personalized treatment plan. This plan prescribes the frequency per week, number and duration of activities during a specified period. Treatment plans are either defined on a case-by-case basis or are based on predefined protocols, called care pathways. SMK's management perceives that the amount of therapy, frequency, and lead time as defined in the treatment plan is often not congruent with realized care. Although there are medical reasons to deviate from the treatment plan incongruence also occurs due to undesirable therapist behaviour and inefficient deployment of therapists.

Incongruence can lead to over- or undertreatment of patients, unpredictable care and impediment of scheduling appointments of other patients. Insight in the degree and causes of incongruence allows management to steer on congruence. In addition, these insights give direction to the development and implementation of interventions to improve congruence.

Approach

We investigate care and scheduling processes, describe planning and control functions, and identify bottlenecks through expert interviews and observation sessions at the planning department of the rehabilitation centre. We define and operationalize the concept of congruence and perform a baseline measurement in two care units of the rehabilitation centre. To improve utilization of capacity and thereby congruence, we propose an integer linear program (ILP) for automated appointment scheduling. The ILP was based on earlier research of Braaksma [1], and was adapted and expanded for application in SMK. The ILP's objective is to schedule all appointments of a single patient congruent to a care pathway, while planning rules of SMK are abided as much as possible. We evaluate the performance of the ILP and two additional interventions – therapist schedules that are better aligned with demand for care and decreased differentiation of therapists into specialized teams – in a simulation study. For this simulation study, we use data from two care units of the SMK rehabilitation centre; the same units that were included in the baseline measurement.

Results

The table below shows the most important results of our baseline measurement and simulation study. For *Appointments both prescribed and realized* and *Therapy frequency*, a score is given between 0 and 1, where 1 is optimal. Baseline measurements were performed for congruence between care pathways and realized care. Our simulation model rejects patients if no feasible solution is found after a defined number of attempts.

	Baseline	Simulation policy			
		1	3	4	6
		Current policy	No therapist differentiation	3 + Improved therapist schedules	4 + High therapist utilization
Appointments both prescribed and realized	≤0.69[1]	0.9994	0.9994	0.9999	0.9994
Therapy frequency	≤0.34[1]	0.9994	0.9993	0.9998	0.9987
Rejected patients	Unknown	1.4%	0.7%	0.3%	4.4%

Conclusion

Compared to the baseline measurement, our automated appointment scheduling model performs well. Close to 100% of all prescribed appointments are scheduled, while this was 30% lower for the best performing discipline in the baseline measurement. In our simulation, the realized therapy frequency is almost always congruent to the care pathway, while the score for this measure was at least 65% lower in the baseline measurement. Both interventions individually improve the number of rejected patients, while congruence remains high. Increasing therapist utilization does increase the number of rejected patients, but again, congruence remains high.

Comparison between the baseline measurement and simulation results is flawed. First, the treatment plan is a better starting point for baseline measurement than the care pathway, but the lack of useful treatment plan-data made this infeasible. Second, the simulation does not take online (after-scheduling) deviations into account. Finally, the ILP does not consider all preconditions that apply in practice.

Nevertheless, the magnitude of improvement argues for implementation of automated appointment scheduling. In addition, we recommend SMK to look for opportunities to increase the use of generalist therapists and to better align demand for care with therapist schedules.

[1] This indicator was measured per discipline. All disciplines scored equal or worse than the given number.

Managementsamenvatting

Introductie

Dit onderzoek richt zich op het meten en verbeteren van de mate van overeenstemming tussen behandelprotocollen, geïndividualiseerde behandelplannen en gerealiseerde zorg in het revalidatiecentrum van de Sint Maartenskliniek (SMK) te Nijmegen. De mate waarin plannen of protocollen in overeenstemming zijn met gerealiseerde zorg noemen wij congruentie. Het management van SMK merkt op dat behandelplannen vaak niet congruent zijn met gerealiseerde zorg. Echter, ze hebben geen managementinformatie over congruentie, en zijn dus niet bij machte om congruentie te meten en te verbeteren. In dit onderzoek definiëren we hoe congruentie gemeten wordt, stellen we interventies voor om congruentie te verbeteren en evalueren we deze interventies.

Probleembeschrijving

Revalidatiezorg is gekenmerkt door multidisciplinaire behandeltrajecten die bestaan uit repetitieve afspraakpatronen. Nadat een patiënt is aangemeld bij het revalidatiecentrum wordt eerst een behandelplan opgesteld. Dit plan beschrijft de therapiefrequentie per week, het totale aantal afspraken, en de duur van deze afspraken. Behandelplannen zijn op individuele basis samengesteld of zijn gebaseerd op vooraf beschreven protocollen, die we zorgpaden noemen. Het management neemt waar dat de hoeveelheid therapie, de therapiefrequentie en de doorlooptijd, zoals beschreven in het behandelplan, vaak niet congruent is met gerealiseerde zorg. Alhoewel er medische redenen zijn om af te wijken van het behandelplan, neemt men waar dat dit ook komt door ongewenst gedrag van therapeuten en inefficiënte inzet van personeel.

Incongruentie kan leiden tot over- of onderbehandeling, onvoorspelbare zorg en belemmering van het roosteren van afspraken van andere patiënten. Inzicht in de mate en de oorzaken van incongruentie geeft het management handvatten om op congruentie te sturen. Bovendien geven deze inzichten richting aan de ontwikkeling en implementatie van interventies om congruentie te verbeteren.

Aanpak

Middels expertinterviews en observaties onderzoeken we SMK's zorg- en planningsprocessen, beschrijven we plannings- en besturingsfuncties, en identificeren we knelpunten in relatie tot congruentie. We definiëren en operationaliseren het concept congruentie en voeren een nulmeting van congruentie uit in twee behandelunits van het revalidatiecentrum. Om de benutting van capaciteit, en daarme congruentie, te verbeteren ontwikkelen we een *integer linear program* (ILP) voor het automatisch plannen van afspraken. Het ILP is gebaseerd op eerder onderzoek van Braaksma [1], en is aangepast en aangevuld voor toepassing in SMK. Het doel van het ILP is om afspraken van één patiënt zo congruent mogelijk aan het zorgpad in te plannen, terwijl planningsregels van SMK zo veel mogelijk worden gerespecteerd. We evalueren de prestatie van het ILP en twee andere interventies – therapeutenroosters die beter zijn afgestemd op de vraag naar zorg, en verminderde differentiatie van therapeuten in gespecialiseerde teams – in een simulatiestudie. We gebruiken hiervoor data vanuit dezelfde twee behandelunits waarvoor de nulmeting is gedaan. Ons simulatie model wijst patiënten af als na een bepaald aantal pogingen geen oplossing is gevonden.

Resultaten

De tabel hieronder presenteert de belangrijkste resultaten van onze nulmeting en simulatiestudie. Voor *Afspraken zijn zowel voorgeschreven als uitgevoerd* en *Therapiefrequentie* geven we een score tussen 0 en 1, waar 1 optimaal is. De nulmeting is gebaseerd op congruentie tussen zorgpaden en gerealiseerde zorg.

	Nulmeting	Simulatiebeleid			
		1	3	4	6
		Huidig beleid	Geen differentiatie van therapeuten	3 + Verbeterde therapeut-roosters	4 + Hoge bezettingsgraad van therapeuten
Afspraken die zowel zijn voorgeschreven als uitgevoerd	≤0.69[2]	0.9994	0.9994	0.9999	0.9994
Therapiefrequentie	≤0.34[2]	0.9994	0.9993	0.9998	0.9987
Afgewezen patiënten	Onbekend	1.4%	0.7%	0.3%	4.4%

Conclusie

Vergeleken met de nulmeting presteert ons model voor het automatisch plannen van afspraken goed. Bijna 100% van de voorgeschreven afspraken is gepland, terwijl dit zo'n 30% lager was in de nulmeting. Met betrekking tot therapiefequentie was er in onze simulatie bijna nooit verschil tussen het zorgpad en de gerealiseerde zorg, terwijl de score zo'n 65% lager was in de nulmeting. Beide interventies verbeteren afzonderlijk van elkaar het aantal afgewezen patiënten, terwijl congruentie hoog blijft. Het verhogen van de bezettingsgraad van therapeuten zorgt weliswaar voor een stijging van het aantal afgewezen patiënten, maar de congruentie blijft hoog.

De nulmeting en simulatieresultaten kunnen niet één op één met elkaar worden vergeleken. Ten eerste, het behandelplan zou een beter uitgangspunt zijn voor de nulmeting dan het zorgpad. Er was echter geen bruikbare behandelplan-data beschikbaar. Ten tweede, de simulatie neemt geen online afwijkingen (na het roosteren) mee, terwijl die in de praktijk wel voorkomen. Ten derde, het ILP neemt niet alle randvoorwaarden die in de praktijk gelden in overweging.

Niettemin, de mate van verbetering pleit voor invoering van het automatisch plannen van afspraken met behulp van het ILP. Daarnaast bevelen we SMK aan om mogelijkheden te onderzoeken om het gebruik van generalistische therapeuten te vergroten, en om de vraag naar zorg en het aanbod van therapeuten beter op elkaar af te stemmen.

[2] Deze maat was gemeten per discipline. Alles disciplines scoorden gelijk aan of slechter dan de afgebeelde score.

Preface

During my Bachelor studies in Health Sciences, I discovered the field of Operations Research in Healthcare. I enjoyed analyzing and solving the logistical problems presented in the only course on this subject and was amazed by the opportunities for operations research in health care. Thanks to that course, I signed up for the Industrial Engineering & Management (IE&M) Master program. I never regretted it.

The research I conducted in the rehabilitation center of the Sint Maartenskliniek (SMK) brought me many new experiences. I discovered that the possibilities for process optimization in this field are huge, but also that its environment is complex. I hope that my results are followed by implementation and that this improves the quality of care and processes in SMK.

I could not have conducted this research without the help of many people. I thank my SMK supervisors Carolien and Pauline for their feedback and insights in the world of rehabilitation. Their experience, both in scheduling and management, helped me to understand the organization and the challenges it is facing. I thank Arjan, Jody, Joke, Jolanda, and the planners of the pediatric rehabilitation department for showing me their daily work and explaining the daily problems they encounter. Nikky, Bart, Lenneke, Dianne and Rob, thank you for your help and the ideas you provided during our feedback sessions. Ingeborg, your willingness to read and criticize many draft versions of my report has certainly improved its quality. I thank Aleida for introducing me to her research and encouraging me to apply her model. Siep, thank you for teaching me how to work with SMK's data warehouse. This enabled me to collect most data by myself. I want to thank all those other people of SMK who helped me to retrieve data or took the time to express their ideas. You really helped me to progress. Tim, Peter, Maaike, Rogier, Niels, Colin, Joanne and Opa: thank you for lending me your laptops. Otherwise, I could not have conducted all experiments in time.

I also want to thank my UT supervisors, Erwin and Ingrid. Ingrid, when I struggled with the direction of my research, your advice has been very helpful. Erwin, your lectures have made me enthusiastic for process optimization in healthcare in the first place. Thanks to your tips and encouragements, I left with new ideas and a positive attitude after all our appointments – no matter how indecisive or deprived of ideas I was before.

Finally, I thank Joanne and my parents for their continuous support. *Pa en ma*, you made it possible for me to study and supported me in all my decisions. Joanne, you encouraged me when I needed it, but also ensured that I did not forget to enjoy the other things in life.

Contents

Abbreviations

AMC	Academic Medical Center Amsterdam
ACT	activity therapist (*activiteitentherapeut*)
AT	access time
BAG	movement therapist (*bewegingsagoog*)
CAO	chronic pain, amputation and orthopedic rehabilitation (*chronische pijn, amputatie en orthopedische revalidatie*)
CP	care pathway (*zorgpad*)
DIET	dietician (*diëtist*)
DUR	congruence measure with respect to duration per activity
ET	occupational therapist (*ergotherapeut*)
FT	physiotherapist (*fysiotherapeut*)
FRQ	congruence measure with respect to frequency of activities
HIS	hospital information system (*ziekenhuisinformatiesysteem*)
ILP	integer linear program
LG	speech therapist (*logopedist*)
LT	congruence measure with respect to lead time
MILP	mixed integer linear program
MW	social worker (*maatschappelijk werk*)
NUMA	congruence measure with respect to the number of added activities
NUMO	congruence measure with respect to the number of omitted activities
PS	psychologist (*psycholoog*)
SIR	spinal injury rehabilitation (*dwarslaesierevalidatie*)
SKL	sexologist (*sexuoloog*)
SMK	Sint Maartenskliniek
SS	simultaneous start
TDURA	congruence measure with respect to adding total therapy duration
TDURO	congruence measure with respect to omitting total therapy duration

Chapter 1: Introduction

Rehabilitation care focuses on prevention, reduction and cure of diseases or injuries. During rehabilitation treatment, patients see a range of therapists with varying expertise. Therapists work closely together in a multidisciplinary team, headed by a rehabilitation physician. In 2013, the costs of rehabilitation care in the Netherlands were €497 million [2]. The ratio of inpatients versus outpatients was 1:14, while the ratio of treatment hours of inpatients versus outpatients was 1:2. Compared to 2010, the number of new patients grew with 11% to 56.000.

In Dutch health care, rising health care expenditures have led to the introduction of a performance-based reimbursement system, which increases the importance to provide high quality of care in an efficient way. The Dutch association of rehabilitation centers recognizes the importance to improve logistical efficiency and indicates that the logistical organization of rehabilitation centers can be improved [3]. The organization of rehabilitation care differs from regular hospital care. For example, planning in hospitals is regularly focused on material resources such as operation rooms, while human resources are the focus in rehabilitation care [4]. The multidisciplinary character of rehabilitation care makes it difficult to efficiently deploy these resources, while quality of care is guaranteed.

Per patient, deployment of resources is specified in an early stage of treatment. Rehabilitation physicians define on beforehand how often patients should see a specific therapist and when treatment should be finished. This is documented in a so-called treatment plan. However, in practice, realized care often differs from the treatment plan. This can be due to the medical necessity to deviate, inefficient use of capacity or therapists who do not consider the treatment plan. Although deviations are sometimes medically justified, not abiding the treatment plan can lead to over- or undertreatment, logistical inefficiencies and reduced cost-effectiveness.

In this research, we evaluate why realized care differs with planned care. Moreover, we introduce measures to gain insight in the degree of deviation between treatment plans and realized care. Finally, we introduce interventions with the aim to reduce such deviations.

The chapter is structured as follows: Paragraph 1.1 describes the hospital and department where the study is performed. Paragraph 1.2 discusses the motivation for this research. Paragraph 1.3 gives the problem description, and Paragraph 1.4 defines the research objective and demarcates the scope. Paragraph 1.5 describes the research questions, including an outline of the report.

1.1 Organization

The Sint Maartenskliniek (SMK) is a Dutch hospital specialized in musculoskeletal and neuromuscular conditions and offers orthopedic, rehabilitation and rheumatism care. SMK has locations in Nijmegen, Woerden, Boxmeer, and Tiel, all in the Netherlands. In addition, it has outpatient clinics in Panningen and Mijdrecht. SMK describes itself as a 'leading hospital in treating conditions in movement and posture [5]'. In 2012, the hospital realized a turnover of €161,8 million, had 1.890 employees and 317 accredited beds [6].

The rehabilitation center at the hospital in Nijmegen offers inpatient and outpatient care and consists of four *care units.* The *pediatric rehabilitation* care unit offers treatment to children with conditions in motion and posture. As of 2014, there are three care units for adults. At the *neurologic rehabilitation* care unit patients recover after a nervous system injury, such as a cerebrovascular accident. Moreover, the unit treats patients with cerebral palsy and several neuromuscular conditions. The *chronic pain, amputation and orthopedic rehabilitation (CAO)* care unit involves, among other things, rehabilitation after amputation and orthopedic interventions. Finally, patients with spinal injury and several other related conditions, such as Guillain-Barre, rehabilitate at the *spinal injury rehabilitation (SIR)* care unit [7]. In 2013, the rehabilitation center had 13.355 outpatient visits, 21.168 nursing days, 434 inpatient admissions and 2.541 first consults [6; 8].

1.2 Motivation for research

In a document on its strategic direction for 2013 to 2016, SMK stresses the importance to steer more firmly on its costs and logistic operations [9]. The clinic aims to improve efficiency by optimally aligning the chains in the patient's pathway through the clinic. In August 2014, SMK established a department with the specific task to optimize logistic processes. The problems and solutions that the department is dealing with often relate to operations research.

As a part of SMK, the rehabilitation center also aims to increase efficiency. Currently, management has the impression that the amount and frequency of care that patients receive is unpredictable, practitioners have unbalanced workload and waiting lists are too long. SMK's focus on optimization of logistical processes and, more specific, inefficiencies at the rehabilitation center are the motivation for the current research.

1.3 Problem description

Patients in rehabilitation care often need a series of treatments, offered by a wide range of therapists, namely physiotherapists (FT), occupational therapists (ET), psychologists (PS), activity therapists (ACT), movement therapists (BAG), social workers (MW), dieticians (DIET), sexologists (SKL) and speech therapists (LG). After a first consult with the assigned physician, the physician draws a personal plan for treatment. This so-called *treatment plan* describes the frequency, duration and number of diagnosis and therapy activities during a specified period. Sometimes predefined protocols dictate treatment plans, but physicians frequently define plans on a case-by-case basis. After establishing the treatment plan, the scheduling department schedules the treatment and therapy can begin.

The management of the rehabilitation center perceives that the amount, frequency and lead time of realized therapy is not always equal to the treatment plan. We define the degree of accordance between a treatment plan and realized care as *congruence.* In some cases, there is a medical reason to deviate from the treatment plan. Since the progress of recovery is unpredictable for many patient groups, such deviations are sometimes unavoidable. However, it is not always obvious that there is a medical need to alter the treatment plan, or that the grounds for deviations are less clear. Additionally, schedulers cancel appointments due to an apparent lack of resource capacity. These deviations can lead to under- or overtreatment and add up to unpredictable care, resulting in inefficient logistic processes.

Congruence is currently not measured in SMK. In fact, the rehabilitation center does not know how to measure congruence. Therefore, SMK has no insight in the magnitude and causes of incongruence between treatment plans and realization. The hospital has thus no objective data serving as a basis to improve congruence.

1.4 Research objective and demarcation of scope

We define our research objective as follows:

> To investigate the aspects of congruence in rehabilitation care, pinpoint factors that lead to incongruence, define measures for congruence, design interventions for improving congruence and evaluate the performance of these interventions.

The scope of defining congruence and finding factors that lead to incongruence is the whole rehabilitation center. The scope of intervention design is the SIR and CAO care unit. These care units provide the best preconditions for evaluating interventions.

1.5 Research questions

To achieve the above stated research objective, we define the following research questions:

1. *How can we define congruence in the rehabilitation center of SMK?*

After describing the care process in SMK, Chapter 2 provides a general definition of congruence and related terms that we use throughout this thesis. It defines care pathways, treatment plans and treatment schedules as *planning levels*. In this chapter, we argue that congruence can be measured between these different planning levels.

2. *How is planning and scheduling of treatment plans currently done in SMK and what bottlenecks are experienced? Which interventions do we recommend, and which of these deserve further evaluation?*

Chapter 2 continues with a context analysis of treatment plan scheduling in SMK. The chapter subsequently discusses the application of treatment plans and care pathways, the scheduling process, patient groups, planning and control functions and bottlenecks with regard to treatment planning and execution. The chapter concludes with recommendations on interventions and a delimitation of interventions to be further evaluated.

3. *What is known from the literature with regard to congruence measurement and the selected set of interventions?*

Chapter 3 discusses the literature with respect to congruence measurement and the set of interventions chosen in Chapter 2.

4. *What measures for congruence can we define? What is the current performance regarding congruence?*

Chapter 4 introduces measures for congruence and discusses their mathematical notation. The chapter concludes with a baseline measurement of congruence.

5. *How do we design the selected interventions?*

Chapter 5 describes the design of the selected interventions.

6. *How can we evaluate the effect of the selected interventions on congruence and other relevant performance measures?*

Chapter 6 introduces the applied methods to evaluate the selected set of interventions.

7. *What is the effect of the selected interventions on congruence and other relevant performance measures?*

Chapter 7 discusses experiment results.

8. *How can SMK implement congruence measurement and the proposed interventions?*

Chapter 8 discusses recommendations with respect to implementation of congruence measurement in SMK. In addition, it gives recommendations on the implementation of the evaluated interventions. Implementation itself is not a part of the research project.

Chapter 9 concludes the report with a conclusion, discussion, recommendations and directions for future research.

Chapter 2: Context analysis

This chapter provides a context analysis of scheduling and execution of treatment plans in SMK. The chapter starts with a description of the care process in Paragraph 2.1. Then, Paragraph 2.2 defines care pathways, treatment plans, congruence and related terms. Paragraph 2.3 discusses application of care pathways and treatment plans in SMK. Paragraph 2.4 discusses SMK's scheduling process. Then, Paragraph 2.5 describes patients groups, Paragraph 2.6 discusses planning decisions and Paragraph 2.7 gives an overview of perceived bottlenecks. Paragraph 2.8 gives a summary of SMK's operational goals. The chapter finishes with recommendations on the perceived bottlenecks and a delimitation of research in Paragraph 2.9.

2.1 Care process description

This paragraph provides a description of the care process of patients in the rehabilitation center. Figure 2.1 gives a schematic view of the care process of a single patient.

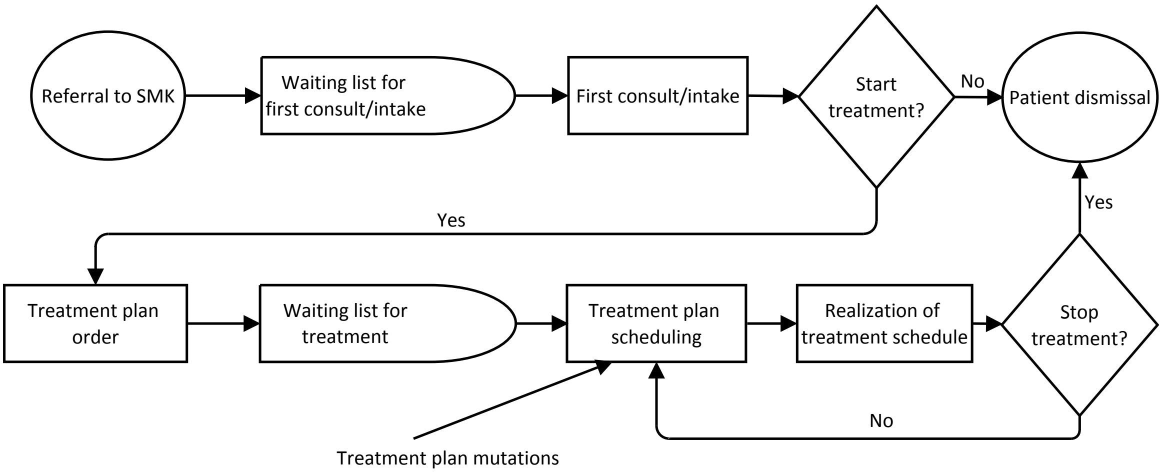


Figure 2.1 Care process for patients at the rehabilitation center of SMK

For outpatients, schedulers immediately schedule an appointment for a first consultation after referral to SMK. However, it can take up to a few months until the first consult takes place. Therefore, in the figure, the patient first enters a waiting list. During the first consult, the physician decides whether the patient is eligible for treatment. Reasons to not admit a patient include complexity of care, travel distance and patient availability.

For inpatients, the first steps of the process are mainly the same, although there is no first consult. Instead, a team of nurses and physicians decides, based on information from the referring hospital, whether the patient is eligible for treatment.

If the patient is admitted, the physician composes a treatment plan and the patient is put on the waiting list for treatment. The first treatment plan is usually aimed at establishing a diagnosis, but if the diagnosis is already clear, the treatment plan may be directly aimed at treatment[3]. Based on urgency and waiting time, patients are eventually admitted for treatment. At this point, the appointments are scheduled.

Approximately once every six weeks, the multidisciplinary treatment team of the patient discusses the progression of the patient in a meeting. During the first meeting, the team discusses whether the termination date as stated in the treatment plan is still applicable, or, if not yet defined, determines a termination date. Two weeks before the expected termination date, the team determines whether the date is still accurate (during a weekly, not-patient specific meeting), and decides whether to change it (and thus, whether to mutate the treatment plan). During the multidisciplinary meeting, the team also discusses other treatment plan mutations, which are scheduled subsequently. Treatment plan mutations are not exclusive to multidisciplinary team meetings; they can occur throughout the whole treatment execution phase.

[3] In the CAO care unit, diagnosis consists of a screening program. This program has a separate waiting list.

2.2 Definitions

In this thesis, we use interrelated terms with respect to treatment planning and execution, which are used interchangeably in practice. To avoid ambiguity, this section defines these terms. Figure 2.2 gives a schematic representation of definitions and the hierarchic relation between these terms. Dashed lines mark optional aspects. Below the figure, the terms are defined one by one. The paragraph finishes with explaining relations between terms.

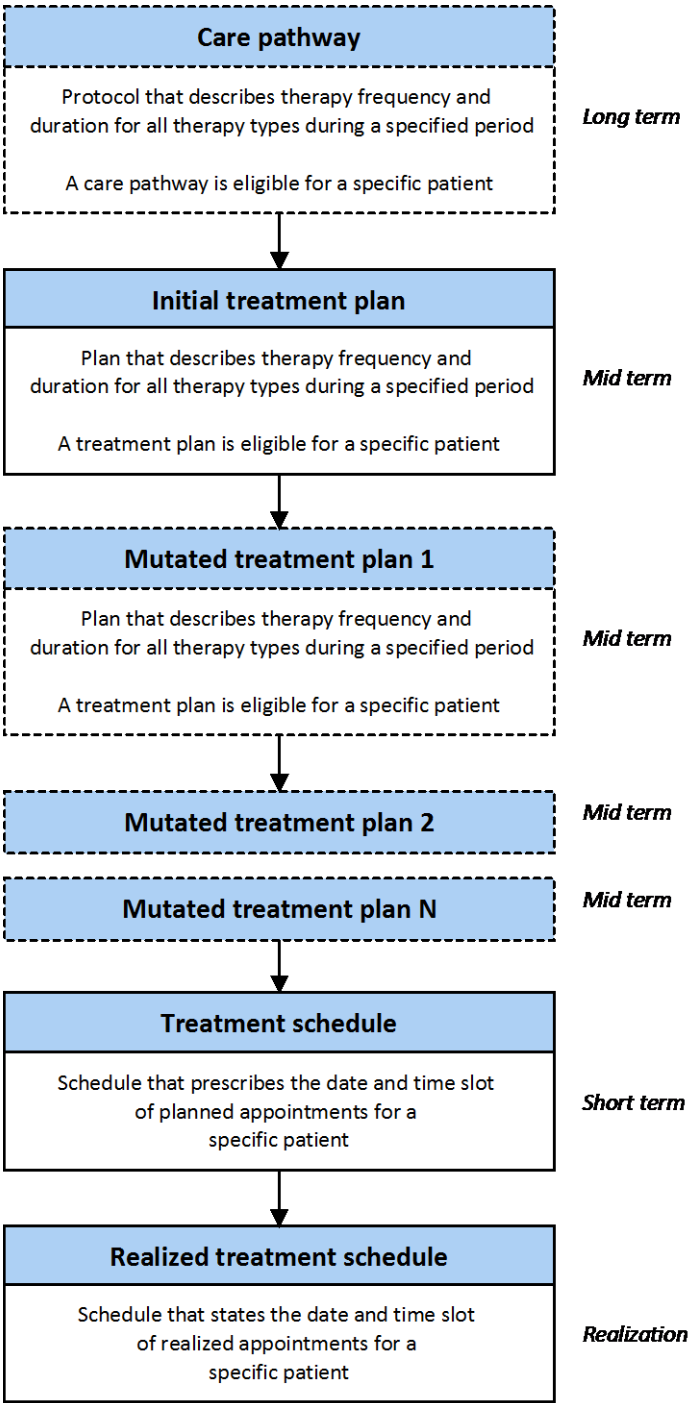


Figure 2.2 Schematic representation of interlinked terms used in this thesis

Care pathway

Although there is no universally accepted definition, care pathways (CPs, Dutch: zorgpaden) can be described as a method for the patient-care management of a defined patient group during a defined period of time. It coordinates roles and sequences activities of the multidisciplinary care team [10]. In rehabilitation care, CPs are used as protocols that describe the frequency, duration, and number of appointments for all relevant therapy types of a specific patient group. A therapy type consists of a discipline and the indication whether the therapy is provided in groups or individual. The CP also prescribes the amount of administrative time related to a specific patient per week, referred to as indirect patient time. Time used for therapy is referred to as direct patient time. The CP includes an expectation of lead time (Dutch: doorlooptijd). Finally, the CP states whether care should be provided either in- or outpatient.

The appointments in CPs often follow a repetitive pattern. For example, a patient may have two appointments a week with a physiotherapist during six weeks. Moreover, CPs typically are of a multidisciplinary nature: the patient sees various disciplines.

The patient group for which the CP is written refers to one or more diagnoses or symptoms, for example "all patients with a spinal injury at the seventh thoracic vertebrae or higher". The CP refers to a treatment phase: diagnosis, treatment or aftercare. Since not all patients can be related to a CP, its definition in Figure 2.2 is presented in a dashed text box.

Treatment plan and initial treatment plan

We define a treatment plan (Dutch: behandelplan) as a plan that indicates the frequency, duration and number of appointments for all relevant therapy types of a single patient. The treatment plan covers the same aspects a care pathway does, but the treatment plan is not standardized and is defined independently for each patient. However, care pathways can and often do serve as input for the treatment plan.

The initial treatment plan (Dutch: initiëel behandelplan) is the first version of a treatment plan for a specific patient.

Mutated treatment plan

During execution of the treatment plan, the patient's progress may lead to the need to change the initial treatment plan. We define a mutated treatment plan (Dutch: gemuteerd behandelplan) as a treatment plan that is the result of mutations of an earlier treatment plan. Mutations are numbered. For example, the first mutation of an initial treatment plan leads to "Mutated treatment plan 1", and the fourth mutation is called "mutated treatment plan 4". All changes to a treatment plan are regarded as mutations.

Treatment plans are not always mutated. Therefore, the sections that describe mutated treatment plans are dashed in Figure 2.2.

Treatment schedule

A treatment schedule (Dutch: behandelrooster) is an individual schedule that prescribes the date and time slot of appointments for a specific patient. Appointments include information on the discipline of the therapist and whether treatment is given individually or in a group. The treatment schedule also indicates time slots for indirect patient time. Treatment schedules are the result of the scheduling process that takes place before execution of the treatment schedule.

Realized treatment schedule

The realized treatment schedule (Dutch: gerealiseerd behandelrooster) is an individual schedule that states the date and time slot of realized appointments of a single patient. Realized indirect patient time is also included. Realized treatment schedules can differ from treatment schedules due to unexpected events, such as patient or therapist absenteeism or interference of an urgent patient.

Planning levels

We refer to care pathways, treatment plans and treatment schedules as *planning levels*. Figure 2.2 denotes the planning horizon of these plans: long term, midterm, short term or realization. Care pathways are the result of a design process that involves physicians and therapists and is designed for long-term periods. Treatment plans are defined for an individual patient for a defined period of time, which is seen as a midterm period. Treatment schedules are the result of scheduling of appointments on the short-term. Realized treatment schedules are the result of the realization of care.

Relations between planning levels and congruence

The arrows between the planning levels relate to precedence relations: first, an expert panel draws a care pathway to be used for the coming years. Then, the physician draws an individual treatment plan and finally, appointments are scheduled and realized.

Congruence (Dutch: congruentie) is defined as the degree to which one planning level is in accordance with another. We can measure congruence between all planning levels. For example, congruence between the treatment plan and the care pathway is the degree to which the treatment plan is in accordance with the respective care pathway.

There are various aspects of congruence to measure. For example, one can measure congruence with respect to the total number of appointments, or congruence with respect to appointment frequency per week. Chapter 4 defines the types of congruence applied in this research.

2.3 Care pathways and treatment plans in SMK

In SMK, the patient's physician draws the treatment plan and schedulers use it to determine the treatment schedule. SMK has no general guidelines for composing treatment plans. Some care units use care pathways as a guideline for treatment plans, but most care units frequently define treatment plans case-by-case.

Figure 2.3 gives the care pathway, initial treatment plan, mutated treatment plan, treatment schedule and realized treatment schedule for an example patient in SMK's rehabilitation center. Besides depicting incongruence and possible causes, it should also be clear from the figure that registration of treatment plans is not always complete in SMK. For example, the duration of FT and MW appointments is lacking in treatment plans, and for MW the number of appointments is not even mentioned. In practice, treatment plans are often incomplete, which hinders the measurement of congruence.

	Week 1			Week 2			Example of cause of incongruence
Care pathway	2xFT 30min	4xET 30min	1xMW 60min	2xFT 30min	4xET 30min		
Initial TP	4xFT	4xET 30min	MW	4xFT	4xET 30min		Patient specific characteristics
Mutated TP 1	4xFT	4xET 30min	MW	4xFT		1xBAG 30min	Prognosis of patient has changed
Schedule	4xFT 30min	2xET 30min		4xFT 30min	2xET 30min	1xBAG 30min	Lack of capacity
Realization	1xFT 30min	2xET 30min		4xFT 30min	2xET 30min	1xBAG 30min	Therapist absenteeism

Figure 2.3 Care pathway, initial treatment plan (Initial TP), mutated treatment plan (Mutated TP), treatment schedule and realized treatment schedule for an example patient

The application of treatment plans and care pathways differs between care units. For example, at the neurologic and SIR care units physicians write the treatment plans for diagnosis and treatment simultaneously. This enables the early scheduling of treatment appointments and ensures that the patient can start with treatment right away. After the patient is diagnosed, the team decides whether the initial treatment plan for treatment was appropriate and makes adjustments, if necessary. Meanwhile, at the CAO care unit, physicians first describe a treatment plan for diagnosis, perform diagnosis, and then describe a treatment plan for treatment. This allows defining a good initial treatment plan for treatment.

Some care units, such as pediatric rehabilitation, make use of evidence based care pathways. However, there appears to be no rehabilitation center-wide policy for the application of treatment plans, i.e., there is no guideline whether to make use of standardized (and evidence-based) care pathways or to encourage individually defined treatment plans per patient. Moreover, there is no clear policy on treatment plan mutations.

2.4 Scheduling process description

Scheduling is performed in a centralized structure in SMK. Schedulers manage the calendars of therapists in an electronic database system. Comparable to other rehabilitation centers [11], schedulers manually book in appointments for patients based on the prescription in treatment plans. Schedulers also perform re-scheduling of appointments manually. This paragraph discusses the scheduling process in SMK.

We describe the scheduling process for one specific patient. The process starts as the scheduler receives an order to schedule a new treatment plan. The starting date of treatment is determined by evaluating urgency, waiting time and available capacity by the scheduler, sometimes in cooperation with therapists or physicians. When a possible starting date is found, the scheduler informs the patient that he or she can start therapy. If the patient is available, the appointments are scheduled as stated in the treatment plan. For outpatients, the scheduler aims to minimize the number of therapy days per week and tries to schedule repetitive appointments at the same time slots in subsequent weeks. In other words, the scheduler aims to maximize the use of combination appointments and horizontal scheduling, respectively.

From now on, the process follows a weekly pattern. During the week, physicians and therapists can make treatment plan mutations, which are communicated through e-mail, the hospital information system (HIS) or by phone. From Monday to Thursday, the scheduler implements the changes in the patient's treatment schedule. On Thursday, the treatment schedules for the next week are made final. To obtain a feasible treatment schedule, the scheduler solves all appointment conflicts for the coming week: double appointments from a patient perspective (i.e., the patient has two appointments at the same time) as well as a therapist perspective (i.e., the therapist has two appointments at the same time) are removed. This is done by switching appointments, assigning a different therapist, or ultimately cancelling an appointment. Usually, representative members of care teams help to solve conflicts. Once a feasible schedule is obtained, the scheduler further optimizes the schedule in terms of waiting time between appointments and an equal division of appointments over treatment days. Schedules for outpatients are sent by postal service or e-mail, depending on patient preferences. Schedules for inpatients are brought to the ward. The scheduler then makes sure that the appointment conflicts that were solved for the next week are also solved for appointments in the next weeks.

Occasionally, treatment schedules for the next week are adjusted after they have been delivered. For example, it happens that patients or therapists cancel an appointment because of illness. Schedules thus frequently have to be adapted on Friday or during its execution the next week. Inpatient schedules provide more possibilities for changes, since these patients usually do not have any availability constraints.

When treatment is finished, the physician communicates this through the HIS. The scheduler removes all existing appointments, whereby the process is finished.

2.5 Patient groups

As of October 2014, the rehabilitation center consists of four care units, which are further divided in twelve care teams. This paragraph first discusses the care teams and their relation to patient groups. Figure 2.4 gives an organizational chart of the care units and teams in the rehabilitation center.

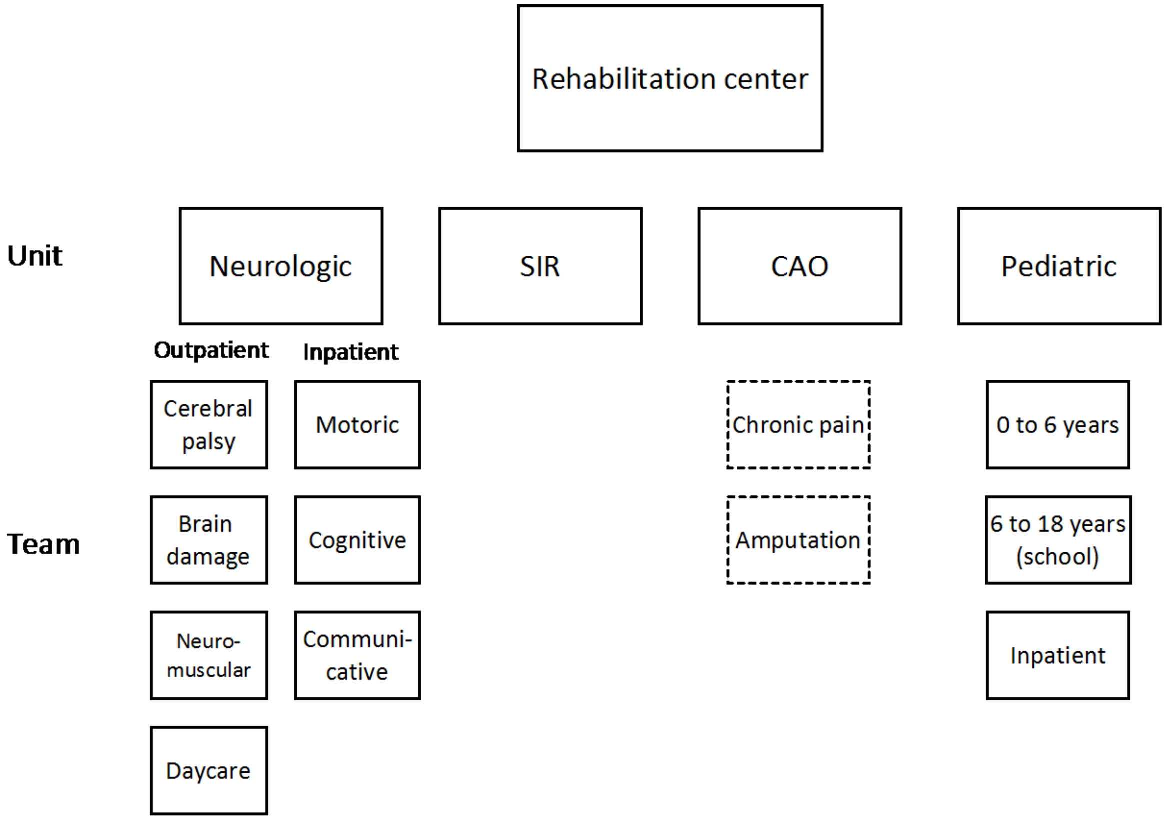


Figure 2.4 Care units and care teams in SMK rehabilitation center (October 2014)

Care teams relate to patient groups. In neurologic rehabilitation, there are inpatient care teams for motoric conditions, cognitive and communicative conditions. In addition, there are outpatient care teams for brain damage, cerebral palsy, neuromuscular conditions and day care. The spinal injury (SIR) care unit has no further differentiation in teams. This unit delivers inpatient and outpatient care. The chronic pain, amputation and orthopedic rehabilitation (CAO) care unit further divides in a chronic pain team and an amputation team. The dotted lines mean that these teams are not formally described, but de facto operate as separate teams. The pediatric care unit is divided in a toddler team, an inpatient team and a team for children from 6 to 18 years. The latter team also provides care for children that attend the adjacent St. Maartenschool, a specialized school for disabled children.

