UNIVERSITY OF TWENTE.

Sint Maartenskliniek

Forecasting demand for inpatient physical therapy

Master Thesis by Jelle Peer

Nijmegen, November 2015

Document Title	Forecasting demand for inpatient physical therapy
Date	25-11-2015

Author	J. Peer j.peer@student.utwente.nl
Educational institution Faculty	University of Twente Faculty of Behavioural, Management and Social Sciences
Educational program Specialisation	Industrial Engineering & Management Production & Logistics Management
Graduation Committee	
University of Twente	Prof. Dr. Ir. E.W. (Erwin) Hans Faculty of Behavioural, Management and Social Sciences University of Twente, Ravelijn 3341 e.w.hans@utwente.nl
	Dr. Ir. L.L.M. (Leo) van der Wegen Faculty of Behavioural, Management and Social Sciences University of Twente, Ravelijn 3355 l.l.m.vanderwegen@utwente.nl
Sint Maartenskliniek	L. Mallekoote Head Healthcare Logistics Sint Maartenskliniek, Nijmegen l.mallekoote@maartenskliniek.nl
	L. Schoonhoven Head Ambulatory Rheumatic Centre Sint Maartenskliniek, Nijmegen l.schoonhoven@maartenskliniek.nl

UNIVERSITY OF TWENTE.

Sint Maartenskliniek

Management summary

Problem description

In the Sint Maartenskliniek, orthopaedic patients receive physical therapy treatments during their postoperative stay, known as inpatient physical therapy. The number of inpatient physical therapy treatments a patient receives on each postoperative day is defined in a treatment protocol. In the current situation, the physical therapist department struggles to efficiently and effectively cope with demand for inpatient physical therapy. To enable the physical therapists to cope with demand more efficiently and effectively, we design a prototype tool to forecast demand for inpatient physical therapy.

Research objective

The research objective is defined as follows:

To provide a prototype tool to forecast demand for inpatient physical therapy and support decision-making in the planning of physical therapist staff

Contribution

We design a prototype forecast tool, which predicts the daily demand for inpatient physical therapy for the next three months. With the prototype forecast tool, the physical therapist department can reduce the frequency and extent of over- and understaffing. Moreover, the orthopaedics department can use the prototype forecast tool to experiment with different OR schedules to create a more stable demand for inpatient physical therapy and possibly other downstream departments. This research contributes to literature by developing a conceptual method that forecasts demand for downstream resources, based on currently scheduled surgeries in the OR.

Method

The forecast tool examines the surgeries that are currently scheduled in a future OR session and determines the probability that each of these surgeries is rescheduled, based on the urgency category and specialty of each scheduled surgery, and the number of days left until the surgery date. Subsequently, the model determines the probability of reaching a final OR schedule, given the scheduled surgeries and the respective reschedule probabilities. This yields a probability distribution of reaching different final OR schedules. A final OR schedule consists of a combination of surgeries that has been performed during an OR session in the past 24 months.

Each surgery in a final OR schedule has a matching physical therapist treatment protocol that determines the number of physical therapist treatments a patient receives during his or her postoperative stay. We use the treatment protocols to determine demand for inpatient physical therapy that follows from each final OR schedule. To aggregate the probability distributions of the final OR schedules for each OR session, we perform discrete convolutions as suggested by Vanberkel et al. [43].

Results

In Figure 1 and 2, we present the results of the prototype forecast tool. Figure 1 shows the 100% and 98% confidence intervals of demand for inpatient physical therapy in treatments per day. The 100% confidence interval includes the absolute maximum and minimum of the predicted number of inpatient physical therapy treatments. Figure 1 also shows the protocolised demand, which is the actual demand on each day when physical therapy inpatients are treated according to protocol. Due to time restrictions, we were only able to observe the protocolised demand until the 23rd of November 2015. The variability in demand can be explained by the fluctuating utilisation of the ORs. In the weekends, there are no surgeries and during holidays a reduced number of ORs is utilised, which causes a temporary dip in demand for inpatient physical therapy.

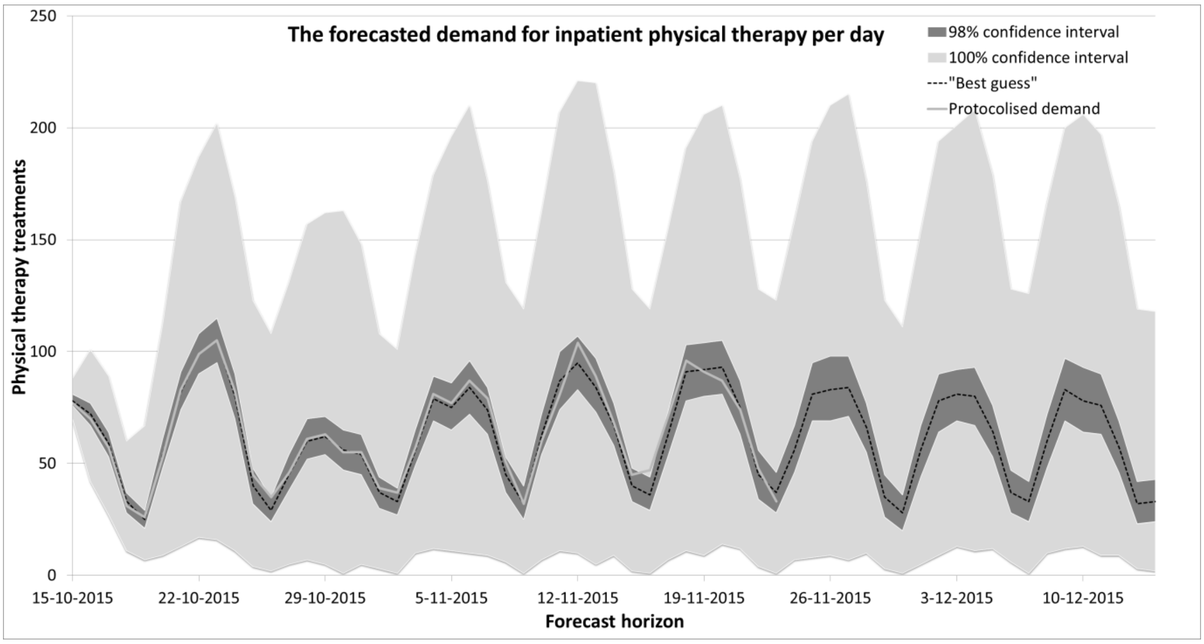


Figure 1 – The actual and forecasted demand for inpatient physical therapy per day

Figure 2 shows the size of the 98% confidence interval of the daily demand for inpatient physical therapy of the designed forecast and the forecast that is currently being utilised. The current forecast predicts demand for inpatient physical therapy based on the number of available ORs and the operating surgeon in each OR. The size of the 98% confidence intervals is calculated as the maximum of the 98% confidence interval minus the minimum of the 98% confidence level. Furthermore, Figure 2 shows the percentage of OR capacity that is planned per day and the average reschedule probability of the scheduled surgeries per day.

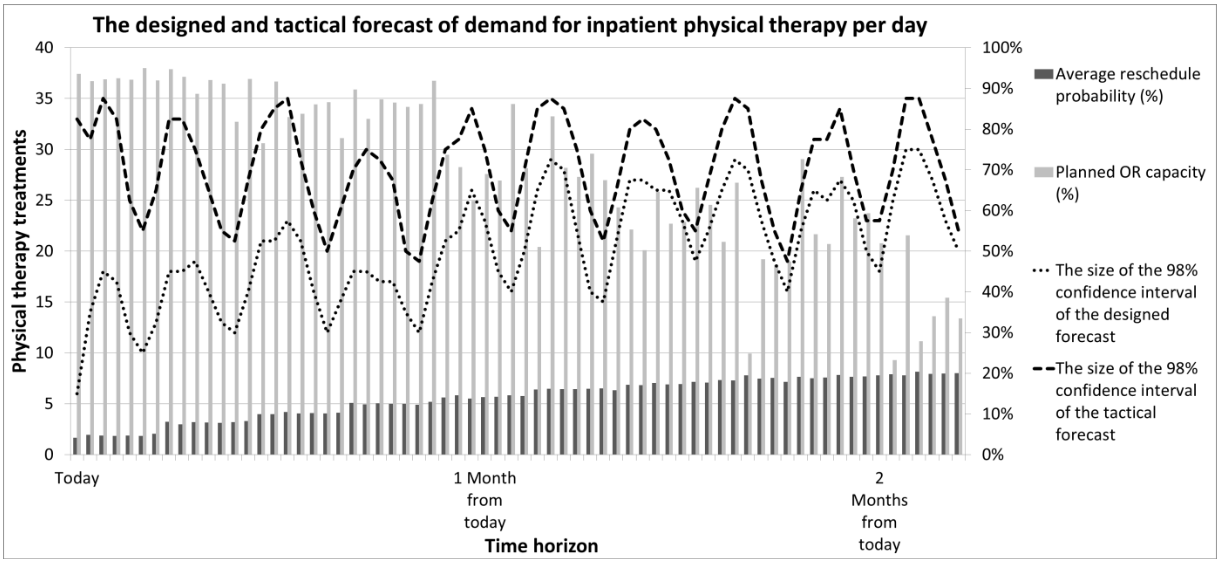


Figure 2 - A comparison between the designed and current forecast

Figure 2 shows that in the first month, the size of the 98% confidence interval for inpatient physical therapy demand of the designed forecast is, on average, 40% smaller than the size of the 98% confidence interval of the current forecast. This can be explained by the high percentage of planned OR capacity (62 – 95 %) and a low percentage of rescheduled surgeries (4 – 15 %) in the first month, because scheduled surgeries are only incorporated in the designed forecast. More scheduled surgeries and a lower reschedule probability means more information is available with a higher reliability, which leads to a more accurate forecast. Due to a limited availability of data, we were unable to determine a forecast error.

Conclusion

With the increased accuracy of the designed forecast, the physical therapist department is able to cope with demand for inpatient physical therapy more efficiently and effectively, which results in a reduction in the amount and frequency of over- and understaffing. Our main recommendation is to professionalise the prototype tool that is designed in this research. For future research, it may be interesting to experiment with different OR schedules to create a more stable demand for inpatient physical therapy.

Preface

During my study Industrial Engineering & Management I learned to improve business processes through quantitative analyses. It was only until later in my master that I came in contact with healthcare, and it did not take long to get infected by the enthusiasm of my mentor during this study, Erwin Hans. I now realise that healthcare, like business, is a sector where the efficiency and effectiveness of processes can be improved or even optimised.

In this research I focused on providing insight in the effect of the OR schedule on a downstream department, namely physical therapy. This facilitates a more efficient planning and scheduling of patients, which is a result I am proud of. However, like in all research, there is room for improvement. Therefore, I hope to encourage you to build on my research or to inspire you to improve the efficiency and effectiveness of processes in healthcare in a different manner.

I would like to thank the Sint Maartenskliniek for providing me with the opportunity to execute this research and for all the time and effort they invested in me and this research. A special thanks goes out to Rob Vromans, who has always been there to discuss my ideas, provide me with advice and ask me brain-cracking questions. I also thank everyone that visited my project meetings in the Sint Maartenskliniek for their feedback and insights.

Finally, I thank my supervisors from the University of Twente, Erwin Hans and Leo van der Wegen, and my supervisors in the Sint Maartenskliniek, Lenneke Mallekoote and Léon Schoonhoven, for all their contributions to this research.

Jelle Peer

Nijmegen, 2015

Contents

List of abbreviations

ARC	Ambulatory Rheumatic Centre
CHOIR	Centre for Healthcare Operations Improvement and Research
DF	Degrees of Freedom
ESP	Employee Scheduling Problem
FTE	Fulltime-equivalent
OIC	Orthopaedic Intervention Centre
OR	Operating Room
SAS	Statistical Analysis System
SMK	Sint Maartenskliniek
SPSS	Statistical Package for the Social Sciences
VBA	Visual Basic for Applications

1. Introduction

In this research we develop a prototype tool to forecast demand for inpatient physical therapy at Sint Maartenskliniek (SMK) in Nijmegen. In 1.1 we provide background information on SMK. In 1.2 we introduce the problem context and discuss the motivation for the research. In 1.3 we formulate the research objective. In 1.4 we present an outline for the remainder of the report in the form of research questions, which we answer in each chapter.

Contents

1.1 Sint Maartenskliniek Nijmegen

SMK was founded in 1936 and is the only hospital in the Netherlands that is completely focused on the posture and movement of the human body. Treatments vary from simple to extremely complex in the areas Orthopaedics, Rheumatology and Rehabilitation. Every year, approximately 1,500 employees [2] treat over 50,000 patients. Figure 3 shows the core values and strategic goals.

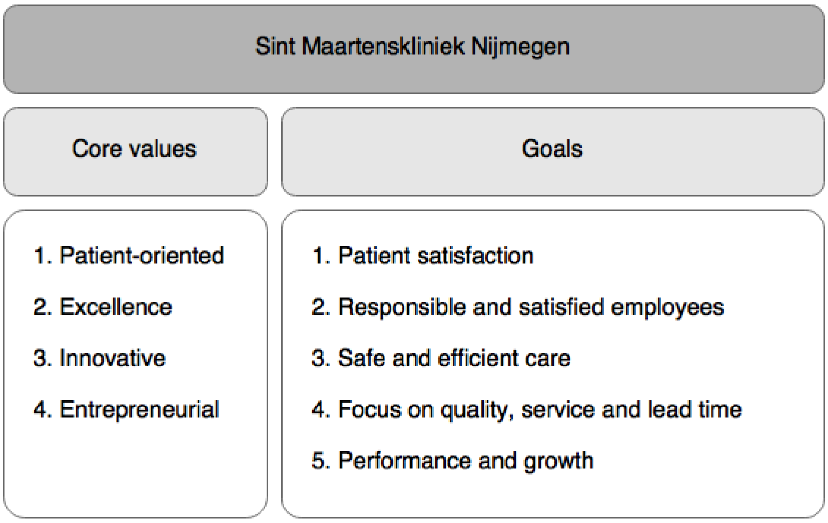


Figure 3 - Core values & goals of SMK [2]

The long-term objective is to improve processes from a medical point of view, by treating patients according to specified protocols, known as care-paths. In order to achieve this, processes have to be improved from a logistics point of view. To support this development, a logistics department was founded in 2015.

1.2 Problem context

SMK strives to maximise the operating room (OR) utilisation, which causes the output of ORs to be highly variable. In literature this phenomenon is referred to as the bullwhip-effect [34]. The downstream departments have to respond to the variable output of the ORs after most planning and scheduling decisions have already been made. As a result, the highly variable output of the ORs causes downstream departments to struggle to deal with the planning and scheduling of personnel to accommodate for patients who were treated in the OR.