2.6 Planning and control

Planning and control is known as the design and organization of processes. It involves setting goals and deciding in advance what to do, when to do it and who should do it. In this paragraph we give an outline of the planning and control decisions in SMK. This should help to understand the relations between planning decisions and to identify missing, inadequately defined or incoherent planning decisions [12]. This again helps us to understand possible causes of incongruence. We use the framework of Hans, Van Houdenhoven and Hulshof to position the planning and control decisions of SMK [13].

2.6.1 Framework for health care planning and control

Hans, Van Houdenhoven and Hulshof propose a framework for health care planning and control. In their framework, health care planning and control comprises four managerial functions, covering medical, financial, renewable resource and consumable resource decisions [13]. Planning and control takes place at four hierarchical levels: strategic, tactical, offline operational and online operational planning. Strategic planning concerns structural decision-making, i.e., defining the organization's mission and translating this mission into the design of the health care delivery process. Tactical planning translates strategic planning decisions to guidelines that facilitate operational planning decisions [12]. Offline operational planning concerns the in advance planning of operations, while online operational planning deals with monitoring the process and reacting to unforeseen events [13].

Combining the four managerial functions and hierarchical levels creates a 4x4 matrix, which is used to identify the nature of planning decisions.

2.6.2 Planning decisions in SMK

This section discusses planning decisions in SMK that are related to treatment planning and scheduling. We relate the planning decisions to positions in the framework for health care planning and control. The included planning decisions relate to medical and resource capacity planning. We classify planning decisions by hierarchical level.

Strategic planning decisions

Service mix. The care unit and care team classification describes the service mix of the rehabilitation center of SMK. SMK describes itself as a 'leading hospital in treating conditions in movement and posture.' The services of most care teams relate to this target audience. However, the conditions treated in the cognitive and communicative care teams in neurologic rehabilitation do not always relate to movement and posture. Within care units, there can be prioritization of conditions.

Case mix. Production targets per care unit are based on historical production and are set by SMK management. However, according to care unit managers the production targets are not always realistic, since demand of care heavily influences actual production.

Resource capacity dimensioning. Staff dimensioning is based on production targets on the one hand, and desired utilization on the other hand. Since production targets often differ with actual production, this approach does not necessarily lead to optimal staff dimensioning. Each care unit performs staff dimensioning. Treatment room capacity is fixed.

Capacity allocation. The current strategy is to have specialist care units based on diagnosis groups (CAO, SIR and neurologic rehabilitation) and age (pediatric rehabilitation). Within care units, the degree of specialization differs: in neurologic rehabilitation, different teams per diagnosis (group) exist, while there is no distinction in care teams at the SIR unit. Therapist are allocated per care unit and team. Informal arrangements between care units determine the allocation of treatment rooms per care unit.

Application of treatment plans and care pathways. Care pathways are defined for most diagnosis and symptoms, but care pathways are not always up to date with practice. All care units make use of treatment plans, but treatment plans are not always based on a care pathway. In most care teams, changing initial treatment plans is allowed and not discouraged. Since the way treatment plans are applied relates to the development and implementation of medical protocols, we see this subject as part of strategic medical planning.

Use of group therapy. Patients generally have a combination of individual therapy and group therapy. In group therapy, one or more therapists provide treatment to more than one patient. Group therapy cannot be applied to all patients and all recovery phases: the patient should be independent enough to do exercises individually, without a therapist being continuously present. Group therapy can be beneficial for the patient, since patients can learn from each other and motivate each other. The use of group therapy is motivated by its therapeutic value, not by efficiency gains. There is no structured focus to maximize the use of group therapy in SMK. Since the decision to provide group therapy is a long-term decision and relates to medical decision making, we see this subject as part of strategic medical planning.

Tactical planning decisions

Shift scheduling. Shift scheduling deals with deciding which shifts to be worked and how many employees to assign to each shift [12]. In SMK, shift scheduling is partly based on history, partly based on demand for therapists over the week and partly motivated by availability of therapists over the week. One goal is to make sure that all disciplines are represented during the whole working week (Monday to Friday). For smaller disciplines, for example social work, this can be problematic. Shift schedules are made by hand.

Block planning of group therapy. Group therapy appointments are usually fixed for a longer period. If a new group is formed, a time slot is selected for which there are no therapist capacity conflicts. Schedulers also avoid time slot conflicts with other groups that are part of the same care pathway. There is no structural periodical evaluation of time slots for group therapy. For some groups, patients can enter the group continuously, while for others start and stop dates are fixed.

Access policy and admission control. Within care units, most care teams have their own waiting list. Sorted on descending priority, patients classify as acute, emergency or elective. The scheduler (outpatient) or intake coordinator (inpatient) controls the admission of patients. Elective outpatients are only admitted if the needed therapy load is available in the coming weeks, while bed occupancy regulates the admission of inpatients. A simultaneous start at all therapies is important in making admission decisions, especially for patients with a short treatment plan. To allow a short access time for acute or emergency patients, schedulers cancel appointments of other patients, if necessary.

Offline operational planning decisions

Patient-to-appointment assignment. At the moment of scheduling of the initial treatment plan, series of appointments are scheduled at once (see Paragraph 2.4). Nevertheless, the date and time slot of an appointment is subject to change until a week before execution. Appointments are scheduled in blocks of (multiples of) 15 minutes. For individual therapy, patients are assigned to a fixed therapist per discipline. However, some care units make use of two fixed therapists if capacity restrictions require this. Time slots for groups are fixed and leading in the scheduling of individual appointments. In group therapy, it is common to have more than one therapist per group therapy sessions, which is referred to as a multi-resource appointment.

For outpatients, the objective is to schedule as many appointments as possible on the same day. However, outpatients never have two individual appointments with the same therapist/discipline on one day. Having more than one appointment on one day is referred to as a combination appointment. For patients with combination appointments, schedulers aim to reduce idle time between appointments as much as possible. However, on indication of the physician or the patient, idle time can be deliberately scheduled between appointments. Inpatients typically have treatment five days per week. Therefore, combination appointments are no issue for them. For outpatients, recurring appointments are preferably scheduled on the same timeslot over the weeks. This is called horizontal scheduling.

If no therapy is provided due to a public holiday, recurring appointments that should be scheduled at that day are not scheduled at all.

Staff-to-shift assignment. Staff-to-shift assignment is performed simultaneously with shift scheduling. Therapists should communicate holidays on a two-week notice, in which case they arrange replacement themselves.

Switching therapists per patient. Although patients are assigned to a fixed therapist, schedulers occasionally switch therapists in order to prevent cancellation of appointments.

Interchangeability of therapists between teams. In case of capacity problems, therapists may work for other care teams than their own. However, there are no rules that define the permission to exchange. Exchange occurs between teams of the same care unit as well as between teams from different units.

Online operational planning decisions

Rescheduling of appointments. For outpatients, rescheduling of appointments only occurs if this has no consequences for the schedule of other patients. If an appointment must be rescheduled, but no alternative time slot can be found, the appointment is cancelled. Since inpatients are already present at the clinic, there are no restrictions on rescheduling for them.

Cancellations and no-shows. If a patient cancels a single appointment within a week before the appointment or does not show up, no replacement appointment is scheduled. If the patient is absent for a longer period, appointments are rescheduled.

Therapist absenteeism. Depending on therapist capacity, appointments are rescheduled to other therapists in case of therapist absenteeism. If no capacity is available, the appointment is cancelled. No replacement appointment is scheduled.

Temporary capacity changes. The use of temporary staff and working in overtime is discouraged. Instead, appointments are cancelled in case of capacity problems.

2.7 Bottleneck analysis

This section discusses bottlenecks related to treatment planning and scheduling. Input for this section is derived from interviews with care unit managers and schedulers. The goal of the bottleneck analysis is to identify causes for incongruence, for which we propose and evaluate interventions.

The bottlenecks are described in relation to their managerial position (medical planning or resource capacity planning) and hierarchical position (strategic, tactical, offline operational, online operational). This allows us to see at what planning level we should look for a solution. The bottlenecks that follow are described as they are perceived by the interviewees.

Treatment plan mutations

Although the advantage of treatment plans is that the amount and type of care is defined in advance, they are frequently mutated. Treatment plan mutations introduce the risk that treatment plans become overfull or empty, poorly matched with patient needs, unpredictable and financially unattractive.

Four causes are distinguished. First, for some patient groups there are treatment plans for the diagnosis phase and the treatment phase. Treatment plans for treatment are sometimes determined before finishing the diagnostic phase. It is obvious that without a clear diagnosis, the validity of the treatment plan for treatment is reduced and the risk of treatment plan mutations increases. Second, there is no culture to steer on congruence between initial treatment plans and realized care. In general, physicians and therapists are (understandably) more concerned with providing optimal care for the patient than with optimizing the care process. They do not hesitate to offer the patient additional therapy if they indicate this is valuable, although the grounds for such deviations are not always clear. Third, if care pathways are the basis for a treatment plan, poorly designed or chosen care pathways can result in the need to make treatment plan mutations. Fourth, the medical prognosis and improvement pace of patients is not always predictable, not even with excellent diagnostics.

In addition, it is not clear which individuals are authorized to make treatment plan mutations. At some care units, only physicians can make mutations, while at others, also therapists are authorized to mutate treatment plans. Allowing multiple persons to make mutations without someone overseeing the treatment plan introduces the risk that treatment plans become incoherent, overfull or empty.

This bottleneck is a result of medical planning decisions. The problem occurs at the offline operational planning level, since treatment plan mutations are done after treatment plan composition, but before treatment plan scheduling. However, the cause of the problem may also lie at the strategic planning level, since a possible cause is the poor design of care pathways.

Perceived capacity shortage

Demand for rehabilitation care is not entirely predictable. If managers and schedulers find insufficient capacity to schedule new patients, waiting lists grow. Some care units try to cope with this problem by downgrading treatment plans or simply not scheduling all appointments of the treatment plan. Another measure is stopping with demand inductive services such as aftercare consults.

In inpatient care, patients that are classified as urgent must be admitted on short notice. If the scheduler cannot find capacity to allow access of the urgent patient, he is forced to cancel appointments of other patients. The available therapist capacity is based on the number of beds and an estimation of the amount of therapy per patient. Managers say that whenever bed occupancy is low, patients get extra therapy in order to remain high staff utilization. If bed occupancy increases, the extra therapy is not always discontinued. The result is a shortage in staff when bed occupancy is high.

By checking the number of empty time slots in schedules of therapists, we can see if the perception of schedulers and managers is correct. Figure 2.5 shows the percentage of empty time slots for disciplines AT, BAG, ET, ET, FT, MW and PS for therapists assigned to the SIR unit and CAO unit respectively, for the period April to December, 2014.

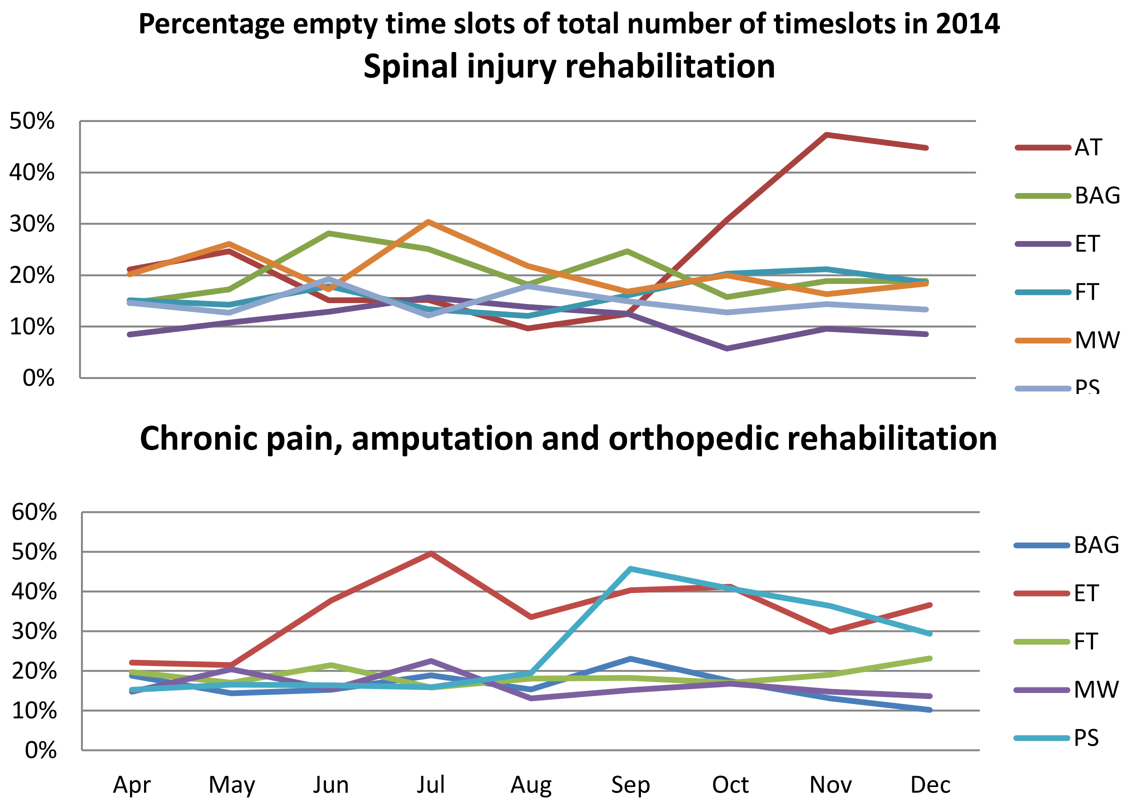


Figure 2.5 Percentage of empty time slots compared to total number of timeslots for two care units

The percentage of empty time slots is never lower than ten per cent, except for ET in the SIR unit during October-December. Of course, planning rules, such as combination appointments and fixed therapists, and patient availability make it hard to realize high utilization. Nevertheless, these results indicate that there is room for improvement.

The problem shows at the tactical planning level (new patient admission decisions), and offline or online operational planning (rescheduling of other patients). The cause of the problem can be poor capacity dimensioning (strategic), capacity allocation (tactical) or shift scheduling (tactical). Additionally, it can be the case that schedulers do not optimally utilize available capacity. The limited intelligent support of scheduling software makes it hard for schedulers to make optimal appointment scheduling decisions.

Limited flexibility of therapists

Interchangeability of therapists between care teams and units is limited, which makes it hard to make efficient use of therapist capacity. Flexibility is also limited by allocating therapists to specialist care units and teams, instead of applying one large team of generalists per discipline. Given the specialized nature of some forms of treatment, it is unclear to what extent interchangeability or forming a team of generalists is possible.

Figure 2.5 gives an example of problems arising from limited flexibility: in October 2014, ETs at the SIR unit only have 5% empty time slots, while the ETs at the CAO unit have over 40% empty time slots. Although there is no data of ETs from CAO working on SIR patients during this period, having one generalist team would have led to more equal division of work in the first place.

Limited flexibility leads to problems in offline and online operational planning. In offline planning, limited interchangeability restricts options to act on demand variations, while in online planning, limited interchangeability restricts rescheduling options in therapist absenteeism or admission of urgent patients. The cause of the problem lies at capacity allocation (tactical) and the degree of applying interchangeability (offline operational).

Poor matching of shift schedules with demand

Care unit managers struggle with finding optimal shift schedules. Schedules often evolve historically and are made by hand. Mandatory meetings and limited staff availability hinder realizing good shift schedules. Most therapists are required to work on Tuesdays, since most meetings take place at that day. On Fridays and Wednesdays there is limited staff availability, because these are the typical days off for part-time personnel. This results in a concentration of appointments on a few weekdays, and restricts scheduling options. . Figure 2.6 shows deviation in therapist availability per day, for all therapists in SCI and CAO as of April 2015.

Moreover, shift schedules do not always properly connect to the time that treatment is given. For example, at the SIR care unit, therapists are present at 8 A.M., while patients are available two hours later.

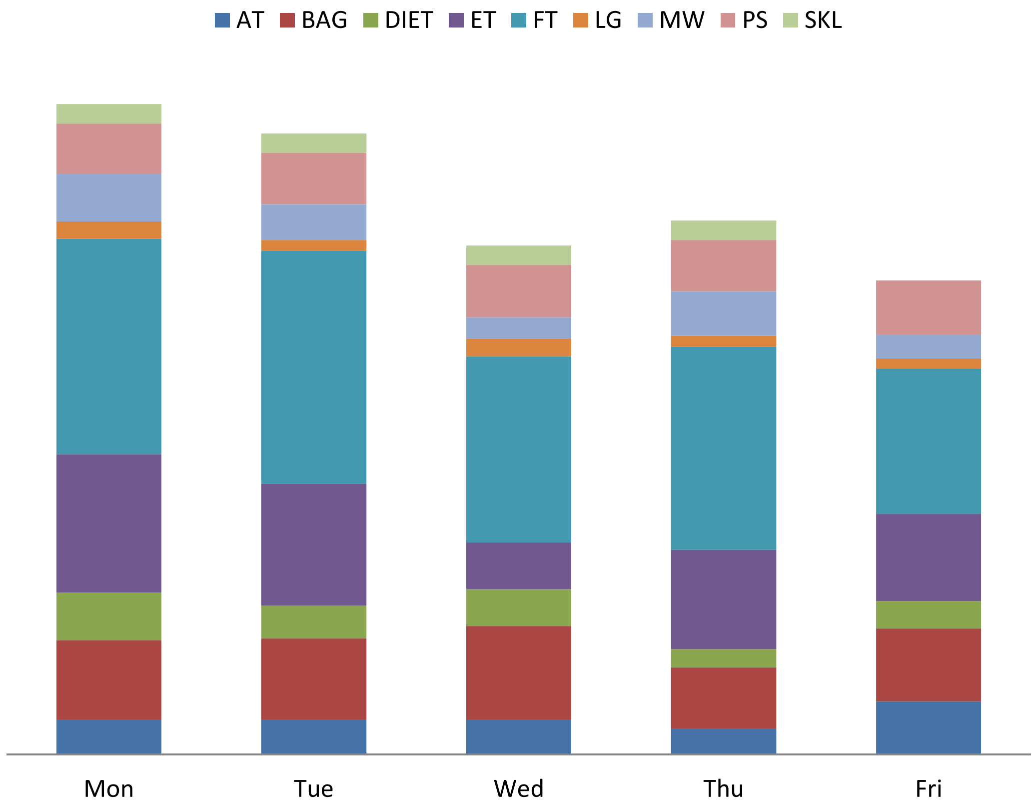


Figure 2.6 Number of working hours per day per discipline in CAO and SCI combined

This bottleneck relates to the tactical planning level, since shift schedules are made in the mid-term.

Meeting structure

Therapists and physicians need to consult one another to discuss the patient's progress and to give shape to the multidisciplinary process. However, the number and organization of these (formal and informal) meetings is a bottleneck.

With respect to resource capacity planning, scheduling meetings is of a tactical nature. However, it also has a strategic medical aspect, since the frequency of meetings is prescribed by medical protocols.

No resource capacity data to make patient admission decisions

Most units in the rehabilitation center have trouble with predicting future capacity needs of current patients, because treatment plans are often tailored and the number of treatment plan mutations is high, while both treatment plans and mutations cannot be obtained from the data warehouse. This makes it hard to decide when patients can start therapy. Admission of new inpatients is solely based on bed capacity, and no data on therapist availability is used. The result is that in some cases patients are admitted to the rehabilitation center, while therapy cannot start or appointments of other patients have to be cancelled.

The problem relates to patient admission decisions, which are made in the mid-term, and has therefore a tactical nature.

Group therapy complicates the scheduling of other appointments

Group therapy appointments are fixed over long periods and are thus leading in scheduling individual appointments. This complicates scheduling individual therapy. For example, a group consists of eight patients and all these patients also need individual therapy. Since SMK strives to combine appointments and reduce idle time between appointments, individual appointments should be scheduled shortly before or after group therapy. This is troublesome, because therapist capacity is limited.

Group therapy planning is determined in the mid-term. The problem thus has a tactical nature.

Therapy cancellations and no-shows

The number of online cancellations of therapy (that is, after offline scheduling) by patients and no-shows is considered to be a bottleneck, and can be positioned as an online operational problem. Moreover, schedulers indicate that therapists often communicate their days off on a short notice (10 days is the rule), leading to treatment plan mutations. This occurs at the online and offline operational level.

2.8 Organizational goals

This paragraph defines organizational goals for SMK, which result from a meeting with two managers. Organizational goals serve as input for defining congruence measures.

Quality and safety of care

To achieve patients' treatment goals, treatment plans should fit with the patient's individual needs and realized care should be congruent with the treatment plan. SMK believes that quality of care partly depends on quality of process: a properly organized process ensures an equitable access time and continuity of care. SMK strives to compose evidence based treatment plans. Finally, competent employees and safe equipment are important values for the quality and safety of care.

Financial health

SMK strives to deploy staff, treatment rooms and equipment efficiently. Treatment plans should be financially viable. Reimbursement of rehabilitation care is based on diagnosis related care products. These products are specified for a patient group and are composed by a governmental organization. A care product includes the delivered care for a specified period (called a treatment trajectory) and is based on weighted treatment hours or hospitalized days. The value of a care product increases step-wise. For example, for a specific diagnosis group the reimbursement tariff is equal for all treatment trajectories that contain up to 58 weighted treatment hours, 59 to 128 hours, and so further. To obtain financially viable treatment trajectories, the reimbursement structure should thus be considered. This means that not only treatment plans should be designed cost-effectively before treatment, but also that the plan should be adhered to in execution. In addition, SMK actively steers on staff utilization, since staff costs account for 95% of the rehabilitation center's costs.

Patient satisfaction

The patient's goals are the foundation in developing a treatment plan. For example, patients can have the goal to be able to walk their dog or visit the supermarket. Therefore, it is important to conduct the treatment plan as agreed. Outpatients generally prefer no or limited waiting time between appointments and want to limit the number of treatment days in a week. Moreover, patients prefer a short access time and prefer that their availability is considered in appointment scheduling.

Staff satisfaction

Staff typically demands an acceptable workload, variation in tasks, flexibility with respect to days off and holidays, sufficient treatment rooms and equipment, autonomy in appointment scheduling, and working days and hours that are aligned with private life.

2.9 Recommendations and delimitation

This paragraph concludes the chapter with recommendations for SMK resulting from the context analysis, which mainly originate from the discussion on planning and control functions and bottlenecks in Paragraphs 2.6 and 2.7.

The final part of this thesis focuses on the design and evaluation of interventions that are acting upon identified bottlenecks and thereby aim to improve congruence. This paragraph delimitates our research with respect to which interventions to design and evaluate.

2.9.1 Recommendations

Many of the problems discovered in the bottleneck analysis involve decision making by clinicians and managers. The use of care pathways, treatment plan composition and the freedom to deviate from the treatment plan are examples of this. Implementation of recommended interventions should therefore be designed by or in close cooperation with medically informed professionals.

Standardize composition of care pathways

Currently, the use of care pathways varies throughout the rehabilitation center. To allow steering on care pathways and treatment plans, we propose that care pathways are composed for as many diagnostic groups as possible in a standardized manner. Of course, care pathways should abide the definition of care pathways provided in this thesis.

Restrict authority to approve treatment plan mutations

Some care units allow that both physicians and therapists mutate treatment plans. The bottleneck analysis shows that this can lead to a lack of oversight of the treatment plan, resulting in incoherent or overfull treatment schedules. Only one person should have the authority to approve treatment plan mutations. Such a policy might simultaneously lessen the number of mutations.

Invest in a culture of initial treatment plan congruence

Treatment plan congruence is currently no issue for physicians and therapists. Optimizing the quality of care is seen as a license to deviate from initial treatment plans through the course of treatment. Creating awareness of the importance of congruence for quality of care, patient satisfaction and process optimization might improve treatment plan congruence. Moreover, putting emphasis on the diagnostic trajectory and evidence-based care pathways might improve the quality of initial treatment plans, reducing the need for treatment plan mutations. Finally, the importance of early communication of days-off on treatment plan congruence should be emphasized.

Use operations research methods in shift scheduling

The scheduling of shifts for therapists is currently done by hand and based on historical schedules, therapist availability and therapist preferences. Schedules made by hand rarely provide optimal solutions with respect to utilization. Ernst et al provide a literature review on staff scheduling methods from operations research [14]. Such methods might be used to enhance shift schedules.

Optimize scheduling of group therapy

Group therapy requires multiple resources and serves more patients than individual appointments. Scheduling group therapy sessions has a large influence on scheduling individual appointments of group participants. Optimizing group therapy scheduling might have a large influence on the ability to schedule appointments (on time) and therefore on congruence.

Invest in automated scheduling

Scheduling appointments in rehabilitation care is very complex due to the enormous number of variables, constraints and performance criteria. Therefore it is very unlikely to provide an optimal solution by hand. Although there are algorithms for automated scheduling in rehabilitation care (e.g., [1]), these methods cannot be directly implemented in SMK. However, given the high workload of manual scheduling and the importance of good schedules, we recommend future research on automated scheduling.

Explore the effect of specialists versus generalists on scheduling performance

Currently, therapists are assigned to one or more care teams. Although interchanging therapists between teams occasionally occurs when capacity problems arise, there is no formal policy on interchangeability. Increased interchangeability might increase efficient use of therapist capacity.

Another possible measure is to abandon the idea of assigning therapists to teams. In her thesis, Dedden shows that one large team of physiotherapists for a whole rehabilitation clinic provides optimal results with respect to number of appointments scheduled [15]. Although it is questionable whether a team of generalists is desirable for the quality of care, taking steps towards more generalists should be considered.

Investigate the rate and causes of no-shows and therapy cancellations

The perceived high rate of no-shows and therapy cancellations should be further investigated. Is the number of no-shows and cancellations really that high? What are the causes of no-shows and cancellations? Congruence might improve by better communication with patients about restrictions in the patients' availability and putting emphasis on the importance of attending therapy and timely cancellation.

Evaluate the effect on performance of leaving the “fixed therapist” principle

The assignment of one therapist per discipline to a patient reduces the number of scheduling options, and therefore limits flexibility. The effect of leaving the fixed therapist principle on performance should be evaluated. Of course, the effects on quality of care should not be neglected.

Improve insight in current and future resource capacity utilization

It follows from the bottleneck analysis that perceived capacity shortage leads to downgrading of treatment plans and to cancelled appointments due to admission of other, more urgent patients. Although the methods proposed in this section might improve utilization and thus reduce perceived capacity problems, improving insight in current and future capacity must be the first step of improvement. Insight in and steering on resource capacity is currently poor: admission decisions of inpatients are based on bed capacity instead of therapist capacity and outpatients are admitted if the scheduler indicates available capacity by manual checking. Moreover, access times are not predictable because future resource utilization is unknown and it is hard to timely and properly address over- or underutilization of staff resources.

Measurement of congruence is essential for providing current capacity information and future capacity predictions. Such data enables the development of a tool that produces insight in current capacity usage and is able to predict future resource demand on the mid-term.

Improve the quality of measurement data

Currently, several issues prohibit measurement of congruence in the rehabilitation center of SMK. First, treatment plans and care pathways do not always provide all the information as is defined in this thesis (Paragraph 2.2). Second, input of treatment plans in the HIS is done through a combination of option buttons (i.e., select a value from a predefined list) and free text fields. Free text fields allow an infinite number of different values to be entered, prohibiting data analysis. Third, in the HIS, treatment plans and care pathways are not coupled with the treatment schedule and realized treatment schedule. Manual coupling of such information is cumbersome and prone for error. Fourth, mutations to treatment plans are communicated by a large number of means. Only communication of mutations through the HIS ensures storage of treatment plan mutations in the data warehouse.

Therefore, care pathways and treatment plans should be entered in the HIS according to a standardized structure, such that all relevant information as stated in the definition of a care pathway and treatment plan in this thesis is always provided and stored. In addition, implementing a new storage format for care pathways and treatment plans that only consists of mandatory non-free text input fields is essential for the quality of data. Moreover, initial and mutated treatment plans should be automatically coupled with the treatment schedule and realized treatment schedule in the HIS. Finally, treatment plan mutations should only be communicated through the HIS, again in a standardized manner and through a standardized input format.

2.9.2 Delimitation

Although all recommendations deserve further exploration, we make a selection of interventions for design and evaluation. We identify three types of causes of incongruence: inefficient use of capacity, medical necessity to deviate from treatment plans and cultural aspects leading to incongruence. For examples, see Figure 2.7.

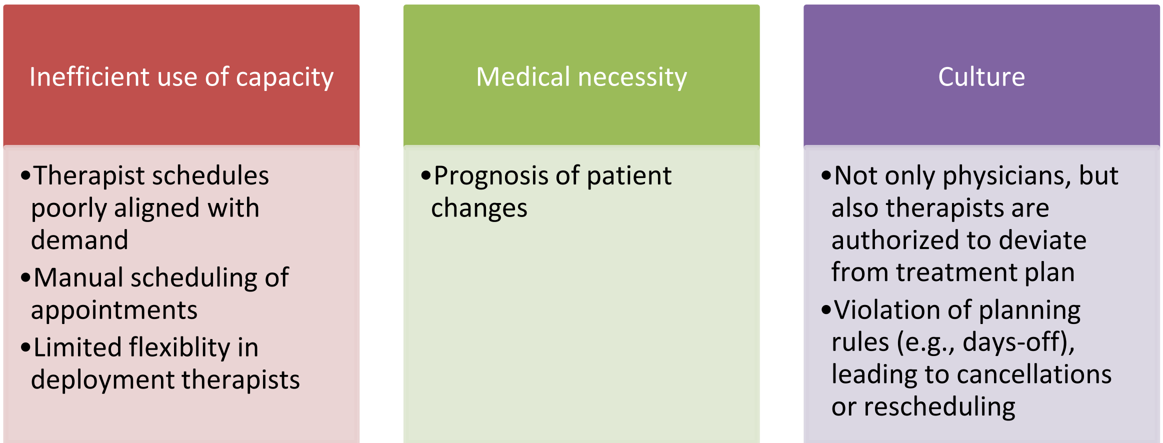


Figure 2.7 Categorization of causes of incongruence

Solving the cultural causes for incongruence is a matter of defining rules and ensuring that those rules are abided. This works best if staff understands the importance of abiding to those rules. Medical causes are hard to solve. Making sure that the initial treatment plan suits the patient's needs is all that can be done. Deviations because of medical reasons are not undesirable from the patient's perspective. Improving efficient use of capacity is often done by applying operations research techniques. Examples are decision support tools in appointment scheduling and optimization techniques for generating staff schedules. Given the operations research background of the author, we think that we can make the largest impact with interventions that improve efficient use of capacity.

Our bottleneck analysis indicated that schedulers perceive capacity shortages and that methods for staff scheduling and appointment scheduling disallow efficient use of capacity. Making more efficient use of capacity increases the number of appointments that can be scheduled (in time), and therefore improves congruence.

We choose three interventions for further exploration.

First, we develop an *automated appointment scheduling model* which is able to comply with the existing planning rules in SMK, appointment types and number of appointments per patient. This model also performs group appointment scheduling. We evaluate the performance of the scheduling model in a simulation study. This intervention introduces intelligent support for making scheduling decisions.

Second and third, we assess the effect of *generalist therapist teams* and *improved staff schedules* within the same simulation study. We hypothesize that generalist therapist teams and improved staff schedules enlarge scheduling possibilities. We hypothesize that all interventions independently improve the ability to schedule treatment plan appointments (on time), and therefore congruence.

Evaluating the interventions for the whole rehabilitation center requires a huge effort in generation of input data, while the simulation model for appointment scheduling is unlikely to be able to handle such amount of data. However, to assess the effect of generalist therapist teams, we need to focus on at least two care units. Since the care units CAO and SIR have a set of properly described care pathways, we decided to focus on the CAO and SIR care units for the rest of this thesis. However, the congruence measurement method (introduced in Chapter 4) and automated appointment scheduling can be applied to all care units of the rehabilitation center.

Chapter 3: Literature

This chapter discusses the literature on congruence measurement in Paragraph 3.1 and appointment scheduling in Paragraph 3.2. Appendix I provides an outline of the applied search strategy.

3.1 Congruence measurement

Congruence measurement in health care has received considerable attention in scientific literature. It is referred to as variance measurement [16; 17; 18], adherence measurement [19; 20; 21] or compliance measurement [22; 23]. The importance of evaluating the use and improvement of CPs is widely recognized [16; 22; 18], although lacking support from IT and incomplete or unavailable health records often restrict congruence measurement [16; 17].

Zander [18] identifies the need to measure congruence between care pathways and realized care at an early stage in 1997. The author argues that the use of congruence data has lagged behind the development of care pathways. Caminiti *et al.* [19] define a set of quality indicators to measure congruence between care pathways and realized care. This set contains process as well as outcome indicators. The authors applied a binary approach: process indicators measured whether patients received activities as prescribed in the CP. Kinsman [22] applies a similar approach. Milchak *et al.* [21] report the development of criteria to measure adherence to hypertension guidelines. These authors also apply a binary approach: the criteria measure whether activities are performed as defined in the guideline. Konrad, Tulu & Lawley [17] distinguish between omission of activities and addition of activities in measuring congruence between a CP and realized care. Huang *et al.* [23] propose an online adherence auditing service that gives near real-time insight in congruence between CPs and realized care. The system can report violations in the form of reports for management or reminders for medical staff.

According to Van de Klundert, Gorissen & Zeemering [20], binary approaches offer limited insight in congruence. Instead, their model allows parallelism and exclusive alternatives, and considers precedence relations. It enables valuing omissions, substitutes or additional activities by means of deviation costs. Congruence is measured by finding the minimum total deviation costs of a realized treatment trajectory over all feasible realizations of the CP. Since the model allows alternative sub pathways, there can be more than one feasible realization. Experts define deviation cost parameters for substituting, omitting or adding an activity. Dynamic programming is applied to find a feasible realization with minimum deviation cost.

Hartholt [24] developed measures for congruence with respect to the number of activities, duration and frequency, and aggregated these measures to one congruence score. When this score is higher than some threshold, a signal is send out to the treating physician. Hartholt's congruence measures are based on absolute deviations. In a case study, the author coupled patients to care pathways by using characteristics of patients that were known to follow a certain care pathway.

Unlike acute care, which is the setting of most reviewed articles, recurring activities are common in rehabilitation care, while precedence relations are rare. As a result, it is not only of interest whether a prescribed activity has been performed, but frequency and total amount of care are also important. With the exception of Hartholt, no articles were found that explicitly address recurrent activities, although van de Klundert *et al.* identifies recurrent activities as a possible extension to their model [20]. Unfortunately, the model of van de Klundert includes irrelevant aspects for rehabilitation care, such as precedence relations and exclusive alternatives. This would make congruence measurement unnecessary complex for our purpose. The sole article that concerns congruence in rehabilitation care by Hartholt may serve as a good starting point, but has some drawbacks when applied for our purpose. First, it uses absolute deviations. This makes the direction of deviations unclear, which hinders steering on congruence. Second, the aggregation of different aspects of congruence to one score is arbitrary, and it is unclear what the resulting score means.

We conclude that the reviewed congruence measurement methods do not address the needs in the current situation. Nevertheless, the types of congruence as defined by Hartholt and the distinction between omission and addition of activities as introduced by Konrad, Tulu & Lawley can be applied in our congruence measurement model.

3.2 Appointment scheduling in rehabilitation care

While there is a vast amount of literature on scheduling in health care, only a few articles focus on scheduling in rehabilitation hospitals [11]. However, some authors consider that the multidisciplinary nature of rehabilitation care complicates manual scheduling and that the lack of computerized support for scheduling in rehabilitation care negatively affects both quality of care and logistical efficiency [1; 11].

In an early work, Podgorelec and Kokol developed a genetic algorithm for scheduling multiple appointments of multiple patients to a number of therapists or other resources, while performance with regard to waiting time, utilization and lead time was optimized [25]. In genetic algorithms, each potential solution is represented by a chromosome. The algorithm randomly generates an initial population of chromosomes. Then, the population evolves and new chromosomes are created in the process. Eventually, the chromosomes that represent the best solutions survive [26]. Chien, Tseng & Chen formulated rehabilitation patient scheduling as a hybrid shop scheduling problem (HSSP), which considers precedence relations. A genetic algorithm was proposed to solve the HSSP [27]. Motivated by precedence relations between appointments, Huang, Zheng and Chien [26] applied a similar approach in an inpatient rehabilitation center.

Ogulata, Koyuncu & Karakas present a hierarchical mathematical model which generates weekly staff schedules in physiotherapy service [28]. It provides a schedule that maximizes the number of selected patients, while workload of physiotherapists is balanced and waiting time is minimized. The problem was broken down into three stages, since solving the problem at once would lead to numerical intractability. Stage one creates a list of patients scheduled during the next week, stage two involves patient-to-physiotherapist assignment, and stage three assigns patient-physiotherapist combinations to time slots. Patients can be assigned to only one time slot.

Schimmelpfeng, Helber & Steffen focus specifically on scheduling in rehabilitation care [11]. The authors developed a mixed-integer linear program (MILP) to determine appointments for patients. Since large instances cannot be solved with this program, the authors decompose the model to achieve acceptable solving times. Stage one assigns appointments to days, stage two assigns appointments to time slots and stage three assigns resources to appointments. The authors consider group appointments as well as individual appointments and include the requirement to schedule appointments with a fixed therapist. The authors do not consider access time or lead time violation, i.e., appointments are either scheduled or not within the prescribed time window, but deviation is not allowed.

Braaksma *et al.* propose an integer linear program (ILP) for scheduling sets of appointments for a single patient in rehabilitation care [1]. The ILP schedules all appointments of a predefined care pathway in one or more iterations. The ILP aims to schedule all appointments within a preferred range of timeslots, while steering on performance indicators with respect to combination appointments, horizontal scheduling, access time and lead time. The ILP does not consider multi-resource appointments and group therapy. Requests for scheduling care pathways are fulfilled immediately after arrival of the request, a concept the authors call *online scheduling.* All other scheduling methods discussed in this section refer to *offline scheduling*, i.e., a set of patients is saved up before execution of the request. The authors performed a case study within the rehabilitation outpatient clinic of the Academic Medical Center (AMC) in Amsterdam and reported significant improvement of performance indicators for access time (22.9% of patients with an access time <2 weeks in baseline, versus 53.7% or more in experiments), simultaneous start (52.6% versus ≥90.8%) and the number of unscheduled appointments (<0.33% in experiments).

We found that the model of Braaksma *et al.* is applicable to the rehabilitation center of SMK to a considerable extent. Similarly to Braaksma's model, SMK currently fulfills planning requests one by one and all appointments of a care pathway are scheduled at once (although mutations occur frequently afterwards). Moreover, Braaksma's ILP steers on KPIs with respect to the number of scheduled appointments, combination appointments, horizontal scheduling, access time and lead time; KPIs that are also important to SMK. Finally, Braaksma's ILP-modeling technique allows modification, such that certain constraints can easily be omitted or added.

The automated scheduling model developed in this research builds on the ILP developed by Braaksma *et al.* However, the setting in SMK differs with AMC. The instances used in Braaksma's case study included only outpatients. These patients generally have lower appointment frequencies and total number of appointments than inpatients. Moreover, multi-resource and group appointments were not considered. SMK, on the other hand, serves many inpatients, and group and multi-resource appointments are very common. Optimizing scheduling group therapy timeslots is one of our recommendations, and should therefore be part of the scheduling model. The high number of prescribed appointments in many of SMK's treatment plans and care pathways requires that a decomposition approach, as applied in [28] and [11], is necessary to maintain numerical tractability.

Chapter 4: Congruence measurement

This chapter discusses congruence measurement. The proposed congruence measures are the result of the context analysis and discussions with SMK management. We deliberately avoid the term performance indicator. Incongruence is not necessarily a bad thing: if realized care is incongruent with the care pathway due to specific patient characteristics, this may be beneficial for the patient and SMK. Therefore, we prefer the term measure over performance indicator.

Paragraph 4.1 discusses the notation applied in congruence measurement. Then, Paragraphs 4.2 and 4.3 introduce congruence measures. Paragraph 4.4 describes the aggregation of these measures to discipline, unit or rehabilitation center-wide measures. Paragraph 4.5 presents baseline measurements for congruence.

In addition to measure development and a baseline measurement, we developed a prototype tool for congruence measurement. Chapter 8 discusses this tool and its implementation.

4.1 Notation

This paragraph introduces notation for congruence measurement. Say p is the index for patients and z is the index for care pathways. Let $y = (p, z)$ be a patient-care pathway identifier, which is a unique combination of the patient and a care pathway. We use c for disciplines, w for therapy periods and a for activities. The duration in days of therapy period w is defined as β_{yc} and is equal to the maximum number of days between two subsequent activities for a specific y and c, rounded down to equivalents of whole weeks (e.g., 7 days, 14 days, etc.), as defined in the care pathway[4].

To allow measurement of congruence between care pathways, initial treatment plans, mutated treatment plans, treatment schedules and realized treatment schedules, we denote these planning levels by $s \in S = \{CP, ITP, MTP^n, TS, RTS\}$. n indicates the mutation sequence for mutated treatment plans.

See Table 4.1 for an overview of parameters and their related sets.

Table 4.1

Overview of indices and sets

Index/parameter	Set	Description of index/set
$\boldsymbol{p}$	P	All patients
$\boldsymbol{z}$	Z	All care pathways
$\boldsymbol{y}$	Y	All care pathway-patient combinations
$\boldsymbol{c}$	C	All disciplines
$\boldsymbol{s}$	S	All planning levels
$\boldsymbol{w}$	W	Therapy period (within a subset of y, c and/or s)
$\boldsymbol{a}$	A	All activities (within a subset of y, c, s and/or w)

[4] If discipline c is not mentioned in the care pathway, but we need to know the duration of a period to calculate congruence, $\beta_{yc} = 7$.

Numbering of w starts during the first planned or realized week of therapy, irrespective of the discipline. $Duration_{ycwa}^{s}$ is the duration in minutes of activity a in week w, at discipline c, for patient-care pathway combination y at planning level s.

We can define all possible sets by using the parameters from Table 4.1. In these sets, the planning level is denoted by superscript, while other indices are presented as subscripts. For example, W_{yc}^{s} is the set of therapy periods for planning level s, patient-care pathway combination y and discipline c.

Figure 4.1 gives an example of our notation. It shows the realized physiotherapy appointments of one example patient.

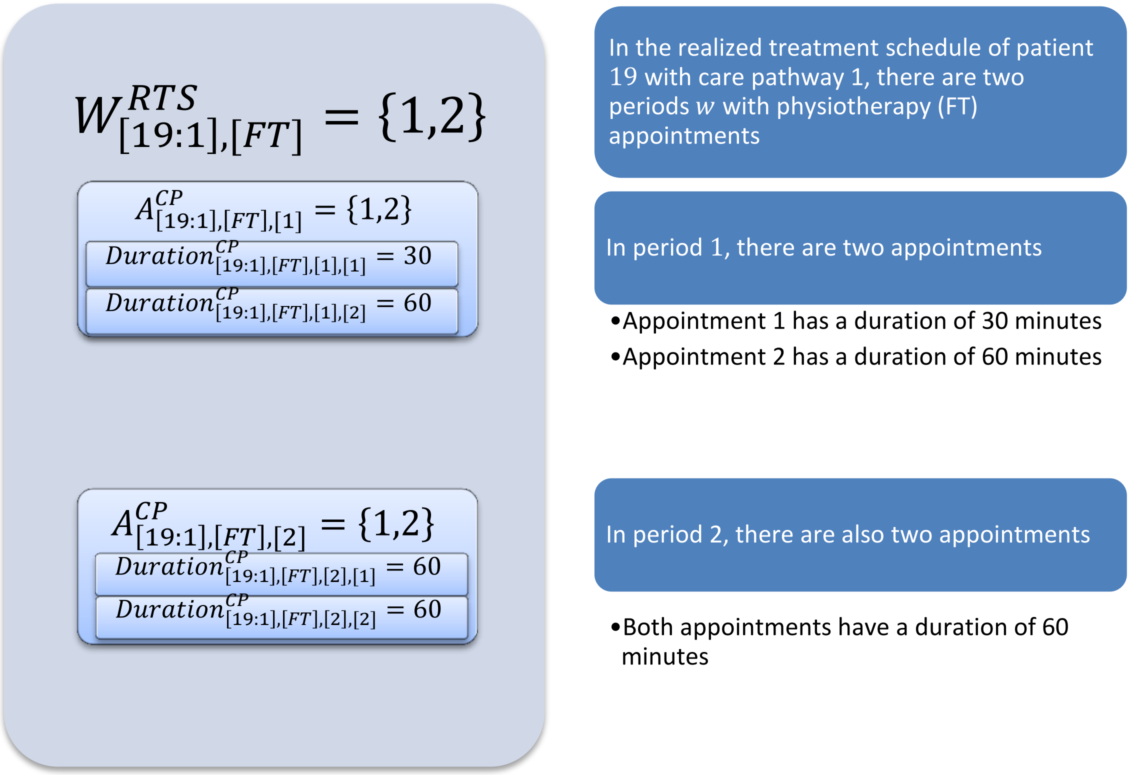


Figure 4.1 Example of notation for the realized physiotherapy appointments of one patient

4.2 Congruence measures

In this paragraph, we introduce seven congruence measures, discuss their importance for congruence between treatment plans and realization of care, and introduce their mathematical notation.

The measures we introduce indicate congruence between two planning levels. The relation between planning levels is denoted by a superscript. For example, $NUMO_{yc}^{s'\to s}$ gives the score of $NUMO$ between planning level s' and s for patient-care pathway identifier y and discipline c. Note that s always denotes the higher planning level (e.g., care pathway) , and s' the lower planning level (e.g., realized treatment schedule). The notation does not indicate which type of appointments should be included in a specific set. For example, we can calculate separate congruence measures for group appointment and individual appointments, direct and indirect patient time, and so on.

We define measures per patient-care pathway combination y and discipline c. Measures can be aggregated to a score for a specific patient, care team, care pathway or the whole rehabilitation center. Paragraph 4.5 discusses aggregation of measures.

Congruence with respect to the total number of planned activities

The importance of congruence with respect to the total number of planned activities is intuitive for process optimization. It increases predictability of demand of care, which allows making better patient admission decisions and informing new patients earlier when therapy can start. Moreover, since variability is reduced, better scheduling decisions can be made. Finally, if more or less activities are realized than planned, this may indicate over- or undertreatment. We introduce two measures for congruence with respect to the total number of activities: number of added activities ($NUMA$) and number of omitted activities ($NUMO$). If we would define one measure for both elements, aggregation of data would be pointless. The definitions of $NUMO$ and $NUMA$ are based on Konrad, Tulu and Lawley's work [17]. Hartholt also measures deviation of the number of activities, but uses absolute values [24].

We define $NUMO$ as the number of activities prescribed at the higher planning level s (e.g., treatment plan), but missing at the lower planning level s' (e.g., realized schedule), divided by the number of activities at planning level s. We subtract the result from 1, to derive a score between 0 and 1: 0 represents no congruence and 1 represents full congruence.

In formula form, $NUMO$ is defined as follows:

$$NUMO_{yc}^{s'\to s} = 1 - \frac{|A_{yc}^{s'} \backslash A_{yc}^{s}|}{|A_{yc}^{s}|} \qquad (4.1)$$

The vertical bars represent set cardinality. Thus, the numerator indicates set difference, i.e., the number of activities that is present in s but not in s'. The denominator represents the total number of activities in s.

We define $NUMA$ as the number of activities not prescribed at the higher planning level s, but was added at the lower planning level s', divided by the number of activities at planning level s'.

We subtract the result from 1 to derive a score between 0 and 1: 0 represents no congruence and 1 represents full congruence. Note that the denominator is different from formula 4.1. This is necessary to obtain a score between 0 and 1. The result is the following formula:

$$NUMA_{yc}^{s' \to s} = 1 - \frac{|A_{yc}^{s} \backslash A_{yc}^{s'}|}{|A_{yc}^{s'}|} \tag{4.2}$$

The numerator represents the number of appointments that is present in s' but not in s. The denominator represents the total number of appointments in s'.

If a patient has omitted activities, $NUMA$ is not applicable. If a patient has added activities, $NUMO$ is not applicable. Thus, patients have either a score for $NUMO$ or for $NUMA$. The only exception is when congruence between planning levels is 100%. In that case, both $NUMO$ and $NUMA$ are equal to 1.

Congruence with respect to the total duration of planned activities

Just as $NUMO$ and $NUMA$, congruence with respect to the total duration of planned activities is important for increasing predictability of total demand of care. Measuring congruence with respect to duration in addition to measuring congruence with respect to the number appointments is necessary, because duration of appointments can differ between planning levels. Additionally, this measures indicates whether the patient has received the amount of care as specified in the treatment plan. If cost-effectiveness is taken into account in the design of care pathways or treatment plans, this measure can be used to assess cost-effectiveness of realized care. In that case, one would have to match costs and revenues to the amount of planned and realized care.

We introduce two measures for congruence with respect to the total duration of planned activities: $TDURO$ and $TDURA$. $TDURA$ is for addition of duration, $TDURO$ for omission. We define $TDURO$ as the fraction of total duration of activities in s that was not present at planning level s'. We define $TDURA$ as the fraction of the total duration of activities in s' that was not present at planning level s. For both measures, we subtract the score from 1: a score of 1 represents full congruence, a score of 0 represents no congruence.

We formulate $TDURO$ and $TDURA$ as follows:

$$TDURO_{yc}^{s' \to s} = 1 - \frac{\max\left(0, \sum_{w \in W_{yc}^{s}} \sum_{a \in A_{ycw}^{s}} Duration_{ycwa}^{s} - \sum_{w \in W_{yc}^{s'}} \sum_{a \in A_{ycw}^{s'}} Duration_{ycwa}^{s'}\right)}{\sum_{w \in W_{yc}^{s}} \sum_{a \in A_{ycw}^{s}} Duration_{ycwa}^{s}} \tag{4.3}$$

$$TDURA_{yc}^{s' \to s} = 1 - \frac{\max\left(0, \sum_{w \in W_{yc}^{s'}} \sum_{a \in A_{yc}^{s'}} Duration_{ycwa}^{s'} - \sum_{w \in W_{yc}^{s}} \sum_{a \in A_{ycw}^{s}} Duration_{ycwa}^{s}\right)}{\sum_{w \in W_{yc}^{s'}} \sum_{a \in A_{ycw}^{s'}} Duration_{ycwa}^{s'}} \tag{4.4}$$

In accordance with $NUMO$ and $NUMA$, either $TDURO$ or $TDURA$ is applicable, except when congruence is 100%.

Congruence with respect to the frequency of planned activities

Congruence with respect to the planned frequency of activities is a measure for the continuity of care. This is important for the quality of care and patient satisfaction, but also for reducing variability, which results in being able to make better scheduling and patient admission decisions.

The goal of this measure is not to find the direction of incongruence with respect to frequency, since this is already captured in measuring $NUMO$ and $NUMA$. Thus, we simply need a measure for the absolute deviation from the prescribed frequency of activities.

We introduce the measure FRQ for congruence with respect to the frequency of planned activities. We define FRQ as the average absolute percentage deviation of the activity frequency in the lower planning level s' to the activity frequency in the higher planning level s, where frequency is measured per period w. To obtain this measure, we first calculate the average absolute deviation of frequency in s' compared to s:

$$ABSFRQ_{yc}^{s'\to s} = \frac{1}{|W_{yc}^{s} \cup W_{yc}^{s'}|} \sum_{w \in W_{yc}^{s} \cup W_{yc}^{s'}} \mathrm{abs}(|A_{ycw}^{s'}| - |A_{ycw}^{s}|) \quad (4.5)$$

After the summation sign, the absolute difference of number of activities per period between s' and s is calculated. We include all periods w that are present in W_{yc}^{s} and/or $W_{yc}^{s'}$. Before the summation sign, the average absolute deviation per week is calculated. The result is the average absolute deviation of frequency in s' compared to s, measured in number of appointments.

We can now define FRQ. This is done by dividing $ABSFRQ$ with the average activity frequency at s. We subtract the score from 1: a score of 1 represents full congruence, a score of for example 0.3 means that frequency at s' differs on average 70% from the frequency at s.

As a result, we find the following formula for FRQ:

$$FRQ_{yc}^{s'\to s} = 1 - |W_{yc}^{s}| \frac{ABSFRQ_{yc}^{s'\to s}}{\sum_{w \in W_{yc}^{s}} |A_{ycw}^{s}|} \quad (4.6)$$

Note that this measure is affected if disciplines do not start therapy as planned. For example, if occupational therapy starts 3 weeks later in s' than in s, congruence with respect to frequency would be zero in the first three weeks, which would dramatically affect the total frequency congruence score. Moreover, FRQ can only be calculated if the number of appointments in s for discipline c is ≥1.

Congruence with respect to the duration of individual activities

Measuring congruence with respect to the duration of individual activities gives insight to what extent the duration of individual activities is equal at different planning levels. The goal of this measure is not to find the direction of incongruence with respect to planned duration, since this is captured in $TDURO$ and $TDURA$. Therefore, we simply want to find a measure for deviation from the prescribed duration per activity. We introduce the measure DUR for congruence with respect to the duration of individual activities.

We define DUR as the average absolute percentage deviation of the planned duration of single activities in the lower planning level s' to the planned duration of single activities in the higher planning level s.

Congruence with respect to planned duration of activities is measured by taking the average of the absolute deviation of duration in s' compared to s over all activities a and periods w. We only include activities that are both mentioned in s and s'. We subtract the result from 1: a score of 1 represents full congruence, a score for example 0.7 states that duration of single activities at s' differs on average 30% from duration of single activities at s.

As a result, we find the following formula for DUR:

$$DUR_{yc}^{s'\to s} = 1 - \frac{1}{\sum_{w\in W_{yc}^{s}\cap W_{yc}^{s'}} |A_{ycw}^{s} \cap A_{ycw}^{s'}|} \sum_{w\in W_{yc}^{s}\cap W_{yc}^{s'}} \sum_{a\in A_{ycw}^{s}\cap A_{ycw}^{s'}} \frac{\text{abs}(Duration_{ycwa}^{s'} - Duration_{ycwa}^{s})}{Duration_{ycwa}^{s}} \tag{4.7}$$

After the summation sign, the absolute difference of duration of activities between s' and s is calculated, for all activities a and therapy periods w. This is summed over all activities a that are present in both A_{ycw}^{s} and $A_{ycw}^{s'}$ and again summed over all periods w that are present in both W_{yc}^{s} and $W_{yc}^{s'}$. We take the average by dividing through the number of activities that are present in both s and s'. The result is the percentage average deviation of duration in s'compared to s.

Congruence with respect to the planned lead time

Having control over lead time allows better patient admission decisions and the ability to give the patient a better prediction of the total lead time. Therefore, congruence with respect to planned lead time is important for process optimization.

We define the measure for congruence with respect to the planned lead time as the difference between the lead time as derived from the lower planning level s' (e.g., realized schedule) minus the lead time as derived from the higher planning level s (e.g., treatment plan), divided by the lead time as derived from s. Lead time is defined as the total number of weeks between the first and the last appointment at a planning level. We can thus take the maximum of the number of periods in $W_{yc}^{s'}$ multiplied by the number of weeks per period, denoted by $\frac{\beta_{yc}}{7}$.

We define the formula for LT as follows:

$$LT_{y}^{s'\to s} = \frac{\max_c(|W_{yc}^{s'}| \cdot \frac{\beta_{yc}}{7}) - \max_c(|W_{yc}^{s}| \cdot \frac{\beta_{yc}}{7})}{\max_c(|W_{yc}^{s}| \cdot \frac{\beta_{yc}}{7})} \tag{4.8}$$

$LT_{y}^{s'\to s}$ thus gives the percentage deviation of the lead time in s' compared to s, and can both be positive (longer lead time in s') and negative (shorter lead time in s').

4.3 Additional measures for congruence

In addition to the aforementioned measures, we define additional measures that are relevant to congruence measurement, but cannot be described as measures that describe congruence between planning levels.

Access time

Access time is an important aspect for patient satisfaction. When access time is defined as the time between treatment plan composition and start of treatment, it is also an important aspect for congruence. As the time between the composition of a treatment plan and execution of the plan increases, the probability that intervening circumstances reduce the applicability of the plan also increases. One thus might expect that the larger the access time, the larger the incongruence between the initial treatment plan and mutated treatment plan(s).

We define access time as the time between the definition of a treatment plan and the first treatment appointment (i.e., in the realized treatment schedule). Define TPD_y as the date that the treatment plan is written for patient-care pathway identifier y and FTD_y as the date that the first therapy appointment is realized. Then, we define the performance indicator for access time for patient-care pathway identifier y as:

$$AT_y = FTD_y - TPD_y \tag{4.9}$$

The result is the access time in days.

Simultaneous start

In rehabilitation care, it is important for patients to have a simultaneous start of therapy at all planned disciplines. A patient-care pathway combination has a simultaneous start if all disciplines that should start in the first week of treatment as stated in the initial treatment plan start within five days from the first therapy appointment. Then, we can define the measure for simultaneous start, SS, as the fraction of therapists that realized a simultaneous start:

$$SS_y = \frac{\left|C_y^{S\prime}: should\ start\ in\ first\ week\ and\ does\ start\ within\ 5\ days\right|}{\left|C_y^{S}: should\ start\ in\ first\ week\right|} \tag{4.10}$$

4.4 Aggregation of measures

We can translate the measures introduced in Paragraph 4.3 – defined per patient-care pathway identifier (and discipline) – to aggregated measures.

For aggregation of a measure for y and c to a measure for y, we take the weighted average over disciplines c. We use weights, since the relative importance of disciplines to congruence is subjective. Say that δ_c is the relative importance weight for discipline c.

Then, for example, aggregation over disciplines for $NUMO$ is performed as follows:

$$NUMO_y^{s'\to s} = \frac{\sum_{c \in C_y^{s'} \cup C_y^s} \delta_c NUMO_{yc}^{s'\to s}}{\sum_{c \in C_y^{s'} \cup C_y^s} \delta_c \left|\left\{A_{yc}^{s'} \leq A_{yc}^{s}\right\}\right.} \tag{4.11}$$

In the numerator we take the sum of the weighted score for all disciplines that are stated in s and/or s'. If $NUMO_{yc}^{s'\to s}$ is not applicable for a specific y and c (because appointments were added instead of omitted), it is not included in the calculation. We divide the score by the total sum of the weights for disciplines that are stated in s and/or s'. Aggregation over disciplines is performed in similar fashion for other measures.

In order to aggregate $NUMO_y^{s'\to s}$ to $NUMO^{s'\to s}$, we have to aggregate over patient-care pathway identifiers. For example, aggregation over patient-care pathway identifiers for $NUMO$ is performed as follows:

$$NUMO^{s'\to s} = \frac{\sum_{y\in Y} NUMO_y^{s'\to s}}{|Y|} \tag{4.12}$$

Aggregation of other measures is done in a similar fashion. Additional to these examples, one can also aggregate per care pathway, discipline, and so on.

4.5 Baseline measurement

Since we have defined congruence measures, we can perform a baseline measurement of congruence in SMK. The first step of a baseline measurement is data gathering. We encountered several problems during data gathering. In addition to the lack of structured data registration in SMK (see Paragraph 2.9), the two required sources of data – treatment plans and care pathways, versus (realized) treatment schedules – are not coupled in the data warehouse. For example, a realized appointment of patient x does not have a unique identifier which couples the appointment to care pathway y or treatment plan z. To enable a baseline measurement of congruence, we manually coupled data. Since treatment plans are poorly accessible due to data registration problems, we limited ourselves to measurement of congruence between care pathways and realized treatment schedules.

4.5.1 Data gathering

We obtained data from the data warehouse of SMK by using SAS Enterprise Guide. Data coupling, cleansing and analysis was carried out by a program written in RStudio, specially developed for this purpose.

Our timeframe was 01-2013 to 01-2015. We only considered CAO and SIR care units and disciplines ACT, BAG, DIET, ET, FT, LG, MW, PS and SKL. We generated a list of care pathways (CPs) and their complete description[5]. Only currently used CPs were included, the CP *Other* was excluded. See Appendix II for an overview of CPs. We obtained all orders that instructed the scheduling of an initial treatment plan. These treatment plan orders are used for communication of treatment plans between the physician and the scheduler. We extracted all relevant

[5] That is, per discipline: frequency and duration of appointments, lead time; per appointment: indication whether appointment concerns group or individual therapy, indication whether the appointments concerns direct or indirect patient time.

information from the orders, including patient number, CP and the date of order, which was regarded as the start date of treatment. So-called treatment trajectories indicate the time horizon that a patient is in treatment for a specific care need. End dates of treatment were derived from treatment trajectories. If the treatment trajectory is not finished, its end date was set at 31-12-2999.

zTreatment plan orders, CP descriptions and treatment trajectories were used to obtain a CP-patient combination, including all prescribed appointments and the timeframe of treatment. Realized appointments were coupled to CP-patient combinations based on the appointment date (between start and end date) and patient number. Hereby the coupling process is finished, and congruence can be calculated. See Figure 4.2 for a schematic description of this process.

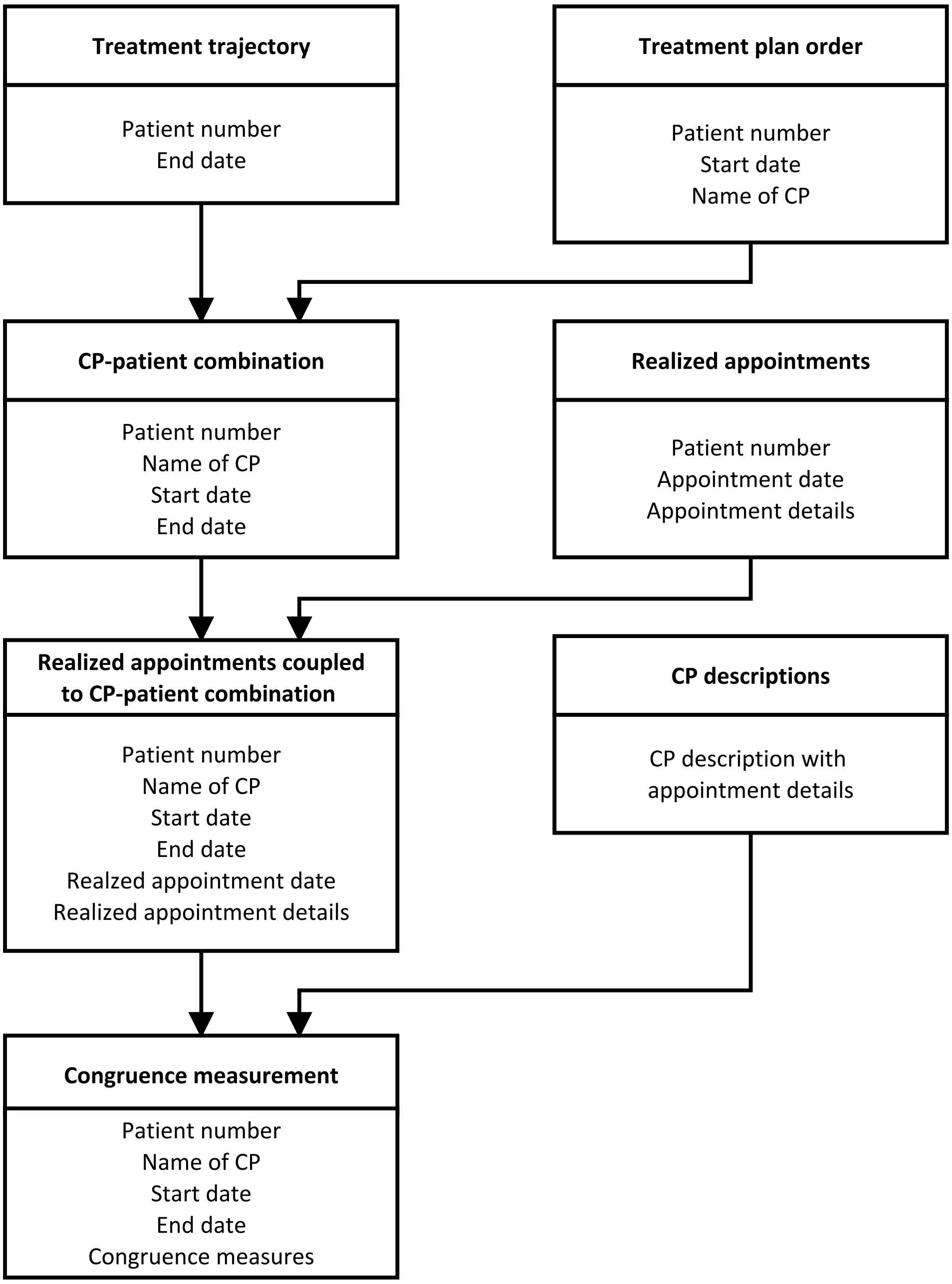


Figure 4.2 Schematic description of data coupling method

The abovementioned method does not guarantee that all realized appointments are coupled to CP-patient combinations. For example, in the case of a patient with two parallel treatment trajectories it is unclear which treatment trajectory is related to the treatment plan order under investigation. Moreover, registration errors result in missing or incorrect end dates of treatment trajectories. Therefore, we performed data cleansing on our data sets. We removed data entries in the following situations:

- Unable to uniquely couple treatment plan order to treatment trajectory
    - Missing start or end date in treatment trajectory
    - Patient number not present in both datasets
    - Parallel treatment trajectories
    - End date of treatment trajectory is earlier than start date in treatment plan order
- Unable to uniquely couple realized appointment to CP-patient combination
    - Patient number not present in CP-patient combination dataset
    - Date of appointment not between start date and end date in CP-patient combination dataset
- Able to derive multiple CP-patient combinations with the same patient number and care pathway, but differing start dates.

Table 4.2 gives an overview of the number of data entries of each dataset generated in the steps of Figure 4.2.

Table 4.2

Comparison of datasets. Number of entries after filtering on SIR and CAO care units, CPs and disciplines

Number	Dataset description	Number of entries
1	Treatment plan orders	904 CPs
2	CP-patient combinations	687 CPs
3	Realized appointments (not coupled to CPs)	1258 patients, 114624 appointments
4	Realized appointments coupled to CP-patient combinations	583 CPs, 522 patients, 54757 appointments
5	Congruence measurement	578 CPs, 517 patients, 54223 appointments

The 522 patients in dataset 4 had a total of 65310 appointments in dataset 3, which means that 84% of the appointments in dataset 3 could be coupled to a CP. In the original dataset of realized appointments, the care unit was sometimes missing. If we include appointments were the care unit is missing, the 522 patients in dataset 4 had 67211 appointments with the selected disciplines. 81% of these appointments was included in dataset 4.

Dataset 4 still contains appointments that are wrongly coupled to CP-patient combinations. If administrators fail to register the end date of a treatment trajectory when treatment for a specific care need has finished, and the patient has realized appointments for a new care need but no new treatment trajectory is defined, these appointments are wrongly coupled to the CP-patient combination for the initial care need.

4.5.2 Results

We performed a baseline measurement for congruence for direct individual activities. Baseline measurements were performed independently for the disciplines ACT, BAG, DIET, ET, FT, LG, MW, PS and SKL. As mentioned before, congruence was measured between the care pathway and the realized treatment schedule.

Figure 4.3 gives the results for the baseline measurements for $NUMO$, $NUMA$, $TDURO$, $TDURA$, FRQ and DUR for individual therapy.

Number of omitted and added appointments

In many of the investigated cases, none of the prescribed appointments was realized. In other cases, we therapy was provided, while the related discipline was not prescribed in the CP at all. We illustrate our findings in Figure 4.3.

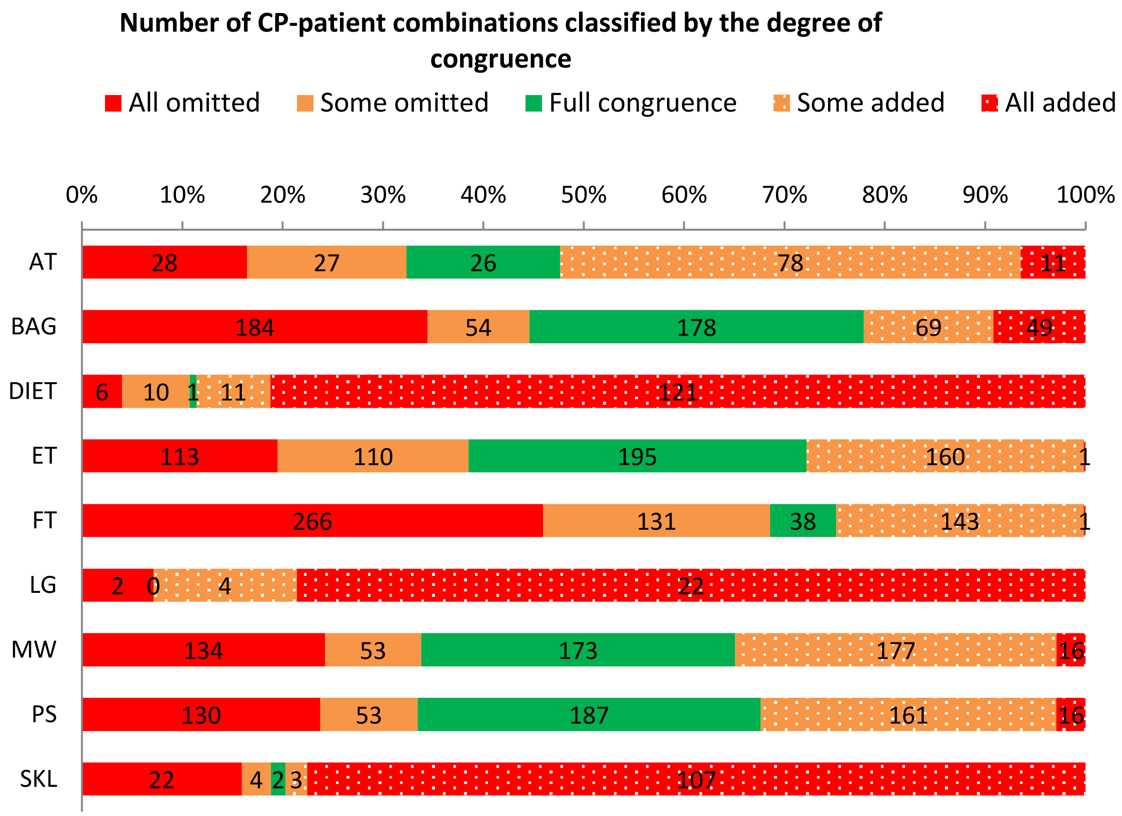


Figure 4.3 Number of CPs classified by the degree of congruence

The figure shows that for the smaller disciplines (DIET, LG, SKL) in most occasions all appointments were omitted, or all the appointments were added with respect to the CP. Overall, congruence with respect to $NUMO$ or $NUMA$ was 0 (red labels) in 27% of the measurements. Congruence was 1 (green labels) in 24% of the cases.

If we look at the cases where $NUMO$ was larger than 0, but smaller than 1, the average $NUMO$ score was between 0.24 and 0.46 for all disciplines. This means that on average between 54 and 76 per cent of the prescribed appointments was omitted, if any but not all appointments were omitted. If we look at cases where $NUMA$ was larger than 0, but smaller than 1, the average

$NUMA$ was between 0.18 and 0.50. This indicates that on average between 50 and 82 percent of the appointments was added compared to the CP.

Based on $NUMO$ and $NUMA$, we can calculate the average deviation from the CP with respect to the number of appointments, irrespective of the direction of deviation. The average deviation was between 53 and 78 per cent for the largest five disciplines. For all results, see Table 4.3.

Table 4.3

Average NUMO and NUMA scores and average absolute deviation

Disc.	Average $NUMO$ (if some, but not all appointments were omitted)	Average $NUMA$ (if some, but not all appointments were added)	Average deviation (all cases)
AT	0.40	0.43	58%
BAG	0.41	0.37	58%
DIET	0.24	0.32	95%
ET	0.46	0.29	53%
FT	0.43	0.28	78%
LG	-	0.18	97%
MW	0.40	0.42	65%
PS	0.43	0.40	59%
SKL	0.28	0.50	97%

Total therapy duration

As can be seen in Table 4.4, congruence with respect to total therapy duration is comparable to congruence with respect to the number of appointments for most disciplines. When we look at the average deviation, the results were equal. The differences between $TDURO$ and $NUMO$ and $TDURA$ and $NUMA$ can be explained by the fact that less cases were included in the calculations for $NUMO$ and $NUMA$ presented in Table 4.4. For example, for ET, more CP-patient combinations had full congruence for $NUMO$ (195) than for $TDURO$ (12), which results in more cases included in the score for $TDURO$. This in intuitively logical: it is “easier” to deviate from the total duration than from the number of appointments.

Table 4.4

Average TDURO and TDURA scores and average absolute deviation

Disc.	Average $TDURO$ (if some, but not all duration was omitted)	Average $TDURA$ (if some, but not all duration was added)	Average deviation (all cases)
AT	0.53	0.53	58%
BAG	0.39	0.37	58%
DIET	0.25	0.36	95%
ET	0.72	0.31	53%
FT	0.43	0.29	78%
LG	-	0.22	97%
MW	0.45	0.47	65%
PS	0.58	0.47	59%
SKL	0.31	0.50	97%

Therapy frequency and duration per appointment

Table 4.5 shows that congruence with respect to the frequency of appointments, FRQ, was close to zero for most disciplines. For the five largest disciplines, FRQ was between 0.07 and 0.34, indicating that the frequency differed on average between 68 and 93 per cent from the care pathway.

Table 4.5

Average FRQ and DUR scores

Disc.	Average FRQ (if not all appointments were omitted)	Average DUR
AT	0.06	0.94
BAG	0.09	0.94
DIET	0.14	0.67
ET	0.21	0.85
FT	0.34	0.94
LG	-2.11	1
MW	0.07	0.94
PS	0.07	0.95
SKL	0.02	1.00

Access time, lead time and simultaneous start

The mean score for the measure for lead time, LT, was 1.4 for CAO (n=376), 2.7 for SIR (n=160) and 1.8 overall. This means that the prescribed lead time is on average exceeded by 80%. The mean score for access time, AT, was equal to 53 days for CAO (n=376), 22 days for SIR (n=160) and 42 days overall. For five patients no score for AT could be calculated. The quality of data prohibited a baseline measurement of SS, the measure for a simultaneous start.

4.5.3 Conclusion

We have included about 50% of the number of patients within our scope in the dataset for congruence measurement. About 80% of the appointments of these patients was used for measurements. Therefore, our results should be interpreted with care.

Although there are no targets defined for congruence, our results indicate that in the SIR and CAO care units differences between care pathway and realized care are enormous. There is no clear direction of incongruence found, although omission occurs slightly more often than addition of activities. We have measured congruence between the highest planning level (care pathway) and the lowest planning level (realized treatment schedule). This makes it hard to explain our results, because incongruence can occur at all planning levels in between. One should measure congruence between two proximate planning levels for more useful results. For example, many omitted activities between treatment schedule and realized treatment schedule would indicate a high amount of last-minute therapy cancellations.

Chapter 5: Automated appointment scheduling model

In Chapter 2 we delimited our research to the development and evaluation of three main interventions. The first intervention is an automated appointment scheduling model that is capable to schedule treatment plans. This chapter introduces this model.

We formulated the scheduling task for one patient as a mathematical model and applied integer linear programming (ILP) as an optimization technique to achieve the best treatment schedule. The ILP derives the best treatment schedule by considering a set of, sometimes conflicting, goals, which are based on the results of our context analysis. This is done by modeling these goals as soft constraints and penalizing the slack variables used in these constraints in the objective function. Paragraph 5.2 gives a more deliberate explanation of soft constraints. Our ILP formulation is based on earlier work of Braaksma et al [1].

Recall that our second and third interventions are generalist therapist teams and improved staff schedules. These interventions and the ILP are evaluated by using the ILP in a simulation model, and varying the settings of the model. Therefore, we describe these interventions when we discuss the simulation model. The simulation model is described in Chapter 6. Experimental results can be found in Chapter 7.

This chapter is organized as follows. Paragraph 5.1 discusses model assumptions. Paragraph 5.2 introduces the model by subsequently describing decision variables, constraints and the objective. Paragraph 5.3 gives the solution approach. Paragraph 5.4 discusses some preliminary experiments and model improvement suggestions.

5.1 Model requirements and assumptions

The goal of the ILP is to schedule a set of appointments (based on a treatment plan or care pathway) for a single patient, while a set of constraints should be met as much as possible. For the remainder of this chapter, we refer to such a set of appointments as the care pathway.

The ILP must be able to schedule individual as well as group appointments, and should allow allocating one or two therapists to an appointment. While some constraints make sure that the ILP steers on congruence, others take planning decisions (section 2.6.2) and other organizational goals (section 2.8) as formulated by SMK into account. Moreover, the ILP should allow different input and parameter settings to enable evaluation of interventions.

We start by making some general model assumptions:

- Appointments are scheduled in time slots of 30 minutes
- No prioritization is made between emergency patients and elective patients (for example, with respect to the maximum allowed access time)
- All resources, except therapists, have unlimited capacity
- All resources, except therapists, have unlimited capacity
- There are no transition times between appointments
- There are no precedence relations between appointments
- Group therapy time slots are not fixed

- Group therapy is only differentiated per care team, unit and discipline. In practice, there are different groups per discipline (one group for walking, one group for hands, et cetera.)
- Multi-resource appointments only occur in group therapy
- Multi-resource appointments are always provided by two therapists
- Patients have no availability constraints
- The duration of scheduled appointment cannot deviate from the duration of the appointment as stated in the care pathway
- Patients have at most eight appointments per therapy type (group or individual) per discipline per week
- All patients have the same preferences with respect to combination appointments and horizontal scheduling
- Team meetings are not considered

5.2 Model description

This paragraph introduces the ILP for automated appointment scheduling. It introduces the model notation, decision variables, constraints and objective function. Although some indices are equivalent to the notation used in the congruence measurement (Chapter 4), notation is completely (re)introduced in this chapter.

5.2.1 Notation

The input of the model consists of a specific (part of a) care pathway, which includes a set of appointments A, a set of available therapists H, and a set of possible time slots T, where $T = \{1,2,3, \dots, |T|\}$. Set C covers disciplines. The (part of a) care pathway or treatment plan that is used as input for the ILP is called an instance. Therapy is scheduled in time slots t of 30 minutes. A day d consists of $D = 21$ time slots, and a week w consists of $W = 5 \cdot 21 = 105$ time slots. The length $|T|$ of the planning horizon depends on the care pathway to be scheduled. Appointments with equal characteristics are modeled as one appointment a. Appointments have equal characteristics if all parameters related to the appointment, such as discipline and during which period the appointment is preferably scheduled, are equal. Per appointment, parameter $NumberApp_a$ indicates how often it should be scheduled.

The ILP uses a considerable number of parameters and variables. Table 5.1 gives a complete overview of the model notation. Parameters and variables are also introduced when they are first applied in a constraint. All parameter names start with an uppercase letter, while variable names start with a lowercase letter. Appendix III provides a recap of the model notation, constraints and objective function.