In 2014, over 5,500 orthopaedic patients received surgery. 73%[1] of these orthopaedic patients received one or more treatments of physical therapy during their postoperative stay, known as inpatient physical therapy. In total, the orthopaedic patients required more than 22,500 inpatient physical therapy treatments, which translates to over 7,500 hours of treatment. Evidently, demand for inpatient physical therapy is affected by the output of the OR in particular.

The physical therapist department experiences three main issues related to the inability to accurately match supply and demand (Figure 4).

Area	Criteria	Consequence
Physical therapy inpatients	Quality of care	Understaffing leads to non-conformance of treatment protocols
Physical therapists	Motivation	Working overtime on one day and having no work on the next day is experienced as frustrating by the employees
SMK	Costs	Overstaffing leads to unwanted extra costs

Figure 4 - Consequences of the mismatch between supply and demand

Increased boundaries on flexible staff through a recent change in law[2] have intensified the need for a solution.

1.3 Research objective

To enable the physical therapists to cope with demand more efficiently and effectively, we design a prototype tool to forecast demand for inpatient physical therapy. The research objective of this study is formulated as follows:

To provide a prototype tool to forecast demand for inpatient physical therapy and support decision-making in the planning of physical therapist staff

[1] Based on a study of orthopaedic patients treated in 2014

[2] http://www.rijksoverheid.nl/onderwerpen/arbeidsovereenkomst-en-cao/kabinetsplannen-positie-flexwerkers

More transparency in demand for inpatient physical therapy leads to a more efficient physical therapist schedule by reducing the frequency and extent of over- and understaffing. This reduces costs, improves quality of care and boosts motivation of personnel, since “A high quality personnel roster can lead to a more content and thus more effective workforce” [10].

We believe that providing insight in the effect of the OR schedule on one of the downstream departments is a critical step towards an integrally optimised OR schedule. After all, how can you integrally optimise the OR schedule if you do not know the effect of the OR schedule on downstream departments?

To ensure a scientific approach, this research uses the Managerial Problem Solving Method[3] (MPSM) as a basis for the research methodology.

1.4 Research questions

In pursuit of the research objective, this section defines several research questions that we will answer in order to obtain knowledge on the core problem.

Research question 1:	How is the current treatment and scheduling process composed?
Chapter 2	Examines the current treatment and scheduling process to identify bottlenecks and possible areas of improvement.
Research question 2:	What methods can be used to forecast demand?
Chapter 3	Presents a literature study on demand uncertainty to identify methods to forecast demand.
Research question 3:	How can we forecast demand for inpatient physical therapy?
Chapter 4	Formulates a solution approach to forecast demand for inpatient physical therapy.
Research Question 4:	What are the results of the designed forecast?
Chapter 5	Evaluates the results of the designed forecast.
Chapter 6	Discusses the research in terms of limitations, provides recommendations and argues topics for further research.

[3] Also known as the “Algemene Bedrijfskunde Probleemaanpak” or ABP [41]

2. Context analysis

In this chapter we analyse the context of the core problem. In 2.1 we examine the treatment process of physical therapy patients. In 2.2 we examine the scheduling process of the OR. In 2.3 we examine the uncertainties present in the OR schedule. In 2.4 we examine the scheduling process of physical therapy. In 2.5 we measure the current performance of the physical therapy scheduling process. In 2.6 we provide an overview of the identified bottlenecks and a demarcation of the scope. In 2.7 we end the chapter with a conclusion.

Contents

2.1 Treatment process

In this section we examine the treatment process of physical therapy inpatients. Physical therapy inpatients start their treatment process as orthopaedic patients. Therefore, we start this section with an overview of the orthopaedic chain in 2.1.1. In 2.1.2 we identify the different types of physical therapy patients. In 2.1.3 we discuss treatment protocols, which is key to the number of physical therapy treatments a patient receives. Finally, we look at demand for inpatient physical therapy over 2014 in 2.1.4.

2.1.1 The orthopaedic chain

Orthopaedic patients go through a process known as the orthopaedic chain, see Figure 5. Orthopaedic patients with the highest urgency classification are defined as acute patients and can enter the process in multiple phases. For the different urgency classifications, see Figure 6.

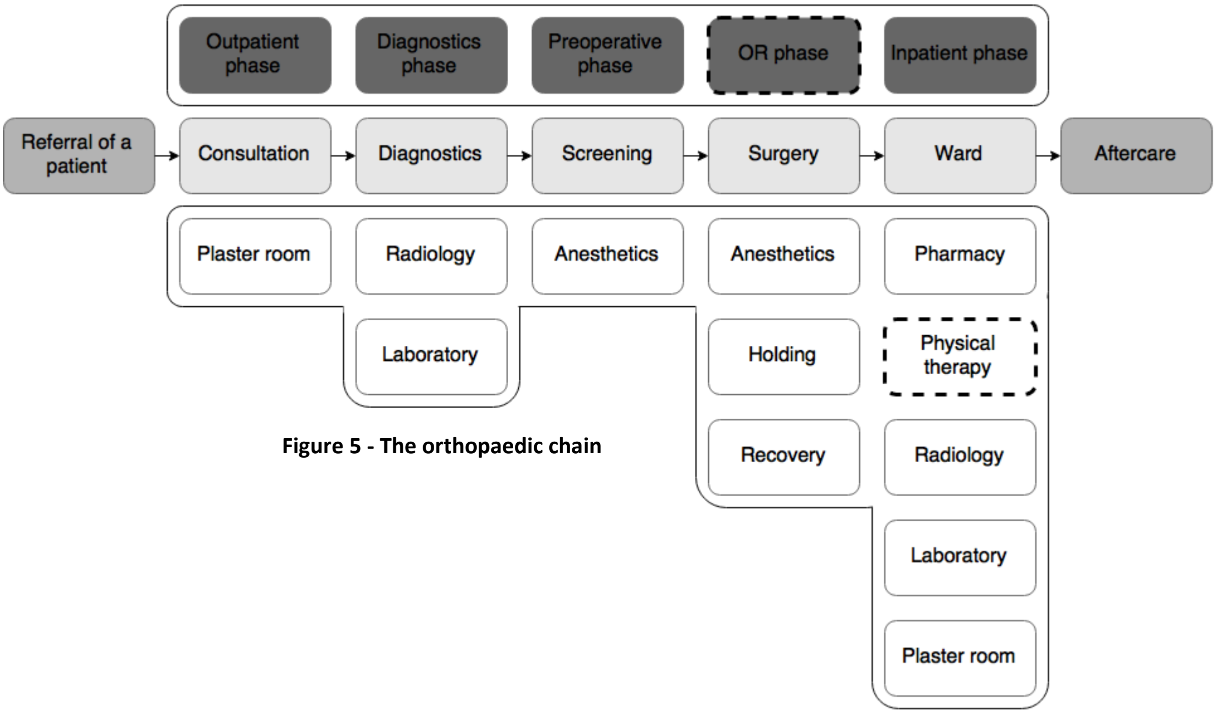


Figure 5 - The orthopaedic chain

Outpatient phase

Orthopaedic patients enter the process via a referral of another specialist or a general practitioner. After the referral, the patient has a consultation with a surgeon to assess the injury.

Diagnostics phase

In the diagnostics phase the injury is assessed with relevant equipment, for instance with an x-ray at the radiology department.

Preoperative phase

If the patient requires surgery, the patient is subjected to a screening in the preoperative phase. During the screening, all the information required for the surgery is collected and the patient is informed how he or she can contribute to the success of the surgery.

Urgency category	Norm
Elective	Treated within 1 year
2 Months	Treated within 2 months
1 Month	Treated within 1 month
Emergency	Treated within 2 weeks
Acute	Treated within 48 hours

Figure 6 - Urgency classifications for orthopaedic patients

OR-phase

In the OR-phase, the patient receives surgery.

Inpatient phase

In 2014, 73% of the orthopaedic patients received one or more physical therapy treatments during their postoperative stay at the ward, known as inpatient physical therapy.

2.1.2 Physical therapy treatments

SMK distinguishes five types of physical therapy, which are portrayed in Figure 7.

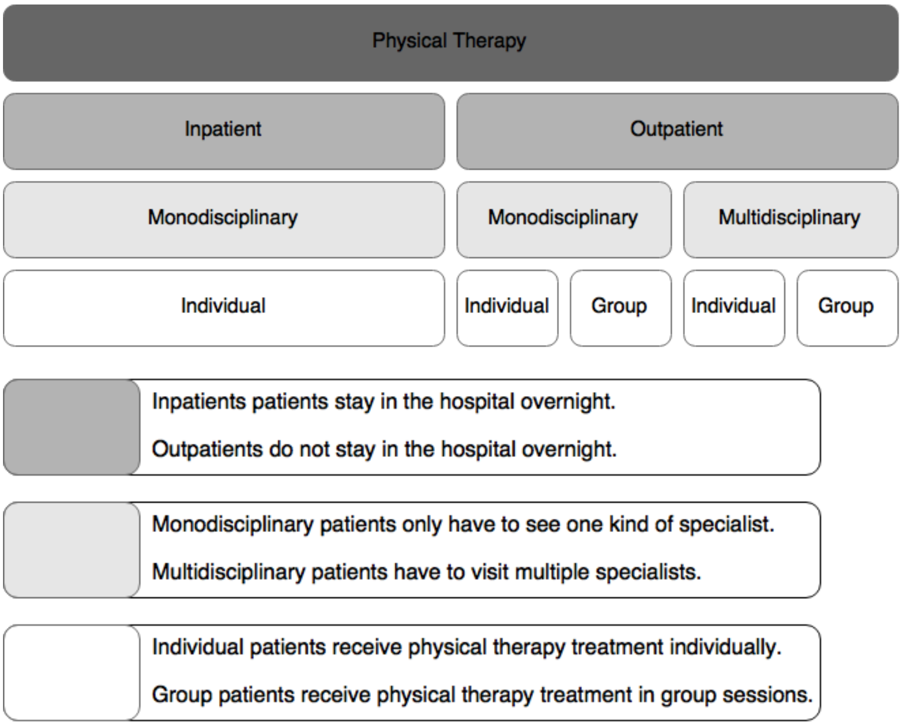


Figure 7 - Physical therapy patient classifications [4]

Approximately 60% of demand for physical therapy consists of inpatient physical therapy [4]. Physical therapy inpatients require a specific number of treatments after being treated in the OR. The number and frequency of the treatments is specified in a treatment protocol. Contrary to inpatients, outpatients do not require physical therapy treatments at fixed time intervals. This means that outpatients can be planned more flexibly.

2.1.3 Treatment protocols

Care-paths determine the treatment trajectory for physical therapy inpatients. A care-path is a multidisciplinary protocol in which all the activities of different specialties, over a certain timespan and for a specific patient group, have been defined. This ensures that different departments work together, it is clear for the patient what his or her recovery process is going to look like and results can be tested objectively according to set targets. For each available surgical procedure a care-path has been defined, such that a planning can be made and the patient knows what to expect from SMK [2]. An example of a treatment protocol for a physical therapy inpatient is given in Figure 8.

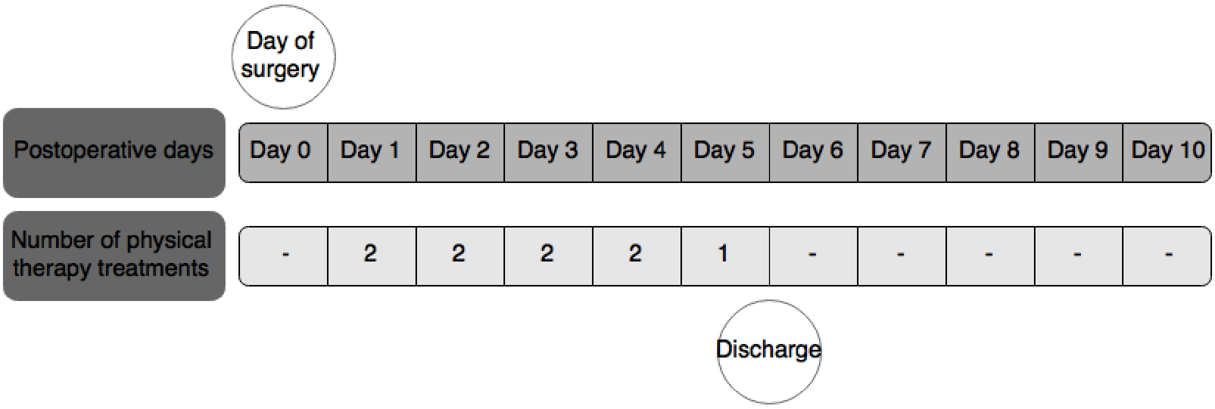


Figure 8 - Example of a treatment protocol

In the treatment protocol above we can see that this patient does not receive physical therapy on the day of surgery, also known as day 0. One day after the surgery, the patient receives two physical therapy treatments. In total, this patient will receive nine physical therapy treatments dispersed over six postoperative days. There are 578 different orthopaedic procedures that are followed by inpatient physical therapy treatments and thus have a matching inpatient physical therapy treatment protocol.

2.1.4 Protocolised demand

Demand for inpatient physical therapy is calculated by matching the performed surgeries on each day with the related physical therapy treatment protocols. This shows us how many physical therapy treatments follow from each surgery on each postoperative day. Afterwards, we iteratively add the number of inpatient physical therapy treatments per day. The result is referred to as the protocolised demand for inpatient physical therapy per day and provides insight in demand for inpatient physical therapy if all patients are treated according to their protocols. Figure 9 shows the protocolised demand for inpatient physical therapy in treatments per day in 2014.