5.2.2. Decision variables

Per appointment a, the ILP decides how often the appointment is scheduled, and if the appointment is scheduled, in which time slot(s) t it starts. Moreover, a therapist h must be picked. This is regulated by decision variables x_{aht}:

$$x_{aht} = \begin{cases} 1 \text{ if appointment } a \text{ starts at time slot } t \text{ and is assigned to therapist } h \\ 0 \text{ otherwise} \end{cases}$$

Table 5.1	
Model notation	
Indices and sets	
$\boldsymbol{a}, \hat{\boldsymbol{a}} \in \boldsymbol{A}$	All appointments in current instance
$\boldsymbol{t}, \hat{\boldsymbol{t}} \in \boldsymbol{T}$	All time slots in current instance
$\boldsymbol{h}, \hat{\boldsymbol{h}} \in \boldsymbol{H}$	All therapists in current instance
$\boldsymbol{c} \in \boldsymbol{C}$	All disciplines
$\boldsymbol{d} \in \boldsymbol{D}$	Days
$\boldsymbol{w} \in \boldsymbol{W}$	Weeks
Parameters	
$\boldsymbol{AccesstimeInpatient}$	Desired maximum access time for inpatients
$\boldsymbol{AccesstimeOutpatient}$	Desired maximum access time for outpatients
$\boldsymbol{B_{ht}}$	Number of patients who can be scheduled with therapist h and who start therapy at time slot t, not including patients who are already scheduled at therapist h at time slot t
$\boldsymbol{Day}$	Duration of a day in time slots
$\boldsymbol{Duration_a}$	Duration of appointment a in time slots
$\boldsymbol{F_{ac}}$	1 if appointment a must be scheduled at discipline c; 0 otherwise
$\boldsymbol{FirstApp_{ac}}$	1 if $MinWeek_a = 1$ and a is the first appointment at discipline c as stated in the CP; 0 otherwise
$\boldsymbol{G_{hc}}$	1 if therapist h has discipline c; 0 otherwise
$\boldsymbol{GroupApp_{ht}}$	1 if a group therapy appointment is scheduled at time slot t with therapist h
$\boldsymbol{GroupDur_{ht}}$	Duration of group therapy with therapist h starting at time slot t
$\boldsymbol{Group_a}$	1 if appointment a is a group appointment; 0 otherwise
$\boldsymbol{Inpatient}$	1 if the current instance is related to an inpatient; 0 otherwise
$\boldsymbol{M_1, M_2, M_3}$	Big-M parameters, i.e., large numbers
$\boldsymbol{MaxApp}$	Maximum number of appointments to be scheduled for a patient on one day
$\boldsymbol{MaxDev}$	Maximum allowed value for $deviationearlier_a$ and $deviationlater_a$
$\boldsymbol{MaxPatGroup}$	Maximum number of patients that is allowed in a group
$\boldsymbol{MaxWeek_a}$	Last week of the range of weeks during which appointment a is preferably scheduled
$\boldsymbol{MT}$	Maximum number of time slots between two appointments on the same day
$\boldsymbol{MinTherDays}$	Minimum number of days that is needed to schedule all appointments
$\boldsymbol{MinWeek_a}$	First week of the range of weeks during which appointment a is preferably scheduled
$\boldsymbol{Multi_{h\hat{h}t}}$	1 if therapist h and therapist $\hat{h}$ have an existing multi-resource appointment at time slot t; 0 otherwise
$\boldsymbol{MultiResource_{a\hat{a}}}$	1 if appointment a must be scheduled simultaneously with appointment $\hat{a}$ and thereby represents a multi-resource appointment; 0 otherwise
$\boldsymbol{NewPatient}$	1 if the current instance is related to a first sequence of appointments; 0 otherwise
$\boldsymbol{NumberApp_a}$	Number of times appointment a should be scheduled
$\boldsymbol{Outpatient}$	1 if the current instance is related to an outpatient; 0 otherwise
$\boldsymbol{SimultaneousStart}$	Number of days for which a simultaneous start holds
$\boldsymbol{Z_{t\hat{t}}}$	1 if time slot t is on the same day as time slot $\hat{t}$
$\boldsymbol{Week}$	Duration of a week in time slots
Variables	
$\boldsymbol{appatday_d}$	1 if one or more appointments are scheduled on day d; 0 otherwise
$\boldsymbol{auxil_t}$	1 if an appointment is scheduled at t or earlier; 0 otherwise
$\boldsymbol{deviationearlier_a}$	Number of time slots that appointment a is scheduled earlier than $MinWeek_a$
$\boldsymbol{deviationlater_a}$	Number of time slots that appointment a is scheduled later than $MinWeek_a$
$\boldsymbol{exceed}$	Number of time slots that exceed the maximum allowed access time
$\boldsymbol{extraappdisc_{cd}}$	1 if two individual appointments are scheduled at day d with discipline c for this patient; 0 otherwise
$\boldsymbol{extraappdiscgroup_{cd}}$	1 if two group appointments are scheduled at day d with discipline c for this patient; 0 otherwise
$\boldsymbol{extragroup_a}$	Number of new group therapy time slots caused by scheduling appointment a
$\boldsymbol{extratherdays}$	Number of scheduled treatment days more than $MinTherDays$
$\boldsymbol{firstday}$	Day of the earliest scheduled appointment in the current instance
$\boldsymbol{firsttimeslot}$	Time slot of the earliest scheduled appointment in the current instance
$\boldsymbol{firstweek}$	Week of the earliest scheduled appointment in the current instance
$\boldsymbol{lasttimeslot}$	Time slot of the last scheduled appointment in the current instance
$\boldsymbol{leadtime}$	1 if $lasttimeslot$ is greater than the maximum of $MaxWeek_a$over a; 0 otherwise
$\boldsymbol{newday_d}$	1 if an appointment is scheduled on day d and no appointment has been scheduled before on the weekday of day d; 0 otherwise
$\boldsymbol{notsimult_c}$	1 if the first appointment at a discipline (as defined in de CP) is scheduled later than $firstday + SimultaneousStart$
$\boldsymbol{notplanned_a}$	Difference between the number of times a should be scheduled according to the CP and the number of times a is scheduled
$\boldsymbol{smallest_t}$	1 if t is the smallest time slot for which an appointment is scheduled 0 otherwise
$\boldsymbol{x_{aht}}$	1 if appointment a starts at time slot t and is assigned to therapist h; 0 otherwise

5.2.3 Constraints

Scheduling appointments is bound to constraints. For example, a patient cannot be present at two appointments at the same time. This may never be violated and is therefore a *hard constraint*.

In addition to hard constraints, we introduce *soft constraints*. A soft constraint is preferably complied with, but can be violated if necessary. We define planning decisions and organizational goals (as discussed in Paragraph 2.6 and 2.8) as soft constraints. For example, one aims to maximize the use of combination appointments. Then, the soft constraint is that the number of visits should be equal to the theoretical minimum number of visits. However, the ILP also allows that the number of visits is higher than the minimum. In that case, a slack variable is equal to the difference in visits. The weighted sum of all slack variables is minimized in the objective function. Steering on measures for congruence, e.g., frequency and number of omitted appointments, is also modeled by using soft constraints.

This section discusses all constraints that are included in the ILP.

Schedule all appointments as often as prescribed

All appointments should be scheduled exactly $NumberApp_a$ times. Although it is highly undesirable, the model should allow that appointments are scheduled less than $NumberApp_a$ times. Therefore, we introduce slack variable $notplanned_a$, which indicates the number of times that appointment a is not scheduled.

The sum of x_{aht} over h and t plus the number of times the appointment is not scheduled should be equal to $NumberApp_a$. Constraint set 5.1 models this requirement:

$$\sum_{h,t} x_{aht} + notplanned_a = NumberApp_a \;\; \forall a \tag{5.1}$$

Make sure that multi-resource appointments are scheduled accordingly

For some appointments it is prescribed that two therapists are present at the appointment. Such an appointment is called a multi-resource appointment. We say that appointment a and $\hat{a}$ must be scheduled at the same time slot and thereby create a multi-resource appointment. We introduce the parameter $MultiResource_{a\hat{a}}$ to indicate simultaneity:

$$MultiResource_{a\hat{a}} = \begin{cases} 1 & \text{if appointment } a \text{ should be scheduled} \\ & \text{simultaneously with appointment } \hat{a} \\ 0 & \text{otherwise} \end{cases}$$

The following constraint set ensures that multi-resource appointments are scheduled simultaneously or not at all:

$$MultiResource_{a\hat{a}} \cdot \sum_{h} x_{aht} - MultiResource_{a\hat{a}} \cdot \sum_{h} x_{\hat{a}ht} = 0 \;\; \forall a, \hat{a}, t \tag{5.2}$$

Some appointments require a multi-resource appointment with two therapists of the same discipline. Multi-resource appointments must be scheduled with two different therapists. Constraint set 5.3 ensures that an appointment is not scheduled twice with the same therapist:

$$\sum_{a} x_{aht} \leq 1\,\forall h, t \tag{5.3}$$

Start therapy earlier than maximum desired access time

We aim to start therapy within a predefined number of weeks, which is dependent on the type of patient. In order to check whether the first appointment is within the maximum allowed access time, we need to find the time slot of the first appointment. We introduce the binary auxiliary variable $smallest_t$ to find that time slot.

$$smallest_t = \begin{cases} 1 \text{ if } t \text{ is the smallest value for which } x_{aht} = 1 \\ 0 \text{ otherwise} \end{cases}$$

Moreover, we include the auxiliary variable $auxil_t$:

$$auxil_t = \begin{cases} 1 \text{ if } auxil_{t-1} \text{ is equal to 1 or if an appointment is scheduled at } t \\ 0 \text{ otherwise} \end{cases}$$

We add the following constraint sets to make sure that $auxil_t$ and $smallest_t$ have the correct value (the constraint sets are explained below):

$$auxil_t - \sum_{a,h} \left(x_{aht} \cdot \frac{2 - \sum_{\hat{a} \neq a} MultiResource_{a\hat{a}}}{2} \right) \geq 0\,\forall t \tag{5.4}$$

$$smallest_t - auxil_t + auxil_{t-1} = 0\;\;\forall t \tag{5.5}$$

$$auxil_0 = 0 \tag{5.6}$$

$$smallest_t - \sum_{ah} x_{aht} \leq 0\,\forall t \tag{5.7}$$

$$\sum_{t} smallest_t \;= 1 \tag{5.8}$$

Constraint set 5.4 states that $auxil_t$ must be 1 if an appointment is scheduled at t. Constraint set 5.5 ensures that $smallest_t$ is only equal to 1 if $auxil_t = 1$ and $auxil_{t-1} = 0$. Since $\min_{t \in T}(t) = 1$, we must define $auxil_0 = 0$ (constraint 5.6). Constraint set 5.7 makes sure that $smallest_t$ can only be 1 if an appointment is scheduled at time slot t. This also ensures that $auxil_t$ cannot be equal to 1 if t is smaller than the smallest time slot: in that case constraint set 5.5 would not hold. Finally, constraint 5.8 states that exactly one $smallest_t$ must be equal to 1. Therefore, if $auxil_{t-1} = 1$, $auxil_{\hat{t}}$ must be 1 for all $\hat{t} \geq t$ (constraint set 5.5). Note that constraint set 5.4 ensures that appointments are scheduled simultaneously only if

$\sum_{\hat{a} \neq a} MultiResource_{a\hat{a}} = 1$ and prevents that other appointments are scheduled simultaneously.

Simply put, the constraints ensure that $auxil_t$ is equal to 1 if an appointment is scheduled at time slot t or later. Then, $smallest_t$ is equal to 1 for the $auxil_t$ with the smallest t. Thereby we have found the first time slot.

To obtain the value of t for which $smallest_t = 1$, we add the auxiliary variable $firsttimeslot$. The value of this variable is equal to the first time slot and is regulated by the following constraint:

$$firsttimeslot - \sum_t t \cdot smallest_t = 0 \tag{5.9}$$

The ILP allows scheduling both patients that have been scheduled before and patients that have not been scheduled before. To find out if the current instance is related to a new patient, we introduce the binary parameter $NewPatient$:

$$NewPatient \begin{cases} 1 \text{ if the current instance is related to a first sequence of appointments} \\ 0 \text{ otherwise} \end{cases}$$

Since access times differ for different patient groups, we introduce binary parameters to indicate whether the instance is related to an inpatient or outpatient:

$$Outpatient \begin{cases} 1 \text{ if the current instance is related to an outpatient} \\ 0 \text{ otherwise} \end{cases}$$

$$Inpatient \begin{cases} 1 \text{ if the current instance is related to an inpatient} \\ 0 \text{ otherwise} \end{cases}$$

Moreover, we add parameters $AccesstimeOutpatient$ and $AccesstimeInpatient$, representing the desired maximum access time in days. Finally, we introduce the variable $exceed$ that indicates the number of time slots the access time has been exceeded.

Constraint 5.10 checks whether the first appointment is scheduled within the desired access time and ensures that $exceed$ has the correct value.

$$\begin{aligned} NewPatient \cdot firsttimeslot - NewPatient \cdot exceed \\ \leq D \cdot Outpatient \cdot AccesstimeOutpatient + D \\ \cdot Inpatient \cdot AccesstimeInpatient \end{aligned} \tag{5.10}$$

If the first appointment is scheduled on a time slot that has a higher value than the allowed access time, $exceed$ will be equal to the difference between $firsttimeslot$ and the allowed access time. If the current instance is solved for a patient that has been scheduled before, $exceed$ is always equal to zero.

Perform activities in the preferred week

In order to steer on performing activities in the preferred week, and therefore steer on congruence with respect to frequency, we punish the scheduling of appointments that take place earlier or later than preferred. Care pathways indicate the week during which an appointment should preferably take place. Parameters $MinWeek_a$ and $MaxWeek_a$ indicate the range of weeks, counting from the first week of therapy, during which appointment a is preferably scheduled.

Since we want to compare the time slot of an appointment to the week of the first appointment, we need to find the first day of treatment. Therefore, we introduce the integer variable $firstweek$, which is equal to the first treatment day. The correct value of $firstweek$ is regulated by the following constraints:

$$firstweek - firsttimeslot \cdot \left(\frac{1}{Week}\right) \geq 0 \tag{5.11}$$

$$firstweek - firsttimeslot \cdot \left(\frac{1}{Week}\right) < 1 \tag{5.12}$$

Constraint 5.11 ensures that $firstweek$ is not smaller than the actual first week of treatment, and constraint 5.12 regulates that $firstweek$ is not larger than the actual first week.

The number of time slots that an appointment is scheduled later than preferred is measured by the integer variable $deviationlater_a$, and the number of time slots that an appointment is scheduled earlier than preferred is measured by the variable $deviationearlier_a$. The following constraint sets ensure that an appointment is scheduled within the preferred range of weeks or that the variables $deviationlater_a$ or $deviationearlier_a$ are equal to the deviation in time slots from the preferred range:

$$\begin{aligned} &Week \cdot NewPatient \cdot firstweek \\ &\qquad - \sum_h t \cdot x_{aht} - deviationearlier_a + \sum_h x_{aht} \cdot M_1 \\ &\qquad \leq M_1 + Week \cdot NewPatient - Week \cdot (MinWeek_a - 1) - 1 \quad \forall a, t \end{aligned} \tag{5.13}$$

$$\begin{aligned} &\sum_h t \cdot x_{aht} - Week \cdot NewPatient \cdot firstweek - \ deviationlater_a \\ &\qquad \leq Week \cdot MaxWeek_a - Week \cdot NewPatient \forall a, t \end{aligned} \tag{5.14}$$

If $NewPatient = 0$, $notplanned_a = 0$ and $deviationearlier_a$ = 0, the left hand side is equal to the negative of the time slot of the appointment plus M_1. The right hand side is equal to the negative of the earliest time slot the appointment can be scheduled. If the time slot of the appointment would be smaller than the earliest time slot the appointment should be scheduled, $deviationearlier_a$ is equal to the difference. If $notplanned_a = 1$, M_1 regulates that $deviationearlier_a$ can be equal to 0. If $NewPatient = 1$, we take the start week of treatment into account.

Constraint set 5.14 operates in a similar manner as constraint set 5.13. See Example 5.1 for a demonstration of constraint set 5.13.

Example 5.1

Say that $x_{1,1,211} = 1$, $MinWeek_1 = 2$, $NewPatient = 1$, $firstweek = 3$ and $notplanned_1 = 0$. Since there are 105 timeslots in a week, the appointment is scheduled in week 3 (211 is the first time slot of week 3). The first scheduling week is $firstweek = 3$, and the appointment is preferable scheduled in the second scheduling week, which is week 4. The appointment is thus scheduled one week earlier than preferred. Then, constraint 5.13 for $t = 211$, $a = 1$ and $h = 1$ is equal to:

$$\begin{aligned} 105 \cdot 1 \cdot 3 - 211 \cdot 1 - deviationearlier_1 + 1 \cdot M_1 \\ \leq M_1 + 105 \cdot 1 - 105 \cdot (2-1) - 1 \end{aligned}$$

$$315 - 211 - deviationearlier_1 + M_1 \leq M_1 + 105 - 105 - 1$$

$$104 - deviationearlier_1 \leq -1$$

$$deviationearlier_1 = 105$$

This is equal to 105 timeslots, exactly 1 week, which is equal to the deviation we found by hand.

Since the value of M_1 has a large effect on calculation time, we want to choose M_1 as small as possible. The following calculations show that M_1 should be larger than or equal to $2 \cdot |T| - 2 \cdot Week + 1$. We model the situation where no patient is scheduled, which is when M_1 is used. We take the maximum of $MinWeek_a \cdot Week$ and the maximum of $Week \cdot NewPatient \cdot firstweek$.

$$|T| \leq M_1 + Week - (|T| - Week) - 1$$

$$M_1 \geq 2 \cdot |T| - 2 \cdot Week + 1$$

Schedule appointment with correct discipline

If discipline c is related to appointment a, this appointment may only be scheduled with therapist h if therapist h belongs to discipline c. We introduce two sets of binary parameters that model these dependencies.

Each therapist h belongs to exactly one discipline c, which is determined by the binary parameter G_{hc}:

$$G_{hc} \begin{cases} 1 & \text{if therapist } h \text{ belongs to discipline } c \\ 0 & \text{otherwise} \end{cases}$$

In addition, each appointment a is related to exactly one discipline c. This is determined by binary parameter F_{ac}:

$$F_{ac} = \begin{cases} 1 \text{ if appointment } a \text{ must be scheduled at discipline } c \\ 0 \text{ otherwise} \end{cases}$$

The following constraint set ensures that $x_{aht} = 1$ can only hold if discipline c of therapist h is equal to the discipline that is related to appointment a:

$$G_{hc} \cdot x_{aht} \leq F_{ac} \; \forall a, h, t, c \qquad (5.15)$$

It is not intuitive that this constraint set ensures that appointments are scheduled with the correct therapist: it seems that if $G_{hc} = 0$, $x_{aht} = 1$ can still hold. Example 5.2 illustrates why this is not true and why both G_{hc} and F_{ac} must be equal to one to allow scheduling appointment a with therapist h.

Example 5.2

Say that $a = 2$, $c = 3, h = 4$, $F_{23} = 1$ and $G_{43} = 0$. Then one might say that in constraint 5.13, x_{24t} can be both zero or one for all t. Since both therapists and appointments belong to exactly one discipline, there must be another $G_{4c} = 1$ and another $F_{2c} = 0$, which forces x_{24t} to be equal to zero for all t. In conclusion, x_{aht} can only be equal to 1 if both G_{hc} and F_{ac} are equal to one.

In the simulation study that follows, the input of the LP consists of one therapist per discipline, i.e., $\sum_h G_{hc} = 1$ for all c. In the case of a multi-resource appointment with two therapists of the same discipline, the input of the LP must consist of two therapists for that discipline. The "second therapist" can only be used for multi-resource appointments. Constraint set 5.16 regulates this requirement:

$$x_{aht} \leq \sum_c G_{hc} \cdot \left(\sum_{\hat{a}} MultiResource_{a\hat{a}} \cdot F_{ac} \cdot F_{\hat{a}c} \right) \; \forall a, h, t \qquad (5.16)$$

This constraint is only evaluated for h that are marked as "second therapists". This constraint is not necessary if the input of the LP consists of more therapists per discipline.

Respect the maximum number of appointments per day

We introduce the parameter $MaxApp$, which indicates the maximum number of appointments a patient can have during one day. The following constraint set ensures that no more than $MaxApp$ appointments are scheduled per day. Of course, multi-resource appointments should be counted only once:

$$\sum_{t=1+(d-1)\cdot D}^{d\cdot D} \sum_{a,h} x_{aht} \cdot \frac{2 - \sum_{\hat{a}\neq a} MultiResource_{a\hat{a}}}{2} \leq MaxApp \ \forall d \tag{5.17}$$

Schedule all appointments within preferred lead time

In order to determine whether the lead time of the patient's schedule exceeds the lead time as defined in the care pathway, we need to find the first time slot and the last time slot of the patient's schedule. The first time slot is equal to $firsttimeslot$. We introduce the variable $lasttimeslot$, which is equal to the last time slot. The following constraint set sets a lower bound to $lasttimeslot$:

$$t \cdot x_{aht} - lasttimeslot \leq 0 \ \forall a,h,t \tag{5.18}$$

Since a higher value than the lower bound neither affects the objective value nor worsens the objective value, no constraint is needed to set an upper bound to $lasttimeslot$. In addition to $lasttimeslot$, we add the binary variable $leadtime$:

$$leadtime = \begin{cases} 1 \text{ if } lasttimeslot \text{ is greater than the maximum of } Week \cdot MaxWeek_a \text{ over } a \\ 0 \text{ otherwise} \end{cases}$$

The value of $leadtime$ is regulated by the following constraint:

$$lasttimeslot - NewPatient \cdot firsttimeslot - M_2 \cdot leadtime \leq Week \cdot \max_a(MaxWeek_a) - NewPatient \tag{5.19}$$

Example 5.3 makes clear how this constraint works.

Again, M_2 should be chosen as small as possible. Say that $lasttimeslot = |T|$, $\max_a(MaxWeek_a) = 1$ and $NewPatient = 0$. Then $|T| - M_2 \leq Week$ and thus $M_2 \geq |T| -$

Example 5.3

Say that $lasttimeslot = 211$, $firsttimeslot = 1$, $NewPatient = 1$ and $\max_a(MaxWeek_a) = 2$. The last appointment of the patient was at the first time slot of the third scheduling week (there are 105 time slots in a week), while it should have been scheduled in the second scheduling week.

Then, constraint 5.19 is as follows:

$$211 - 1 \cdot 1 - M_2 \cdot leadtime \leq 105 \cdot 2 - 1$$

$$-M_2 \cdot leadtime \leq -1$$

$$leadtime = 1$$

Since $lasttimeslot$ is greater than $Week \cdot MaxWeek_a$, this is correct.

$Week$.

Allow scheduling of group therapy

Binary parameter $Group_a$ indicates whether appointment a is an individual or a group appointment:

$$Group_a = \begin{cases} 1 \text{ if appointment } a \text{ is a group appointment} \\ 0 \text{ otherwise} \end{cases}$$

Group appointments preferably start at time slots that are already assigned to a group appointment. Binary parameter $GroupApp_{ht}$ indicates whether therapist h starts a group therapy session at time slot t:

$$GroupApp_{ht} \begin{cases} 1 \text{ if a group therapy appointment is scheduled at time slot } t \text{ with therapist } h \\ 0 \text{ otherwise} \end{cases}$$

If it is not possible to schedule a group appointment on a time slot that is already assigned to group therapy, a new time slot for group therapy is created. To enable steering on the number of new groups created, we introduce the variable $extragroup_a$, which indicates the number of new group therapy time slots caused by scheduling appointment a.

Constraint set 5.20 makes sure that $extragroup_a$ has the correct value:

$$\sum_{h,t} x_{aht} \cdot Group_a - extragroup_a - \sum_{h,t} x_{aht} \cdot GroupApp_{ht} = 0 \;\forall a \tag{5.20}$$

Individual appointments cannot be scheduled at time slot-therapist combinations that are reserved for group therapy. Constraint set 5.21 arranges this restriction:

$$(1 - Group_a) \cdot x_{aht} \leq \; (1 - GroupApp_{ht}) \;\forall a, h, t \tag{5.21}$$

Group appointments can be scheduled at time slot-therapist combinations that are reserved for group therapy only if the duration of the group that starts at this time slot is equal to the duration of the appointment to be scheduled. The parameter $Duration_a$ indicates the duration in time slots of appointment a and parameter $GroupDur_{ht}$indicates the duration in time slots of group therapy with therapist h starting at time slot t.

The following constraint set makes sure that appointments are only scheduled at existing group therapy time slots with the correct duration:

$$x_{aht} \cdot GroupApp_{ht} \cdot Duration_a - x_{aht} \cdot GroupApp_{ht} \cdot GroupDur_{ht} = 0 \;\forall a, h, t \tag{5.22}$$

Finally, if the group appointment is part of a multi-resource appointment, it can only be scheduled at an existing group therapy time slot t if this time slot is assigned to a multi-resource appointment and both therapists h and $\hat{h}$ provide therapy at that time slot. We introduce parameter $Multi_{h\hat{h}t}$ to represent this situation:

$$Multi_{h\hat{h}t} = \begin{cases} 1 \text{ if therapist } h \text{ and therapist } \hat{h} \text{ have an existing} \\ \quad \text{multi resource appointment at time slot } t \\ 0 \text{ otherwise} \end{cases}$$

Constraint set 5.23 arranges the abovementioned condition:

$$Multi_{h\hat{h}t} \cdot \sum_{a} x_{aht} - Multi_{h\hat{h}t} \cdot \sum_{a} x_{a\hat{h}t} = 0 \; \forall h, \hat{h}, t \tag{5.23}$$

Moreover, appointments that are not part of a multi-resource appointment should not be scheduled at time slots that are assigned to multi-resource appointments:

$$\sum_{\hat{h}} Multi_{h\hat{h}t} \cdot (1 - \sum_{\hat{a}} MultiResource_{a\hat{a}}) \cdot x_{aht} = 0 \; \forall a, h, t \tag{5.24}$$

Constraint set 5.23 and 5.24 are only evaluated for $a, h, \hat{h}$ and t for which $Multi_{h\hat{h}t}$ or $\sum_{\hat{a}} MultiResource_{a\hat{a}}$ are equal to 1.

Therapist and patient must be available at time slot(s) of appointment

Therapist availability is limited due to the therapist's working hours and earlier scheduled appointments.

The parameter B_{ht} indicates the number of patients that can be scheduled at therapist h at time slot t, not including patients that are already scheduled at therapist h at time slot t. For individual appointments, B_{ht} is either 1 or 0. The parameter $MaxPatGroup$ indicates the maximum number of patients in a group session. For group appointments, B_{ht} can be $\{1, \dots, MaxPatGroup\}$.

Constraint sets 5.20 and 5.21 model therapist availability requirements:

$$x_{aht} \leq B_{ht} \; \forall a, h, t \tag{5.25}$$

$$x_{aht} \cdot (1 - Group_a \cdot GroupApp_{ht}) \leq B_{h\hat{t}} \; \forall a, h, t, t < \hat{t} < t + Duration_a \tag{5.26}$$

If an appointment is scheduled at x_{aht}, $B_{ht} > 0$ should hold during t and the next $t + Duration_a - 1$ time slots. This is regulated in constraint set 5.25 and 5.26. However, B_{ht} can be larger than 0 if $GroupApp_{ht} = 1$. We need to avoid that other appointments than the appointments related to that group are scheduled at such time slots. Therefore we say that if a group appointment starts at t, $B_{h\hat{t}} = 0$, instead of $B_{h\hat{t}} = B_{ht}$ for all $t < \hat{t} \leq t + Duration_a - 1$.

If $Group_a = 1$ and $GroupApp_{ht} = 1$, constraint set 5.26 allows the scheduling of appointment a even if $B_{h\hat{t}} = 0$. Simply put, we make sure that the availability of all time slots after the first time slot of a group appointment is (virtually) equal to zero. This avoids scheduling of other appointments at those time slots. Then, we also say (constraint 5.26) that group appointments can be scheduled at such time slots, even if there is (virtually) no availability.

Since B_{ht} is a parameter, the abovementioned constraint sets do not prevent that no appointments are scheduled at $t+1$ if another appointment of the current instance with duration of two or more time slots is scheduled at t. It is thus required that if an appointment is scheduled at time slot t, no other appointments are scheduled during time slots between t and $t + Duration_a - 1$. Constraint set 5.27 models this requirement:

$$Duration_a \cdot x_{aht} + \sum_{\hat{t}=t+1}^{t+Duration_a-1} x_{\hat{a}\hat{h}\hat{t}} \leq Duration_a \ \forall a,h,t,\hat{a},\hat{h} | Duration_a > 1 \tag{5.27}$$

Respect the maximum number of appointments per discipline per day

It is highly preferable that no more than one individual appointment per discipline per day is scheduled. Since patients can be scheduled with at most one therapist per discipline, this means that no more than one individual appointment per discipline per day should be scheduled. Moreover, no more than one group appointment per discipline per day should be scheduled.

Although it is highly undesirable, it should be possible to schedule more than one appointment per discipline per day: the care pathway can prescribe a higher number of appointments per therapist per week than the number of days a therapist is available. Therefore, we introduce slack variables $extraappdisc_{cd}$ and $extraappdiscgroup_{cd}$:

$$extraappdisc_{cd} = \begin{cases} \text{1 if two individual appointments are} \\ \text{scheduled at day } d \text{ with discipline } c \\ \text{0 otherwise} \end{cases}$$

$$extraappdiscgroup_{cd} = \begin{cases} \text{1 if two group appointments are} \\ \text{scheduled at day } d \text{ with discipline } c \\ \text{0 otherwise} \end{cases}$$

Constraint sets 5.28 and 5.29 model, respectively, that no more than one individual or group appointment is scheduled per day, or the abovementioned variables are equal to 1:

$$\sum_{t=1+(d-1)\cdot D}^{d\cdot D} \sum_{a,h} x_{aht} \cdot (1 - Group_a) \cdot G_{hc} - extraappdisc_{cd} \leq 1 \ \forall c,d \tag{5.28}$$

$$\sum_{t=1+(d-1)\cdot D}^{d\cdot D} \sum_{a,h} x_{aht} \cdot Group_a \cdot G_{hc} \cdot \frac{2 - \sum_{\hat{a} \neq a} MultiResource_{a\hat{a}} \cdot F_{\hat{a}c}}{2} - extraappdiscgroup_{cd} \leq 1 \ \forall c,d \tag{5.29}$$

In constraint set 5.29, we have to correct for multi-resource appointments, such that those appointments are not double counted. Since only group appointments can require multiple resources, this is not included in constraint set 5.28.

Realize a simultaneous start

If the patient cannot start therapy at all different disciplines within a prescribed number of days, we say that the patient does not have a simultaneous start at all disciplines. The reference point is the appointment to be scheduled first according to the care pathway. To find out whether appointment a is the first appointment in the care pathway, we introduce the binary parameter $FirstApp_{ac}$:

$$FirstApp_{ac} = \begin{cases} 1 \text{ if } MinWeek_a = 1 \text{ and } a \text{ is the first appointment} \\ \quad \text{at discipline } c \text{ as stated in the care pathway} \\ 0 \text{ otherwise} \end{cases}$$

Only appointments for which the care pathway prescribes that they should take place in the first treatment week should be considered. For example, if the patient should see the psychologist in the third treatment week for the first time, this appointment is not considered. Therefore, $FirstApp_{ac}$ can only be 1 if $MinWeek_a = 1$.

Since we want to compare the day of an appointment to the day of the first appointment, we need to find the first day of treatment. Therefore, we introduce the integer variable $firstday$, which is equal to the first treatment day. The following constraints regulate that the value of $firstday$ is correct:

$$firstday - firsttimeslot \cdot \left(\frac{1}{Day}\right) \geq 0 \tag{5.30}$$

$$firstday - firsttimeslot \cdot \left(\frac{1}{Day}\right) < 1 \tag{5.31}$$

Constraint 5.30 ensures that $firstday$ is not smaller than the actual first day, and constraint 5.31 regulates that $firstday$ is not larger than the actual first day.

Moreover, we introduce the parameter $SimultaneousStart$, which indicates the number of days for which a simultaneous start holds. The binary variable $notsimult_c$ indicates whether discipline c has realized a simultaneous start with respect to $firstday$:

$$notsimult_c = \begin{cases} 1 \text{ if } a \text{ for which } FirstApp_{ac} = 1 \text{ is scheduled later than} \\ \qquad firstday + SimultaneousStart \\ 0 \text{ otherwise} \end{cases}$$

Constraint set 5.32 realizes that $notsimult_c$ has the right value:

$$\begin{aligned} \sum_{a,h} FirstApp_{ac} \cdot t \cdot x_{aht} \cdot \frac{2 - \sum_{\hat{a} \neq a} MultiResource_{a\hat{a}}}{2} - Day \\ \cdot firstday \; - M_3 \cdot notsimult_c \\ \leq Day \cdot (SimultnaeousStart - 1) \; \forall c, t \end{aligned} \tag{5.32}$$

Example 5.4 demonstrates the working of constraint set 5.32.

Example 5.4

Say that $firstday = 1$, $x_{1,1,106} = 1$, $SimultaneousStart = 5$, $FirstApp_{11} = 1$. Thus, the patient starts treatment at day 1 and appointment 1 is the first appointment at discipline 1. All first appointments should be scheduled within 5 days, but appointment 1 is scheduled at day 6 (106 is timeslot 1 of day 6). Therefore, this patient has not realized a simultaneous start.

Then, constraint 5.32 is as follows:

$$1 \cdot 106 \cdot 1 \cdot \frac{2}{2} - 21 \cdot 1 - M_3 \cdot notsimult_1 \leq 21 \cdot (5 - 1)$$

$$85 - M_3 \cdot notsimult_1 \leq 84$$

$$notsimult_1 = 1$$

Again, M_3 should be minimized. If $c = 1, t = |T|$, $x_{1,1,|T|} = 1$, $FirstApp_{11} = 1$ $firstday = 1$

$SimultaneousStart = 1$ and $\sum_{\hat{a} \neq 1} MultiResource_{1\hat{a}} = 0$ then:

$$|T| - Day - M_3 \leq 0$$
$$M_3 \geq |T| - Day$$

Maximize use of combination appointments

Especially for outpatients, we want to minimize the number of visits to (or treatment days at) the rehabilitation center. Thus, as far as other constraints allow this, multiple appointments should be provided on the same day. Recall that having multiple appointments on a single day is defined as a combination appointment.

We define the minimum number of treatment days for a discipline as the maximum number of appointments per discipline and therapy type (group or individual) per week as defined in the care pathway. The parameter $MinTherDays$ is equal to the maximum of this number over all disciplines and therapy types. A schedule with a number of treatment days that is equal or close to $MinTherDays$ means that the use of combination appointments is (nearly) optimized.

In order to find if the number of treatment days is higher than $MinTherDays$, we first need to find this number. The binary variable $appatday_d$ indicates whether an appointment is scheduled at day d:

$$appatday_d = \begin{cases} 1 \text{ if one or more appointments are scheduled at day } d \\ 0 \text{ otherwise} \end{cases}$$

Constraint set 5.33 realizes a lower bound for $appatday_d$:

$$\sum_{t=1+(d-1)\cdot D}^{d\cdot D} \sum_{a,h} x_{aht} - D \cdot appatday_d \leq 0 \ \forall d \tag{5.33}$$

The slack variable $extratherdays$ measures the number of treatment days more than $MinTherDays$. Constraint 5.34 realizes a lower bound for $extratherdays$:

$$\sum_{d} appatday_d - extratherdays \leq MinTherDays \tag{5.34}$$

Maximize horizontal scheduling

Especially for outpatients, it is desirable that treatment is scheduled at the same weekdays over the weeks. We refer to this as horizontal scheduling. We introduce the binary variable $newday_d$ and constraint set 5.35 to maximize horizontal scheduling:

$$newday_d = \begin{cases} 1 \text{ if an appointment is scheduled on day } d \text{ and no appointment} \\ \qquad \text{has been scheduled before on the weekday of day } d \\ 0 \text{ otherwise} \end{cases}$$

$$appatday_d - \sum_{w|w\cdot 5<d} appatday_{d-w\cdot 5} - newday_d \leq 0 \ \forall d|d > 5 \tag{5.35}$$

Start and end of appointment on the same day

An appointment cannot start at one day and finish on the other. Constraint set 5.36 avoids this behavior:

$$t \cdot x_{aht} \leq 1 + D \cdot \big((t-1) \text{ div } D + 1\big) - Duration_a \ \forall a, h, t \tag{5.36}$$

Set a maximum to the number of omitted appointments

Although we allow that some appointments are not scheduled, the maximum number of appointments not to be scheduled per discipline is 20%. The following constraint set ensures that no more than 20% of the appointments per discipline is not scheduled:

$$\sum_{a} F_{ac} \cdot notplanned_a \leq \left\lfloor 0.2 \cdot \sum_{a} F_{ac} \cdot NumberApp_a \right\rfloor \forall c | \sum_{a} F_{ac} > 0 \tag{5.37}$$

Set a maximum to the number of time slots between appointments on the same day

Especially for outpatients, long waiting times between appointments on the same day are undesirable. The parameter MT indicates the maximum number of time slots between two appointments. In addition, binary parameters $Z_{t\hat{t}}$ indicate whether time slot t is on the same day as time slot $\hat{t}$:

$$Z_{t\hat{t}} = \begin{cases} 1 \text{ if time slot } t \text{ is on the same day as time slot } \hat{t} \\ 0 \text{ otherwise} \end{cases}$$

Constraint set 5.38 ensures that an appointment can only be scheduled at time slot t if 1) the number of time slots between completion of the appointment and the next appointment is smaller than $MT + 1$, or 2) no appointment is scheduled during the remaining time slots of the day.

$$\sum_{\hat{t}=t+Duration_a+MT+1}^{t+D} Z_{t\hat{t}} \cdot \sum_{\hat{a},\hat{h}} x_{\hat{a}\hat{h}\hat{t}} - \sum_{\hat{t}=t+Duration_a}^{t+Duration_a+MT} Z_{t\hat{t}} \cdot \sum_{\hat{a},\hat{h}} x_{\hat{a}\hat{h}\hat{t}} \cdot MaxApp + x_{aht} \cdot MaxApp \leq MaxApp \ \forall a, h, t \tag{5.38}$$

Example 5.5 illustrates the working of constraint set 5.38.

Example 5.5

Say that, $x_{ah3} = 1$, then $Z_{3\hat{t}} = 1$ for $\hat{t} = 1,2, \dots, 21$, because day 1 comprises of time slot 1 to 21. The third term in constraint 5.38 is equal to $MaxApp$. Then, if the first term in the equation is greater than 1 (i.e., one or more appointments are scheduled more than MT time slots later than time slot 3, but on the same day), the second term must be ≥ 1, indicating that one or more appointments are scheduled less than MT time slots later than 3. Otherwise, the constraint does not hold. If the first term in the constraint is 0, the constraint holds in all situations.

Set a maximum to the deviation of the preferred week range

The parameter $MaxDev$ sets a limit to the maximum deviation in time slots from the preferred week range. Constraints 5.39 and 5.40 ensure that $deviationlater_a$ and $deviationearlier_a$ are smaller than or equal to $MaxDev$:

$$deviationlater_a \leq MaxDev \ \forall a \tag{5.39}$$

$$deviationearlier_a \leq MaxDev \ \forall a \tag{5.40}$$

5.2.4 Objective function

Most planning rules are modeled as soft constraints. The slack variables that make sure these constraints are satisfied, are reflected as cost functions in the objective function. Thus, if a slack variable is greater than 0, this increases the objective value. The objective function aims to minimize the total cost of slack variables. However, the relative importance of satisfying different soft constraints – represented by weights – is arbitrary. To obtain proper weights, we consulted the management of SMK.

Formula 5.41 describes the objective function. β_i indicates the weight for variable i.

$$\min\left\{\beta_1 \cdot \sum_a notplanned_a + \beta_2 \cdot exceed + \beta_3 \cdot \sum_a (deviationearlier_a + deviationlater_a) + \beta_4 \cdot leadtime + \beta_5 \cdot \sum_{cd} extraappdiscgroup_{cd} + \beta_6 \cdot \sum_{cd} extraappdisc_{cd} + \beta_7 \cdot notsimult + \beta_8 \cdot \sum_a extragroup_a + \beta_9 \cdot extratherdays + \beta_{10} \cdot \sum_d newday_d\right\} \tag{5.41}$$

5.2.5 Summary

In words, the ILP is described as follows:

Minimize the sum over:

1. β_1 times the number of not planned appointments
2. β_2 times the exceeding of the access time
3. β_3 times the total number of time slots that appointments are scheduled earlier and later
4. β_4 times the exceeding of the lead time
5. β_5 times the total number of appointments more than one per day per discipline (group appointments)
6. β_6 times the total number of appointments more than one per day per discipline (individual appointments)
7. β_7 times the variable that indicates a non-simultaneous start
8. β_8 times the number of new groups
9. β_9 times the number of therapy days more than the minimum number of therapy days (combination appointments)
10. β_{10} times the number of days that deviate from the treatment days in the first week of treatment (horizontal scheduling)

Subject to:

1. All appointments should be scheduled as many times as prescribed, or a fine is given for every appointment that is not planned
2. Appointments that require the presence of two therapists, must be executed by two different therapists simultaneously
3. The first appointment should be scheduled before the maximum allowed access time, or a fine is given for the number of time slots exceeded
4. All appointments should be scheduled within the preferred range of weeks, or a fine is given for the number of time slots deviated
5. All appointments should be scheduled with a therapist of the discipline that is related to the appointment
6. The number of appointments per day should not exceed the maximum allowed number of appointments per day
7. All appointments should be scheduled within the lead time as stated in the CP, or a fine is given for the number of time slots exceeded
8. Appointments can only be scheduled at a time slot if a therapist is available at that time slot and, if applicable, the subsequent time slots that are required for the appointment
9. Appointments can only be scheduled at a time slot if no other appointments are scheduled at that time slot and the subsequent time slots that are required for the appointment
10. Per day, discipline and therapy type (group or individual), only one appointment can be scheduled, or a fine is given if two appointments are scheduled (more than two is not allowed)
11. The first appointments of each discipline must start within a given number of days, or a fine is given.
12. Group therapy appointments should be scheduled at existing time slots for group therapy, or a new group is created and a fine is given
13. Individual appointments cannot be scheduled at time slot-therapist combinations that are reserved for group therapy
14. Group therapy appointments can only be scheduled at existing time slots for group therapy if the duration of appointment is equal to the duration of the existing group therapy session
15. New multi-resource appointments can only be scheduled at existing time slots for multi-resource appointments if the therapists who attend the existing multi-resource appointment are equal to the therapists who performs the new multi-resource appointment
16. Single resource appointments cannot be scheduled at time slot-therapist combinations that are reserved for multi-resource appointments.
17. The number of days with therapy should be equal to the mathematically minimum number of therapy days, or a fine is given (combination appointments)
18. Appointments in the second week and further should be scheduled on the same weekdays as the appointments in week 1, or a fine is given for each extra weekday (horizontal scheduling)
19. Appointments should start and finish on the same day

20. The maximum percentage of appointments that are not planned is equal to 20% per discipline
21. For appointments that are scheduled on the same day, the number of time slots between appointments should be less than a given maximum.
22. The deviation of the time slot of an appointment from the preferred range of weeks must be equal or lower than a given maximum.