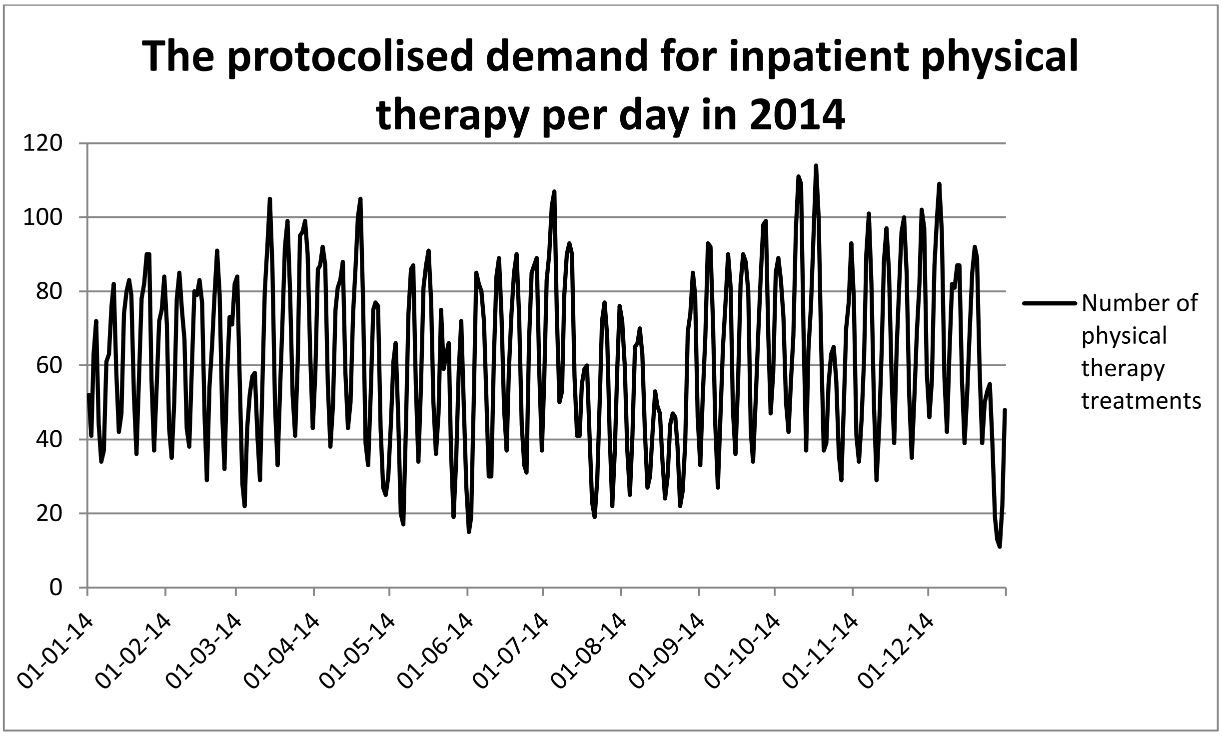


Figure 9 - Protocolised demand for inpatient physical therapy in 2014 per day [14]

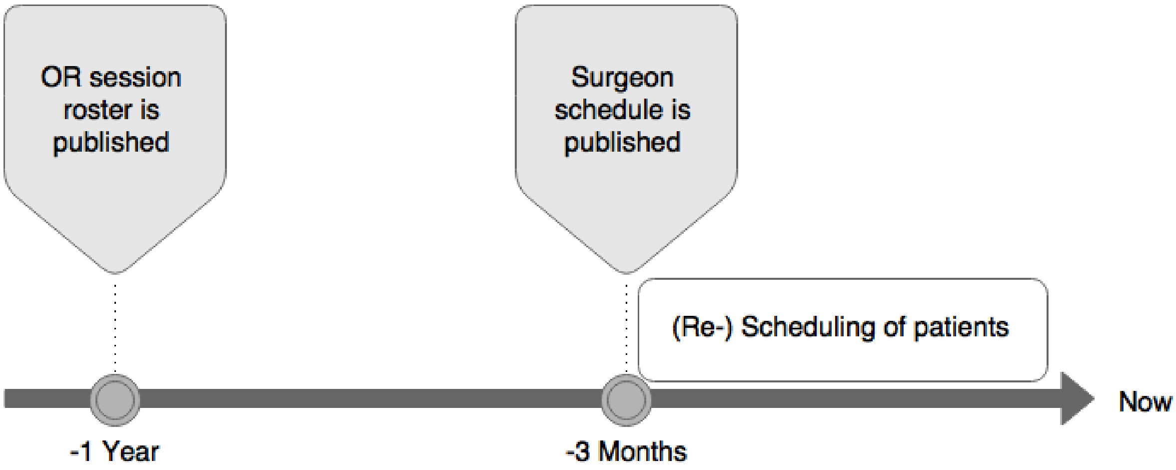
Figure 9 shows that demand for inpatient physical therapy in 2014 was variable. Unless there is an accurate forecasting technique and the personnel roster is flexible, the variable demand foreshadows a mismatch between supply and demand.

2.2 OR scheduling

The OR schedule determines which patients will receive surgery on a specific day. In combination with the related physical therapy treatment protocols, this is a valuable source of information regarding demand for inpatient physical therapy. In 2.2.1 we examine the relevant events in the OR scheduling process and place them on a timeline. In 2.2.2 we zoom in on the scheduling of patients into the ORs.

2.2.1 OR scheduling events in a timeline

The events of the OR scheduling process are displayed in Figure 10.



Event	Frequency	Description
OR session roster is published	Yearly	The OR session roster determines how many ORs are available on each day of the next year.
Surgeon schedule is published	Monthly	The surgeon schedule determines which surgeon will perform surgery in which OR on which day of the month, 3 months from now.
(Re-) Scheduling of patients	Daily	Patients can be planned into the OR schedule until the day of surgery.

Figure 10 - Timeline of events in the OR scheduling process

2.2.2 Scheduling of patients

Figure 11 shows the manner in which orthopaedic patients are planned over the span of four months.

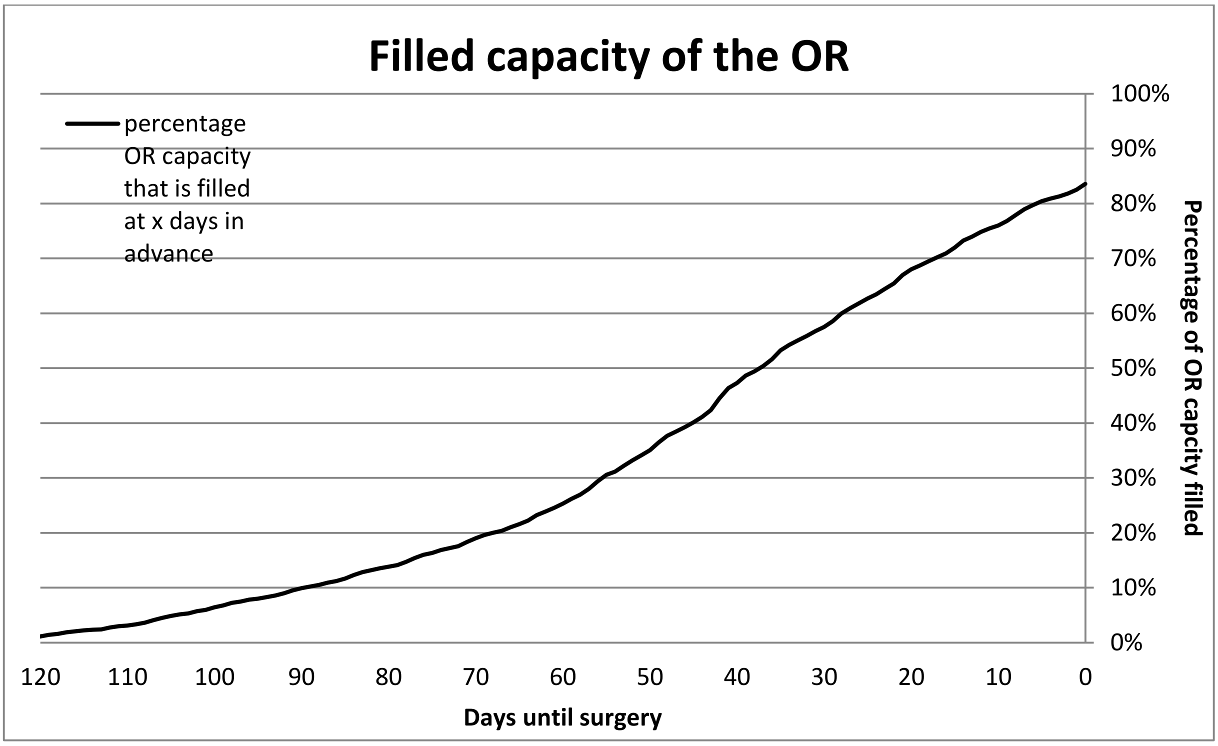


Figure 11 - The percentage of capacity of the OR that are planned, in time [14][4]

Figure 11 shows that 58% of the OR capacity was occupied one month in advance. It also shows that 83.6% of the OR capacity was occupied at the day of surgery. This means that 69.4% ($\frac{0.58}{0.836} = 0.694$) of the surgeries that were eventually executed, were planned at least one month before the surgery. It should be noted that Figure 11 only contains the surgeries that were eventually executed. It is therefore possible that the planned percentage of the OR capacity was higher at certain times, but appointments were cancelled or replaced with different surgeries. We discuss modifications in the OR schedule more extensively in 2.3.

2.3 Uncertainty in the OR schedule

There are several factors of uncertainty in the OR schedule that may affect demand for inpatient physical therapy. This section revolves around Figure 12, which shows the different causes of uncertainty in the output of the OR. First, we discuss how available capacity in the OR schedule affects the output of the OR in 2.3.1. Second, we examine how modifications in the OR schedule affect the output of the OR in 2.3.2. Third, we discuss the influence of human impact in the OR scheduling process in 2.3.3. Finally, we examine at what moment modifications in the OR schedule take place in 2.3.4.

[4] The data used was obtained over the period 3rd of March 2014 till 29th of May 2015

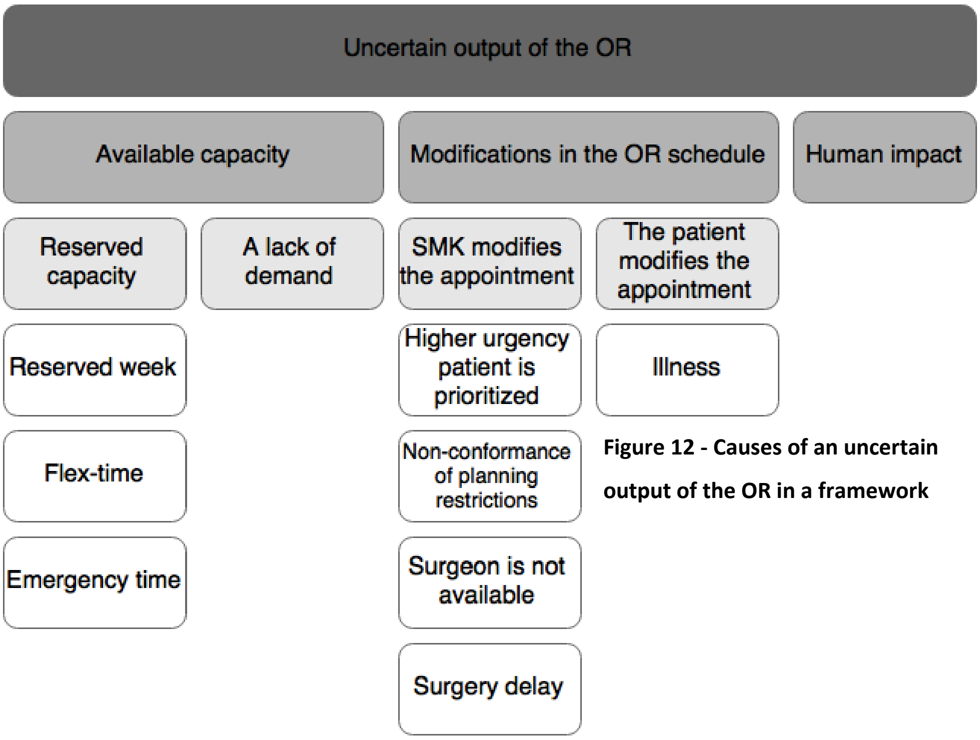


Figure 12 - Causes of an uncertain output of the OR in a framework

2.3.1 Available capacity

When we consider the OR schedule at a certain moment, some capacity may still be available to schedule surgeries. Available capacity means an uncertain output, because different surgeries can still be scheduled. Available capacity in the OR schedule can have two causes. Namely, the capacity is reserved or there is currently not enough demand to fill the available capacity in the OR schedule.

Reserved capacity

Reserved capacity can be caused by a reserved week, flex-time or emergency time. We elaborate on these terms below.

Reserved week

One week of every month remains unplanned until eight weeks before the surgery date. This week is called a reserved week and its purpose is to restore the balance between the OR schedule and demand. For instance, when there are more patients that require knee surgery than expected, more OR capacity is allocated to treat knee patients.

Flex-time

Due to the possibility of the arrival of acute patients, the OR planners reserve capacity in the OR schedule. This is referred to as flex-time and takes up a total of one and a half hours of OR time per day.

Emergency time

Due to the possibility of the arrival of emergency patients in the last two weeks before the surgery date, the OR planners reserve capacity in the OR schedule. This is referred to as emergency time. The amount of emergency time that is reserved depends on the operating surgeon.

Lack of demand

Although uncommon, capacity in the OR schedule may remain unscheduled due to a lack of demand.

2.3.2 Modifications in the OR schedule

The fact that a planned surgery can be rescheduled causes uncertainty in the OR schedule. First, we define a performance measurement for reschedules. Second, we look at the different causes of reschedules.

Definition

We determine the reschedule probability as follows:

$$Reschedule\ probability\ = \frac{Number\ of\ reschedules}{Number\ of\ appointments}.$$

We use this definition, because when we observe an arbitrary scheduled appointment, we do not know whether this is the first appointment of the patient.

Example

In Figure 13, appointments A2, B3, C1 and E2 were completed. The other appointments were cancelled or rescheduled. According to this information, the reschedule probability of an arbitrary appointment would be equal to $\frac{5\ Reschedules}{9\ Appointments} = 56\%$. With this definition we find that, on average, 22.1% of the orthopaedic appointments were rescheduled[5].

[5] Over the period August 2013 – July 2015

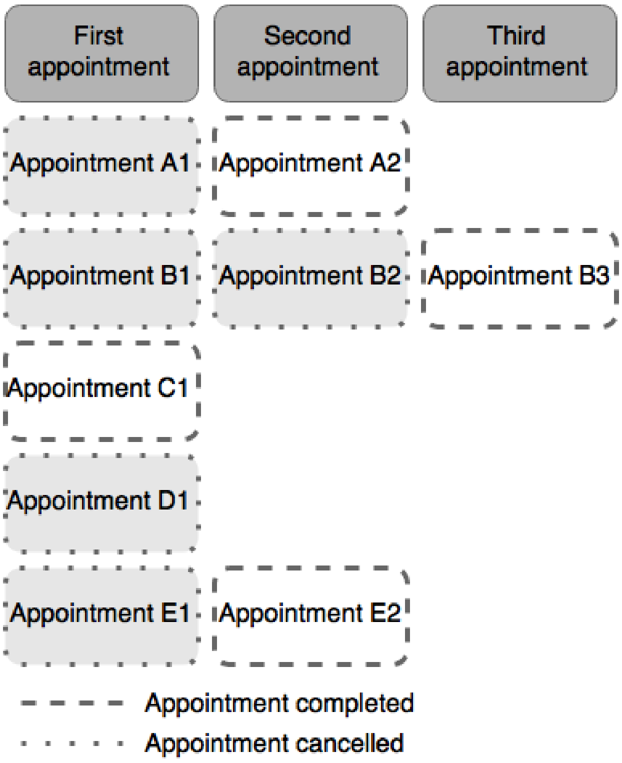


Figure 13 - An example to define the percentage of appointments that is rescheduled

SMK modifies the appointment

We discuss the different causes to modify an initial appointment below.

Urgency related

An emergency patient requires surgery within two weeks. If a new emergency patient enters the hospital and the OR capacity for the first two weeks is occupied, this patient has priority over lower urgency patients and one or more patients will have to be rescheduled to create an opening for the emergency patient. Because it is undesirable to reschedule a single patient for a large amount of time, this may cause a ripple effect where multiple patients are moved for a smaller amount of time. It seems evident that this has major consequences for the uncertainty in the output of the OR. This also happens for lower priority urgency categories, but this is less common.

Non-conformance of planning restrictions

There is a long list of restrictions that the OR planners have to comply with when planning patients in the OR schedule, for instance a limited availability of certain orthopaedic instruments. It may occur that an OR schedule is created and a restriction was exceeded. When this happens, a patient will have to be rescheduled to create a valid OR schedule.

Surgeon is not available

It should be noted that the surgeon is formally committed to the roster when it is made three months in advance. The surgeon can therefore only cancel with a legitimate reason, such as illness. The consequences of this can be quite severe, especially when there is no surgeon available to replace the cancelled surgeon. It can also happen that there is no surgeon available that can execute the same procedures that were planned for that day, which results in rescheduling all the planned surgeries.

Surgery delay

Surgery durations are variable and may take longer than initially expected, which can cause a delay in the OR schedule. When this delay becomes too large, a planned surgery has to be cancelled to avoid overtime.

The patient modifies the appointment

The main reason for a patient to modify the appointment is in case of illness.

2.3.3 Human impact

There is also human impact on uncertainty in the OR scheduling process. Human actions can be unpredictable, whereas a computer will always apply the same algorithm, which causes the decisions made to be more predictable. This, for instance, applies to OR planners, who schedule surgeries in the OR schedule, and to surgeons, who determine the urgency classification of an orthopaedic patient.

2.3.4 Rescheduling in a time perspective

Not all modifications occur evenly throughout the time span of three months. For instance, delay in the surgery schedule will most likely be known on the day of the surgery itself. Figure 14 shows that on the day of surgery, 22.1% of the appointments are rescheduled. We can deduce that 47.6% $(\frac{10.5\%}{22.1\%})$ of the modifications occur more than 30 days before the surgery. This means that 52.4% of the reschedules happen in the last 30 days. Therefore, we can conclude that demand will remain uncertain until the last few weeks before the surgery date.

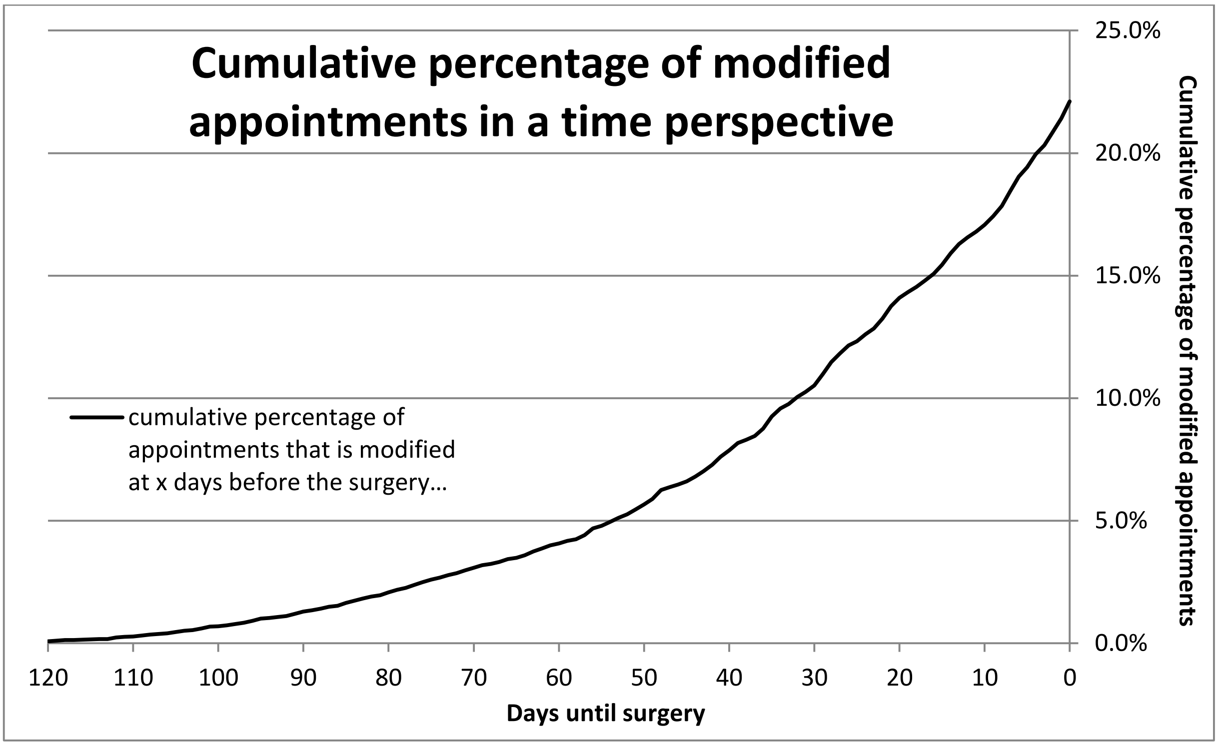


Figure 14 - The cumulative percentage of modified appointments [14][6]

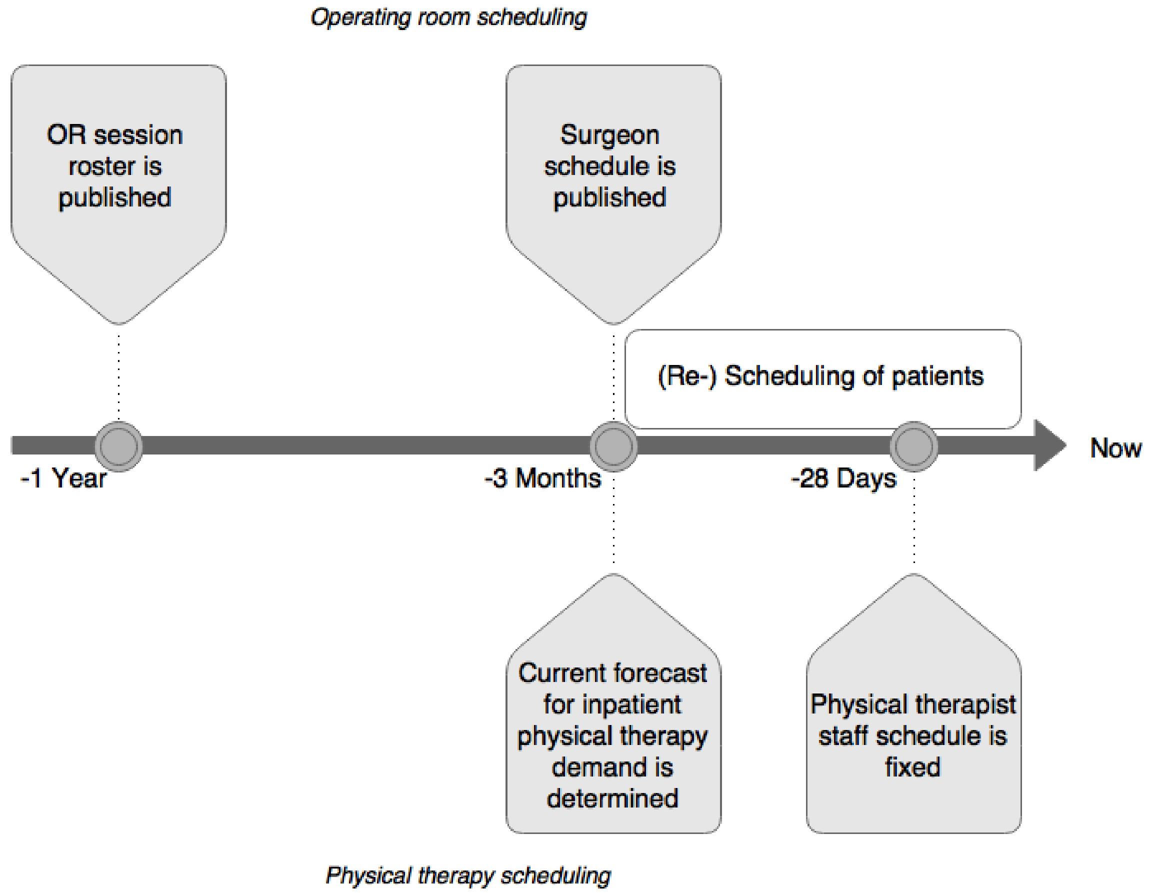
2.4 Physical therapy scheduling

In this section we examine the scheduling process of physical therapy. In 2.4.1 we use Figure 10 from 2.2.1 as a basis to gain insight in the physical therapy scheduling events in relation to the OR scheduling process. In 2.4.2 we examine the scheduling process of physical therapists. In 2.4.3 we examine how SMK currently forecasts demand for inpatient physical therapy.

2.4.1 Physical therapy scheduling events in a timeline

The relevant events of the OR- and physical therapist scheduling process are displayed in Figure 15.

[6] Based on data obtained over August 2013 – July 2015



Event	Frequency	Description
Current forecast for inpatient physical therapy demand is determined	Monthly	The current forecast is based on the published surgeon schedule and determines the demand for inpatient physical therapy for each day of the month, 3 months from now.
Physical therapist staff schedule is fixed	Daily	28 days in advance the physical therapist schedule is formally fixed. From this point forward it can only be altered in consultation with the employees.

Figure 15 - Timeline of events in the OR- and physical therapy scheduling process

2.4.2 Inflexible supply

The number of physical therapist staff available on a certain day is based on a fixed personnel roster, which can be adjusted at least 28 days in advance. Demand for inpatient physical therapy is still uncertain at that time, since the OR schedule can be altered until the day itself. Evidently, the physical therapists experience days with over- and undercapacity, which foreshadows an inefficient employee schedule.

2.4.3 Current forecast

Currently, the physical therapy department is running a pilot to predict demand for inpatient physical therapy with a forecast. This forecast predicts the surgeries that will be executed in the OR, based on two decisions in the orthopaedic chain. Namely, the number of ORs that is available on a specific day, which is determined one year ahead, and the operating surgeons on that day, which is determined three months ahead. The forecast matches the predicted surgeries with the physical therapist treatment protocols to determine the number of inpatient physical therapy treatments that follows from an OR roster.

2.5 Current performance

In 2.5.1 we determine the relevant performance measures. In 2.5.2 we measure the performance of the scheduling process of physical therapists. In 2.5.3 we measure the performance of the current forecast. In 2.5.4 we discuss the assumptions that were made.

2.5.1 Performance measures

To establish the need for research we verify two aspects. The questions that need to be answered to verify these aspects are presented below.

1. The physical therapy department struggles to determine the correct number of staff to treat inpatients (2.5.2).
    - Is there enough capacity to treat physical therapy inpatients according to protocol?
    - To what extent are physical therapy inpatients treated according to protocol?

If there is enough capacity to treat the physical therapy inpatients according to protocol, but patients are not treated according to protocol, this is an indication that the physical therapy department indeed struggles to determine the right number of staff to treat inpatients.

2. The current forecast is not accurate enough to determine the correct number of staff required (2.5.3).
    - Does the current forecast provide sufficient information to accurately match supply and demand for inpatient physical therapy?

2.5.2 Physical therapist performance

To analyse the physical therapist performance we first answer the following question:

Is there enough capacity to treat physical therapy inpatients according to protocol?

To gain insight in this matter, we compare the available capacity according to the personnel roster with demand for inpatient physical therapy. This illustrates whether there is enough capacity to cope with demand.

Demand

The physical therapist personnel roster contains staff that treats both inpatients and outpatients. It is currently not known how much FTE is available for inpatient physical therapy. Therefore, we choose to compare the personnel roster with the total demand for physical therapy. First, we determine the protocolised demand for inpatient physical therapy, similar to in 2.1.4. To determine demand for outpatient physical therapy we measure the completed number of physical therapy treatments. All the calculations in this section are based on data from 2014.

$Total\ physical\ therapy\ demand = outpatient\ physical\ therapy\ demand + protcolised\ inpatient\ physical\ therapy\ demand = 4{,}331\ hours + 7{,}550\ hours = 11{,}881\ hours.$

Capacity

In order to effectively compare the available staff with demand, we have to translate the roster capacity to direct time, since direct time is the actual time available to treat the patient. Figure 16 below presents a breakdown structure of the different time classifications according to set norms (e.g. direct time should be 65% of the net available time).

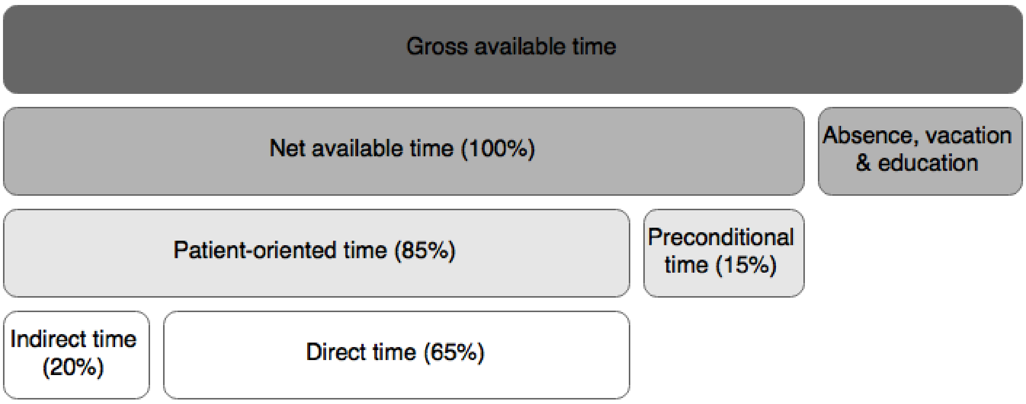


Figure 16 - Breakdown of time classifications [4]

The physical therapy department employs the following figures:

$Net\ available\ time\ per\ year = 1{,}552\ hours\ per\ 1\ FTE.$

$Total\ physical\ therapy\ FTE\ in\ 2014 = 13.78.$

$Total\ net\ available\ time\ per\ year = 13.78 * 1{,}552 = 21{,}387\ hours.$

The percentage of direct time is multiplied with the total net available time to obtain the direct time that was available in 2014.