Auxiliary constraints are not included in this list. All decision variables are integer.

5.3 Solution approach

The resulting ILP is solved with the branch and bound (B&B) algorithm. This method is based on the observation that the integer solution to an LP has a tree structure [29]. For integer variables with n possible values, the B&B algorithm divides the solution space in n disjunctive partitions of the solution tree. In each partition, B&B searches for feasible solutions by further partitioning, solves the LP relaxation of new nodes[6], and calculates upper and lower bounds for the optimal solution. The algorithm cuts of nodes for which it can show that it, or any further nodes, does not lead to an optimal solution. This prevents the tree from growing too much. An optimal solution is found if the bound on the best value is equal to the value of the current node. For a more comprehensive introduction to integer linear programming and branch and bound, we refer to [30]. The speed of the B&B algorithm depends on its number of binary and integer variables. Therefore, the tractability of the ILP depends on the size of the model.

The total number of variables in terms of appointments a, therapists h, time slots t, disciplines c, and days d is as follows:

- Total number of variables: $aht + 2(cd) + 4a + 2t + c + d + (d - 5) + 7$
- Number of binary variables: $aht + 2(cd) + 2t + c + d + (d - 5) + 1$
- Number of non-binary variables: $4a + 6$

The ILP is implemented in RStudio version 0.99.235 and is solved by Gurobi 6.0.0. Before applying branch and bound, Gurobi employs a set of presolving methods. These methods can be viewed as pre-processing techniques that reduce the size of the model and improve the strength of the model formulation [31]. For example, the constraint $x_1 + x_2 \leq \frac{1}{2}$ for integer x_1 and x_2 implies that $x_1 = x_2 = 0$. This constraint can be removed from the set of feasible solutions for the LP relaxation. This kind of model tightening is important for solving the ILP in reasonable time [32]. For our ILP, presolve typically removes more than 90% of the constraints and variables before branch and bound is applied.

In addition, Gurobi applies cutting planes [32]. Cutting planes tighten the problem formulation by removing fractional solutions of LP relaxations that lead to infeasibility for the ILP.

[6] An LP relaxation is the original problem formulation without integrality constraints, which can be solved by the simplex algorithm.

5.4 Preliminary experiments and model improvement

We performed experiments to assess the computational performance of the ILP. Subsequently, we present valid inequalities as a model improvement technique and compare performance of the improved model with the original model.

5.4.1. Computational performance of original model

We solved the model[7] for 100 patients (359 LP instances) with varying care pathways. Figure 5.1 gives the cumulative computation time for solving all instances.

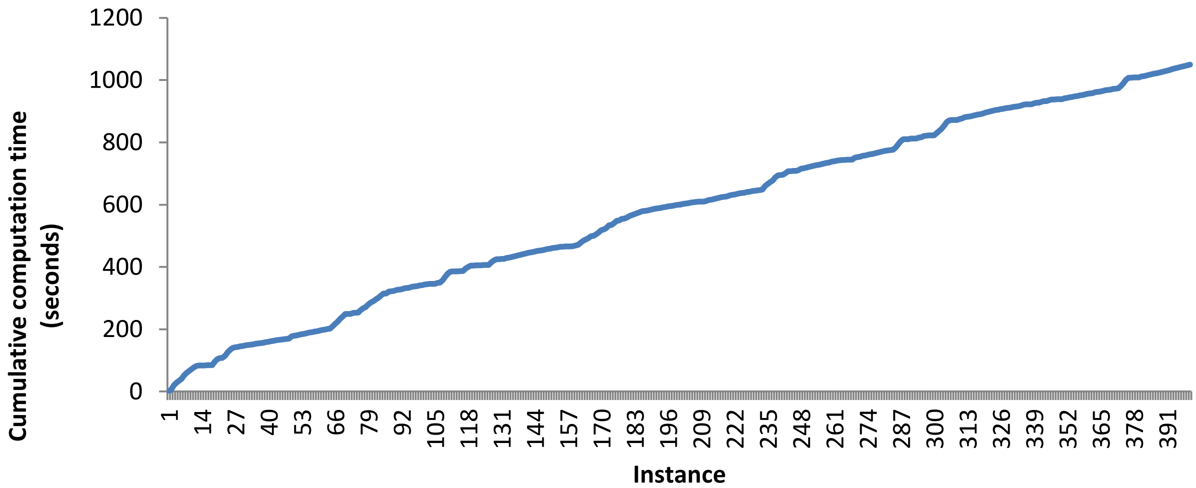


Figure 5.1 Cumulative computation time for solving 100 patients (400 instances)

The cumulative ILP computation time for 100 patients is about 18 minutes (excluding time needed to construct the constraint matrix). Full-size experiments are likely to have a run length of much more than 2000 patients, and are usually replicated obtain valid results. Therefore we explore methods to reduce computation time. We apply *valid inequalities* with the aim to reduce the solution space of our model, and thereby computation time.

5.4.2 Valid inequalities

Given an instance of the ILP, we can calculate minima of some variables before solving the ILP. For example, if $Group_a = 1$, $NumberApp_a = 4$ and $GroupApp_{ht} = 0$ for all therapists h of discipline c for which $F_{ac} = 1$ and for all t that are allowed for scheduling a, one is sure that $newgroup_a + notplanned_a = 4$. Simply put, if the patient needs to be scheduled in four groups, and there are no existing groups to schedule the appointments, the sum of appointments that are not scheduled plus the sum of newly formed groups is equal to four.

This information is used to set lower bounds for the objective value, which is done by defining *valid inequalities*. Effectively, valid inequalities cut away regions of the solution space that contain no feasible solutions. An inequality $\pi^T x \leq \pi_0$, where π_0 is the found lower bound, is a valid inequality for set $X \subseteq \mathbb{R}^n$ if $\pi^T x \leq \pi_0$ for all $x \in X$ [33].

[7] Constraints 5.4 to 5.12, 5.18, 5.19, 5.30, 5.31 and 5.32 were excluded, see Paragraph 6.1

We add valid inequalities for the minimum number of new groups and the minimum number of extra appointments per day per discipline. Table 5.2 provides an overview of the notation of the parameters that are introduced for valid inequalities.

Table 5.2

Additional parameters for valid inequalities

$\boldsymbol{NewGroup_a}$	1 if appointment a will per definition cause the scheduling of a new group therapy time slot if the appointment is scheduled; 0 otherwise
$\boldsymbol{DaysWithFreeTimeslots_{cw}}$	Number of days with free time slots for individual appointments for discipline c in week w
$\boldsymbol{DaysWithFreeTimeslotsGroup_{cw}}$	Number of days with free time slots for group appointments for discipline c in week w
$\boldsymbol{MinAppWeek_c}$	Minimum number of individual appointments per week in the care pathway
$\boldsymbol{MinAppWeekGroup_c}$	Minimum number of group appointments per week in the care pathway
$\boldsymbol{MinExtraApp_{cw}}$	Minimum number of times that two individual appointments should be scheduled per day for discipline c and week w (given that all appointments are scheduled within the prescribed lead time)
$\boldsymbol{MinAppWeekGroup_c}$	Minimum number of times that two appointments should be scheduled per day for discipline c and week w (given that all appointments are scheduled within the prescribed lead time)

Number of new groups

We can determine a lower bound for the number of new groups per appointment. We define the parameter $NewGroup_a$, which denotes the minimal number of new group therapy time slots the scheduling of appointment a will cause, if all instances of appointment a are scheduled.

The value of $NewGroup_a$ is determined by finding existing allowed group therapy time slots. If no allowed time slot is found, $NewGroup_a = 1$.

In order to find $NewGroup_a$, we must know the planning horizon for which it is evaluated whether there are no existing group therapy time slots. The first time slot that is taken into consideration is the first time slot in the first week of the preferred range, minus the maximum allowed deviation from the preferred range. If this leads to a negative result, we say that the first time slot is equal to 1. The last time slot that is taken into consideration is the last time slot of the last week of the preferred range, plus the maximum allowed deviation from the preferred range. If this leads to a number that is higher than $|T|$, we take $|T|$ as the upper bound. We define the first and last time slots that are taken into consideration as LB and UB, respectively:

$$LB = \max(1,1 + (MinWeek_a - 1) \cdot W - MaxDev$$

$$UB = \min(|T|, MaxWeek_a \cdot W + MaxDev)$$

Now, $NewGroup_a$ is determined as follows:

1. Determine whether a is a group appointment
2. Find the discipline c that is related to a
3. Find therapists h that are related to c
4. $NewGroup_a$ is 1 if there are no existing group appointments between LB and UB at therapists h that can be used for scheduling appointment a

In formula form, $NewGroup_a$ is given by:

$$NewGroup_a = \sum_c Group_a \cdot F_{ac} \cdot \left(NumberApp_a - \min\left[NumberApp_a, \left\{ \sum_{h|G_{hc}=1} \sum_{t=LB}^{UB} min(1, B_{ht} \cdot GroupApp_{ht}) \right\} \right] \right) \forall a$$

Constraint set 5.42 ensures that $extragroup_a$ over a is larger than or equal to $NewGroup_a$, except when the appointment is not scheduled.

$$extragroup_a + notplanned_a \geq NewGroup_a \; \forall a \tag{5.42}$$

Number of extra appointments per day per discipline

Since the maximum number of days therapists work per week is an upper bound for the number of therapy days per week for that discipline, a lower bound can be calculated for $extraappdisc_{cd}$ and $extraappdiscgroup_{cd}$, the variables that regulate that scheduling more than one appointment per discipline per therapy type (group or individual) is penalized.

First, we find the number of days with free times slots for discipline c during week w, by calculating parameters $DaysWithFreeTimeslots_{cw}$ and $DaysWithFreeTimeslotsGroup_{cw}$:

$$DaysWithFreeTimeslots_{cw} = \sum_{d=(w-1)\cdot 5+1}^{w\cdot 5} \min\left(1, \sum_{t=(d-1)\cdot D+1}^{d\cdot D} \sum_h B_{ht} \cdot (1 - GroupAppointment_{ht}) \cdot G_{hc}\right) \forall c, w$$

$$DaysWithFreeTimeslotsGroup_{cw} = \sum_{d=(w-1)\cdot 5+1}^{w\cdot 5} \min\left(1, \sum_{t=(d-1)\cdot D+1}^{d\cdot D} \sum_h B_{ht} \cdot G_{hc}\right) \forall c, w$$

Time slots for group appointments should not be taken into account for determining $DaysWithFreeTimeslots_{cw}$, since these are not available for individual appointments.

The minimum number of appointments per week per discipline, $MinAppWeek_c$ and $MinAppWeekGroup_c$, are the other parameters to set. We need to know the minimum over *all* weeks, since in all other cases it is allowed to schedule an appointment earlier or later. In case of multi-resource appointments with two therapists of the same discipline, we have to count the appointment only once. This is only applicable in group appointments.

$$MinAppWeek_c = \min_w \left\{ \sum_{a|(MinWeek_a = MaxWeek_a = w)} F_{ac} \cdot NumberApp_a \cdot (1 - Group_a) \right\} \forall c$$

$$MinAppWeekGroup_c = \min_w \left\{ \sum_{a|(MinWeek_a = MaxWeek_a = w)} F_{ac} \cdot NumberApp_a \cdot \frac{2 - \sum_{\hat{a} \neq a} MultiResource_{a\hat{a}} \cdot F_{\hat{a}c}}{2} \cdot Group_a \right\} \forall c$$

Now, the lower bound for the number of times that more than one appointment per discipline per day is scheduled can be calculated for all weeks.

$$MinExtraApp_{cw} = \max(0, MinAppWeek_c - DaysWithFreeTimeSlots_{cw}) \ \forall c, w$$

$$MinExtraAppGroup_{cw} = \max(0, MinAppWeekGroup_c - DaysWithFreeTimeSlotsGroup_{cw}) \ \forall c, w$$

The following constraint sets define a lower bound for $extraappdisc_{cd}$ and $extraappdiscgroup_{cd}$. Since not scheduling appointments and increasing lead time should be allowed, slack variables $notplanned_a$ and $leadtime$ are included in the formulas.

$$\sum_{d=(w-1)\cdot 5+1}^{w \cdot 5} extraappdisc_{cd} + \sum_a notplanned_a \cdot F_{ac} \cdot (1 - Group_a) + leadtime \cdot MinExtrApp_{cw} \geq MinExtrApp_{cw} \ \forall c, w \tag{5.43}$$

$$\sum_{d=(w-1)\cdot 5+1}^{w \cdot 5} extraappdiscgroup_{cd} + \sum_a notplanned_a \cdot F_{ac} \cdot Group_a + leadtime \cdot MinExtrAppGroup_{cw} \geq MinExtrAppGroup_{cw} \ \forall c, w \tag{5.44}$$

5.4.3 Performance of enhanced model

Figure 5.2 gives the cumulative computation time for solving all instances for four model configurations: no valid inequalities, valid inequalities for number of extra appointments per day and per discipline (5.42), valid inequalities for number of extra groups (5.43, 5.44), and all valid inequalities (5.42, 5.43, 5.44).

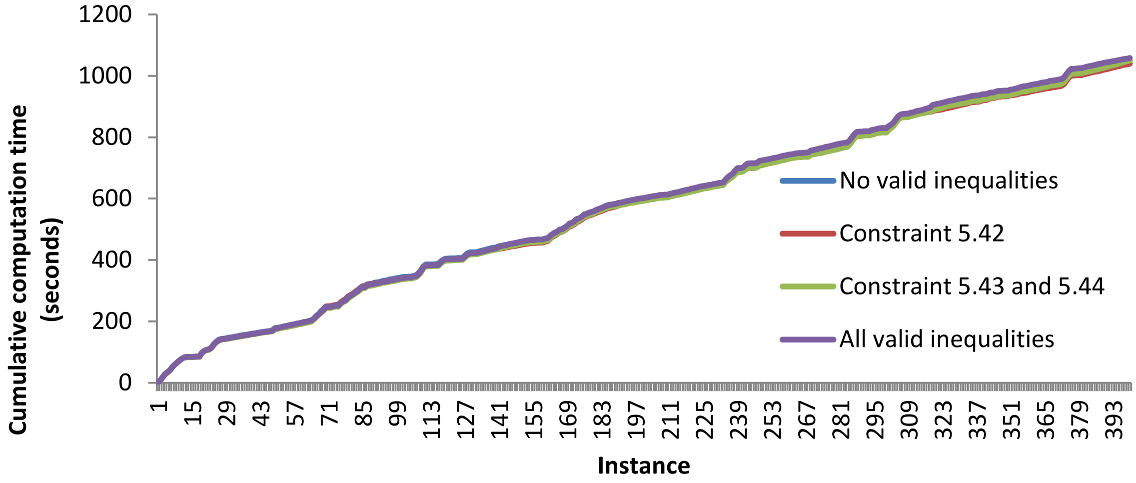


Figure 5.2 Cumulative computation time for solving 100 patients (400 instances) for four model configurations: no valid inequalities, valid inequalities for number of extra groups (constraint 5.42), valid inequalities for number of extra appointments per day and per discipline (constraints 5.43 and 5.44), and all valid inequalities (constraints 5.42, 5.43, 5.44).

5.4.3 Conclusion

We conclude that adding the valid inequalities to the ILP has no effect on computation time. One explanation is that the presolving methods of Gurobi already reduce the solution space by the same amount as our valid inequalities do. Although we succeeded to reduce the solution space by hand, we do not include the valid inequalities to the ILP formulation.

Chapter 6: Experiment approach

We apply discrete event simulation to evaluate the performance of the automated appointment scheduling. This is done by simulating the arrival process of patients and subsequently scheduling appointments of these patients with the ILP.

Directly after a patient arrives, we create a therapy schedule with the ILP, which input is based on the patient's care pathway. If no feasible solution can be found, we increase the access time with one week and try again. If no feasible solution is found after a specified number of attempts, the patient is rejected. After scheduling appointments with the ILP, we update relevant parameters. These parameters include therapist availability and whether a timeslot is linked to a group or multi-resource appointment. Then, we wait for the next patient to arrive, call the ILP again, and so on.

Recall that we decided to evaluate the application of generalist therapist teams and improved therapist schedules. We perform multiple experiments with different settings of the simulation model, which reflect the different interventions, and compare the results.

This chapter discusses the simulation model. The majority of care pathways applied in SMK cannot be solved in one instance in reasonable time. Therefore, Paragraph 6.1 first discusses some techniques we use to reduce the model size. Then, Paragraph 6.2 discusses the model input, Paragraph 6.3 describes the simulation process and Paragraph 6.4 gives the output measures. Chapter 7 describes all scenarios that are evaluated with the simulation model and presents experiment results.

6.1 Reduction of model size

Some of the care pathways of SMK include long, intensive programs. ILP instances based on these care pathways are very large and not solvable in a reasonable amount of time. The valid inequalities we introduced do not reduce computation time. Therefore, we look at two other methods to reduce computation time: splitting up care pathways and selecting therapists before solving the ILP. This paragraph discusses these methods, states which constraints of the ILP are removed due to these methods, and describes their effect on the quality of the solution of the ILP.

Splitting up care pathways

We decided to schedule care pathways not at once, but to them up in instances of length $Horizon$, where $Horizon$ is smaller or equal to the length of the care pathway. If $Horizon = 4$, the first instance solves the ILP for the first four weeks of the care pathway, the second instance solves the ILP for week five to eight, and so on. The value of $Horizon$ depends on the number of appointments and therapists to be scheduled per week.

The set of timeslots T contains $Horizon \cdot Week$ timeslots. This means that appointments cannot be scheduled later than the last preferred week as stated in the CP (i.e., $\max(MaxWeek_a)$).

Picking a fixed therapist per discipline

Since patients in SMK are assigned to a fixed therapist, our scheduling method should do this as well. However, the current ILP does not pick a fixed therapist per discipline. This can be solved in two ways: 1) add a constraint to the ILP that selects one therapist per discipline, or 2) before solving the ILP, apply a heuristic that selects one therapist per discipline. Option 1 would require that all therapists are included in the ILP formulation, which would increase model size. Since computation time is dependent on the model size, we go for option 2.

In addition to selecting one therapist per discipline, the heuristic allows scheduling group appointments at time slots that are already assigned to a group appointment. Instead of adding an additional therapist for group therapy, the heuristic temporarily assigns the therapist for individual appointments to the existing group appointments of an additional therapist. The result is used as input for the ILP. After solving the ILP, availability and assignments to group appointments are restored. As a result, we only have to include one therapist per discipline in the ILP instead of all therapists, which greatly reduces model size. In the case of multi-resource appointments with two therapists of the same discipline, an additional therapist is selected, which can only be used for multi-resource appointments.

The heuristics for selecting therapists and their optimization criteria are described in Appendix IV.

Removal of redundant constraints

The abovementioned methods affect the quality of the schedule and make some constraints redundant. This section states which constraints are removed from the original ILP as defined in Chapter 5 and discusses the effect of model reduction on the performance with respect to output measures.

Since $|T| = Horizon \cdot Week$, the planning horizon does not allow that appointments are scheduled later than $\max(MaxWeek_a)$, i.e., lead time cannot be exceeded. This makes constraint 5.18 and 5.19 and variables $leadtime$ and $lasttimeslot$ redundant.

Splitting up care pathways and the limited planning horizon significantly reduces the possibility to exceed maximum allowed access time in the ILP (constraint 5.10). Scheduling the first appointment later than the allowed access time is theoretically still possible, but because appointments cannot be scheduled later than $\max(MaxWeek_a)$, this is highly unlikely. For the same reason, it is unlikely that a patient has a non-simultaneous start. Therefore, constraint sets 5.10 and 5.27 are of reduced value. Note that the actual access time can still be larger than the maximum allowed access time. If the ILP is infeasible, appointments are scheduled (at least) one week later and the access time, as derived from the number of attempts to schedule the care pathway, increases.

Because of the minimal value of steering on lead time, access time and simultaneous start in the ILP, we remove constraints 5.4 to 5.12, 5.18, 5.19, 5.30, 5.31 and 5.32 and variables $auxil_t$, $smallest_t$, $firsttimeslot, firstweek, lasttimeslot, leadtime, firstday$ and $notsimult_c$ from the ILP formulation. Since constraint sets 5.4 to 5.8 also regulated that appointments could only be scheduled simultaneously if this was requested, we need to add the following constraint set:

$$\sum_{a,h} x_{aht} \cdot \frac{2 - \sum_{\hat{a} \neq a} MultiResource_{a\hat{a}}}{2} \leq 1 \ \forall t$$

Moreover, we change constraint sets 5.13 and 5.14, since $firstweek$ is no longer of interest:

$$- \sum_{h} t \cdot x_{aht} - deviationearlier_a + \sum_{h} x_{aht} \cdot M_1 \leq M_1 + Week - 1 - Week \cdot MinWeek_a \ \forall a, t \tag{5.13'}$$

$$\sum_{h} t \cdot x_{aht} - deviationlater_a \leq Week \cdot MaxWeek_a \ \forall a, t \tag{5.14'}$$

In this situation, $M_1 = |T| - Week + 1$.

The objective function can now be defined as follows:

$$\min \left\{ \beta_1 \cdot \sum_{a} notplanned_a + \beta_3 \cdot \sum_{a} (deviationearlier_a + deviationlater_a) \cdot \beta_5 \sum_{cd} extraappdiscgroup_{cd} + \beta_6 \cdot \sum_{cd} extraappdisc_{cd} + \beta_8 \cdot \sum_{a} extragroup_a + \beta_9 \cdot extratherdays + \beta_{10} \cdot \sum_{d} newday_d \right\}$$

The total number of variables of the resulting ILP in terms of appointments a, therapists h, time slots t, disciplines c, and days d is as follows:

- Total number of variables: $aht + 2(cd) + 4a + d + (d - 5) + 1$
- Number of binary variables: $aht + 2(cd) + d + (d - 5)$
- Number of non-binary variables: $4a + 1$

Effect of model reduction on solution quality

Model reduction affects the performance of the ILP with respect to output measures. Splitting up care pathways limits the possibility to schedule appointments later or earlier than prescribed, which reduces the number of feasible solutions. Furthermore, splitting up care pathways leads to optimization of horizontal scheduling per instance. Thus, if horizontal scheduling is optimized in the ILP, a patient is assigned to fixed weekdays for therapy during the course of the current instance. However, the next instance may result in a new set of fixed weekdays.

Although these side-effects are unwanted, we believe they are of limited effect on performance and are justified by the necessity to obtain numerical tractability.

6.2 Input

The input of the model consists of patients with a set of appointments based on care pathways, and therapists with a set of available time slots.

Patients, care pathways and appointments

Patient arrivals are generated before starting the simulation. Patients are coupled to a care pathway. The arrival rates of patients with a specific care pathway are based on an estimate that is derived from data from the hospital information system of SMK. We define λ_z as the arrival rate of patients per week for care pathway $z \in Z$. We generate arrivals by using the exponential distribution with density $a(x) = \lambda e^{-\lambda x}$. The first scheduling week for patient p is one week after the arrival week and denoted by $FirstWeek_p$. The set of all patients to be scheduled is called P. P depends on patient arrival rates and the simulation run length in weeks. Per patient p we define sets T_p for timeslots, H_p for therapists and A_p for appointments.

Per care pathway z, the following information is known:

- The minimum number of therapy days, parameter $MinTherDays$
- The number of weeks per instance, $Horizon$.

The following information about appointments a is known:

- The duration in number of time slots, parameter $Duration_a$
- Whether a is a group appointment, parameter $Group_a$
- Whether appointment a is a simultaneous appointment with appointment $\hat{a}$, parameter $MultiResource_{a\hat{a}}$, for all $\hat{a}$
- The range of preferred weeks between which a is scheduled, parameters $MinWeek_a$ and $MaxWeek_a$
- Whether appointment a can be scheduled at discipline c, parameter F_{ac}
- The minimum number of new group therapy time slots that appointment a will cause, parameter $NewGroup_a$.

Therapists and disciplines

Per therapist h, the following information is known:

- Whether therapist h belongs to discipline c, parameter G_{hc}
- Whether therapist h can treat patients with care pathway z, $Spec_{hz}$.
- Whether therapist h is available at time slot t, parameter B_{ht}.
- Whether therapist h has a group appointment at time slot t, parameter $GroupApp_{ht}$
- The duration in number of time slots of the group appointment of therapist h at time slot t, $GroupDur_{ht}$
- Whether therapist h has a multi-resource appointment with therapist $\hat{h}$ at time slot t, $Multi_{h\hat{h}t}$

Per discipline c, the input is:

- The target utilization rate, $MaxUtil_c$.

6.3 Simulation process

Figure 6.1 gives a flowchart of the simulation process. This paragraph explains the steps as denoted in this figure. The parameter $Attempts$ counts the number of attempts to schedule the care pathway of the current patient. $MaxAttempts$ is the maximum number of attempts per

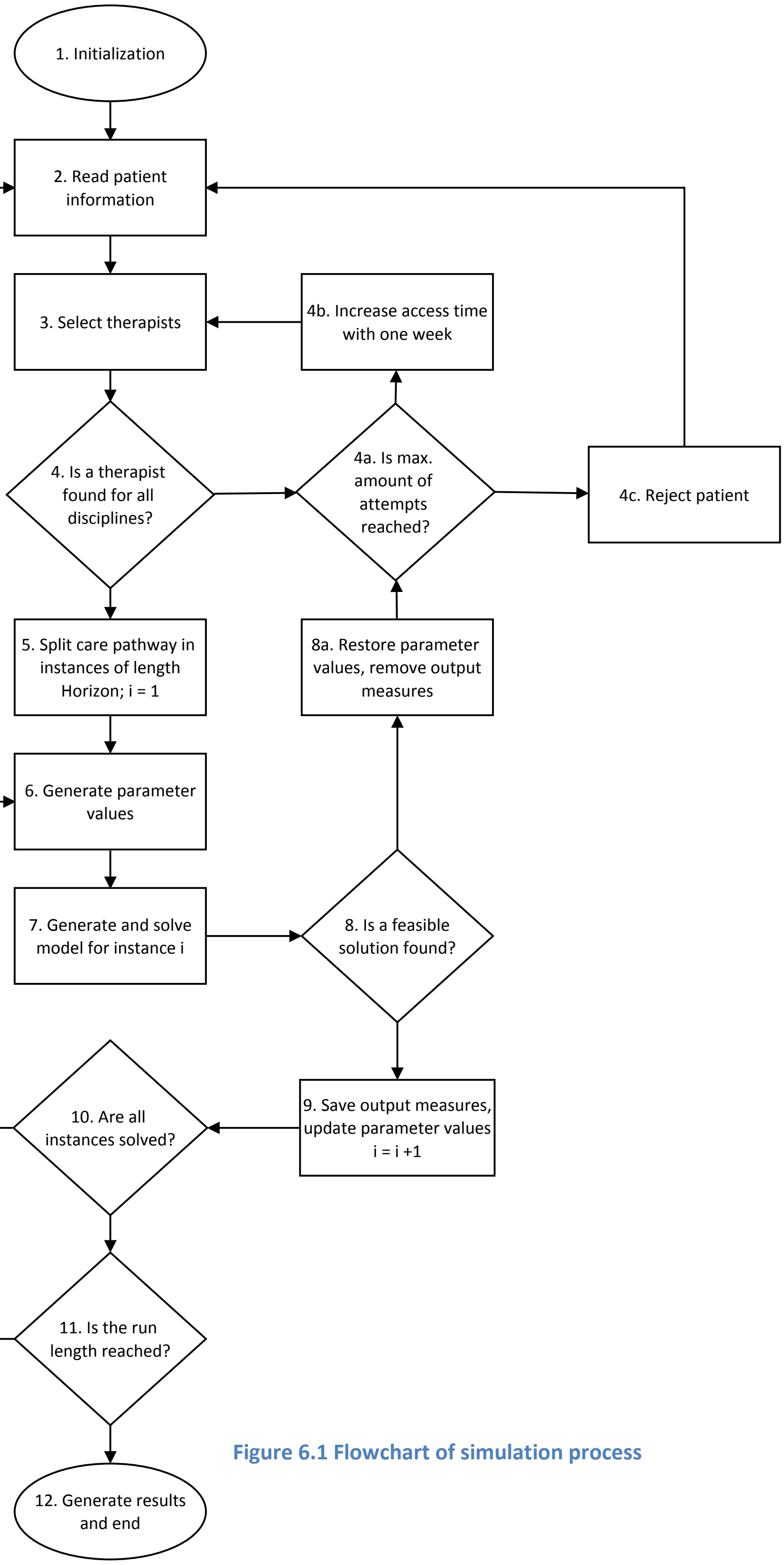


Figure 6.1 Flowchart of simulation process

patient.

1. Initialization

Initialization concerns the generation of input information as defined in Paragraph 6.1.

2. Read patient information

Out of the patients that are not yet scheduled, one patient for which $FirstWeek_p = \min(FirstWeek_p)$ is picked. $Attempts$ is initialized at 1.

3. Select therapists

Select a therapist per discipline, following the heuristics described in Paragraph 6.1 and Appendix IV. The resulting set of therapists H_p is used as input for the ILP.

4. Is a therapist found for all disciplines?

If no individual therapist can be found in one of the iterations of Heuristic IV.1, the heuristic is quitted (step 2.7 of heuristic IV.1), $Attempts = Attempts + 1$ and the simulation moves to step 4a. In all other cases, the simulation moves to step 5.

If an instance of the ILP cannot be solved (step 10) *or* no therapist can be found for any discipline (step 4), step 4a checks whether the maximum number of attempts is reached. If this is false, we increase the access time with one week (step 4b) and go to step 3. If this is true, the patient is rejected (step 4c) and we move to step 2.

5. Split care pathway in instances of length Horizon; $\boldsymbol{i = 1}$

The care pathway is split in instances of $Horizon$ weeks. For example, if the prescribed lead time of a care pathway is 13 weeks, and $Horizon = 4$, the number of instances is 4 (week 1 to 4, week 5 to 8, week 9 to 12 and week 13). Instance number i is initialized at 1.

6. Generate parameter values for instance $\boldsymbol{i}$

We have to generate subsets of all time, appointment and therapist related parameters. Therefore we first define sets T_i and A_i:

$$A_i = \{a \in A_p | (i-1) \cdot Horizon + 1 \leq MinWeek_a \leq i \cdot Horizon\}$$

$$T_i = \{t \in T_p | [(i-1) \cdot Horizon + FirstWeek_p + Attempts - 2] \cdot W + 1 \leq t \leq i \cdot Horizon \cdot Week\}$$

Where

$$T_p = \{(Attempt + FirstWeek_p - 2) \cdot Week + 1, \dots, \\ (Attempt + FirstWeek_p - 2 + \max(MaxWeek_a)) \cdot Week\}$$

Simply put, T_p includes all timeslots starting from the time of access until the last week during which appointments are preferable scheduled and T_i (A_i) includes all timeslots (appointments) of the current instance.

Subsequently, we can construct subsets of all input parameters for the current instance.

7. Generate and solve model for instance $\boldsymbol{i}$

The constraints, decision variables and objective function of the ILP are generated. Subsequently, Gurobi is called to solve the ILP.

8. Is a feasible solution found?

If a feasible solution is found, we move to step 9. If no feasible solution is found we restore all parameter values to their values of before scheduling the current patient. Moreover, all generated output measures of earlier (feasible) instances of the current patient are removed.

9. Save output measures, update parameter values, $\boldsymbol{i} = \boldsymbol{i} + \mathbf{1}$

Output measures are saved and parameter values with respect to group appointments and therapist availability are updated. If one or more group therapists were selected in step 3, we make sure that availability and group therapy appointments are restored. Moreover, we increase instance number i with 1.

10. Are all instances solved?

If all instances are solved (i.e., if i is equal to the total number of instances), we move to step 11. Else, we go back to step 6 and solve the ILP for the next instance.

11. Is the run length reached?

If all patients are scheduled, we move to step 12. Else, we move to step 2 and schedule the next patient.

12. Generate results and end

A report is generated including all output measures, the appointment schedule and computational performance.

6.4 Output

Per instance, the following output measures are gathered:

- The number of unscheduled appointments
- The number of new groups scheduled
- The number of times that two individual appointments for the same discipline are scheduled on the same day
- The number of times that two group appointments for the same discipline are scheduled on the same day
- The number of time slots that appointments are scheduled too late with respect to the preferred range of weeks
- The number of time slots that appointments are scheduled too early with respect to the preferred range of weeks
- The number of therapy days more than the minimum needed number of therapy days (combination appointments)
- The number of weekdays that the patient has appointments more than the minimum needed number of weekdays (horizontal scheduling)
- Access time (based on the value of $Attempts$)
- Whether the patient was rejected

Per patient p, we calculate the following congruence measures:

- $NUMO^{CP \to RTS}$, the measure for the number of appointments that is in the care pathway but not in the realized treatment schedule
- $FRQ^{CP \to RTS}$, the measure for congruence between the care pathway and the realized treatment scheduled with respect to appointment frequency
- AT, the measure for access time

$NUMA^{CP \to RTS}$ is not applicable since the ILP does not schedule extra appointments. $TDURO^{CP \to RTS}$. $TDURA^{CP \to RTS}$ and $DUR^{CP \to RTS}$ are also not applicable, since the ILP does not allow deviation in terms of duration per appointment. $LT^{CP \to RTS}$ is not applicable since the ILP does not allow deviation of the lead time from the care pathway. AT is calculated based on the number of attempts to schedule the appointments of the patient.

Additionally, we calculate therapist utilization by comparing B_{ht} in the final schedule with B_{ht} from the empty schedule. We also use B_{ht} to calculate group utilization, i.e., the number of patients in a group divided by the maximum number of patients in a group.

Chapter 7: Experimentation

This chapter discusses the experimentation with the simulation model. Paragraph 7.1 describes the input data. It describes how care pathways are constructed from the data in SMK and how therapists and therapist availability are derived. Paragraph 7.2 discusses the applied scenarios. Then, Paragraph 7.3 gives the parameter settings. Paragraph 7.4 describes the verification and validation process of the simulation model. Paragraph 7.5 discusses the applied warm-up length and Paragraph 7.6 deals with determining the number of experiment replications. Finally, Paragraph 7.7 describes the experiment results, analysis of results and gives conclusions.

7.1 Input data

Care pathways and patient arrivals

As discussed in Chapter 2, SMK is familiar with CPs, although they are not always up to date in practice and individual treatment plans are often used instead. It would make sense to use individual treatment plans as input for the ILP. However, given the data structure of treatment plans in SMK it would be time-consuming and prone to error to obtain individual treatment plans. The only method to obtain individual treatment plans is through treatment plan orders. These orders are written in “free text” fields, which make it hard to obtain valid treatment plan descriptions. Therefore, we choose to use existing CPs as input for the simulation model. Since we want to assess the effect of applying generalistic therapist teams, we are forced to select two or more units for experimentation. The SIR and CAO unit have properly described CPs. Therefore, these units were selected. The SIR unit uses 21 different CPs, the CAO unit eleven.

We estimated patient arrival rates by analyzing treatment plan orders obtained from the HIS. Treatment plan orders were used because only these orders link patient numbers to care pathways. All treatment plan orders were selected for the year 2014. If the combination of the CP and patient was also present in 2013, the patient was omitted. Thus, only new patients were selected. Since more than one order can be written for the same treatment plan (e.g., in case of a mutation), only unique patient number-care pathway combinations were selected. Table II.1 in Appendix II gives an overview of CPs, their arrival rate, care unit, care team and whether the care pathway corresponds to out- or inpatients. In addition, it provides the prescribed lead time and the planning horizon that is used in the ILP (i.e., the parameter $Horizon$). Care pathways include all prescribed appointments for ACT, BAG, ET, FT, LG, PS, SKL, MW and DIET and all related parameters (see Paragraph 6.2).

Therapists and therapist schedules

The schedulers of the SIR and CAO unit provided a list of therapists per unit. Only therapists with the discipline ACT, BAG, ET, FT, LG, PS, SKL, MW or DIET were included in our experiments. For the CAO unit, it was specified to which care team a therapist belonged. Some therapists worked for more than one team or even for both units. Staff schedules were obtained through SP-Expert, the hospital staff scheduling software. Table II.2 in Appendix II gives an overview of staff members and the units and teams they belong to.

7.2 Scenarios

This paragraph describes the scenarios that are evaluated with the simulation model. We designed six scenarios to evaluate the effect of two interventions: introducing generalist therapist teams and improving staff schedules. Moreover, we do experiments with different expected utilization. Table 7.1 gives an overview of the scenarios:

Table 7.1

Scenario overview

Scenario	Abbreviation	Degree of specialization	Staff schedule	Expected utilization
1	SPEC++/CURRENT/UTILLOW	Specialization per care team	Current	Current
2	SPEC+/CURRENT/UTILLOW	Specialization per care unit	Current	Current
3	GEN/CURRENT/UTILLOW	No specialization	Current	Current
4	GEN/SMOOTH/UTILLOW	No specialization	Smoothened	Current
5	GEN/SMOOTH/UTILMED	No specialization	Smoothened	Medium
6	GEN/SMOOTH/UTILHIGH	No specialization	Smoothened	Target

Degree of specialization

Scenario 1 applies specialization per care team. This is the degree of specialization that is currently applied in SMK. Scenario 2 considers specialization per care unit. Thus, care teams are not considered when assigning a therapist to a patient. In scenario 3 to 6, full generalization is considered. Thus, any therapist of discipline x can be scheduled with any patient who is prescribed therapy of discipline x. See Table II.2 in Appendix II for assignment of therapists to care teams and units, as applied in scenario 1 and 2.

Expected utilization

We calculated expected demand of care and expected utilization for scenario 1 to 4. To obtain the expected utilization per discipline, we divided the expected demand per week by therapist availability per week. For these calculations, we assumed that groups are fully utilized, i.e., if a patient has a group appointment and six patients can be scheduled in a group, demand is divided by six. Moreover, we did not take differentiation in teams into account.

Figure 7.1 gives the expected utilization of all disciplines in all scenarios. The expected utilization in the current situation, scenario 1 to 4, indicates that there is a surplus of therapist availability for all disciplines. Therefore, we add two scenarios. We reduce the available therapist capacity based on an expected utilization of 50% in scenario 5 and based on an expected utilization equal to the targets applied by SMK in scenario 6.[8] In our study limitations in Paragraph 9.2, we discuss why the expected therapist utilization is low in scenario 1 to 4.

[8] For dieticians (DIET), speech therapists (LG) and sexologists (SKL), no targets were defined. Therefore we applied the lowest target (52%) for these disciplines. Moreover, we use a minimum of 20 hours per discipline. With 20 hours per week, SKL and LG still had very low utilization, due to low demand for care.

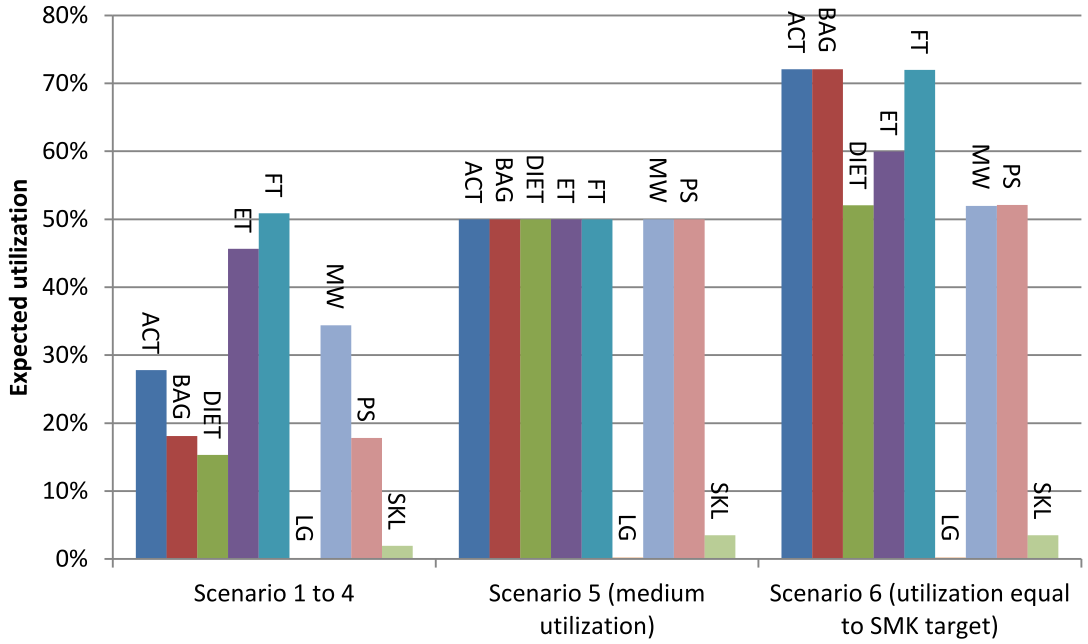


Figure 7.1 Expected utilization for all scenarios

Staff schedules

In scenario 1 to 3, we applied current staff schedules. Figure 7.2 gives the capacity per day per discipline for these schedules. The height of a bar indicates the total number of hours per day. The numbers represent the number of hours per discipline per day. Although not depicted in the figure, we applied the exact start and end times of shifts as currently applied.

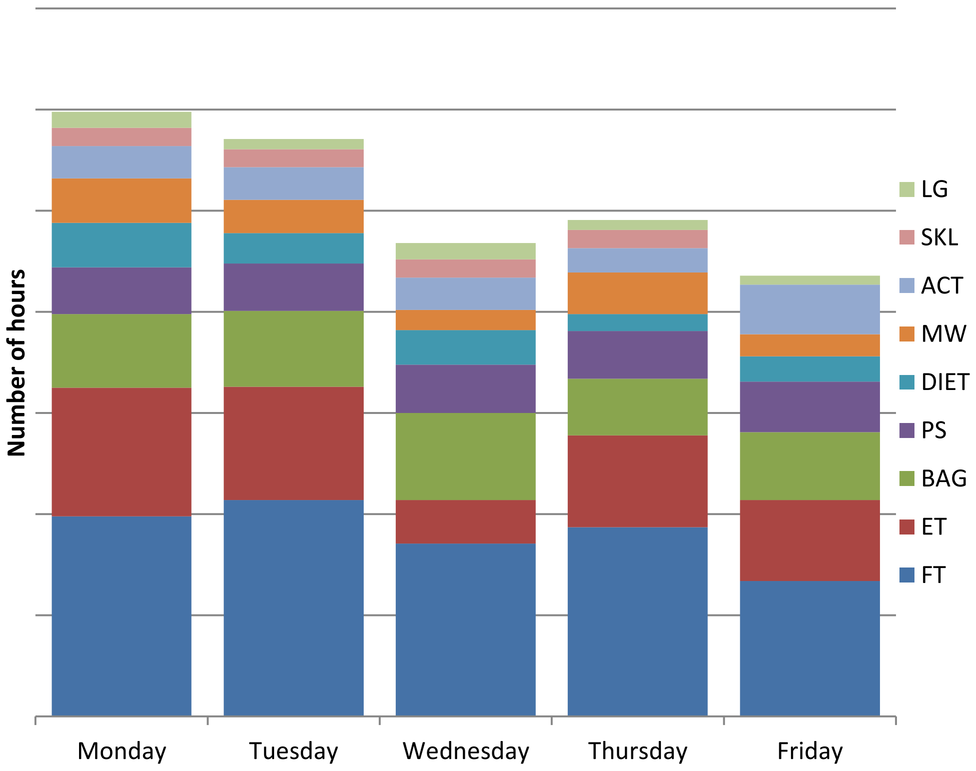


Figure 7.2 Therapist capacity per day in scenario 1 to 3 (current staff schedules)

Since demand for care is equal over the weekdays, it is clear that current schedules are not aligned with demand for care: Monday and Tuesday are the busiest days. Occupational therapist (ET) capacity on Wednesday is only 30-50% compared to other days, while movement therapists (BAG) have a relatively high capacity on Wednesday.

Figure 7.3 depicts the therapist capacity per day for all scenarios. It is clear that the staff schedules are better matched with demand for care in scenario 4 to 6.

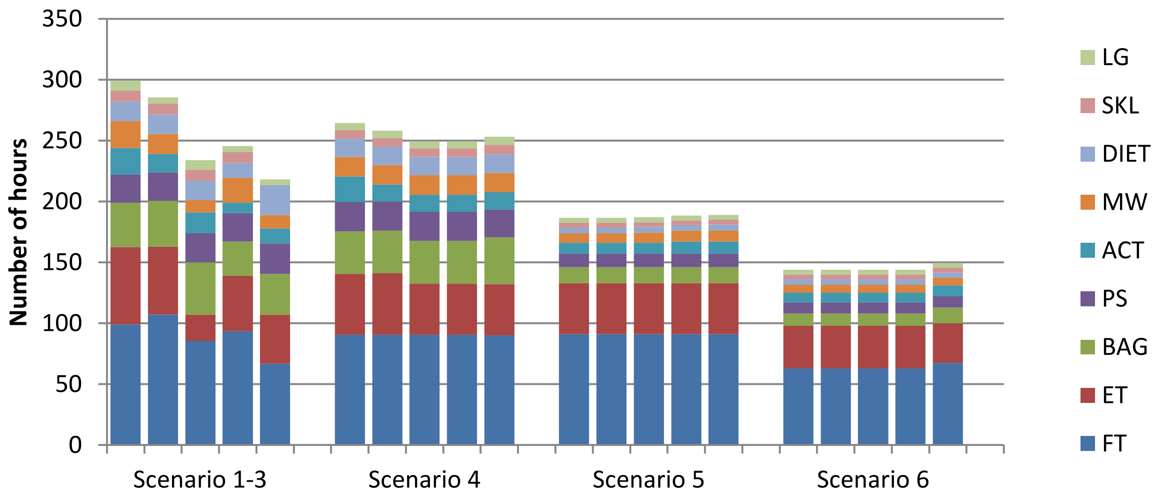


Figure 7.3 Therapist capacity in all scenarios

For scenario 4 to 6, we maximized the number of working hours and days per therapist and thereby minimized the number of therapists. The maximum number of hours per week per therapist was 40. The minimum number of hours per week per discipline was 20. We also reduced variation in start and end times of shifts and made sure that disciplines are represented throughout the whole working day (i.e., 8:00h to 18:00h).

Comparison between scenarios

We make confidence intervals for pairwise comparisons to determine significance of differences between scenarios. For an example comparison, this means that replication i of scenario j is compared with replication i of scenario $j+1$. We apply common random numbers to reduce variance and to obtain smaller confidence intervals. Thus, replication 1 of scenario 1 uses the same arrival rate of patients as replication 1 of scenario 2, and so on. For a comprehensive discussion on pairwise comparisons and common random numbers in simulation, see Law [34].

7.3 Parameters

Table 7.2 gives an overview of the remaining parameter settings used for simulation. The weights are picked in cooperation with SMK management.

Table 7.2

Parameter settings

Parameter	Description	Setting
$MaxApp$	Maximum number of appointments per patient per day	5
$MaxPatGroup$	Maximum number of patients in a group	6
MT	Maximum number of time slots between two appointments on the same day	2
$MaxDev$	Maximum deviation of appointment time slot from preferred range of weeks, in number of time slots	105
β_1	Weight for number of appointments not scheduled	1000
β_3	Weight for deviation of appointment time slot from preferred range	100
β_5	Weight for extra appointments per discipline per day (groups)	10
β_6	Weight for extra appointments per discipline per day (individual)	1
β_8	Weight for extra groups	10
β_9	Weight for extra therapy days (combination appointments)	1
β_{10}	Weight for scheduling appointments at other weekdays than in the first therapy week (horizontal scheduling)	1

The weights indicate the factor by which a variable value is multiplied in the objective function. By entering weights, one can influence which solution would be optimal. Adding a new group results in adding a value of $1 \cdot 10 = 10$ to the objective function. The alternative, not scheduling the appointment, results in adding $1 \cdot 1000 = 1000$ to the objective value. Since we want to minimize the objective value, the ILP would schedule a new group instead of not scheduling the appointment.

Although we carefully determined parameter values, parameter values remain somewhat arbitrary. Sensitivity analysis could indicate to what extent different parameter values influence the performance of the ILP. Analyzing these results helps in picking the right parameter values.

7.4 Verification and validation

Verification of the simulation model considers the assessment whether the computer model acts as expected based on the model description. During programming, we tested and debugged the model each time new code was added. This was done for a small number of patients to allow quick testing for reasonability. The whole model was verified after programming was finished.

Since scheduling methods and input data with respect to care pathways differed between reality and the simulation model, we could not perform quantitative validation. However, we qualitatively validated our simulation model. Before developing the ILP, we consulted two managers to formulate and discuss constraints that are required for the automated appointment scheduling model. Moreover, we discussed model assumptions and data gathering methods. Throughout the model development, the same two managers were consulted to assess whether the model describes real-life requirements properly.

7.5 Warm-up period

Since we have a non-terminating simulation model, we have to calculate its warm-up period. For determining the warm-up period, we apply Welch's graphical procedure [35]. Shortly put, by applying Welch's graphical procedure one creates a graph of the moving average of an output measure of interest. Then, the user chooses the warm-up period l as the value beyond which the moving average appears to have converged. For a comprehensive discussion on this procedure, we refer to Law [36].

We calculated the desired warm-up period for the output measures as defined in Paragraph 6.3. We made five replications of all scenarios, each of length 208 weeks (4 years). We included 3500 patients, which is roughly the number of patient scheduled in four years, for patient-related output measures. Four output measures did not reach convergence within the run length. This is due to the rareness of the events related to these measures. Reaching equilibrium would require a very long run length or high number of replications, which is unattainable given the model size and available time. Valid conclusions with regard to these measures can thus not be obtained with the applied run length and number of replications.

For illustration, Figure 7.4 shows the moving average for scenario 1 for six output measures. The red dot indicates the value of l. Table 7.3 shows the maximum values of l over all scenarios.

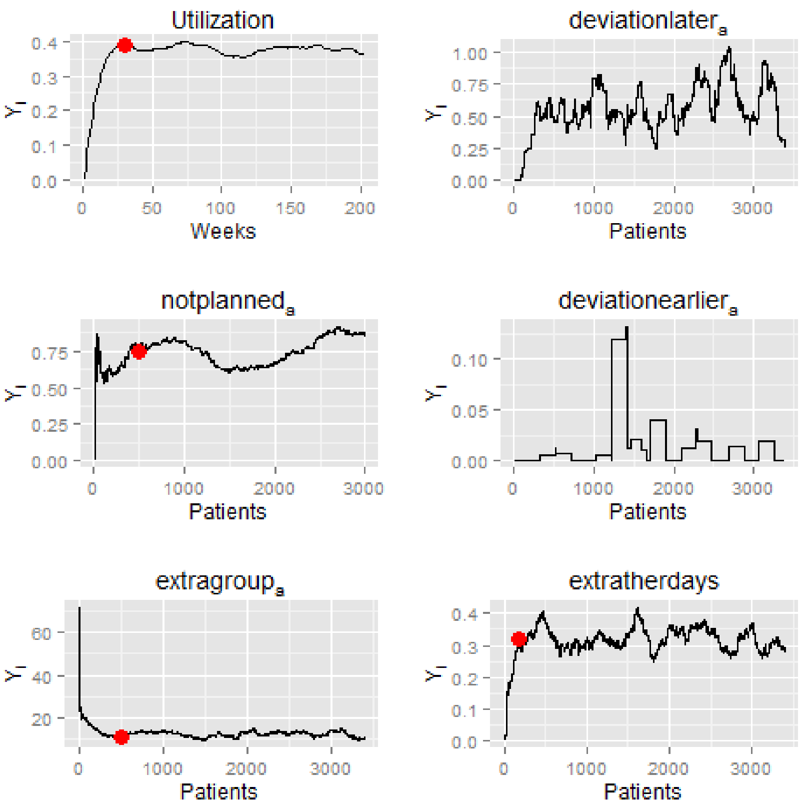


Figure 7.4. Moving average (Y_i) for six output measures. Note that for two output measures no convergence was indicated.

Table 7.3		
Desired warm-up period for all output measures. The largest found value of $\boldsymbol{l}$ over all scenarios is presented. The window $\boldsymbol{w}$ indicates the window applied in calculating the moving average		
Output measure	Window w	Warm-up length l
Therapist utilization	5 weeks	40 weeks
Extra therapy days (combination appointments)	100 patients	300 patients
Unscheduled appointments	500 patients	600 patients
Extra groups	200 patients	500 patients
Access time	200 patients	600 patients
Number of times two individual appointments per day per discipline	100 patients	400 patients
Number of times two group appointments per day per discipline	-	-
Deviation of appointment time slot from preferred range (earlier)	-	-
Deviation of appointment time slot from preferred range (later)	-	-
Number of new weekdays (horizontal scheduling)	-	-

We applied a warm-up period l of 40 weeks or $\left(\frac{40}{208}\right) \cdot 3500 \approx 675$ patients. Not that these warm-up periods are not entirely equal. For example, patient 700 can have appointments from week 35 to 50. Then, the patient is included in the measures based on the number of patients, but the appointments before week 40 are not included in measures based on the number of weeks.

7.6 Run length and number of replications

We want to set a run length and number of replications such that estimates of output measures with relative error y and confidence level $100(1-\alpha)$ can be obtained, while total computation time remains tractable. We apply the so-called approximate procedure to obtain the number of replications. Although this procedure provides only a rough estimate, the more precise sequential procedure requires more $n \geq 10$ replications, while we aim to obtain $n < 10$ to limit total computation time. We refer to Law for a more comprehensive discussion on the approximate and sequential procedure [36].

Our calculations are based on five replications with a run length of 208 weeks or 3500 patients. Table 7.4 gives an overview of the number of needed replications per scenario for the six output measures that reached convergence within the warm-up period. We apply $a = 0.05$.

Table 7.4

Needed number of replications for all output measures and scenarios (1 to 6).

Output measure	y	Number of replications per scenario						
		1	2	3	4	5	6	Max
Utilization	0.05	4	4	4	4	4	3	4
Extra therapy days	0.10	6	5	4	7	5	6	7
Appointments not scheduled	0.10	5	9	6	5	40	7	40
Extra groups	0.05	3	3	3	5	5	4	5
Access time	0.05	3	3	3	3	9	8	9
Number of times two individual appointments per day	0.10	3	4	3	10	13	4	13

Our analysis indicates that we need 40 replications to obtain estimates of these output measures with relative error y and confidence level of 95%. However, due to limited available time, we apply five replications per scenario.

7.7 Results

This paragraph presents the experimental results. In interpreting the results in this paragraph, please note that the warm-up period we applied was insufficient to reach convergence for some output measures (see Paragraph 7.5); and that the number of replications (five) is insufficient to obtain an estimate of the mean with 95% confidence level and relative error of 5% or 10% for most output measures (see Paragraph 7.6). Therefore, the results should be interpreted with care.

This paragraph starts with a summary of the most important results. The remainder of the paragraph addresses more detailed analysis of results. The paragraph finishes with conclusions and a discussion regarding the results.

7.7.1 Summary

Table 7.6 presents the average scores for twelve output and two congruence measures. Cell colors indicate to which extent a result is better or worse than the result of the same output measure in other scenarios (green is good compared to others, red is bad compared to others). As a reminder, we provide the descriptions of horizontal scheduling, combination appointments, $NUMO$ and FRQ in Table 7.5.

Table 7.5

Output measures descriptions

Measure	Description	Notation in Table 7.6
NUMO	Fraction of unscheduled appointments	NUMO
FRQ	Relative deviation from the prescribed therapy frequency	FRQ
Combination appointments	Number of therapy days more than the theoretical minimum	Extra therapy days (days)
Horizontal scheduling	Number of new weekdays compared to the weekdays in the schedule of the first week	New therapy weekdays (days)

The results are averages per patient, unless stated otherwise. Per output measure, measurement units are indicated between brackets. For example, *Deviation later* is measured in time slots per patient. *Two ind apps/disc/day* and *Two group/apps/disc/day* indicate the number of times two appointments per discipline per day were scheduled, for individual and group appointments, respectively.

Table 7.6a

Simulation results of twelve output measures for all scenarios. The presented results are averages per patient, unless stated otherwise

	Not scheduled (appointments)	Deviation later (time slots)	Deviation earlier (time slots)	Rejected patients (percentage)	Therapist utilization (percentage)	Access time (weeks)
1: SPEC++/CURRENT/UTILLOW	0.81	0.61	0.02	1.4%	38%	1.06
2: SPEC+/CURRENT/UTILLOW	0.67	0.6	0.01	1.4%	38%	1.07
3: GEN/CURRENT/UTILLOW	0.78	0.52	0.02	0.7%	41%	1.06
4: GEN/SMOOTH/UTILLOW	0.11	0.47	0.01	0.3%	43%	1.04
5: GEN/SMOOTH/UTILMED	0.09	0.33	0.01	1.2%	57%	1.42
6: GEN/SMOOTH/UTILHIGH	0.24	1.8	0.07	4.4%	67%	1.76

	Extra therapy days (days)	New therapy weekdays (days)	Two individual app/disc/day (occurrences)	Two group app/disc/day (occurrences)	Extra groups (groups/patient)	Group utilization (percentage)
1: SPEC++/CURRENT/UTILLOW	0.31	0.004	1.96	5.59	12.44	45%
2: SPEC+/CURRENT/UTILLOW	0.38	0.005	1.95	5.6	12.67	44%
3: GEN/CURRENT/UTILLOW	0.4	0.005	2.09	6.04	14.95	41%
4: GEN/SMOOTH/UTILLOW	0.09	0.001	0.39	5.21	16.76	38%
5: GEN/SMOOTH/UTILMED	0.1	0.001	0.42	5.09	16.43	39%
6: GEN/SMOOTH/UTILHIGH	0.2	0.002	0.55	4.6	14.27	41%

Table 7.6b

Simulation results of congruence measures for all scenarios

	$NUMO^{CP \to RTS}$	$FRQ^{CP \to RTS}$
1: SPEC++/CURRENT/UTILLOW	0.9994	0.9994
2: SPEC+/CURRENT/UTILLOW	0.9995	0.9994
3: GEN/CURRENT/UTILLOW	0.9994	0.9993
4: GEN/SMOOTH/UTILLOW	0.9999	0.9998
5: GEN/SMOOTH/UTILMED	0.9999	0.9998
6: GEN/SMOOTH/UTILHIGH	0.9994	0.9987

Scenario 4 and 5 led to the best results for most outcome and congruence measures; although therapist utilization is undesirably low in scenario 4 (43%) and this scenario has the worst group utilization.

We perform pairwise comparisons between all scenarios to indicate whether found differences were significant, based on a 95% confidence interval. For the output measures that reached convergence within the warm-up period (see Paragraph 7.4), differences between combinations of scenario 1, 2 or 3 and scenario 4, 5 or 6 were all significant. For the results of all pairwise comparisons, we refer to Appendix V.

7.7.2 Analysis of results

This paragraph addresses a detailed analysis of the results per output measure. We discuss which scenario performs best per output measure. In addition, we describe relationships between outputs, to allow better interpretation of the results and suggest model (configuration) improvement.

Rejected patients, unscheduled appointments and therapist utilization

As can be seen in table 7.5a, applying generalist therapist teams instead of specialist therapist teams significantly reduces the number of rejected patients, while the number of unscheduled appointments per patient does not increase. Thus, with respect to the possibility to schedule appointments, applying generalist therapist teams significantly improves performance. If we also apply smooth therapist schedules, both the number of rejected patients and unscheduled appointments further improve significantly. If we increase therapist utilization, the number of unscheduled appointments remains low, while the number of rejected patients increases from 0.3% (current utilization) to 1.2% (expected utilization of 50%) or 4.6% (expected utilization equal to SMK targets).

It is remarkable that patients are rejected all, since both overall utilization and the number of unscheduled appointments are low. A bottleneck in therapist capacity at one discipline could explain why rejection still occurs. To identify such a bottleneck, Figure 7.5 gives the average therapist utilization for all disciplines and scenarios.

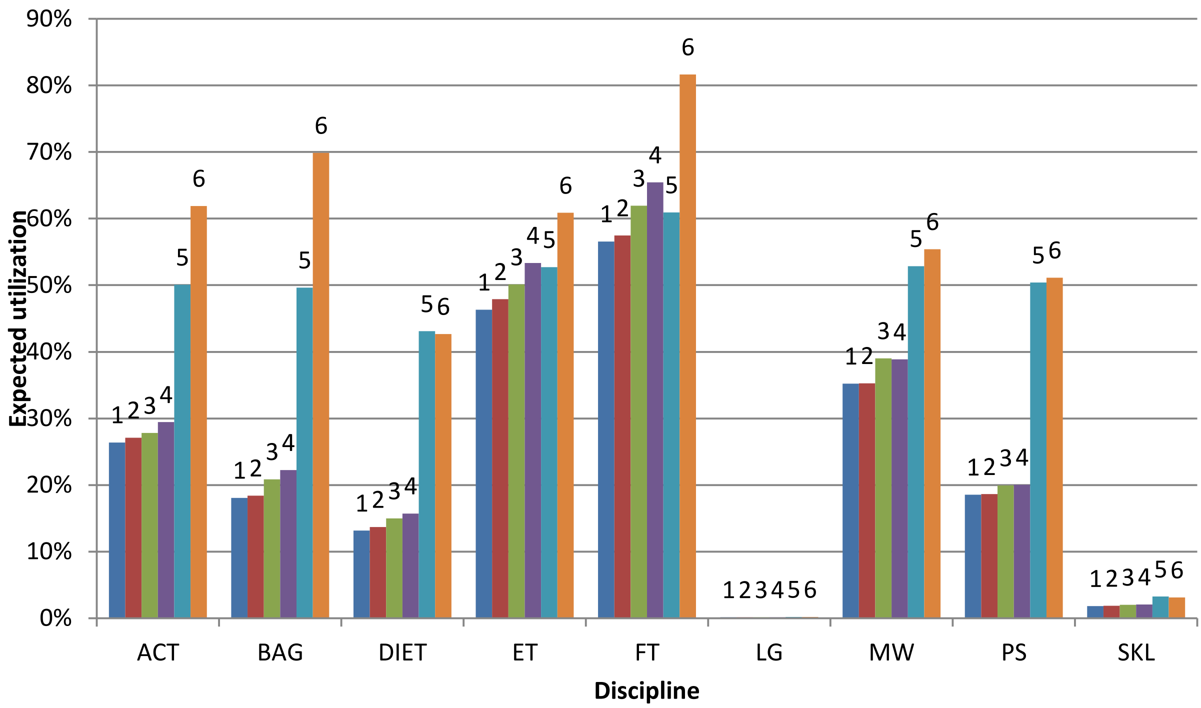


Figure 7.5 Therapist utilization per discipline and scenario. The numbers above bars indicate scenario numbers

The utilization rate of physiotherapists is on average the highest of all disciplines, but is particularly high in scenario 6 (>80%). Figure 7.6 plots the number of rejected patients per week and the utilization rate of physiotherapists of that week for one experiment of scenario 6 (GEN/SMOOTH/UTILHIGH).

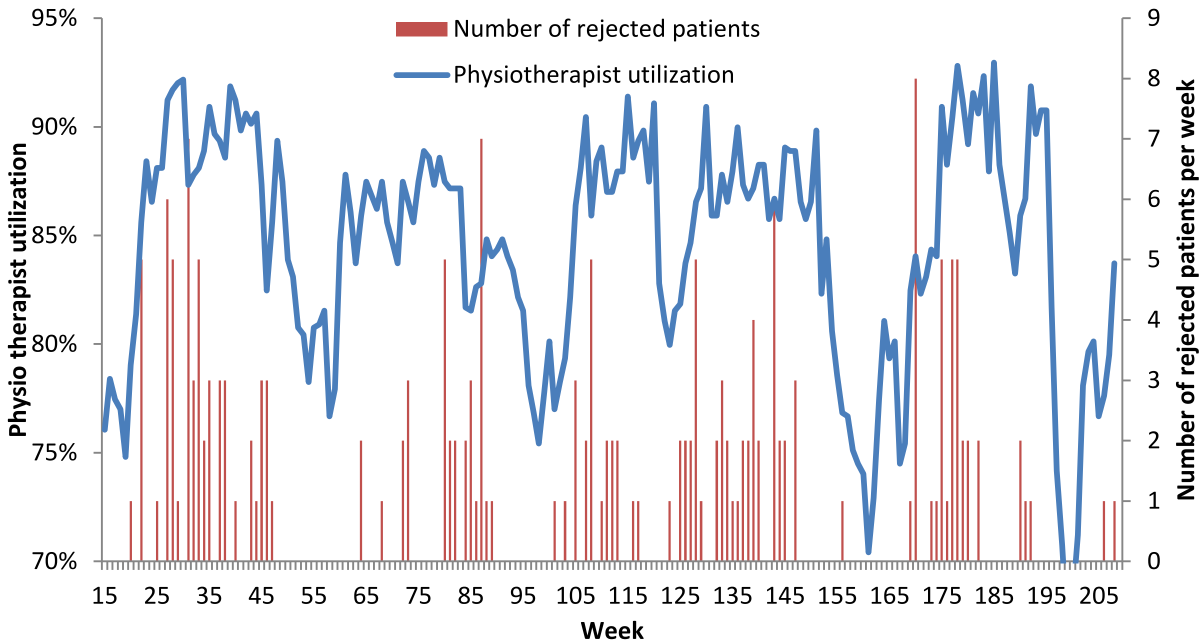


Figure 7.6 Physiotherapist utilization versus number of rejected patients for one experiment of scenario 6 (GEN/SMOOTH/UTILHIGH).

We can deduce a small correlation from Figure 7.6[9]. It appears from the figure that when physiotherapist utilization increases, the number of rejected patients also increases. Despite that overall therapist utilization was only 67% in scenario 6, overloaded physiotherapists induced the rejection of patients. Also, note the fluctuation in therapist utilization, which is arguably (partly) caused by increasing and decreasing levels of patient rejection

On the one hand, the average number of unscheduled appointments per patient is small, but on the other hand, other patients are rejected. Therefore, we expect that many patients have zero unscheduled appointments, while a few have multiple unscheduled appointments (close to the limit of 20% per discipline). This would explain infeasibility of the ILP: if there would be no patients close to the limit for unscheduled patients, it would be hard to believe that other patients are rejected because they violate this limit.[10] For one example experiment of scenario 6, 92% of all patients had no unscheduled appointments. The histogram in Figure 7.7 shows that if appointments are not scheduled, in 45% of the cases the percentage of unscheduled appointments is between 15 and 20% for that specific discipline.

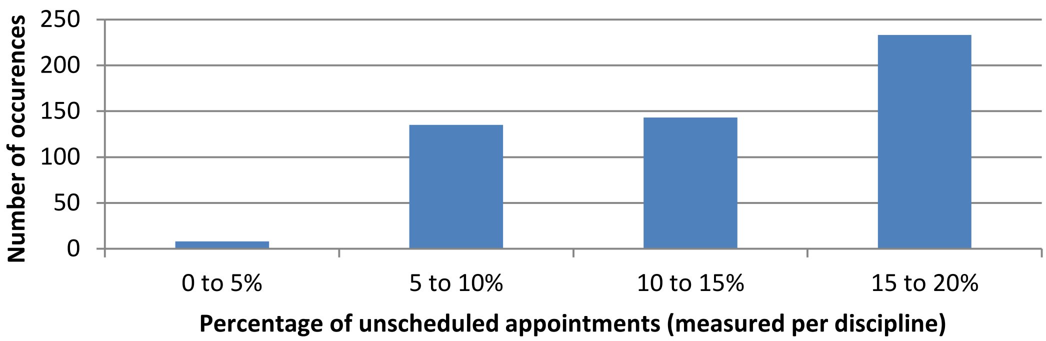


Figure 7.7 Percentage of unscheduled appointments if there are any unscheduled appointments for one experiment of scenario 6

Number of new groups, group utilization and therapist utilization

Scenario 1 (SPEC++/CURRENT/UTILLOW) had the lowest number of new groups per patient and highest group utilization. This is remarkable because the high specialization degree in scenario 1 made us expect that it is harder to make full use of group capacity. The higher percentage of rejected patients in scenario 1 – patients with presumably intensive care pathways and many group appointments resulting in new groups – could explain the difference in group utilization between scenario 1, 2 and 3.

Group utilization and the number of new groups per patients score better in scenario 6 (UTILHIGH) than in scenario 4 and 5 (UTILLOW / UTILMED), while the number of unscheduled appointments is only slightly higher in scenario 6. This suggests that in scenario 6 more

[9] The Pearson correlation coefficient between physiotherapist utilization and the number of rejected patients is 0.24.

[10] Recall that increasing access time and ultimately rejection occurs for two reasons: 1) the heuristic for therapist selection cannot find therapist(s) with enough available time slots, or 2) the ILP cannot produce a feasible schedule. We did not record why patients were rejected. However, we observed during simulation that rejection happened regularly due to ILP feasibility.

appointments are forced to be scheduled in existing group appointments instead of new groups, because, for example, they could not be scheduled otherwise. This suggests that appointments are not "forced hard enough" to be scheduled at existing time slots for group therapy. Increasing the weight for generating new groups (variable $extragroup_a$) might improve group utilization. Another explanation for low group utilization could be the heuristic we use for assigning therapists to patients. Since we assign one therapist for group therapy to a patient, the possibilities for scheduling a patient into an existing group are limited.

Recall that we based the available therapy hours per discipline on the expected therapist utilization. In calculating expected therapist utilization, we assumed that group utilization was 100%. Since we did not reach 100% group utilization by far, therapist utilization is higher than what we expected. To illustrate this, Figure 7.8 presents the expected and average therapist utilization, number of groups and average group utilization for one experiment of scenario 6.

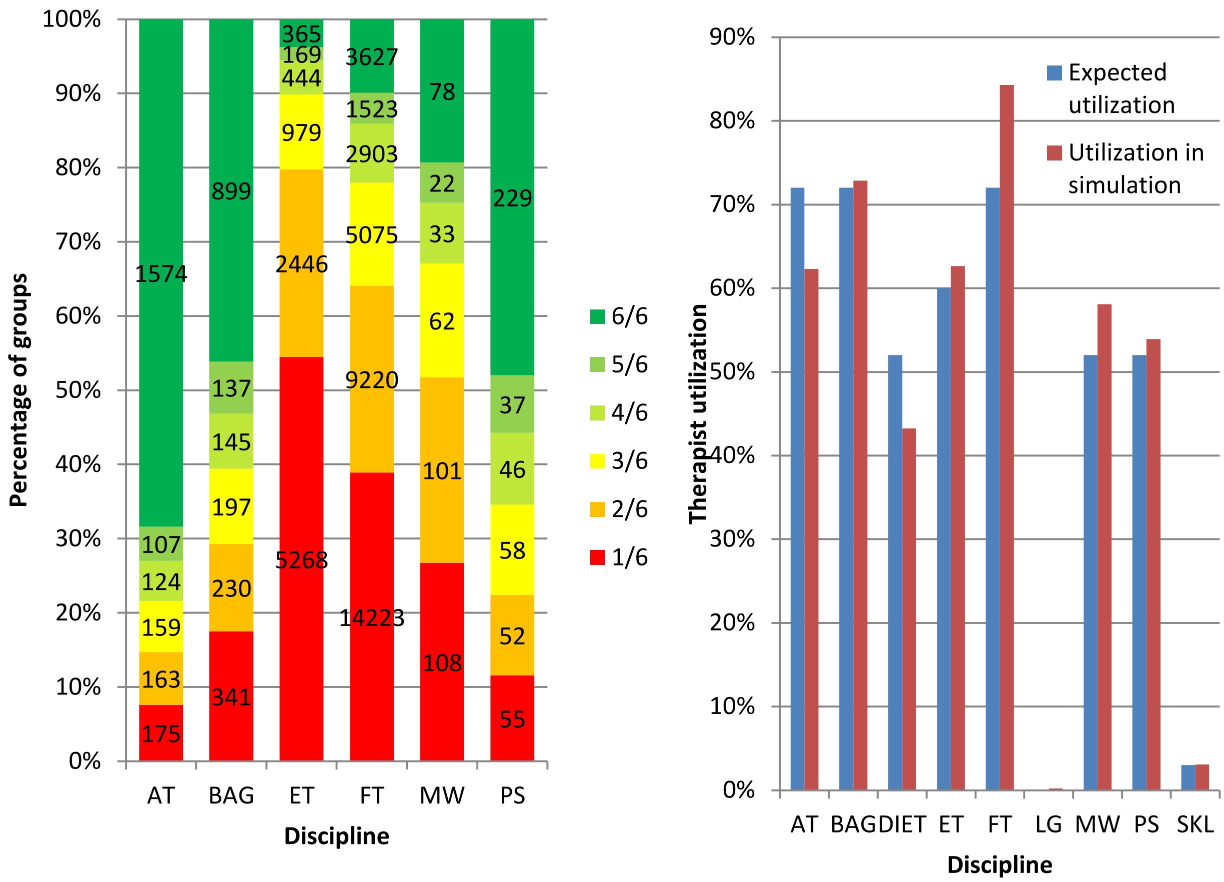


Figure 7.8 ***Left***: **Group utilization for one experiment of scenario 6. The heights of the bar segments indicate the percentage of groups with the given group utilization (1/6, 2/6, etc.). SKL, LG and DIET are not included since these disciplines do not provide group therapy**

Right: **Therapist utilization per discipline for one experiment of scenario 6.**

Figure 7.8 shows that if group utilization is low, therapist utilization is higher than the expected utilization. Thus, low group utilization explains why there is a bottleneck in physiotherapist capacity, which led to rejecting 4.6% patients on average in scenario 6.

Remarkably, AT, BAG and PS make much better use of group capacity than ET, FT and MW. ET and FT have more multi-resource appointments than the other disciplines. Multi-resource appointments impose additional constraints when scheduling patients to an existing group appointment (and thus, less patients can be scheduled in a group), explaining the lower score for ET and FT. The relatively poor score for MW is explained by the low total number of group therapy appointments, since fewer appointments mean fewer possibilities to schedule the patient in an existing group.

Access time

Scenario 4 (GEN/SMOOTH/UTILLOW) yields the best results with respect to the average access time. Differences among scenario 1 to 3 were not significant, but scenario 4 performed significantly better than scenario 1, 2 and 3. When therapist utilization increases in scenario 5 and 6, access time also increases. Table 7.7 shows the percentages of access times within a certain number of weeks and the number of rejections per scenario.

Table 7.7

Incidence of access time

Scenario	1 week	2 weeks	3 weeks	4 weeks	Rejected
1: SPEC++/CURRENT/UTILLOW	95.4%	1.6%	0.9%	0.8%	1.4%
2: SPEC+/CURRENT/UTILLOW	95.1%	1.6%	1.1%	0.8%	1.4%
3: GEN/CURRENT/UTILLOW	96.4%	1.4%	1.0%	0.6%	0.7%
4: GEN/SMOOTH/UTILLOW	97.7%	1.3%	0.4%	0.3%	0.3%
5: GEN/SMOOTH/UTILMED	75.6%	11.3%	7.7%	4.2%	1.2%
6: GEN/SMOOTH/UTILHIGH	62.3%	10.3%	12.9%	10.2%	4.4%

Since an access time higher than 1 week factually means that the patients is rejected at some point in time, the explanation given for the high number of rejected patients when utilization increases also applies to access times. Further research could be done to investigate whether increasing the maximum allowed access time leads to better overall results.

Horizontal scheduling

Horizontal scheduling was almost always fully achieved in all scenarios (*New therapy weekdays* in Table 7.5a). Partly, this can be explained by splitting up care pathways: the ILP optimizes horizontal scheduling per instance, and not per patient. The question arises why horizontal scheduling is almost always achieved, while other appointments remain unscheduled and patients are rejected. One explanation is that patient rejection and unscheduled appointments occurs mostly for patients with intensive care pathways. These (in)patients are treated 5 days per week. In that case, horizontal scheduling is always achieved. The opportunity to disobey horizontal scheduling only arises in care pathways with a few appointments per discipline per week. These care pathways however, can typically be scheduled without any problems. Figure 7.8 shows the number of unscheduled appointments per care pathway for one experiment in scenario 6. The figure confirms that unscheduled appointments mostly occur in care pathways with a higher number of appointments per week.

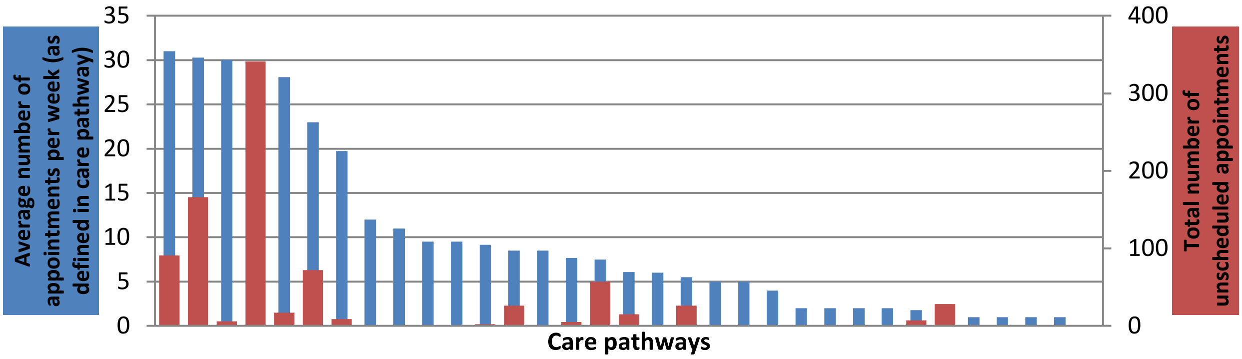


Figure 7.8 Average number of appointments versus number of unscheduled appointments

Combination appointments and number of appointments per day

In the scenarios with generalist therapist teams (scenario 2 and 3), the ability to realize combination appointments (*Extra therapy days* in Table 7.6a) is reduced, compared to scenario 1 (SPEC++/CURRENT/UTILLOW). This is counter-intuitive: with more flexibility in choosing therapists, one would expect better results compared to inflexible specialist therapist teams. The only explanation for this is that utilization increases when generalist teams are applied, making it harder to realize combination appointments. However, if therapist schedules are aligned with demand for care ánd generalist teams are applied (GEN/SMOOTH/UTILLOW**)**, performance with regard to combination appointments improves.

Smoothening therapist schedules is key in an equal subdivision of appointments per discipline over the days in the week. The average number of times that two individual appointments per discipline per day were scheduled is around two per patient in scenario 1 to 3 (no smoothened schedules), but 0.4 to 0.6 per patient in scenario 4 to 6 (smoothened schedules).

Additionally, we investigated to which extent appointments are equally subdivided over the days in the week. Figure 7.9 shows the average relative deviation from the average total number of appointments per weekday, for all scenarios (days with no appointments were excluded).

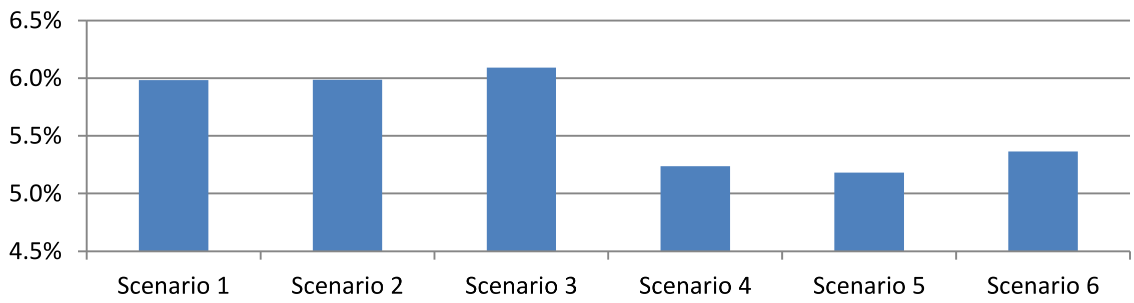


Figure 7.9 Average relative deviation of the from the average number of appointments per weekday

Although we did not steer on minimizing variation of the total number of appointments per weekday, the ILP appears to naturally divide appointments over the weekdays appropriately. The ability to do so increases when therapist schedules are aligned to demand for care (scenario 4, 5 and 6).

Congruence with respect to $\boldsymbol{NUMO}$ and $\boldsymbol{FRQ}$

The number of unscheduled appointments serves as a basis for $NUMO$, while FRQ depends on the number of unscheduled appointments and deviation of appointment time slots from the prescribed range of time slots (*Deviation later* and *Deviation earlier* in Table 7.6a). Deviations later or earlier were uncommon in all scenarios. In the scenario with the worst results on this measure, GEN/SMOOTH/UTILHIGH, the average deviation was 1.8 (later) and 0.07 (earlier) time slot per patient. Although the number of replications was too low to make valid conclusions about these deviations, we can say that the ILP almost never schedules appointments earlier or later than prescribed. This is at least partly caused by splitting up care pathways, since this reduces the possibility to schedule appointments in another week than prescribed.