$Percentage\ of\ direct\ time = 65\%.$

$$Total\ direct\ time\ available\ in\ 2014 = total\ net\ available\ time * percentage\ of\ direct\ time = 21{,}387 * 65\% = 13{,}901\ hours.$$

Capacity vs demand

In Figure 17 we compare the total direct time available with the total demand for physical therapy and the amount of time that patients were actually treated.

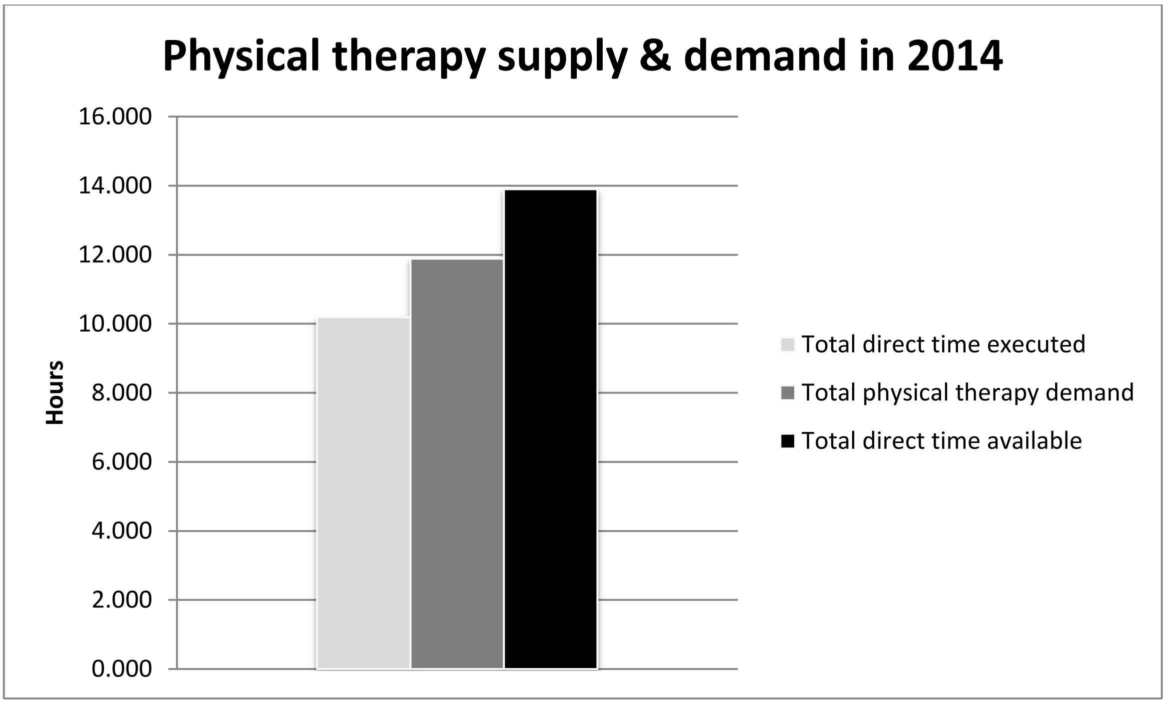


Figure 17 - Physical therapy capacity & demand in 2014 [14]

Yes, there is enough capacity to treat physical therapy inpatients according to protocol. From Figure 17 we conclude that there is enough capacity available to cope with demand, when treating physical therapy inpatients according to the predetermined protocols. Assuming perfect information, there would have been an average overcapacity of 17%.

The second question we examine is:

To what extent are physical therapy inpatients treated according to protocol?

To determine to what extent inpatients are treated according to the predetermined protocols we compare the protocolised demand for inpatient physical therapy with the executed inpatient physical therapy treatments. The result is presented in Figure 18 and illustrates to what extent physical therapy inpatients received care according to their protocol.

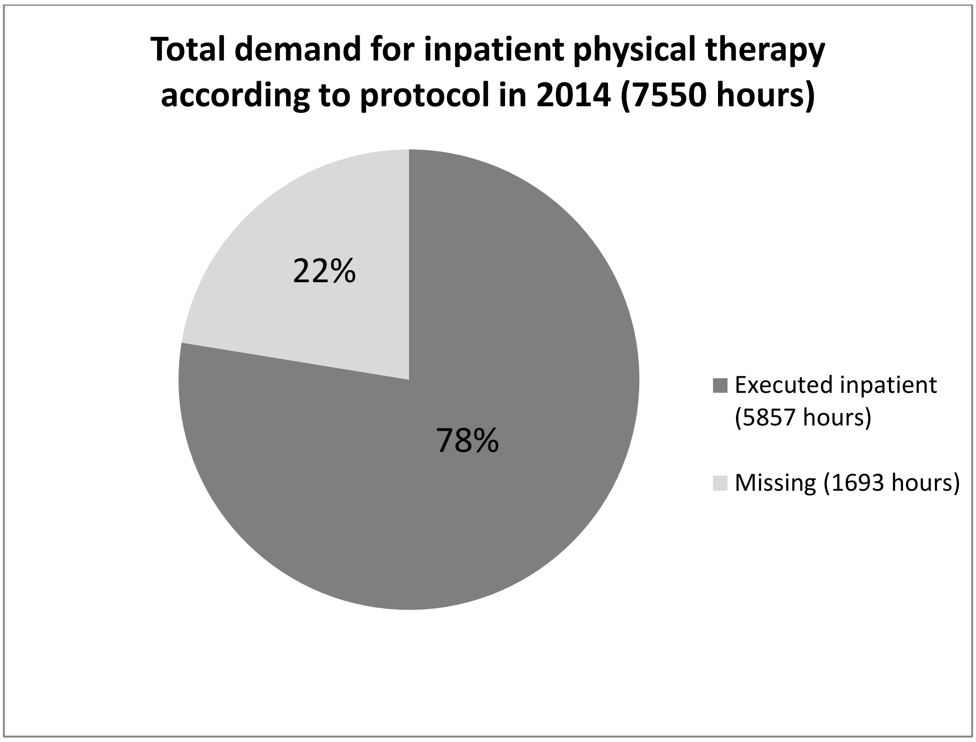


Figure 18 – Protocolised demand for inpatient physical therapy and executed inpatient physical therapy treatments [14]

Physical therapy inpatients received 22% fewer treatments than defined in the treatment protocols. In Figure 18 we can see that physical therapy inpatients received 22% fewer treatments than defined in the protocols, even though there was enough capacity to actually treat these patients according to protocol.

We conclude that the physical therapist department struggles to effectively match the supply of physical therapists and demand for inpatient physical therapy. This originates from a lack of available information regarding the patient arrival process and a lack of effectiveness in dealing with the patient flow coming from upstream, in this case the OR.

2.5.3 Current forecast performance

If the current forecast provides sufficient information to match supply and demand, the problem is solved. Therefore, we answer the following question:

Does the current forecast provide sufficient information to accurately match supply and demand for inpatient physical therapy?

The current forecast is performed after the surgeon schedule is published. This occurs every month, three months in advance. Due to a lack of available information three months before the surgery date, there are still multiple surgeries that may be performed in the OR. Therefore the current forecast provides a probability distribution of the expected surgeries that can follow from the

OR schedule. This is translated to a probability distribution of demand for inpatient physical therapy with the inpatient physical therapy protocols, which determines the number of inpatient physical therapy treatments on each postoperative day.

In Figure 19 we translated the probability distribution of demand for inpatient physical therapy over 2014 to a confidence interval. Figure 19 can be interpreted as follows, in 100% of the cases the required number of FTE to treat all patients according to protocol is higher than 3.7 and lower than 10.6 FTE. Similarly, in 10% of the cases the required number of FTE to treat all patients according to protocol is lower than 6.1 and higher than 3.7.

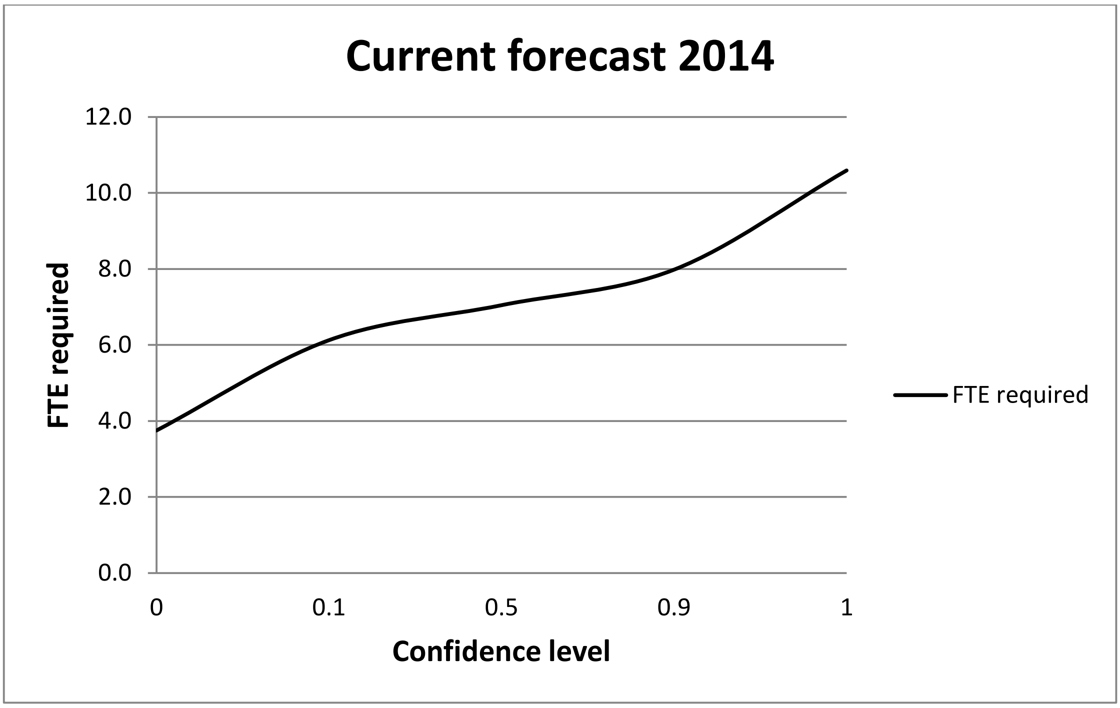


Figure 19 - Results of the current forecast over 2014 [4]

In order to be able to treat all inpatients according to protocol, the physical therapist department needs to have enough staff in 100% of the scenarios. At a confidence level of 1, the FTE required equals 10.6. This is similar to

$$10.6\ FTE * 1552\ hours\ per\ FTE * 65\%\ direct\ time = 10{,}693\ hours.$$

In the previous section we showed that the total demand for inpatient physical therapy when treating all patients according to protocol, was equal to 7,550 hours over 2014. Thus, an extension of the current forecast to include additional information that becomes available after the surgeon schedule is published, can reduce the required number of FTE by up to 29%[7].

[7] Based on data obtained over 2014

No, the current forecast does not provide sufficient information to accurately match supply and demand for inpatient physical therapy.

2.5.4 Assumptions

In the calculations above, several assumptions were made. Below we discuss the assumptions and the associated arguments that explain why the assumption is considered valid.

Assumption 1: The treatment protocol is representative of the treatment that the patient actually receives, also known as the personal treatment plan.

Argument 1: SMK wants to treat patients according to treatment protocols as determined in the long-term plan.

Assumption 2: The roster reflects the average available capacity.

Argument 2: In order to not exceed budget limits, it is critical for the roster to be a realistic projection of the actual number of hours the personnel is at work.

Assumption 3: Data from 2014 is representative for the current situation.

Argument 3: Data from 2014 is the most recent available data for a whole year and is least affected by changes in case-mix, physical therapist staff and other factors during the past months.

Assumption 4: All inpatient physical therapy treatments take 20 minutes.

Argument 4: In 2014, the average inpatient physical therapy treatment duration was 20.53 minutes and 16380 out of 17649 treatments took exactly 20 minutes.

2.6 Overview of bottlenecks and demarcation of the scope

In 2.6.1 we provide an overview of the identified bottlenecks. In 2.6.2 we demarcate the scope of the research using a hierarchical planning framework.

2.6.1 Overview of bottlenecks

In 2.5 we established that SMK has difficulties to match supply of physical therapist staff with the arrival of physical therapist inpatients. The identified causes are displayed in Figure 20.

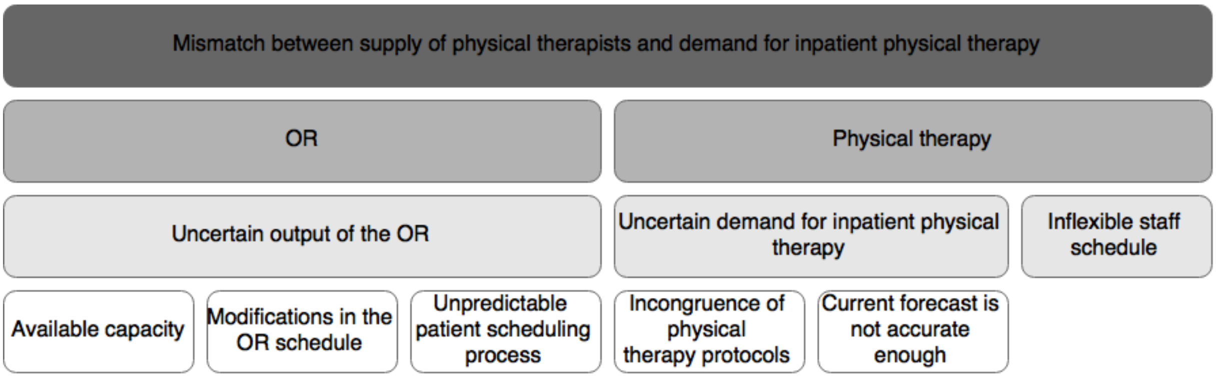


Figure 20 - Overview of bottlenecks

Uncertain output of the OR

In 2.2 we saw that the uncertain output of the OR has three causes. In this section we discuss how these causes impact this research.

Available capacity

In this research we predict demand for inpatient physical therapy by determining what the OR schedule will look like at the day of surgery, referred to as the final OR schedule. This means that we have to predict which surgeries will fill the available capacity. If the amount of available capacity is lower at the moment the forecast is performed, this will increase the accuracy of the forecast.