In the baseline measurement, congruence with respect to the number of omitted appointments ($NUMO$) was not higher than 0.46 for individual appointments for any discipline, and congruence with respect to therapy frequency (FRQ) was not higher than 0.35 for all disciplines. In our simulation, congruence was not lower than 0.998 for both FRQ and $NUMO$[11]. Both FRQ and $NUMO$ were optimal in scenario 4 (GEN/SMOOTH/UTILLOW), with significant differences between scenario 4 and all other scenarios (except for the difference between scenario 4 and 5 for $NUMO$).

However, we cannot directly compare the baseline measurement with simulation results for three reasons:

- The baseline measurement was flawed by the limited quality of data.
- The baseline measurement relates to congruence between care pathway and realized care. Incongruence can occur on all in-between planning levels (i.e., initial treatment plan, treatment plan, treatment schedule, realized treatment schedule), due to for example medical reasons to deviate, no-shows, therapist absenteeism, or inability to find capacity to schedule appointments. In our simulation, incongruence can only occur if the ILP cannot find a feasible solution. All other causes for incongruence are neglected.
- We did not consider patient availability or meeting structures, which would arguably reduce scheduling performance.

7.7.3 Conclusions

This section provides conclusions with regard to the experimentation with the model. We start with conclusions regarding the performance of the ILP and the heuristic for therapist selection. Then, we conclude which scenarios result in the best performance, and simultaneously, whether the proposed interventions deserve recommendation.

[11] For the calculation of $NUMO^{CP \rightarrow RTS}$, we assumed that the relative importance weight for discipline c, δ_c, is 1 for all c.

Performance of automated appointment scheduling

We conclude that our automated appointment scheduling approach as described in Chapter 5 and 6 is a promising method to improve the performance of appointment scheduling and thereby congruence.

The model schedules appointments congruent to the care pathway with respect to appointment frequency and the total number of appointments. Although performance targets are missing, we conclude that results with respect to the number of unscheduled appointments, therapy frequency, combination appointments, horizontal scheduling and access time are excellent in all scenarios. However, we find that the number of rejected patients, when compared to therapist utilization, is unacceptable in all scenarios (4.6% in scenario 6). Moreover, we find the group utilization (41% in scenario 6) insufficient.

We conclude that the performance of automated appointment scheduling is high in a simulation setting, even if therapist utilization is equal to SMK targets. Nevertheless, the model needs adjustments to reduce the number of rejected patients and improve group utilization.

Effect of applying generalist therapist teams

Scenario 1, 2 and 3 represented levels of differentiation of therapists into care teams and care units. All these scenarios were carried out with low therapist utilization, which enables scheduling according to planning rules to a large extent. Therefore, it was to be expected that performance is high in all three scenarios. However, scenario 2 (differentiation into care units) performed significantly better than scenario 1 (differentiation into care units and teams) concerning the number of unscheduled appointments. For other output measures, performance was comparable or slightly better in scenario 1. In conclusion, reducing the degree of specialization with a small amount (scenario 2) has little influence on performance.

The number of rejected patients was 50% lower in scenario 3 (generalist therapist teams) than in scenario 1 and 2. Performance of other output measures was slightly worse, but therapist utilization was higher. Overall, we conclude that applying generalist therapist teams improves scheduling performance in our simulation setting.

Effect of smoothening therapist schedules

Aligning therapist schedules to demand for care significantly increases performance on all aspects. The number of rejected patients was 50% lower in scenario 4 (aligned schedules) than in scenario 3 (current schedules). Despite higher therapist utilization in scenario 4, the number of unscheduled appointments decreased by 85% and planning rules were better abided. When therapist utilization is increased in scenario 5 and 6, performance on these aspects remains superior compared to scenario 3.

We conclude that aligning therapist schedules to demand for care has a large effect on scheduling performance and that this effect is larger than applying generalist therapist teams.

7.7.4 Discussion

We first discuss generalization of our results to practice. Then, we make recommendations for model improvement.

Generalization of conclusions to practice

Simulation modeling inherently gives a limited view on real performance. For example, the assumption that patients and material resources have unlimited availability (see Paragraph 5.1) does not hold in practice. Moreover, performance in practice will be influenced by treatment plan mutations, no-shows, therapist absenteeism or medical decision making. However, we believe that because automated appointment scheduling leads to such good results in a simulation setting, it will also lead to performance improvement in practice. However, only implementation in practice will gain insight in the model's real performance. The SIR and CAO care units served as the setting for our simulation. The structure of care pathways is comparable in other care units. Therefore, we can generalize our conclusions to the other care units of SMK.

The conclusion that applying generalist therapist teams and smoothened therapist schedules result in better scheduling performance can be generalized to practice. The main conclusion is that these interventions increase scheduling flexibility. In a practical situation, they will also increase scheduling flexibility, regardless of the circumstances. Even if SMK continues manual scheduling, we are convinced that both decreased differentiation of therapists into units or teams and applying more smoothened therapist schedules will improve performance.

Suggestions for model improvement

We make the following recommendations for model improvement and additional experiments:

- Splitting up care pathways decreases scheduling opportunities. If we are able to reduce computation time, this also decreases the need to split up care pathways. We suggest the following improvements:
    - The number of variables affects computation time. We can reduce the number of variables by excluding variables x_{aht} for which it can be shown that appointment a cannot be scheduled at time slot t at all. For example, if $B_{ht} = 0$ (the therapist is not available), we know on beforehand that appointment a cannot be scheduled with therapist h at timeslot t and variable x_{aht} can be omitted.
    - Currently, we only accept an ILP solution if the optimal solution is found. Arguably, solutions with a relaxation gap of x% (that is, the solution is less than or equal to x% short of the optimal solution) are also acceptable. Terminating the ILP when a certain relaxation gap is achieved will improve computation time.
    - Valid inequalities can be improved by taking the duration of appointments into account.
- Our results suggest that performance might improve if the maximum allowed access time is increased or if weights for penalizing planning rules are changed. Therefore, we recommend performing sensitivity analysis on parameter settings.

- The current model results in low group utilization. We recommend two model improvements:
  - Currently, a patient is coupled to one therapist for group therapy per discipline. Changing the ILP such that group appointments can be scheduled at any existing group therapy timeslot of the right discipline might improve performance. This can be modeled by adding a virtual therapist $\tilde{h}$ for which $GroupApp_{\tilde{h}t} = 1$ for timeslots t with existing group therapy timeslots of all therapists of the discipline related to therapist $\tilde{h}$. The appointment is allocated to a therapist with available capacity after solving the ILP.
  - Increase the weight for adding a new group ($extragroup_a$) compared to other weights.
- To better reflect reality, differentiation of groups into subcategories (e.g., one group for walking, another for hands) can be introduced. This would also require a specification of the "group type" in the care pathway.
- In addition to the two interventions we evaluated by simulation, generalist therapist teams and therapist schedules that are better aligned to demand for care, the simulation model could also be used to evaluate interventions with regard to the fixed therapist principle. For example, a scenario with two or more therapists per discipline can be examined.
  - We can avoid that the number of therapists in the model, and thereby the model size, increases by applying the job sharing principle: two or more therapists are modeled as one therapist h, for which a time slot is available if any of the therapists is available at that time slot. After solving the ILP, appointments are allocated one by one to a therapist with available capacity on the chosen time slot.
- Generalist therapist teams may not be implemented due to its effects on quality of care. In order to compromise between generalist and specialized therapist teams, the ILP can be enhanced such that patients are preferably scheduled with a specialized therapist, and only assigned to a less specialized therapist if no specialized therapist is available.

Chapter 8: Implementation

This chapter discusses implementation of our research results to practice. Paragraph 8.1 discusses the implementation of congruence measurement in SMK. Paragraph 8.2 discusses the implementation of the ILP for automated appointment scheduling in SMK and Paragraph 8.3 discusses implementation of the interventions with respect to introducing generalist therapist teams and staff schedules in SMK.

8.1 Congruence measurement

Congruence measurement provides valuable insights for managers, physicians and therapists. Managers can monitor the overall congruence of a specific care unit, care pathway or discipline. Physicians can use congruence measurement to indicate whether a specific patient has received the amount of treatment as was prescribed. We developed a tool that makes it possible to easily retrieve congruence information on the different detail-levels that are demanded by managers and physicians. The tool can show congruence on the most detailed level of a specific discipline of one patient, but also allows aggregation of data to present congruence measured per care pathway or care team. The tool was developed in RStudio and used the R-extension *Shiny.* Figure 8.1 shows the startup screen of the tool (in Dutch).

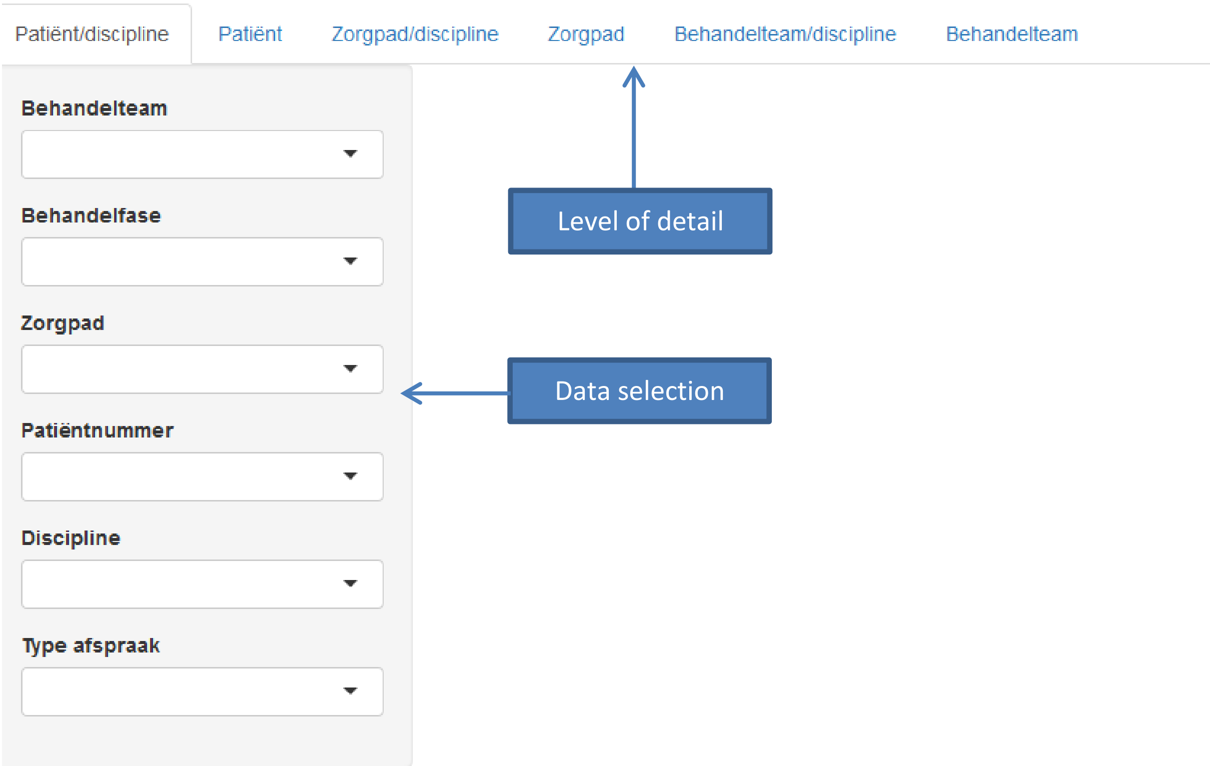


Figure 8.1 Startup screen of congruence analysis tool

In the menu at the top, the user can choose the detail level of information: discipline per patient, patient, discipline per care pathway, care pathway, discipline per care team, or care team. On the left menu, the user can select data. This menu is dependent on the chosen detail level. For the detail level *discipline per patient*, the user picks a care team, treatment phase, care pathway, patient number, discipline and type of appointment (group, individual or indirect). The tool then automatically generates output. If the user changes input on the left menu, the output automatically updates.

Figure 8.2 shows the output screen for one instance of congruence for direct physiotherapy appointments for one patient. A graph represents the total appointment duration per period over the course of treatment: the care pathway is red, realized care is black. Below the graph, all congruence measures are shown.

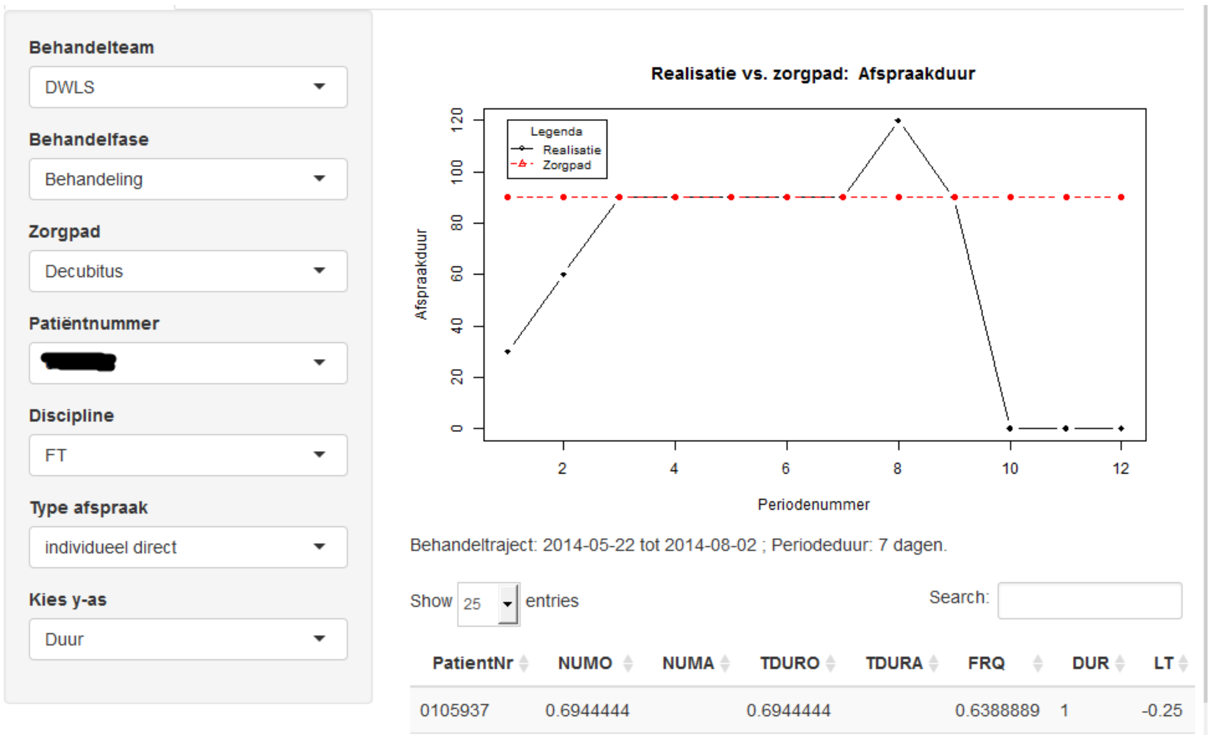
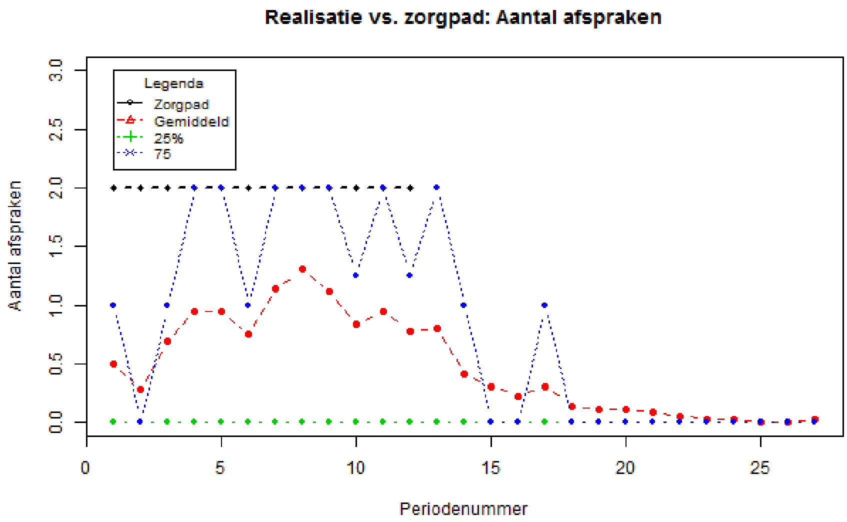


Figure 8.2 Example of congruence for physiotherapy with a specific patient

For a higher detail level, for example discipline per care pathway, the tool provides average congruence scores, as well as the median, 25th percentile, 75th percentile, minimum and maximum score, and the number of patients included in the calculation. Additionally, a graph is created that shows the care pathway, mean realization and the 25th and 75th percentile. For an example, see Figure 8.3.



Periodeduur: 7 dagen.

Show 25 entries

Search:

Maat	NUMO	NUMA	TDURO	TDURA	FRQ	DUR	LT
Gemiddelde	0.49	0.96	0.49	0.94	0.36	0.87	0.11
Minimum	0	0.96	0	0.94	0	0.56	-0.92
25%	0.33	0.96	0.35	0.94	0.17	0.83	-0.25
50%	0.54	0.96	0.55	0.94	0.42	0.94	0.17
75%	0.71	0.96	0.69	0.94	0.54	0.96	0.42
Maximum	0.92	0.96	0.88	0.94	0.71	1	1.42
N	38	38	38	38	38	38	38
Niet leeg	37	1	37	1	38	36	38

Figure 8.3 Congruence output for one specific care pathway and discipline

As an alternative to this tool, congruence measurement could be applied more proactively. For example, a congruence monitoring system could automatically alert managers or physicians by means of a generated e-mail if congruence is below a certain threshold.

The quality of required data is insufficient to obtain reliable congruence information. Once our recommendations to improve the quality of data as stated in section 2.9.1 are followed, SMK can start with implementing congruence measurement.

8.2 Automated appointment scheduling

Experiments revealed that our automated appointment scheduling method leads to good performance with respect to congruence and other output measures in a simulation setting. Although differences with practice are considerable, we argued that it is likely that performance in practice will benefit from our scheduling model. This paragraph discusses implementation of our ILP and heuristics, and discusses difficulties that can arise in implementation.

We imagine the implementation of our ILP in the form of a decision support system. The system automatically retrieves resource and patient availability constraints from the HIS, and returns a schedule based on the chosen treatment plan. In our experiments, the ILP is able to return an optimal solution within a minute in almost all situations, which makes is suitable for generation of schedules on the fly.

Patient availability is not considered in the current ILP, but it can be easily added. For example, we could add the constraint $x_{aht} \leq A_{\hat{t}}$ $(\forall\, a, h, t, t \leq \hat{t} \leq t + Duration_a - 1)$ where A_t is a binary parameter to represent patient availability. Currently, the ILP does not lead to good performance with regard to rejected patients and group utilization. The model should be improved and tested according to the recommendations in section 7.7.4 before implementation can be carried out.

Of course, the decision support system should allow manual alteration of schedules, for example in case of no-shows, treatment plan mutations or therapist absenteeism. The effect of these online changes is not evaluated in current research. Therefore, the performance of the decision support system compared to the existing scheduling method should be investigated.

The implementation of a decision support tool based on our ILP is hindered by the need to purchase an ILP solver. As of 2015, a compute server license of Gurobi, which would be required for rehabilitation center-wide application of the ILP solver, costs $48.000 [37]. Moreover, interfaces between the hospital information system and the decision support system should be developed and schedulers should be educated in using the scheduling tool.

8.3 Generalist therapist teams and staff schedules

Our results suggest that applying generalist therapist team has a small but positive effect on performance with respect to congruence and other performance measures.

If SMK would only steer on the output measures we evaluated in simulation, applying generalist therapist teams would certainly improve overall performance. However, as we indicated before, therapists specialize to achieve better quality of care. Therefore, the decision whether to increase generalization of therapists should be made bearing both quality of care and quality of process in mind. A compromise is to assign the patient preferably to a specialized therapist, and assign only to a less specialized therapist if no specialized therapists are available. This policy could be included in the ILP as well, as we mentioned in section 7.7.4.

Our results suggest that performance can improve considerably by aligning therapist schedules to demand for care. In revising staff schedules, the emphasis should be on full-time contracts and an equal division of working hours over the week.

Chapter 9: Conclusions and recommendations

This chapter provides conclusions and recommendations. Paragraph 9.1 provides conclusions. Paragraph 9.2 discusses study limitation. Paragraph 9.3 gives recommendations for SMK. Finally, Paragraph 9.4 discusses directions for further research.

9.1 Conclusions

When we started this research, the rehabilitation center of SMK perceived that treatment for many patients was not provided as prescribed. Management was aware of the importance to avoid deviation from the treatment plan for quality of care, quality of process and cost-effectiveness. However, there was no framework describing how to measure these deviations, let alone that causes were identified such that deviations between plan and reality can be reduced. In this thesis, we introduce a new vocabulary for measuring deviation of treatment plans, care pathways and treatment schedules in rehabilitation care and call it congruence. The objective of our research is as follows:

To investigate the aspects of congruence in rehabilitation care, pinpoint factors that lead to incongruence, define measures for congruence, design interventions for improving congruence and evaluate the performance of these interventions.

Seven research questions give direction to the research. We define congruence (1), investigate the processes at SMK rehabilitation center, identify bottlenecks, and give recommendations on interventions to improve congruence (2). We review the literature for congruence measurement and the proposed interventions (3). Then, we propose a set of measures for congruence and perform a baseline measurement (4). We design (5) and evaluate (6) interventions, and give recommendations for the implementation of these interventions (7). The conclusions in this paragraph loosely follow these research phases.

We define congruence as the degree to which a treatment plan or care pathway is in accordance with realized care or another plan. Congruence is defined for all relations between the planning levels, i.e., the care pathway, initial and mutated treatment plan, treatment schedule and realized care. In the CAO and SIR care unit of SMK, we performed a baseline measurement of congruence between the care pathway and realized care. Based on 536 care pathways between 01/2013 and 01/2015, nine disciplines scored no higher than 0.69 on a scale from 0 to 1 for five congruence measures.

We identify that inefficient use of capacity is a bottleneck that inhibits congruence. We propose three interventions aimed at more efficient use of available capacity: 1) automated appointment scheduling, 2) applying generalist therapist teams, 3) matching therapist schedules with demand for care. We propose an integer linear program (ILP), based on Braaksma et al. [1], to automatically schedule a set of appointments for a single patient. We introduce heuristics to reduce computation time of the ILP.

We perform a simulation study to evaluate the performance of the ILP and additional interventions. In this study, we find high levels of congruence with respect to omitted appointments ($NUMO$) and frequency (FRQ), and also high performance for other output measures. See Table 9.1 for an overview.

Table 9.1

Summary of the most important results. The worst result over all scenarios is shown.

Measure	Description	Result
$\boldsymbol{NUMO}$	Fraction of scheduled appointments compared to all prescribed appointments	$\geq$ 0.9994
$\boldsymbol{FRQ}$	Congruence with respect to therapy frequency	$\geq$ 0.9987
Combination appointments	Number of therapy days more than the theoretical minimum	$\leq$ 0.4 days
Horizontal scheduling	Number of new weekdays compared to the weekdays in the schedule of the first week	$\leq$ 0.005 days
Group utilization	Average number of patients in a group compared to maximum capacity	$\geq$ 38%
Rejected patients	Percentage of rejected patients	$\geq$ 4.4%

We find the group utilization and the number of rejected patients in the simulation study unacceptable. We explained these results and provided recommendations for model and parameter improvements.

We conclude that performance of our automated appointment scheduling approach is high. We are confident that, after model improvements, performance of our model will also be acceptable with regard to group utilization and the number of rejected patients. In a practical application of our scheduling approach, far more conditions apply and more factors influence scheduling performance. Nevertheless, the near-optimal results of our simulation experiments make us confident that application of our model will improve performance in practice as well.

We conclude that applying generalist teams instead of specialized therapist teams improves scheduling performance. Therapist schedules that are better aligned with demand for care further improve performance. The effect of better alignment of therapist schedules is larger than applying generalist therapist teams. Also see Table 9.2.

Table 9.2

Comparison of policies

	Rejected patients	Other performance indicators
Current situation	1.4%	
Generalist therapist teams	0.7%	Comparable to current situation
Generalist therapist teams and improved therapist schedules	0.3%	9 out of 12 improved when compared to current situation

These conclusions are based on results from an abstract simulation study and do not directly translate to practice. However, because the effect of increasing generalization and improving therapist schedules is the same in simulation and practice – increased flexibility and better alignment of demand and supply - we think that improvements can also be achieved in the real world.

9.2 Limitations

Our research had several limitations. The following list provides an overview:

- We were not able to perform a valid baseline measurement for congruence between (initial or mutated) treatment plans and realized care, due to lacking and unsuitable data. Such a baseline measurement would have provided more detailed information on where incongruence occurs, such that better recommendations for improvement could be made.
- With respect to our automated scheduling model, we had to do concessions to retain computational tractability. Picking therapists by means of a heuristic does not necessary lead to the optimal solution, while splitting up care pathways in multiple instances causes the model to optimize the schedule for each instance, instead of the whole model. However, our results indicate that overall performance was good, despite these limitations.
- In our ILP, we had to do model assumptions that reduce conformity between the model and practice. For example, we did not prioritize patients on urgency level, only allowed multi-resource appointments for group therapy and did not consider therapist meetings or material resource capacity. Moreover, as stated before, the model uses care pathways as principle and does not consider individual treatment plans, mutations, no-shows or therapist absenteeism.
- With respect to the simulation study, we tried to obtain the best available input data for patient arrivals and therapist schedules. The experiments with the therapist schedules as currently used in SMK result in a therapist utilization of 38%. In reality, therapist utilization is higher. We made two mistakes in establishing therapist schedules:
    - We did not check whether therapists work partly for other care units than SIR and CAO; leading to an overestimation of capacity.
    - Although we did validate our list of therapists with schedulers, we did not perform extra validation of the list with the unit manager. After experimentation, we performed analysis of the validity of the therapist schedules we used. This analysis suggests that at least one therapist was wrongly included.
    - The applied therapist schedules are thus flawed. However, this does not affect our overall conclusions. The comparison between policies remains intact. Moreover, we performed additional experiments with manually increased utilization to assess performance of our model with higher utilization levels.
- With respect to our simulation study, we did not perform sensitivity analysis on parameter settings. Based on our analysis, we expect that performance of the ILP can improve by adjusting variable weights and other parameter settings (e.g., maximum allowed access time)

- For our simulation study, we were not able to perform enough replications to obtain estimates of all variables with relative errors lower than 0.05 or 0.10. Moreover, the warm-up period we applied is based on the variables for which we indicated convergence. Not all variables reached convergence within the applied run-length. Increasing run-length or the number of replications was not feasible, due to time limits.

9.3 Recommendations

Perhaps the most important conclusion for SMK is that large-scale measurement of congruence between (initial and mutated) treatment plans is currently *impossible* due to lack of accurate data. To allow congruence measurement, the design and implementation of data structures that allow congruence measurement should be of the highest priority. The second step would be to introduce a measurement tool (for example, based on our tool presented in Paragraph 8.1) that allows steering on congruence. Moreover, congruence information can be applied to make forecasts on demand for care of existing patients. These forecasts can again be used for, e.g., decisions on the access of new patients or therapist deployment.

The value of being congruent to a treatment plan is increased if the treatment plan is a) based on a care pathway and b) quality of care, therapist capacity and cost-effectiveness are considered in care pathway design. Therefore, we recommend SMK to review their current care pathways on these aspects.

Based on our context analysis, we find that congruence can improve by addressing cultural reasons for deviation. Therapists are eligible to mutate the treatment plan on their own, there is no awareness of the importance of congruence and there is no “case manager” responsible for the resulting treatment plan. We recommend SMK to address these issues. For all recommendations based on our context analysis, see section 2.9.1.

Our research shows that the opportunities for automated appointment scheduling in rehabilitation care are huge. Therefore, we recommend SMK to continue research on automated appointment scheduling. However, before actual implementation can take place, the model must be further improved and evaluated in a more realistic setting (i.e., considering more environmental factors).

Finally, based on our experiment results, we recommend SMK to look at the possibilities to increase the use of generalistic teams of therapists and to better align demand for care with therapist schedules (that is, make sure that therapists are available equally over the week).

9.4 Future research

We give directions for further improvement of our automated scheduling model in section 7.7.4. This paragraph discusses general directions for further research.

- Treatment plan and congruence information can be used to predict demand for care of the current patient population on the mid-term. One option is to use the future appointments as stated in the treatment plan (assuming 100% congruence) as an estimation of future demand. Suppose that therapist capacity is known. Then, based on the prediction of demand for care of the current patient population and patients on the waiting list, rough-cut capacity planning can be applied to predict when a specific patient can start treatment. Instead of using the treatment plan as a principle, another option is to base predictions on the congruence level of historic patients with the same care pathway. This information can be used in decision support for patient access.
- The automated scheduling model we propose schedules appointments per patient without considering future patients. This induces that the schedule may be optimal for the current patient, but that it can result in an unfavorable schedule for future patients. Decomposition of the scheduling task may solve this problem. In such an approach, resources are allocated to a patient in a first step (with a planning horizon of for example 10 weeks), while the actual scheduling to time slots is performed per week. This results in a smaller problem, making it possible to optimize the schedule simultaneously for more patients.
- In many situations, it is likely that the ILP generates more than one optimal solution. Moreover, there are often solutions that are close to optimality. The ILP could be designed in such a way that all solutions that are within x% from the optimal solution are saved. The generation of multiple solutions is useful, because there are often less tangible factors that influence the quality of a proposed schedule. Binary cut or integer cut [38] can be applied to find multiple solutions, but if the number of (near)-optimal solutions is high this would be computationally challenging. The research problem would be to identify when to search for multiple solutions and to ensure that the proposed solutions are not too similar.

Bibliography

[1] *Integral multidisciplinary rehabilitation treatment planning.* **Braaksma, A.; Kortbeek, N.; Post, G.F.; Nollet, F.** 2014, Operations Research for Health Care, Vol. 3, pp. 145-159.

[2] **Revalidatie Nederland.** Branchegegevens revalidatie 2013. *Revalidatie Nederland.* [Online] May 12, 2015. [Cited: July 5, 2015.] URL: http://www.revalidatie.nl/revalidatie-nederland/publicaties-rn/brancherapport.

[3] —. Revalidatie in Beweging. *Revalidatie Nederland.* [Online] 2008. [Cited: July 3, 2015.] URL: http://www.revalidatie.nl/userfiles/File/publicaties/revalidatie-in-beweging-8-lessen.pdf.

[4] *Hierarchical Edge Colorings and Rehabilitation Therapy Planning in Germany.* **Raschendorfer, I.M. and Hamacher, H.W.** 2014. EURO Summer Institute on Operational Research applied to Health in a Modern World. .

[5] **Sint Maartenskliniek.** Over de Maartenskliiek. *De kliniek voor houding en beweging - Sint Maartenskliniek.* [Online] 2014. [Cited: September 10, 2014.] URL: http://www.maartenskliniek.nl/over-de-maartenskliniek/.

[6] —. Maartenskliniek in cijfers. *De kliniek voor houding en beweging - Sint Maartenskliniek.* [Online] 2014. [Cited: September 9, 2014.] URL: https://www.maartenskliniek.nl/over-de-maartenskliniek/maartenskliniek-in-cijfers/.

[7] —. Revalidatie. *De kliniek voor houding en beweging - Sint Maartenskliniek.* [Online] 2014. [Cited: September 10, 2014.] URL: https://www.maartenskliniek.nl/behandelingen/revalidatie/.

[8] —. *Dashboard revalidatie 2014-11.* 2014.

[9] —. *Strategische koers Sint Maartenskliniek 2013-2016*: Van Eck & Oosterink communicatieregisseurs, 2013.

[10] *Defining pathways.* **De Bleser, L.; Depreitere, R.; De Waele, K.; Vanhaecht, K.; Vlayen, J. and Sermeus, W.** 2006, Journal of Nursing Management, Vol. 14, pp. 553-563.

[11] **Schimmelpfeng, K.; Helber, S. and Steffen, K.** *Decision support for rehabilitation hospital scheduling.* Wirtschaftswissenschafliche Fakultät, Leibniz Universität. 2010.

[12] *Taxonomic classification of planning decisions in health care: a structured review of the state of the art in OR/MS.* **Hulshof, P.J.H.; Kortbeek, N.; Boucherie, R.J.; Hans, E.W. and Bakker, P.J.M.** 2012, Health Systems, Vol. 1, pp. 129-175.

[13] **Hans, E.W.; Van Houdenhoven, M. and Hulshof, P.J.H.** A framework for health care planning and control. [book auth.] Randolph (Ed.) Hall. *Handbook of Healthcare System Scheduling.* New York : Springer, 2011, pp. 303-320.

[14] *Staff scheduling and rostering: A review of applications, methods and models.* **Ernst, A.T.; Jiang, H.; Krishnamoorthy, M. and Sier, D.** 2004, European Journal of Operational Research, Vol. 153, pp. 3-27.

[15] **Dedden, A.L.** *Therapist capacity planning.* Enschede : University of Twente, 2014.

[16] *Integrated care pathways: eleven international trends.* **Zander, K.** 2002, Journal of Integrated Care Pathways, Vol. 6, pp. 101-107.

[17] *Monitoring Adherence to Evidence-Based Practices.* **Konrad, R.; Tulu, B. and Lawley, M.** 2013, Applied CLinical Informatics, Vol. 4, pp. 126-143.

[18] *Use of variance from clinical paths: coming of age.* **Zander, K.** Clinical performance and quality of health care, 1997, Vol. 5, pp. 20-30.

[19] *How to promote, improve and test adherence to scientific evidence in clinical practice.* **Caminiti, C., Scoditti, U.; Diodate, F. and Passalacqua, R..** 62, 2005, BMC Health Services Research, Vol. 5.

[20] *Measuring clinical pathway adherence.* **van de Klundert, J., Gorissen, P. and Zeemering, S.** 2010, Journal of Biomedical Informatics, Vol. 43, pp. 861-872.

[21] *Development of explicit criteria to measure adherence to hypertension guidelines.* **Milchak, J.L.; Carter, B.L.; Ardery, .; Black, H.R.; Bakris, G.L.; Jones, D.W.; Kreiter, C.D.** 2006, Journal of Human Hypertension, Vol. 20, pp. 426-433.

[22] *Clinical pathway compliance and quality improvement.* **Kinsman, L.** 18, 2004, Nursing Standard, Vol. 18, pp. 33-35.

[23] *Online Treatment Compliance Checking for Clinical Pathways.* **Huang, Z.; Bao,Y.; Dong, W.; Lu, X.; Duan, H.** 123, 2014, Journal of Medical Systems, Vol. 38.

[24] **Hartholt, W.** *Patiënten en zorpaden: de overeenkomsten en de verschillen.* Enschede : University of Twente, 2009.

[25] *Genetic Algorithm Based System for Patient Scheduling in Highly Constrained Situations.* **Podgorelec, V. and Kokol, P.** 6, s.l. : Journal of Medical Systems, 1997, Vol. 21, pp. 417-427.

[26] *Decision support system for rehabilitation scheduling to enhance the service quality and the effectiveness of hospital resource management.* **Huang, Y-C., Zheng, J-N. and Chien, C-F.** 5, s.l. : Journal of the Chinese Institute of Industrial Engineers, 2012, Vol. 29, pp. 348-363.

[27] *An evolutionary approach to rehabilitation patient scheduling: A case study.* **Chien, C., Tseng, F. and Chen, C.** 2008, Europeaon Journal of Operational Research, Vol. 189, pp. 1234-1253.

[28] *Personnel and Patient Scheduling in the High Demanded Hospital Services: A Case Study in the Physiotherapy Service.* **Ogulata, S.N., Koyuncu, M. and Karakas, E.** 2008, Journal of

Medical Systems, Vol. 32, pp. 221-228.

[29] **Brown, G.G. and Dell, R.F.** *Formulating Integer Linear Programs: A Rogues' Gallery.* Monterey, California, USA : Operations Research Department, Naval Postgraduate School, 2006.

[30] **Chinneck, John.** Integer/Discrete Programming via Branch and Bound. *Practical Optimization: a Gentle Introduction (e-book).* 2010.

[31] *Multi-Row Presolve Reductions in Mixed Integer Programming.* **Achterberg, T., Bixby, R.E.; Gu, Z; Rothberg, E. And Weninger, D..** Hosei University, Tokyo : 2014. Proceedings of the Twenty-Sixth RAMP Symposium. pp. 181-196.

[32] **Gurobi.** MIP Basics. *Gurobi.* [Online] [Cited: July 7, 2015.] URL: http://www.gurobi.com/resources/getting-started/mip-basics.

[33] **Epelman, M.A.** Valid Inequalities. *University of Michigan Web Environment.* [Online] Winter 2012. [Cited: March 25, 2015.] URL: http://www-personal.umich.edu/~mepelman/teaching/IP/Handouts/Handout5.pdf.

[34] **Law, A.M.** Comparing Alternative System Configurations. *Simulation Modeling & Analysis.* New York : McGraw-Hill, 2007.

[35] **Welch, P.D.** *On the problem of the Initial Transient in Steady-State Simulation.* Yorktown Heights, New York : IBM Watson Research Center, 1981.

[36] **Law, A.M.** Output Data Analysis for a Single System. *Simulation modeling & analysis.* New York : McGraw, 2007.

[37] **Gurobi Optimization.** Commerical Pricing. [Online] 2015. [Cited: June 29, 2015.] URL: http://www.gurobi.com/products/licensing-pricing/commercial-pricing.

[38] *Finding multiple solutions to general integer linear programs.* **Tsai, J-F., Lin, M-H. and Hu, Y-C.** 2008, European Journal of Operational Research, Vol. 184, pp. 802-809.

[39] **Braaksma, A.** *Integrale planning van multidisciplinaire behandeltrajecten.* Enschede : University of Twente, 2010.

Appendix I: Literature search strategy

We have used the Scopus search engine for our literature search. We discuss the search strategy for congruence measurement and multidisciplinary appointment scheduling separately.

Congruence measurement

We searched for articles that discussed *measurement* of *congruence* in *care pathways*. Since there are synonymous terms for both congruence and clinical pathways, we tried to include these terms as well. We excluded articles that discussed care pathway effectiveness, implementation of care pathways, guideline adherence instead of pathway adherence, and prescription adherence of patients. Moreover, articles that discussed congruence in a setting other than a hospital or rehabilitation center were omitted. Finally, articles for which no full text could be obtained were omitted. The majority of our search results were excluded due to these criteria.

Table I.1 provides a list of search queries, number of results and included articles per query.

Table I.1

Congruence measurement literature search strategy and results

Query	Number of results	Included articles
measur (adherence AND (clinical OR critical OR care) pathway)*	254	[17] [20] [19] [22]
measur (congruen* AND (clinical OR critical OR care) pathway)*	22	-
measur (compliance AND (clinical OR critical OR care) pathway)*	373	[23]
measur (variance AND (clinical OR critical OR care) pathway*	1058	[18]
"treatment plan adherence"	8	-
"treatment plan congruence"	0	-
"treatment plan compliance"	1	-
"treatment plan variance"	1	-
compliance AND rehabilitation AND "treatment plan"	28	-
adherence AND rehabilitation AND "treatment plan"	16	-
congruence AND rehabilitation AND "treatment plan"	0	-
variance AND rehabilitation AND "treatment plan"	4	-
congruence AND rehabilitation AND "(clinical OR critical OR care) pathway"	0	-
adherence AND rehabilitation AND " (clinical OR critical OR care) pathway"	35	-
Reference search from **[20]**	2	[16] [21]
Reference search from **[39]**[12]	1	[24]

[12] The report of Braaksma [39] was obtained through the thesis database of the University of Twente after a tip.

Multidisciplinary appointment scheduling

We searched for articles that discussed *multidisciplinary appointment scheduling*, either in general or specifically in rehabilitation care. We excluded articles that discussed psychiatric rehabilitation, drug rehabilitation or any other non-medical rehabilitation subjects. Moreover, articles that discussed staff scheduling instead of appointment scheduling were excluded. Research that was conducted in structurally different hospital departments, such as emergency department or the operating room, were also excluded. Finally, articles for which no full text was available were not included.