Modifications in the OR schedule

When we predict the output of the OR, we have to take into account that modifications will take place in the OR schedule.

Unpredictable patient scheduling process

Predicting which surgeries will take place is related to the patient scheduling process. We were unable to identify a standardised patient scheduling procedure. The absence of a standardised patient scheduling procedure causes this process to be uncertain.

Uncertain demand for inpatient physical therapy

There are several bottlenecks in the physical therapy department that make it more difficult to determine demand for inpatient physical therapy. Here we discuss those bottlenecks.

Incongruence of physical therapy protocols

As we saw in 2.5.2, the physical therapy department is currently not treating patients according to the established protocols. There are several consequences of this that harm SMK. First, this reduces the possibility for different departments to coordinate their planning. Second, it is unclear for the patient what his or her recovery process is going to look like. Finally, it is harder to test results according to set targets.

Furthermore, the personal treatment plan of each orthopaedic patient is currently unknown. This is valuable information when trying to determine demand and we advise to start collecting this information in the near future.

Finally, the physical therapy department employs 47 unique treatment protocols. A high number of possible treatment trajectories causes uncertainty in demand for inpatient physical therapy.

Current forecast is not accurate enough

In 2.5.3 we ascertained that the current forecast is not accurate enough to match supply and demand for inpatient physical therapy.

Inflexible staff schedule

The current physical therapist staff schedule is based on a fixed roster, even though demand for inpatient physical therapy is variable (Figure 9). The physical therapy department will only benefit from an accurate forecast if the staff schedule can be adjusted to match the forecast.

2.6.2 Demarcation of the scope of research

In this section we demarcate the scope of the research.

Tactical level

There is a need for an extension of the current forecast. In this research we extend the current forecast to include information that becomes available after the surgeon schedule is published. At that point demand is still uncertain because patients are continuously (re)scheduled until one day before the surgery date. Supply remains uncertain until 28 days before the surgery date. Because we forecast demand with the OR schedule and supply and demand are uncertain, this research focusses on the *tactical level*. Matching supply of physical therapists with demand for inpatient physical therapy concerns the field *resource capacity planning*. With this information, we position the scope of the research in the framework of Hans et al. [26] in Figure 21.

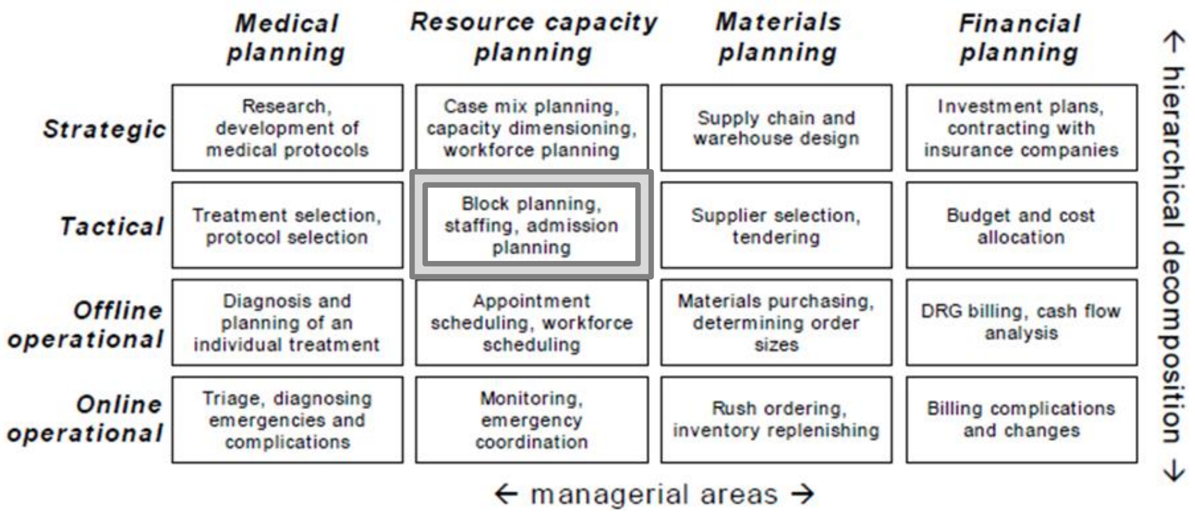


Figure 21 - Scope of the research portrayed in the hierarchical planning framework by Hans et al. [26]

Scope within physical therapy

This research focusses on the effect that the output of the OR has on one of the downstream departments, more specifically the physical therapist department. Within the physical therapist department, the OR output solely affects demand for inpatient physical therapy. Therefore, we demarcate the scope to focus on inpatient physical therapy only. SMK has also indicated that this is one of the departments that is struggling most to match supply and demand.

2.7 Conclusion

In this chapter we examined the treatment and scheduling process of physical therapy inpatients. Physical therapy inpatients start their treatment process as orthopaedic patients and receive physical therapy treatments during their postoperative stay according to the physical therapy protocol that is related to their surgery procedure. We established a need for research and showed that the required number of FTE to treat all inpatients according to protocol can be reduced by up to 29% by including additional information in the current forecast. Additional information that is available consists of scheduled surgeries in the OR schedule. However, we should take into account that the OR schedule may still change until the day of the surgery through cancellations and the scheduling of additional surgeries.

3. Literature

This chapter presents a literature study to identify possible approaches to forecast demand for inpatient physical therapy. In 3.1 we search the scientific literature for possible solution approaches to cope with demand uncertainty. In 3.2 we examine quantitative demand forecasting approaches. In 3.3 we provide an overview of the literature study in a framework and discuss the main findings. In 3.4 we end the chapter with a conclusion.

Contents

3.1 Demand uncertainty

In this section we search the scientific literature for possible solution approaches to cope with demand uncertainty. In 3.1.1 we examine literature on demand uncertainty in healthcare. In 3.1.2 we define the problem in this research with a common term in literature. In 3.1.3 we examine literature to cope with demand uncertainty.

3.1.1 Demand uncertainty in healthcare

The majority of scientific research on the area healthcare logistics has been done on the planning and scheduling of operating rooms [18; 24; 30; 37], due to the dogma of this being the greatest source of revenues and expenses [11]. However, how these OR schedules affect other departments has received far less attention. Back in 1988, Smith-Daniels et al. [40] already pointed out that there would be a need for research focused on the planning and integrating of capacity units in healthcare. In a more recent paper, Erdogan et al. [18] state that, although a vast amount of literature is available considering the uncertainty in surgery durations, uncertainty regarding demand is still largely unexplored. Yet, an inability to meet demand has more serious consequences in healthcare than in other services [29].

3.1.2 Demand uncertainty at SMK

According to Ernst et al. [19], personnel scheduling is the process of constructing work timetables for employees such that an organisation can satisfy demand for its goods or services. This is the area that SMK is struggling to deal with. Therefore, we say that the subject of this research falls into the category of the *Employee Scheduling Problem* (ESP), also referred to as *staff-shift scheduling* [28]. The employee scheduling problem is a widely researched area in the healthcare sector [8; 10], but in other sectors as well [9; 16; 42]. The first step to solving the ESP is executing a demand modelling study that collects and uses historical data to forecast demand [19].

3.1.3 Coping with demand uncertainty

In this section we examine methods to cope with demand uncertainty.

Demand forecasting

According to Archer [5], forecasts provide information to guide decision makers in the scheduling process of employees. Therefore forecasting is key to designing an effective employee schedule. There are two types of approaches of demand forecasting known in literature [5; 38; 44]. The first is a quantitative approach, which includes model construction and can be used to analyse the available data. The second is qualitative and is based on intuition and practical knowledge of experts in the field, which often leads to a less accurate result. An example of quantitative demand forecasting in healthcare can be found in the paper by Kortbeek et al. [33].

Finarelli & Johnson [21] define nine steps to develop an effective quantitative demand forecasting model for healthcare. Cote & Tucker [15] discuss four common procedures for demand forecasting in healthcare using historical data. Jones et al. [31] analyse different forecast models to determine the accuracy. The results indicate that regression techniques are a reasonable approach to forecast the daily patient volumes in the emergency department.

Van den Bergh et al. [42] advise to use a stochastic approach to forecast demand, since real-world scheduling problems have to deal with different sources of uncertainty. In situations where uncertainty has a strong effect on the personnel schedule, such as a volatile demand or last-minute changes, it could prove beneficial to incorporate this uncertainty in the decision-making process. Adan et al. [1] and Min & Yih [35] also advocate the use of stochastic models in situations with uncertainty and multiple departments.

Quantifying the output of a schedule

Fügener et al. [23] suggest a method to integrally optimise the OR schedule. It becomes clear in this article that forecasting the effect of the OR on one of the downstream departments is only a minor, yet important, piece of the puzzle to integrally optimise the OR schedule.

A similar research by Vanberkel et al. [43] states that the total number of patients in recovery at a certain day can be determined using discrete convolutions. We can determine a probability distribution of the surgeries that will be performed in each OR. By matching the postoperative physical therapy treatment protocols with the probability distribution of surgeries, we can determine a probability distribution of the number of inpatient physical therapy treatments on each postoperative day per OR session. Afterwards, we can iteratively perform discrete convolutions on the probability distributions of all the ORs to find a probability distribution of the total demand for inpatient physical therapy per day.

Disruptions in a schedule

Alaeddini et al. [3] determine the no-show probability of a patient based on certain patient characteristics using historical data and a causal model. They state that they only consider one type of disruption in their research, namely no-shows, where it may be interesting to consider other disrupting factors in a schedule as well, such as cancellations. Hulshof et al. [28] define rescheduling as follows: *"Rescheduling may involve moving scheduled surgeries from one operating room to another and delaying, cancelling or rescheduling surgeries"*.

3.2 Quantitative demand forecasting approaches

In 3.1 we saw that a quantitative forecasting approach is more accurate than a qualitative forecasting approach. A quantitative approach can be divided into two different categories [5]. The first category is times-series models, which involves a statistical analysis of historical data. The second category is causal models, which is based on independent variables related to the dependent variable used to forecast demand. In this chapter we zoom in on the two types of quantitative forecasting approaches. In 3.3.1 we examine times-series models and in 3.3.2 we examine causal models.

3.2.1 Times-series models

One of the more meaningful approaches in times-series models is the use of exponential smoothing to produce a weighted moving average of past data [5]. The weights are assigned in geometric progression, where recent data receives heavier weights. This means that older data is discounted proportionally. In this way extrapolation is used to forecast demand.

3.2.2 Causal models

Causal models involve the analysis of independent variables related to the dependent variable, which can be used to forecast demand.

Selecting independent variables

According to Castillo [12], the best way to select an independent variable is based on expertise and knowledge. Because no studies were found that use independent variables to predict the reschedule probability of an orthopaedic patient, we will use statistical techniques in Chapter 4 to select the independent variables.

Armstrong et al. [6] suggest that seasonal factors combined with uncertainty can harm the accuracy of a forecast. Chen & Boylan [13] state that the accuracy of the forecast decreases when seasonal factors are extrapolated from fewer than three years of data. Because we only have access to two years of historical data, seasonal factors are excluded from this research.

Univariate analysis

A univariate analysis can be used to examine a significant relation between individual independent variables and the reschedule probability of an appointment. A powerful univariate statistical tool is the chi-square test [45]. Because the chi-square test is sensitive to high sample sizes and produces a statistically significant result more often in such cases [7; 22], it is advised to also compute Cramer's V, denoted as φ_c.

Regression models

Regression analyses are currently the most common approach for developing and estimating causal models and aim to predict the dependent variable, based on several independent variables [6; 45].

Logistic regression

Logistic regression is a generalised linear model used for binomial regression, which predicts the probability of the occurrence of an event, e.g. a reschedule, by fitting numerical or categorical independent variables in data to a logit function [32].

3.3 Overview of the literature study

In Figure 22 we provide an overview of the different areas studied, acquired sources and the main findings in a framework, which we discuss in the rest of this section.

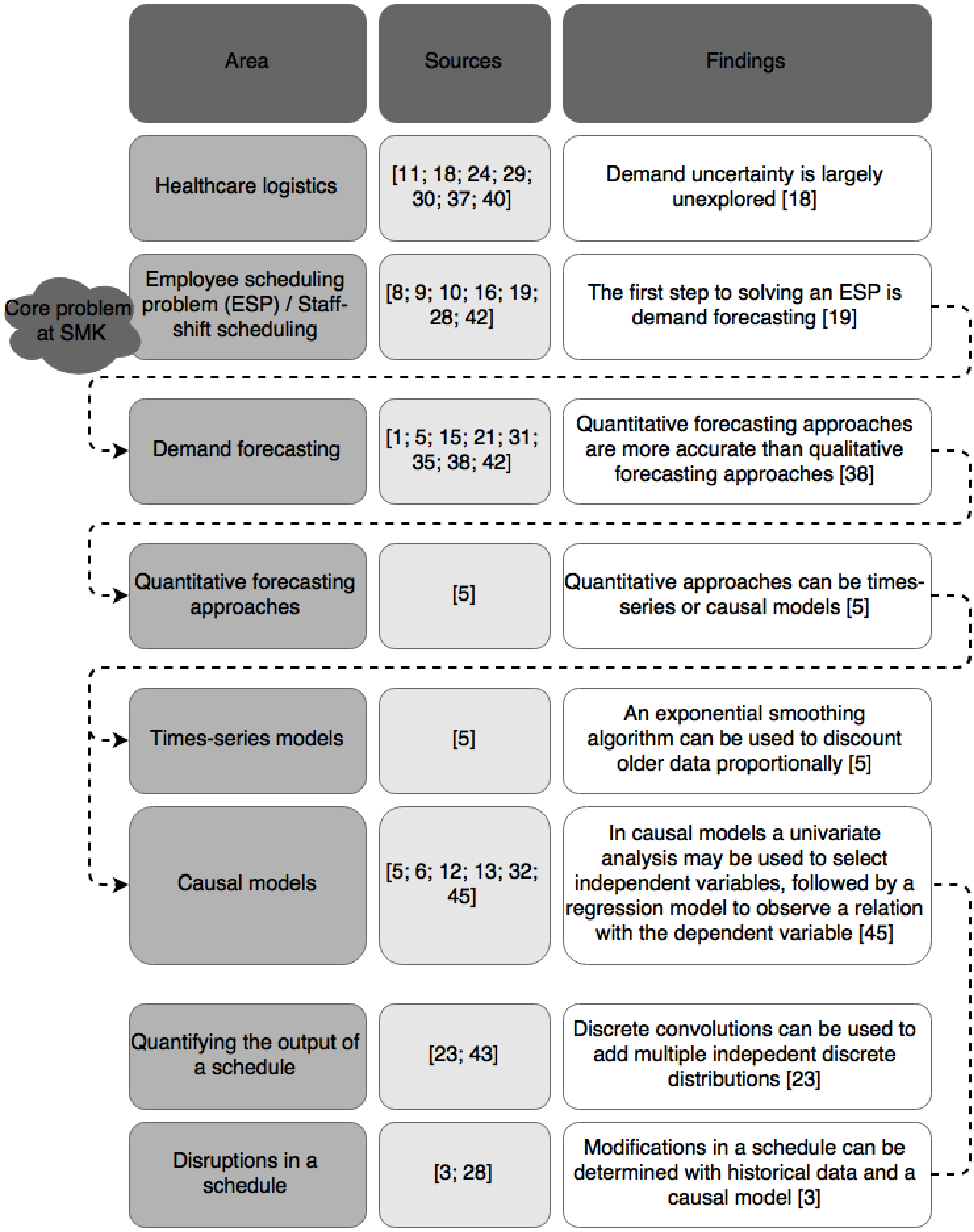


Figure 22 - Literature framework

3.3.1 Demand uncertainty

Initially, we searched for demand uncertainty in healthcare and tried to find a common term in literature for the problem at SMK. We discovered that demand uncertainty is an area that is still largely unexplored in healthcare logistics [18]. The two main definitions used for this topic are *staff-*

shift scheduling and *employee scheduling problem*. From the literature on this topic we deduce that the first step to solving such a problem is demand forecasting [19].

3.3.2 Demand forecasting

We continue our search for literature on the area of demand forecasting. The main finding is that quantitative forecasting approaches are more accurate than qualitative forecasting approaches [5].

3.3.3 Quantitative forecasting approaches

Because quantitative approaches outperform qualitative approaches, we continue our search on the topic of quantitative forecasting approaches. The main finding is that quantitative approaches exist in the form of times-series and causal models.

Times-series models

We searched for times-series models and found that one of the most common times-series models is exponential smoothing. Exponential smoothing can be used to produce a weighted moving average of historical data [5]. In this research we use an exponential smoothing algorithm to provide weights to historical data in geometrical progression to discount older data proportionally.

Causal models

After consulting a statistics professor and examining the suggested book by Wonnacott & Wonnacott [45], a more thorough study on causal models taught us that causal models may use a univariate analysis to select independent variables. The independent variables can be used in a regression model to observe a relation with the dependent variable [45].

3.3.4 Quantifying the output of a schedule

With help from CHOIR[8], we discovered two articles on methods to quantify the output of a schedule. From these articles it follows that we can use discrete convolutions to determine a single distribution from multiple independent discrete distributions [23]. This can be used to determine the output of multiple OR schedules.

3.3.5 Disruptions in a schedule

One of the aspects that is not included in the articles provided by CHOIR, but is relevant in the case of SMK, is that there can be disruptions in a schedule. We found two articles on the disruptions in a schedule. The main finding is that disruptions in a schedule can be predicted with historical data and a causal model [3].

---

[8] CHOIR is a research group of the University of Twente, that aims to improve healthcare operations by developing tailored operations research models for healthcare optimisation problems from practice (https://www.utwente.nl/choir/en/)

3.4 Conclusion

In this chapter we defined the core problem as an *Employee Scheduling Problem* (ESP). We established that the first step to solving an ESP is forecasting demand. Furthermore, to aggregate the probability distributions of the multiple ORs we can perform discrete convolutions as suggested by Vanberkel et al. [43]. We can cope with the modifications that may occur in the OR schedule with a causal model and historical data, similar to the method Alaeddini et al. [3] use to cope with no-shows. We can use an exponential smoothing algorithm to discount older data proportionally. Finally, we established that we can use a univariate analysis, followed by a logistic regression to determine the reschedule probability of a scheduled surgery.

4. Solution approach

In this chapter we present a method to forecast demand for inpatient physical therapy. We design the solution approach to utilise the information obtained in Chapter 2 with methods from literature in Chapter 3. In 4.1 we elaborate the solution approach. In 4.2 we perform a statistical analysis of OR appointments. In 4.3 we explain the algorithm we use to forecast demand for inpatient physical therapy with a simplified example and fictitious data. In 4.4 we finish the chapter with a conclusion.

Contents

4.1 Introduction to the forecast

The method we design, forecasts demand for inpatient physical therapy per day for the coming three months. The designed forecast can be performed at any moment and uses the most recent available data. In this section we examine the relevant information that is used to determine the forecast. The available information is displayed in Figure 23.

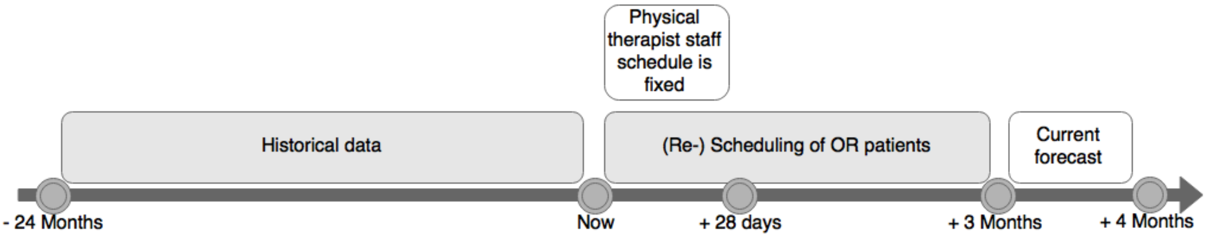


Figure 23 - Information used in the forecast

4.1.1 Historical data

The historical data that is used in the forecast consists of historical OR appointments. This data is used to determine the expected future surgeries for each surgeon and to determine the reschedule probability of future appointments. In the historical data we use an exponential smoothing algorithm to discount older data proportionally.

4.1.2 (Re-) Scheduling of OR patients

As time passes, patients are continuously being scheduled into the OR. Therefore we have to take into account that the OR schedule can still change. An important aspect is the reschedule probability of an appointment, because this provides an indication of the reliability of the scheduled appointment.

4.1.3 Physical therapist staff schedule is fixed

For the coming 28 days the physical therapist schedule is fixed. During this period the physical therapist department can only adjust the number of outpatient appointments to avoid cases of over- and understaffing.

4.1.4 The forecast algorithm

The algorithm assumes that every surgeon will always perform a combination of the surgeries he or she has performed during an OR session in the past. We allocate a higher probability to combinations of surgeries that occurred more often and more recent in the past 24 months.

Next, we examine a future OR schedule. We may see that several surgeries are planned in the future OR schedule. If these planned surgeries are not rescheduled, we know that some final OR schedules can be excluded, due to infeasibility. However, these infeasible combinations of surgeries can still occur if some of the scheduled surgeries are rescheduled before the date of surgery. The probability of this event is related to the reschedule probabilities of each scheduled surgery. In 4.2 we determine which independent variables are related to the reschedule probability of an appointment.

Eventually, we calculate the probability for each historical combination of surgeries to occur in the future, based on the currently scheduled surgeries and the reschedule probabilities. Afterwards, we translate this to the number of inpatient physical therapy treatments per day with the postoperative physical therapy treatment protocols that are linked to each surgery. Finally, we determine demand for inpatient physical therapy per day by taking the sum of the number of physical therapy treatments on each postoperative day. In 4.3 we discuss the forecast algorithm more carefully with an example.

4.2 Statistical analysis of OR appointments

In this section we perform a statistical analysis to determine which properties of an appointment can be used to calculate the reschedule probability of a future appointment.

4.2.1 Dependent and independent variables

Based on a previous study on reschedule probabilities of orthopaedic appointments at SMK, we examine the following independent variables in relation to the reschedule probability of an appointment.

Dependent variable

1. Rescheduled appointment
    - Not rescheduled (0)
    - Rescheduled (1)

A zero indicates that the appointment was not rescheduled and a one indicates that the appointment was rescheduled.

Independent variables

1. Urgency category
    - 1 month
    - 2 months
    - Elective
    - Emergency

We exclude the urgency category acute, because these appointments are scheduled in the reserved flex-time and therefore never cause reschedules.

2. Specialism
    - Spine
    - Hip
    - Knee
    - Upper extremity
    - Feet & ankle

4.2.2 Univariate analysis

To observe whether there is a significant difference between the percentage of rescheduled appointments per urgency category and per specialism, we first conduct a univariate analysis using the statistical software package SPSS 22[9].

Urgency category

We examine the relation between the urgency category of an appointment and the occurrence of a reschedule. As input data we use 11,893 historical orthopaedic appointments with the following urgency categories:

- 1 month
- 2 months
- Elective
- Emergency

Table 1 and 2 show the results of the chi-square test and portray the actual and expected number of appointments that were rescheduled per urgency category. The chi-square test statistic, denoted as χ^2, is calculated as follows:

$$\chi^2 = \sum \frac{(Observed - Expected)^2}{Expected}.$$

Urgency * Reschedules Crosstabulation					
			Reschedules		Total
			0	1	
Urgency	1 month	Count	512	73	585
		Expected Count	450.5	134.5	585.0
	2 months	Count	765	133	898
		Expected Count	691.6	206.4	898.0
	Elective	Count	7387	2486	9873
		Expected Count	7603.4	2269.6	9873.0
	Emergency	Count	495	42	537
		Expected Count	413.6	123.4	537.0
Total		Count	9159	2734	11893
		Expected Count	9159.0	2734.0	11893.0

Table 1 - SPSS output: Urgency * Reschedules Crosstabulation

[9] SPSS Statistics is a software package used for statistical analysis https://en.wikipedia.org/wiki/SPSS

Chi-Square Tests			
	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	166.979[a]	3	.000
Likelihood Ratio	192.884	3	.000
N of Valid Cases	11893		
a. 0 cells (0.0%) have expected count less than 5. The minimum expected count is 123.45.			

Table 2 - SPSS output: Chi-Square Tests for Urgency * Reschedules

We define H_0, H_1 and $\propto$ as follows:

H_0: *The percentage of rescheduled appointments is similar for each urgency category.*

H_1: *The percentage of rescheduled appointments differs significantly per urgency category.*

$\propto = 0.05.$

We observe a chi-square test statistic of 166.979 and a p-value of 0.00. Because the p-value of 0.00 is lower than our alpha of 0.05, we reject H_0 and conclude that there is a significant difference between the percentage of rescheduled appointments per urgency category.

Because the chi-square test is sensitive to high sample sizes and produces a statistically significant result more often in such cases [7; 22], it is advised to also compute Cramer's V, denoted as φ_c. We calculate Cramer's V as follows:

$$\varphi_c = \sqrt{\frac{\chi^2}{N * \min(r-1, c-1)}},$$

$\chi^2 = the\ chi - square\ test\ statistic\ (\chi^2 = 166.979),$

$N = The\ sample\ size\ (the\ sample\ size\ is\ 11{,}893),$

$r = number\ of\ rows\ (we\ have\ four\ urgency\ category's{:}\ r = 4),$

$c = number\ of\ columns\ (the\ event\ of\ a\ reschedule\ is\ binary{:}\ c = 2),$

$$\varphi_c = \sqrt{\frac{166.979}{11{,}893 * \min(4-1, 2-1)}} = 0.118.$$

Symmetric Measures			
		Value	Approx. Sig.
Nominal by Nominal	Phi	.118	.000
	Cramer's V	.118	.000
N of Valid Cases		11893	

Table 3 - SPSS output: Cramer's V for Urgency * Reschedules

Cramer's V is a value between zero and one, where a higher value indicates a stronger relationship. We can see that Cramer's V is equal to 0.118 and the p-value is equal to 0.00. We conclude that there is a small, but significant difference between the percentage of rescheduled appointments per urgency category.

Specialism

To examine the relation between the specialism of an appointment and the occurrence of a reschedule we conduct a similar analysis. As input data we use 12,408 historical orthopaedic appointments with the following specialism categories:

- Spine
- Hip
- Knee
- Upper extremity
- Feet & ankle

For each appointment a zero indicates that the appointment was not rescheduled and a one indicates that the appointment was rescheduled. Table 4 and 5 show the results of the chi-square test and portrays the actual and expected number of appointments that were rescheduled per specialism.

Specialism * Reschedules Crosstabulation					
			Reschedules		Total
			0	1	
Specialism	a. Spine	Count	952	338	1290
		Expected Count	996.8	293.2	1290.0
	b. Hip	Count	1962	529	2491
		Expected Count	1924.9	566.1	2491.0
	c. Knee	Count	3283	864	4147
		Expected Count	3204.5	942.5	4147.0
	e. Upper Extremity	Count	1908	591	2499
		Expected Count	1931.0	568.0	2499.0
	h. Feet & Ankle	Count	1483	498	1981
		Expected Count	1530.8	450.2	1981.0
Total		Count	9588	2820	12408
		Expected Count	9588.0	2820.0	12408.0

Table 4 - SPSS output: Specialism * Reschedules Crosstabulation

Chi-Square Tests			
	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	28.250[a]	4	.000
Likelihood Ratio	28.015	4	.000
N of Valid Cases	12408		
a. 0 cells (0.0%) have expected count less than 5. The minimum expected count is 293.18.			

Table 5 - SPSS output: Chi-Square Tests for Specialism * Reschedules

We define H_0, H_1 and $\propto$ as follows:

H_0: *The percentage of rescheduled appointments is similar for each specialism.*

H_1: *The percentage of rescheduled appointments differs significantly per specialism.*

$\propto = 0.05.$

We observe a chi-square test statistic of 28.25 and a p-value of 0.00. Because the p-value of 0.00 is lower than our alpha of 0.05, we reject H_0 and conclude that there is a significant difference between the percentage of rescheduled appointments per specialism.

Again, we compute Cramer's V:

$$\varphi_c = \sqrt{\frac{28.25}{12{,}408 * \min(5-1, 2-1)}} = 0.048.$$

Symmetric Measures			
		Value	Approx. Sig.
Nominal by Nominal	Phi	.048	.000
	Cramer's V	.048	.000
N of Valid Cases		12408	

Table 6 - SPSS output: Cramer's V for Specialism * Reschedules

We see that Cramer's V is equal to 0.048 and the p-value is equal to 0.00. We conclude that there is a small, but significant difference between the percentage of rescheduled appointments per specialism.

4.2.3 Binary logistic regression

To examine whether the percentage of rescheduled appointments differs significantly per combination of specialism and urgency category, we perform a regression analysis**.** The event of a reschedule is a binary variable, where zero equals an appointment that is not rescheduled and one equals an appointment that is rescheduled. Therefore, we conduct a binary logistic regression analysis and examine the event of a reschedule based on the two nominal independent variables, the specialism and urgency of an appointment.