Table I.2

Congruence measurement literature search strategy and results

Query	Number of results	Included articles
Rehabilitation appointment scheduling	20	[1]
Rehabilitation patient scheduling	208	[11] [1] [26] [27]
Rehabilitation treatment scheduling	93	[11] [1]
Multidisciplinary appointment scheduling	13	[1]
Multidisciplinary rehabilitation scheduling	11	[1]
Multidisciplinary patient scheduling	130	[1]
((care OR clinical OR critical) pathway) AND (appointment scheduling)	11	0
((care OR clinical OR critical) pathway) AND patient scheduling)	96	0
Reference search from **[1]**	2	[25] [28]

Appendix II: Care pathways and resources

This appendix gives an overview of the care pathways as used in the congruence measurement (Chapter 4) and simulation study (Chapter 7), and therapist resources as applied in the simulation study.

Care pathway characteristics

Table II.1

Overview of care pathways, including prescribed lead time, frequency and applied planning horizon

Care pathway	Unit	Team	In/outpatient	Frequency per year	Number of weeks	Planning horizon
ZOM group	CAO	Pain	Outpatient	47	12	3
Screening	CAO	Pain	Outpatient	207	1	1
ZOM individual	CAO	Pain	Outpatient	35	12	4
Amputation training	CAO	Amp	Outpatient	27	6	3
Above knee amputation	CAO	Amp	Outpatient	22	28	2
Below knee amputation	CAO	Amp	Outpatient	14	20	2
CAO regular	CAO		Outpatient	7	12	2
Lokomat	CAO		Outpatient	0	12	6
Sportloket	CAO		Outpatient	2	1	1
Other	CAO		Outpatient	160	13	6
Arm hand function screening	SIR		Outpatient	2	1	1
Spinal cord injury other (diagnosis)	SIR		Inpatient	5	2	2
Spinal cord injury T6 (diagnosis)	SIR		Inpatient	48	2	2
Spinal cord injury T7 (diagnosis)	SIR		Inpatient	42	2	2
Guillain-Barre (diagnosis)	SIR		Inpatient	5	2	2
Oncology (diagnosis)	SIR		Inpatient	8	2	2
Baclofen pump	SIR		Inpatient	7	2	2
Bolus baclofen	SIR		Inpatient	1	1	1
Decubitus	SIR		Inpatient	18	12	6
Former inpatient	SIR		Outpatient	9	12	2
Spinal cord injury other (treatment)	SIR		Inpatient	2	16	1
Spinal cord injury T6 (treatment)	SIR		Inpatient	29	22	1
Spinal cord injury T5 (treatment)	SIR		Inpatient	26	16	1
Guillain-Barre (treatment)	SIR		Inpatient	3	22	1
Lokomat	SIR		Outpatient	3	12	6
Oncology (treatment)	SIR		Inpatient	8	4	2
Other	SIR		Outpatient	123	12	6
Regular outpatient	SIR		Outpatient	14	18	2
Sportloket	SIR		Outpatient	10	1	1
Posture advice	SIR		Outpatient	21	1	1

Total	905

Remarks about calculation of care pathways

Calculation of care pathway Other

Both CAO and SIR use a care pathway named *Other.* This is not a real care pathway, but this care pathway is used for individually described treatment plans that cannot be coupled to any of the other care pathways. We estimated the average amount of realized care for this patient group and used it as a care pathway. Patient-care pathway combinations were linked to treatment trajectories, which provide a start and end date. If more than one treatment trajectory could be linked to the patient-care pathway combination or if no end date was provided, the patient was omitted. Based on the date of the first appointment, the week number of all appointments for direct care was derived. Based on appointment codes, it was derived whether the appointment was a group or an individual appointment. Finally, for SIR and CAO separately, the average amount of realized care per discipline, per therapy type (i.e. group or individual) and per week was calculated. The averages were rounded to the next integer. The result is implemented as the care pathways *Other* for SIR and CAO.

Adjustments of care pathways

The care pathways for treatment of spinal injury T6, spinal injury T7 and Guillain-Barre were adjusted. This was necessary because these CPs prescribe more than ten physiotherapy group sessions per week. The ILP allows scheduling maximally two appointments per discipline per therapy type (group or individual) per day. Since the majority of therapists works only four days in a week (in the current staff schedule), a care pathway that specifies, for example, twelve physiotherapy group appointments per week would lead to four appointments that cannot be scheduled. This is more than 20% of all appointments and would therefore lead to an infeasible solution of the ILP. We reduced the number of physiotherapy group appointments to eight. In reality, more than two group appointments per day per discipline are allowed in these situations. Therefore, this problem does not occur in practice. For future research, we recommend that the ILP is adjusted, such that more than two appointments per discipline can be scheduled per day.

Therapist characteristics

Table II.2

Overview of therapists, including their discipline unit and team in the current situation

Number	Discipline	Unit	Team
1	ET	CAO	Pain, amputation
2	PS	CAO	Pain, amputation
3	MW	CAO, SIR	Pain, amputation, SIR
4	ET	SIR	SIR
5	BAG	CAO	Pain, amputation
6	ET	SIR	SIR
7	FT	SIR	SIR
8	ET	CAO	Pain, amputation
9	DIET	CAO	Pain, amputation
10	BAG	CAO	Pain, amputation
11	FT	SIR	SIR
12	FT	SIR	SIR
13	MW	SIR	SIR
14	MW	CAO	Pain, amputation
15	FT	SIR	SIR
16	FT	CAO	Amputation
17	PS	CAO	Pain, amputation
18	BAG	SIR	SIR
19	FT	CAO	Pain
20	FT	SIR	SIR
21	FT	SIR	SIR
22	FT	SIR	SIR
23	FT	CAO	Pain
24	ACT	SIR	SIR
25	FT	SIR	SIR
26	BAG	CAO	Pain, amputation
27	ET	CAO, SIR	Pain, amputation
28	ET	SIR	SIR
29	FT	CAO	Pain
30	ACT	SIR	SIR
31	DIET	SIR	SIR
32	FT	CAO	Amputation
33	SKL	CAO, SIR	Pain, amputation, SIR
34	FT	CAO, SIR	Pain, amputation, SIR
35	FT	CAO	Pain
36	BAG	SIR	SIR
37	DIET	CAO	Pain, amputation
38	FT	CAO	Amputation
39	ET	SIR	SIR
40	BAG	SIR	SIR
41	PS	CAO	Pain, amputation
42	PS	SIR	SIR
43	LG	SIR	SIR
44	ACT	SIR	SIR
45	ET	SIR	SIR

Appendix III: ILP formulation

Table III.1	
Model notation (including notation for valid inequalities)	
Indices and sets	
$\boldsymbol{a, \hat{a} \in A}$	All appointments of current instance
$\boldsymbol{t, \hat{t} \in T}$	All time slots in current instance
$\boldsymbol{h, \hat{h} \in H}$	All therapists in current instance
$\boldsymbol{c \in C}$	All disciplines
$\boldsymbol{d}$	Days
$\boldsymbol{w}$	Weeks
Parameters	
$\boldsymbol{AccesstimeInpatient}$	Desired maximum access time for inpatients
$\boldsymbol{AccesstimeOutpatient}$	Desired maximum access time for outpatients
$\boldsymbol{B_{ht}}$	Number of patients that can be scheduled at therapist h and start therapy at time slot t, not including patients that are already scheduled at therapist h at time slot t
$\boldsymbol{Day}$	Duration of a day in time slots
$\boldsymbol{DaysWithFreeTimeslots_{cw}}$	Number of days with free time slots for individual appointments for discipline c in week w
$\boldsymbol{DaysWithFreeTimeslotsGroup_{cw}}$	Number of days with free time slots for group appointments for discipline c in week w
$\boldsymbol{Duration_a}$	Duration of appointment a in time slots
$\boldsymbol{F_{ac}}$	1 if appointment a must be scheduled at discipline c; 0 otherwise
$\boldsymbol{FirstApp_{ac}}$	1 if $MinWeek_a = 1$ and a is the first appointment at discipline c as stated in the CP; 0 otherwise
$\boldsymbol{G_{hc}}$	1 if therapist h has discipline c; 0 otherwise
$\boldsymbol{GroupApp_{ht}}$	1 if a group therapy appointment is scheduled at time slot t with therapist h
$\boldsymbol{GroupDur_{ht}}$	Duration of group therapy with therapist h starting at time slot t
$\boldsymbol{Group_a}$	1 if appointment a is a group appointment; 0 otherwise
$\boldsymbol{Inpatient}$	1 if the current instance is related to an inpatient; 0 otherwise
$\boldsymbol{M_1, M_2, M_3}$	Big-M parameters
$\boldsymbol{MaxApp}$	Maximum number of appointment a patient can have during one day
$\boldsymbol{MaxDev}$	Maximum allowed value for $deviationearlier_a$ and $deviationlater_a$
$\boldsymbol{MinAppWeek_c}$	Minimum number of individual appointments per week in the care pathway
$\boldsymbol{MinAppWeekGroup_c}$	Minimum number of group appointments per week in the care pathway
$\boldsymbol{MinExtraApp_{cw}}$	Minimum number of times that two individual appointments should be scheduled per day for discipline c and week w (given that all appointments are scheduled within the prescribed lead time)
$\boldsymbol{MinAppWeekGroup_c}$	Minimum number of times that two appointments should be scheduled per day for discipline c and week w (given that all appointments are scheduled within the prescribed lead time)
$\boldsymbol{MaxPatGroup}$	Maximum number of patients that is allowed in a group
$\boldsymbol{MaxWeek_a}$	Last week of the range of weeks during which appointment a is preferably scheduled
$\boldsymbol{MT}$	Maximum number of time slots between two appointments on the same day
$\boldsymbol{MinTherDays}$	Minimum number of days that is needed to schedule all appointments without increasing objective value
$\boldsymbol{MinWeek_a}$	First week of the range of weeks during which appointment a is preferably scheduled
$\boldsymbol{Multi_{h\hat{h}t}}$	1 if therapist h and therapist $\hat{h}$ have an existing simultaneous appointment at time slot t; 0 otherwise
$\boldsymbol{MultiResource_{a\hat{a}}}$	1 if appointment a must be scheduled simultaneously with appointment $\hat{a}$ and thereby represents a multi-resource appointment; 0 otherwise
$\boldsymbol{NewGroup_a}$	1 if appointment a will per definition cause the scheduling of a new group therapy time slot if it is scheduled; 0 otherwise
$\boldsymbol{NewPatient}$	1 if the current instance is related to a first sequence of appointments; 0 otherwise
$\boldsymbol{NumberApp_a}$	Number of times appointment a should be scheduled
$\boldsymbol{Outpatient}$	1 if the current instance is related to an outpatient; 0 otherwise
$\boldsymbol{SimultaneousStart}$	Number of days for which a simultaneous start holds
$\boldsymbol{Z_{t\hat{t}}}$	1 if time slot t is on the same day as time slot $\hat{t}$
$\boldsymbol{Week}$	Duration of a week in time slots
Variables	
$\boldsymbol{appatday_d}$	1 if one or more appointments are scheduled at day d; 0 otherwise
$\boldsymbol{auxil_t}$	1 if $auxil_{t-1}$is equal to 1 or if an appointment is scheduled at t; 0 otherwise
$\boldsymbol{deviationearlier_a}$	Number of time slots that appointment a is scheduled earlier than $MinWeek_a$
$\boldsymbol{deviationlater_a}$	Number of time slots that appointment a is scheduled later than $MinWeek_a$
$\boldsymbol{exceed}$	Number of time slots that the maximum allowed access time is exceeded
$\boldsymbol{extraappdisc_{cd}}$	1 if two individual appointments are scheduled at day d with discipline c; 0 otherwise
$\boldsymbol{extraappdiscgroup_{cd}}$	1 if two group appointments are scheduled at day d with discipline c; 0 otherwise
$\boldsymbol{extragroup_a}$	Number of new group therapy time slots caused by scheduling appointment a
$\boldsymbol{extratherdays}$	Number of scheduled treatment days more than $MinTherDays$
$\boldsymbol{firstday}$	Day of the earliest scheduled appointment in the current instance
$\boldsymbol{firsttimeslot}$	Time slot of the earliest scheduled appointment in the current instance
$\boldsymbol{firstweek}$	Week of the earliest scheduled appointment in the current instance
$\boldsymbol{lasttimeslot}$	Time slot of the last scheduled appointment in the current instance
$\boldsymbol{leadtime}$	1 if $lasttimeslot$ is greater than the maximum of $MaxWeek_a$over a; 0 otherwise
$\boldsymbol{newday_d}$	1 if an appointment is scheduled on day d and no appointment has been scheduled before on the weekday of day d; 0 otherwise
$\boldsymbol{notsimult_c}$	1 if the first appointment at a discipline (as defined in de CP) is scheduled later than $firstday + SimultaneousStart$
$\boldsymbol{notplanned_a}$	Number of times appointments a is not scheduled
$\boldsymbol{smallest_t}$	1 if t is the smallest value for which $x_{aht} = 1$; 0 otherwise
$\boldsymbol{x_{aht}}$	1 if appointment a starts at time slot t and is assigned to therapist h; 0 otherwise

$$\min\Big\{\alpha\cdot\sum_a notplanned_a+\beta\cdot exceed+\gamma$$
$$\cdot\sum_a(deviationearlier_a+deviationlater_a)+\delta\ \cdot leadtime+\theta$$
$$\cdot\varepsilon\sum_{cd}extraappdiscgroup_{cd}+\zeta\cdot\sum_{cd}extraappdisc_{cd}+\ \eta\cdot notequal+\theta\cdot\sum_a extragroup_a+\vartheta\cdot extratherdays+\ \iota\cdot\sum_d newday_d\Big\}$$

Subject to:

$$\sum_{h,t}x_{aht}+\ notplanned_a=NumberApp_a\ \ \forall a \tag{I.1}$$

$$Simultaneous_{a\hat{a}}\cdot\sum_h x_{aht}-Simultaneous_{a\hat{a}}\cdot\sum_h x_{\hat{a}ht}=0\ \forall a,\hat{a},t \tag{I.2}$$

$$\sum_a x_{aht}\leq 1\ \forall h,t \tag{I.3}$$

$$auxil_t-\sum_{a,h}\left(x_{aht}\cdot\frac{2-\sum_{\hat{a}\neq a}Simultaneous_{a\hat{a}}}{2}\right)\geq 0\ \forall t \tag{I.4}$$

$$auxil_0\ =0 \tag{I.5}$$

$$smallest_t-auxil_t+auxil_{t-1}=0\ \ \forall t \tag{I.6}$$

$$smallest_t-\sum_{ah}x_{aht}\leq 0\ \forall t \tag{I.7}$$

$$\sum_t smallest_t\ \ =1 \tag{I.8}$$

$$firsttimeslot-\sum_t t\cdot smallest_t=0 \tag{I.9}$$

$$NewPatient\cdot firsttimeslot-NewPatient\cdot exceed$$
$$\leq D\cdot Outpatient\cdot AccesstimeOutpatient+D\cdot Inpatient\cdot AccesstimeInpatient \tag{I.10}$$

$$firstweek-firsttimeslot\cdot\left(\frac{1}{Week}\right)\geq 0 \tag{I.11}$$

$$firstweek-firsttimeslot\cdot\left(\frac{1}{Week}\right)<\ 1 \tag{I.12}$$

$$Week\cdot NewPatient\cdot firstweek$$
$$-\sum_h t\cdot x_{aht}-deviationearlier_a+\sum_h x_{aht}\cdot M_1$$
$$\leq M_1+Week\cdot NewPatient-Week\cdot(MinWeek_a-1)-1\ \ \forall a\,,t \tag{I.13}$$

$$\sum_h t\cdot x_{aht}-Week\cdot NewPatient\cdot firstweek-\ deviationlater_a$$
$$\leq Week\cdot MaxWeek_a-Week\cdot NewPatient\forall a,t \tag{I.14}$$

$$G_{hc}\cdot x_{aht}\leq\ F_{ac}\ \forall a,h,t,c \tag{I.15}$$

$$x_{aht}\leq\ \sum_c G_{hc}\cdot\left(\sum_{\hat{a}}Simultaneous_{a\hat{a}}\cdot F_{ac}\cdot F_{\hat{a}c}\right)\ \ \forall a,h,t \tag{I.16}$$

$$\sum_{t=1+(d-1)\cdot D}^{d\cdot D}\ \sum_{a,h}x_{aht}\cdot\frac{2-\sum_{\hat{a}\neq a}Simultaneous_{a\hat{a}}}{2}\leq MaxApp\ \ \forall d \tag{I.17}$$

$$t\cdot x_{aht}-lasttimeslot\leq 0\ \forall a,h,t \tag{I.18}$$

$$lasttimeslot-NewPatient\cdot firsttimeslot-M_2\cdot leadtime\leq W\cdot\max_a(MaxWeek_a)-\ NewPatient \tag{I.19}$$

$$\sum_{h,t}x_{aht}\cdot Group_a-extragroup_a-\sum_{h,t}x_{aht}\cdot GroupApp_{ht}=0\ \forall a \tag{I.20}$$

$$(1-Group_a)\cdot x_{aht}\leq\ (1-GroupApp_{ht})\ \forall a,h,t \tag{I.21}$$

$$x_{aht}\cdot GroupApp_{ht}\cdot Duration_a-x_{aht}\cdot GroupApp_{ht}\cdot GroupDur_{ht}=0\ \forall a,h,t \tag{I.22}$$

$$Simult_{h\hat{h}t}\cdot\sum_a x_{aht}-Simult_{h\hat{h}t}\cdot\sum_a x_{\hat{a}\hat{h}t}=0\ \forall h,\hat{h},t \tag{I.23}$$

$$\sum_{\hat{h}}Simult_{h\hat{h}t}\cdot(1-\sum_{\hat{a}}Simultaneous_{a\hat{a}}\,)\cdot x_{aht}=0\ \forall a,h,t \tag{I.24}$$

$$x_{aht}\leq\ B_{ht}\ \forall a,h,t \tag{I.25}$$

$$x_{aht}\cdot(1-Group_a\cdot GroupApp_{ht})\leq\ B_{h\hat{t}}\ \forall a,h,t,t<\hat{t}<\ t+Duration_a \tag{I.26}$$

$$Duration_a\cdot x_{aht}+\sum_{\hat{t}=t+1}^{t+Duur_a-1}x_{\hat{a}\hat{h}\hat{t}}\leq Duration_a\ \ \forall a,h,t,\hat{a},\hat{h}|Duration_a\ >1 \tag{I.27}$$

$$\sum_{t=1+(d-1)\cdot D}^{d\cdot D}\sum_{a,h} x_{aht}\cdot(1-Group_a)\cdot G_{hc} - extraappdisc_{cd} \leq 1 \ \forall c,d \tag{I.28}$$

$$\sum_{t=1+(d-1)\cdot D}^{d\cdot D}\sum_{a,h} x_{aht}\cdot Group_a\cdot G_{hc}\cdot \frac{2-\sum_{\hat{a}\neq a} Simultaneous_{a\hat{a}}\cdot F_{\hat{a}c}}{2} - extraappdiscgroup_{cd} \leq 1 \ \forall c,d \tag{I.29}$$

$$firstday - firsttimeslot\cdot\left(\frac{1}{D}\right) \geq 0 \tag{I.30}$$

$$firstday - firsttimeslot\cdot\left(\frac{1}{D}\right) < 1 \tag{I.31}$$

$$\sum_{a,h} FirstApp_{ac}\cdot t\cdot x_{aht}\cdot\frac{2-\sum_{\hat{a}\neq a} Simultaneous_{a\hat{a}}}{2} - D\cdot firstday \ - M_3\cdot notequal_c \leq D\cdot(EqualStart-1) \ \forall c,t \tag{I.32}$$

$$\sum_{t=1+(d-1)\cdot D}^{d\cdot D}\sum_{a,h} x_{aht} - D\cdot appatday_d \leq 0 \ \forall d \tag{I.33}$$

$$\sum_{d} appatday_d - extratherdays \leq MinTherDays \tag{I.34}$$

$$appatday_d - \sum_{w|w\cdot 5<d} appatday_{d-w\cdot 5} - newday_d \leq 0 \ \forall d|d>5 \tag{I.35}$$

$$t\cdot x_{aht} \leq 1 + D\cdot\big((t-1)\operatorname{div} D+1\big) - Duration_a \ \forall a,h,t \tag{I.36}$$

$$\sum_a F_{ac}\cdot notplanned_a \leq \left\lfloor 0.2\cdot\sum_a F_{ac}\cdot NumberApp_a\right\rfloor \forall c|\sum_a F_{ac}>0 \tag{I.37}$$

$$\sum_{\hat{t}=t+Duration_a+MT+1}^{t+D} Z_{t\hat{t}}\cdot\sum_{\hat{a},\hat{h}} x_{\hat{a}\hat{h}\hat{t}} - \sum_{\hat{t}=t+Duration_a}^{t+Duration_a+MT} Z_{t\hat{t}}\cdot\sum_{\hat{a},\hat{h}} x_{\hat{a}\hat{h}\hat{t}}\cdot MaxApp + x_{aht}\cdot MaxApp \leq MaxApp \ \forall a,h,t \tag{I.38}$$

$$deviationlater_a \leq MaxDev \ \forall a \tag{I.39}$$

$$deviationearlier_a \leq MaxDev \ \forall a \tag{I.40}$$

Valid inequalities:

$$extragroup_a + notplanned_a \geq NewGroup_a \ \forall a \tag{I.41}$$

$$\sum_{d=(w-1)\cdot 5+1}^{w\cdot 5} extraappdisc_{cd} + \sum_a notplanned_a\cdot F_{ac}\cdot(1-Group_a) + leadtime\cdot MinExtrApp_{cw} \geq MinExtrApp_{cw} \ \forall c,w \tag{I.42}$$

$$\sum_{d=(w-1)\cdot 5+1}^{w\cdot 5} extraappdiscgroup_{cd} + \sum_a notplanned_a\cdot F_{ac}\cdot Group_a + leadtime\cdot MinExtrAppGroup_{cw} \geq MinExtrAppGroup_{cw} \ \forall c,w \tag{I.43}$$

Binary variables: x_{aht}, $auxil_t$, $smallest_t$, $leadtime$, $extraappdisc_{cd}$, $extraappdiscgroup_{cd}$, $notequal_c$, $appatday_d$, $newday_d$

Integer variables: $notplanned_a$, $firsttimeslot$, $lasttimeslot$, $firstday$, $firstweek$, $exceed$, $deviationearlier_a$, $deviationlater_a$, $extragroup_a$, $extratherdays$

Appendix IV: Heuristics for therapist selection

This appendix describes the heuristics used in our simulation study as described in Chapter 6.

Heuristics IV.1 and IV.2 give a technical description of the therapist selection process. Heuristic IV.1 performs some initialization tasks in step 1[13]. Per discipline (step 2.2), a group therapist and therapist for individual therapy and new groups is picked.

Picking a group therapist (heuristic IV.1)

The heuristic first selects a therapist for group therapy, given that the patient's care pathway prescribes group therapy (step 2.2). If the care pathway prescribes multi-resource appointments (step 2.2.2), the heuristic makes a list of therapists who have existing multi-resource group therapy appointments with previously selected therapists during the planning horizon (step 2.2.2 and 2.2.3). In case of multi-resource appointments, the heuristic thus tries to achieve that both therapists of existing multi-resource appointments are picked. If no therapist can be found that complies with this, the heuristic returns a list of therapists with existing multi-resource group therapy appointments, but not necessarily with previously selected therapists. If no therapist with existing multi-resource appointments can be found, the heuristic simply makes a list of therapists with existing group appointments. Out of the resulting list, the heuristic picks the group therapist for which the sum of overall therapist availability on the days of existing group therapy time slots is maximized (step 2.2.5). It thus aims to pick a group therapist for which the number of existing group therapy time slots combined with the number of free time slots of other therapists on the days of group therapy is high. We look at the availability of *all* therapists, because we want to avoid clustering of appointments in general around group appointments (which is a bottleneck as described in Paragraph 2.7).

Picking a therapist for individual therapy and new groups (heuristic IV.1)

After a group therapist is chosen, the heuristic picks a therapist for individual therapy (step 2.3 to 2.6). The heuristic first makes a list of therapists that work on the same days as the group therapy time slots of all previously picked group therapists. Out of the remaining therapists – or all therapists of there are no therapists that comply with this condition – it picks the therapist with the highest number of free time slots in the planning horizon. Group therapy timeslots with available capacity are not included. Therapists that have a higher average utilization rate than the target utilization rate are not taken into consideration.

[13] Step E in Heuristic IV.1 states that $B_{ht}^F = \text{init}(B_{ht})$; this means that B_{ht}^F is equal to B_{ht} as if the schedule is empty, i.e., before any patients are scheduled

Picking a second therapist of same discipline for multi-resource appointments (heuristic IV.2)

If the care pathway includes multi-resource appointments with two therapists of the same discipline, an additional therapist must be picked (step 2.10 of heuristic IV.1), which is done in heuristic IV.2. This heuristic attempts to pick a therapist with the maximum number of existing multi-resource appointments with the individual therapist and group therapist. If no earlier multi-resource appointments are found, the therapist is picked for which the number of time slots that both the individual therapist and the additional therapist are available is maximized. If the picked “second therapist” is equal to the group therapist, it is assured that appointments are not scheduled twice with the same therapist (step 4). This is done by adding additional constraints to the ILP.

Parameter definition (heuristic IV.1)

Finally, the heuristic pretends that the therapist for individual appointments is assigned to the group appointment time slots of the group therapist (step 2.11). We save original assignments and restore values after the ILP is solved. The output of the heuristic is a set of therapists H_I used as input for the ILP. Based on H_I, we make subsets of all therapist related parameters.

Heuristic IV.1: therapist selection

1. Initialization:
   1.1. Define planning horizon $T_p = \{(Attempt + FirstWeek_p - 2) \cdot W + 1, \dots, (Attempt + FirstWeek_p - 2 + \max(MaxWeek_a)) \cdot W\}$
   1.2. Define list of selected individual therapists $H_I = \emptyset$
   1.3. Define list of selected group therapists $H_G = \emptyset$
   1.4. Define list of time slots of appointments with selected group therapists $T_G = \emptyset$
   1.5. Define empty therapist schedule $B_{ht}^F = \text{init}(B_{ht})$
2. $\forall c | \sum_a F_{ac} \geq 1$:
   2.1. Define set $H_1 = \{h \in H | G_{hc} \cdot Spec_h = 1\}$
   2.2. If $\sum_a Group_a \cdot F_{ac} \geq 1$:
      2.2.1. Define set $H_2 = \left\{h \in H_1 | \ \sum_{t \in T_p} GroupApp_{ht} \cdot B_{ht} \ \geq 1\right\}$
      2.2.2. If $\sum_{a\hat{a}} MultiResource_{a\hat{a}} \cdot F_{ac} \geq 1$ and $H_2 \ \neq \emptyset$:
         2.2.2.1. Define set $H_3 = \left\{h \in H_2 | \sum_{\hat{h} \in H, t \in T_p} Multi_{h\hat{h}t} \ \geq 1\right\}$
      2.2.3. If $H_3 \neq \emptyset$:
         2.2.3.1. Define set $H_4 = \left\{\breve{h} \in H_I \cup H_G\right\}$
         2.2.3.2. Define set $H_5 = \{h \in H_3 | \sum_{\breve{h} \in H_4, t \in T_p} Multi_{h\breve{h}t} \ \geq 1\}$
         2.2.3.3. If $H_5 = \emptyset$: $H_5 = H_3$
      2.2.4. If $H_5 = \emptyset$: $H_5 = H_2$
      2.2.5. If $H_5 \neq \emptyset$:
         2.2.5.1. Define sets of time slots $T_h = \left\{t \in T_p | GroupApp_{ht} \cdot B_{ht} \geq 1\right\} \forall h \in H_5$
         2.2.5.2. $h_G^* = \text{argmax}_{h \in H_5} \sum_{\hat{h} \in H} \sum_{t \in T_h} \sum_{\hat{t}=\left\lfloor \frac{t}{D} \right\rfloor \cdot D+1}^{\left\lceil \frac{t}{D} \right\rceil \cdot D} (B_{\hat{h}\hat{t}} - B_{\hat{h}\hat{t}} \cdot GroupApp_{\hat{h}\hat{t}})$
         2.2.5.3. $H_G = H_G \cup \{h_G^*\}$
         2.2.5.4. $T_G = T_G \cup \left\{T_{h_G^*}\right\}$
   2.3. Define set $H_6 = \left\{h \in H_1 | \ \sum_{\hat{t}=\left\lfloor \frac{t}{D} \right\rfloor \cdot D+1}^{\left\lceil \frac{t}{D} \right\rceil \cdot D} B_{h\hat{t}} \ \neq 0 \ \forall \ t \in T_G\right\}$
   2.4. If $H_6 = \emptyset$: $H_6 = H_1$
   2.5. $H_7 = \left\{h \in H_6 \middle| 1 - \frac{\sum_{t \in T_p}(B_{ht} - B_{ht} \cdot GroupApp_{ht})}{\sum_{t \in T_p} B_{ht}^F} < TargetUtil_c\right\}$
   2.6. If $H_7 = \emptyset$:
      2.6.1. $H_6 = H_1$
      2.6.2. $H_7 = \left\{h \in H_6 \middle| 1 - \frac{\sum_{t \in T_p}(B_{ht} - B_{ht} \cdot GroupApp_{ht})}{\sum_{t \in T_p} B_{ht}^F} < TargetUtil_c\right\}$
   2.7. If $H_7 = \emptyset$: $H_I = H_G = T_G = \emptyset$ and BREAK
   2.8. $h_I^* = \underset{h \in H_7}{\text{argmax}} \sum_{t \in T_p} \sum_{t \in T_p} (B_{ht} - B_{ht} \cdot GroupApp_{ht})$
   2.9. $H_I = H_I \cup \{h_I^*\}$
   2.10. If $\sum_{a\hat{a}} F_{ac} \cdot F_{\hat{a}c} \cdot MultiResource_{a\hat{a}} \geq 1$: Call **Heuristic V.2**
   2.11. If $h_G^* \neq \ \emptyset$:
      2.11.1. $B_{h_I^* t} = B_{h_G^* t} \forall t \in T_p$
      2.11.2. $GroupApp_{h_I^* t} = GroupApp_{h_G^* t} \ \forall t \in T_{h_G^*}$
      2.11.3. $GroupDur_{h_I^* t} = GroupDur_{h_G^* t} \ \forall t \in T_{h_G^*}$
      2.11.4. $Multi_{h_I^* \hat{h} t} = Multi_{h_G^* \hat{h} t} \ \forall t \in T_{h_G^*}, \hat{h} \in H$
3. $H_p = H_I$ and end.

Heuristic IV.2: selecting additional therapist is case of multi-resource appointment with two therapists of the same discipline

1. Define $H_{S1} = \{h \in H | G_{hc} \cdot Spec_h = 1, h \neq h_I^* \}$
2. Define $H_F = \{\hat{h} \in h_G^* \cup h_I^*\}$
3. If $\max_{h \in H_{S1}} \sum_{\hat{h} \in H_F | \hat{h} \neq h, t} Multi_{h\hat{h}t} \geq 0$:
    3.1. $h_S^* = \text{argmax}_{h \in H_{S1}} \sum_{\hat{h} \in H_F | \hat{h} \neq h, t} Multi_{h\hat{h}t}$
4. If $h_S^* = \emptyset$:
    4.1. $H_{S2} = \left\{h \in H_{S1} \middle| 1 - \frac{\sum_{t \in T_p}(B_{ht} - B_{ht} \cdot GroupApp_{ht})}{\sum_{t \in T_p} B_{ht}^F} < TargetUtil_c\right\}$
    4.2. If $H_{S2} = \emptyset$
        4.2.1. $H_I = H_G = T_G = \emptyset$ and BREAK
    4.3. $h_S^* = \underset{h \in H_{S2}}{\text{argmax}} \sum_{t \in T_p}(B_{ht} - B_{ht} \cdot GroupApp_{ht})$
    4.4. $H_I = H_I \cup \{h_S^*\}$
5. If $h_S^* = h_G^*$: $\forall t$ in T_G:
    5.1. If $B_{h_I^* t} \cdot GroupApp_{h_I^* t} = 0$: Add constraint to ILP: $x_{a h_I^* t} = 0 \; \forall a$
6. End.

Appendix V: Pairwise comparisons for output measures

This appendix gives the pairwise comparisons as discussed in Chapter 7. Table V.1 presents the pairwise comparisons for output measures of the simulation model. We only provide pairwise comparisons for the output measures for which convergence was achieved within the warm-up period (see Paragraph 7.5).

For constructing confidence intervals for pairwise comparisons, let X_{ij} be the average value or the measure of interest for replication j of scenario i. Define $Z_j = X_{1j} - X_{2j}$ for $j = 1,2, \dots n$ and say that $\bar{Z}(n) = \sum_{j=1}^{n} Z_j / n$ and $\widehat{Var}[\bar{Z}(n)] = \frac{\sum_{j=1}^{n}[Z_j - \bar{Z}(n)]^2}{n(n-1)}$. Then, the 95% confidence interval is defined as $\bar{Z}(n) \pm t_{n-1,0.975}\sqrt{\widehat{Var}[\bar{Z}(n)]}$. For a more comprehensive discussion on pairwise comparisons in simulation, see Law [34].

The pairwise comparisons result in a 95% confidence interval *per pairwise comparison.* The confidence over *all* pairwise comparisons per scenario is lower than 95% with these intervals.

Table V.1

Individual 95% confidence intervals for all pairwise comparisons for six output measures. Bold number and asterisks indicate a significant difference ($Z_j = X_{i_1j} - X_{i_1j}$).

Not scheduled appointments

		i_2				
	Scenario	2	3	4	5	6
i_1	1	$\mathbf{0.13 \pm 0.09}$*	0.02 ± 0.09	$\mathbf{0.69 \pm 0.05}$*	$\mathbf{0.71 \pm 0.04}$*	$\mathbf{0.56 \pm 0.05}$*
	2		$\mathbf{-0.11 \pm 0.07}$*	$\mathbf{0.56 \pm 0.07}$*	$\mathbf{0.58 \pm 0.10}$*	$\mathbf{0.43 \pm 0.06}$*
	3			$\mathbf{0.67 \pm 0.07}$*	$\mathbf{0.69 \pm 0.09}$*	0.54 ± 0.06*
	4				0.017 ± 0.04	$\mathbf{-0.13 \pm 0.01}$*
	5					$\mathbf{-0.15 \pm 0.05}$*

Therapist utilization (multiplied by 10^{-2})

		i_2				
	Scenario	2	3	4	5	6
i_1	1	-0.15 ± 0.57	$\mathbf{-3.16 \pm 0.57}$*	$\mathbf{-4.96 \pm 0.97}$*	$\mathbf{-18.86 \pm 1.45}$*	$\mathbf{-28.87 \pm 0.69}$*
	2		$\mathbf{-3.01 \pm 0.25}$*	$\mathbf{-4.81 \pm 0.58}$*	$\mathbf{-18.71 \pm 1.74}$*	$\mathbf{-28.72 \pm 0.57}$*
	3			$\mathbf{-1.80 \pm 0.48}$*	$\mathbf{-15.70 \pm 1.87}$*	$\mathbf{-25.72 \pm 0.35}$*
	4				$\mathbf{-13.90 \pm 2.27}$*	$\mathbf{-23.91 \pm 0.49}$*
	5					$\mathbf{-10.01 \pm 2.10}$*

Access time (multiplied by 10^{-2})

		i_2				
	Scenario	2	3	4	5	6
i_1	1	-0.69 ± 0.78	0.40 ± 1.33	$\mathbf{2.40 \pm 0.88}$*	$\mathbf{-35.93 \pm 9.55}$*	$\mathbf{-69.97 \pm 10.76}$*
	2		1.09 ± 1.56	$\mathbf{3.10 \pm 1.30}$*	$\mathbf{-35.24 \pm 10.23}$*	$\mathbf{-69.28 \pm 11.39}$*
	3			$\mathbf{2.00 \pm 1.64}$*	$\mathbf{-36.33 \pm 9.73}$*	$\mathbf{-70.38 \pm 11.01}$*
	4				$\mathbf{-38.34 \pm 9.82}$*	$\mathbf{-72.38 \pm 10.14}$*
	5					$\mathbf{-34.04 \pm 11.28}$*

Combination appointments (multiplied by 10^{-2})						
			i_2			
	Scenario	2	3	4	5	6
i_1	1	$\mathbf{-6.87 \pm 2.91}$*	$\mathbf{-8.81 \pm 2.94}$*	$\mathbf{21.94 \pm 2.29}$*	$\mathbf{20.86 \pm 3.74}$*	$\mathbf{10.93 \pm 3.03}$*
	2		-1.95 ± 2.33	$\mathbf{28.80 \pm 2.65}$*	$\mathbf{27.73 \pm 2.55}$*	$\mathbf{17.79 \pm 2.92}$*
	3			$\mathbf{30.75 \pm 1.57}$*	$\mathbf{29.67 \pm 1.43}$*	$\mathbf{19.74 \pm 2.27}$*
	4				-1.08 ± 1.12	$\mathbf{-11.01 \pm 2.62}$*
	5					$\mathbf{-9.94 \pm 2.66}$*

Number of extra groups						
			i_2			
	Scenario	2	3	4	5	6
i_1	1	$\mathbf{-0.23 \pm 0.16}$*	$\mathbf{-2.51 \pm 0.20}$*	$\mathbf{-4.32 \pm 0.54}$*	$\mathbf{-3.98 \pm 0.98}$*	$\mathbf{-1.83 \pm 0.39}$*
	2		$\mathbf{-2.28 \pm 0.15}$*	$\mathbf{-4.09 \pm 0.51}$*	$\mathbf{-3.76 \pm 1.05}$*	$\mathbf{-1.60 \pm 0.28}$*
	3			$\mathbf{-1.81 \pm 0.54}$*	$\mathbf{-1.48 \pm 1.07}$*	$\mathbf{0.68 \pm 0.35}$*
	4				0.33 ± 1.32	$\mathbf{2.49 \pm 0.70}$*
	5					$\mathbf{2.16 \pm 1.24}$*

Number of times more than one individual appointment per day						
			i_2			
	Scenario	2	3	4	5	6
i_1	1	0.01 ± 0.11	$\mathbf{-0.13 \pm 0.08}$*	$\mathbf{1.56 \pm 0.08}$*	$\mathbf{1.54 \pm 0.08}$*	$\mathbf{1.41 \pm 0.06}$*
	2		$\mathbf{-0.14 \pm 0.07}$*	$\mathbf{1.55 \pm 0.05}$*	$\mathbf{1.52 \pm 0.13}$*	$\mathbf{1.40 \pm 0.07}$*
	3			$\mathbf{1.69 \pm 0.04}$*	$\mathbf{1.67 \pm 0.09}$*	$\mathbf{1.54 \pm 0.04}$*
	4				-0.02 ± 0.11	$\mathbf{-0.15 \pm 0.03}$*
	5					$\mathbf{-0.13 \pm 0.08}$*

$NUMO^{CP \to RTS}$						
			i_2			
	Scenario	2	3	4	5	6
i_1	1	$\mathbf{-6.37 \pm 4.29}$*	3.67 ± 6.67	$\mathbf{-44.60 \pm 3.39}$*	$\mathbf{-44.28 \pm 4.18}$*	2.98 ± 13.37
	2		$\mathbf{10.04 \pm 6.63}$*	$\mathbf{-38.32 \pm 2.38}$*	$\mathbf{-33.91 \pm 7.54}$*	9.36 ± 11.20
	3			$\mathbf{-48.26 \pm 6.77}$*	$\mathbf{-47.95 \pm 5.95}$*	-0.68 ± 17.35
	4				0.32 ± 6.95	$\mathbf{47.58 \pm 11.08}$*
	5					$\mathbf{47.27 \pm 17.52}$*

$FRQ^{CP \to RTS}$						
			i_2			
	Scenario	2	3	4	5	6
i_1	1	$\mathbf{-7.25 \pm 7.248}$*	$\mathbf{6.28 \pm 6.11}$*	$\mathbf{-45.81 \pm 6.26}$*	$\mathbf{-34.57 \pm 5.37}$*	$\mathbf{62.51 \pm 45.11}$*
	2		$\mathbf{13.53 \pm 3.25}$*	$\mathbf{-38.65 \pm 3.12}$*	$\mathbf{-27.31 \pm 10.75}$*	$\mathbf{69.76 \pm 39.68}$*
	3			$\mathbf{-52.08 \pm 5.10}$*	$\mathbf{-40.84 \pm 8.44}$*	$\mathbf{56.23 \pm 42.46}$*
	4				$\mathbf{11.24 \pm 10.53}$*	$\mathbf{108.30 \pm 40.39}$*
	5					$\mathbf{67.08 \pm 48.36}$*