Interpreting the results

We define H_0, H_1 and $\propto$ as follows:

H_0: $The\ percentage\ of\ rescheduled\ appointments\ is\ similar\ for\ each\ combination\ of\ specialism\ and\ urgency\ category.$

H_1: $The\ percentage\ of\ rescheduled\ appointments\ differs\ significantly\ per\ combination\ of\ specialism\ and\ urgency\ category.$

$\propto = 0.05.$

Omnibus Tests of Model Coefficients				
		Chi-square	df	Sig.
Step 1	Step	208.676	7	.000
	Block	208.676	7	.000
	Model	208.676	7	.000

Table 7 - SPSS output: Chi-Square Test for Urgency & Specialism * Reschedules

Table 7 portrays the results of the chi-square test. Because the p-value of 0.00 is lower than our alpha of 0.05, we conclude that the percentage of rescheduled appointments differs significantly per combination of specialism and urgency category.

Table 8 portrays several pseudo R-square values. We conclude that the model is only able to explain a small part of the variance in the dependent variable.

Model Summary			
Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	12615.191[a]	.017	.026

Table 8 - SPSS output: R-square values for Urgency & Specialism * Reschedules

Table 9 and 10 portray the results of the Hosmer and Lemeshow Test, which indicates the goodness of fit of the regression model.

Hosmer and Lemeshow Test			
Step	Chi-square	df	Sig.
1	.085	5	1.000

Table 9 - SPSS output: Hosmer and Lemeshow Test for Urgency & Specialism * Reschedules

Contingency Table for Hosmer and Lemeshow Test						
		Rescheduled = 0		Rescheduled = 1		Total
		Observed	Expected	Observed	Expected	
Step 1	1	1178	1176.952	141	142.048	1319
	2	594	595.048	107	105.952	701
	3	2446	2445.207	750	750.793	3196
	4	1440	1437.028	448	450.972	1888
	5	1492	1491.496	526	526.504	2018
	6	1210	1211.885	453	451.115	1663
	7	799	801.384	309	306.616	1108

Table 10 - SPSS output: Contingency Table for Hosmer and Lemeshow Test

We observe a p-value of 1.0, which indicates that the regression model predicts the event of a reschedule adequately. This conclusion is contradicting to the pseudo R-square values and can be explained as follows. The Hosmer and Lemeshow Test is influenced by the number of independent variables and may provide a biased result in this case.

Multicollinearity

Multiple authors show that the results of a logistic regression obtained by most statistical packages are not very accurate when there is a high correlation between the variables in the model [27; 39], known as multicollinearity [20].

We tested for the presence of multicollinearity by comparing the output of the model under multiple iterations with different independent variables and noticed an unstable output - the size and direction of the coefficients differs. An unstable output indicates the presence of multicollinearity [17] and means the estimation of the parameter function is not very accurate [20]. For the output of the iterations we refer to Appendix B.

Dealing with multicollinearity

There are multiple options in dealing with multicollinearity in a regression model. One of the options is to leave the model as is, despite the presence of multicollinearity. This can be an effective measure when the independent variables follow the same pattern of multicollinearity in the new data as in the data on which the regression model is based [25]. Due to a lack of knowledge and expertise and moreover a time restriction, we decide to leave the model as is. This means that we cannot use the coefficient of an individual independent variable in the parameter function that follows from the model to predict the dependent variable.

4.2.4 Conclusion

We conclude that there is a significant difference between the percentage of rescheduled appointments per combination of specialism and urgency category. However, the amount of variance that can be explained in the percentage of rescheduled appointments is low.

4.3 The forecast exemplified

In this section we execute steps one through six of the model in Figure 24, using a simplified example with fictitious data. Afterwards, we show how this information can be used to determine demand for inpatient physical therapy. In the model this occurs in steps seven and eight. In step seven we determine the future demand for inpatient physical therapy that is certain, based on the surgeries that were performed in the past two weeks and the respective inpatient physical therapy protocols. In step 8 we predict demand for inpatient physical therapy that is uncertain and is based on the OR schedule for the coming three months.

We use two programs in the solution approach. We use Statistical Analysis System: Enterprise Guide[10] to obtain the required input data, denoted as SAS in Figure 24 and the rest of the report. We use Excel's Visual Basic for Applications[11] to program the rest of the model, referred to as VBA in Figure 24 and the rest of the report.

[10] SAS is a software suite that can mine, alter, manage and retrieve data from a variety of sources and perform statistical analysis on it. https://en.wikipedia.org/wiki/SAS_(software)

[11] Visual Basic for Applications (VBA) is an implementation of Microsoft's event-driven programming language, Visual Basic 6, and its associated integrated development environment (IDE). https://en.wikipedia.org/wiki/Visual_Basic_for_Applications

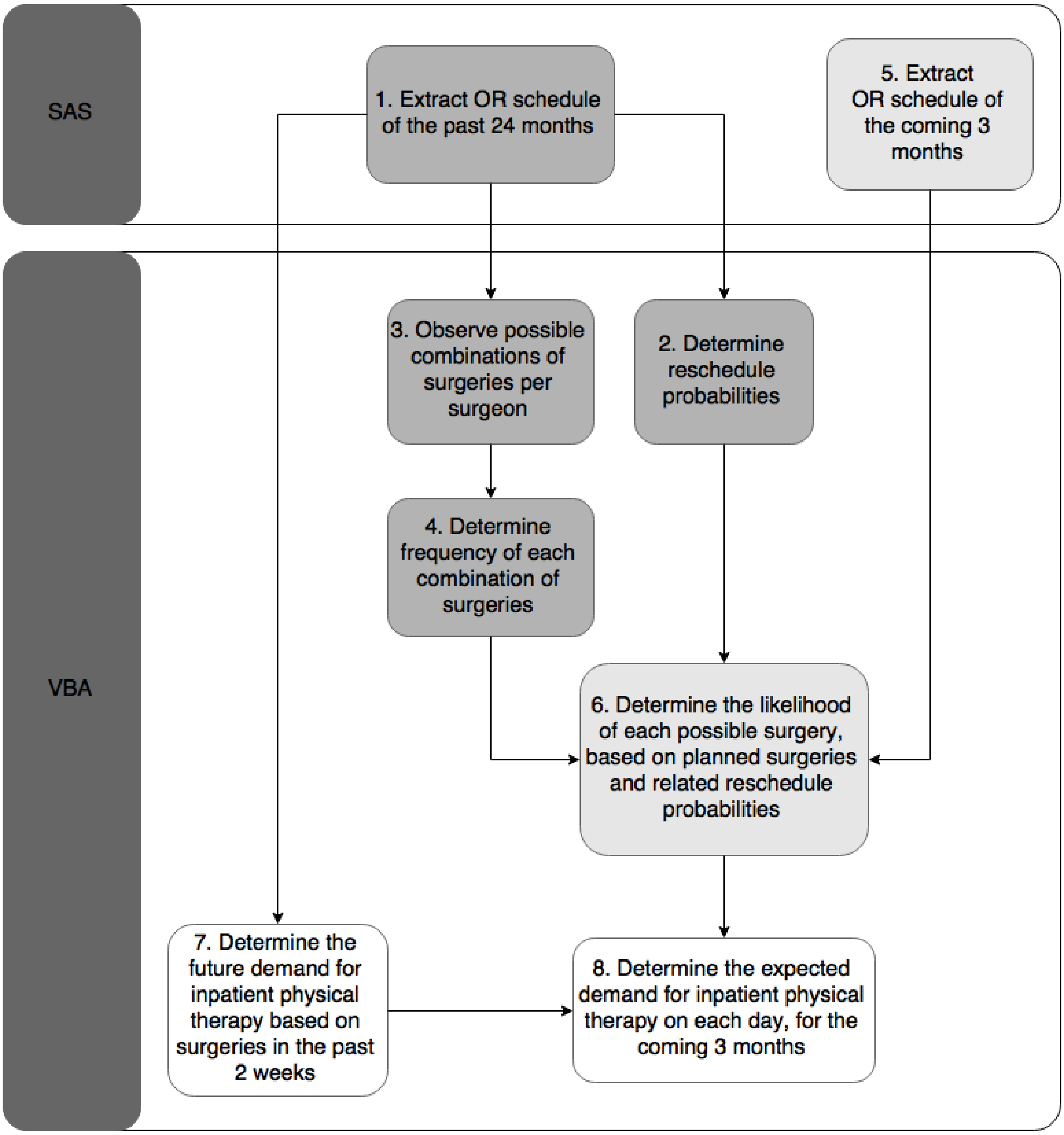


Figure 24 - Model of the solution approach

4.3.1 Step 1: Extract the historical OR schedules

Table 11 shows the output of SAS that is used in the forecast model. We discuss each column in more depth to illustrate the relevance of the obtained information.

Month	Surgeon	Protocol	Urgency	Specialism	Rescheduled	Days before the surgery	Weight
0	A	X	1	Knee	1	10	0.5
0	A	X	2	Knee	0	-	0.5
0	B	Y	2	Knee	0	-	0.5
0	B	Y	2	Knee	1	20	0.5
0	B	Y	1	Knee	0	-	0.5
0	B	Y	1	Knee	0	-	0.5
1	B	Y	1	Knee	0	-	0.25
1	B	Y	1	Knee	0	-	0.25
1	B	Y	2	Knee	0	-	0.25
1	B	Y	1	Knee	0	-	0.25
2	B	X	1	Knee	1	30	0.125
2	B	X	1	Knee	0	-	0.125
2	A	Y	2	Knee	0	-	0.125
2	A	Y	2	Knee	0	-	0.125

Table 11 - An example of a historical OR schedule

Month

The value in the column labelled "Month", represents the number of months ago the data was obtained. Thus, 0 months ago is data obtained during this month. We use this information to discount older data proportionally.

Surgeon

In the example, all surgeries are executed by either surgeon A or surgeon B. The historical combinations of surgeries performed during an OR session by a surgeon is used to determine the probability that each combination of surgeries is performed by that surgeon in the future.

Protocol

In the example, there are two different inpatient physical therapy protocols, classified as X and Y. The protocol is used to define the combinations of surgeries that is executed by a surgeon and determines the number of inpatient physical therapy treatments the patient receives on each postoperative day.

Urgency

In the example, we maintain two urgency categories. Category one is the highest urgency category and category two is the lowest urgency category. We saw in 4.2 that there is a significant difference between the percentage of rescheduled appointments per urgency category.

Specialism

In the example all patients belong to the specialism knee. We saw in 4.2 that there is a significant difference between the percentage of rescheduled appointments per specialism.

Rescheduled

The column "rescheduled" indicates whether the appointment is rescheduled (1) or not rescheduled (0). In 4.3.2 we use this information to determine the reschedule probability of a surgery, based on the urgency category and the specialism.

Days before the surgery

If the surgery is rescheduled, this column shows how many days before the surgery the appointment was rescheduled. This information is used to determine the reschedule probability. It seems apparent that an appointment for surgery the next day has a lower reschedule probability than a similar appointment a few weeks before the surgery date.

Weights

This column presents the weights that are used to discount older data proportionally. The weights are determined with an exponential smoothing algorithm as follows:

$s_k = \propto * \ (1 - \propto)^k.$

Where k is equal to the number of months ago and α is known as the smoothing factor. Higher levels of α reduce the level of smoothing, since the weighted gap between recent and older data becomes larger with higher levels of α. For simplicity purposes we use an alpha of 0.5 in the example.

4.3.2 Step 2: Determine the reschedule probabilities

In this step we determine the reschedule probability of the patients, based on the data from Table 11. The following variables are used to determine the reschedule probability of an appointment.

1. Urgency
2. Specialism
3. Days until the surgery is scheduled to take place

Table 12 shows the expected reschedule probability of an appointment. In the example we only have two types of appointments (specialism = knee, urgency = 1 or 2). The reschedule probabilities at 20 days before the surgery date are highlighted, because we use these values in the next steps.

Urgency	Specialism		Days before the surgery 0	10	20	30
1	Knee	Weighted reschedules	0	0.5	0.5	0.625
		Total weight	2.5	2.5	2.5	2.5
		Probability	***0***	***0.2***	***0.2***	***0.25***
2	Knee	Weighted reschedules	0	0	0.5	0.5
		Total weight	2	2	2	2
		Probability	***0***	***0***	***0.25***	***0.25***

Table 12 - Calculating the reschedule probabilities of two types of patients

The weighted reschedules are calculated cumulatively. When we consider an appointment 20 days before the surgery date, it might be rescheduled 10 days later – at that point the surgery will take place in 10 days. Therefore the weighted reschedules at 20 days before the surgery date is calculated as the sum of weighted reschedules from 0 days to the surgery until 20 days before the surgery. This is formulated as:

$$Weighted\ reschedules_{u,s,d} = \sum_{appointments} \sum_{t=\min(d)}^{t=d} Weight_{u,s}.$$

Next, this is divided by the total weight of all the surgeries of that appointment type. For the appointment type urgency = 1 and specialism = knee, this yields an expected reschedule probability of $\frac{0.5}{2.5} = 0.2$ at 20 days before the surgery. We see that, in the example, a higher urgency category appointment has a lower reschedule probability. The total weight is calculated as follows:

$$Total\ weight_{u,s} = \sum_{appointments} Weight_{u,s}.$$

The reschedule probability of an appointment is defined as:

$$Reschedule\ probability_{u,s,d} = \frac{Weighted\ reschedules_{u,s,d}}{Total\ Weight_{u,s}}, \text{ or}$$

$$Reschedule\ probability_{u,s,d} = \frac{\sum_{appointments} \sum_{t=\min(d)}^{t=d} Weight_{u,s}}{\sum_{appointments} Weight_{u,s}}.$$

$Weight_{u,s,d}$ is the exponential smoothing weight of the appointment, which depends on:

s = Specialism (Knee),

u = Urgency (1,2),

d = Days until the surgery (0 … 30 days).

4.3.3 Step 3 & 4: Determine the combinations of surgeries and their frequency

In Table 13, we see the combinations of surgeries performed by each surgeon. This is based on the data from Table 11 in step 1. We can see that surgeon A performed two different combinations of surgeries in the past. The first combination of surgeries consists of the physical therapy protocols X and X, referred to as X-X. The second combination of surgeries consists of the physical therapy protocols Y and Y, referred to as Y-Y. We use the applied weights to determine the expected probability of each combination of surgeries to occur in the future. We do this by dividing the weight of each combination by the total weight of all the combinations of surgeries of that surgeon.

Surgeon	Previous combinations	Weight	Total	Probability
A	X-X	0.5	0.625	***0.8***
	Y-Y	0.125	0.625	***0.2***
B	Y-Y-Y-Y	0.75	0.875	0.86
	X-X	0.125	0.875	0.14

Table 13 - Calculations of the probability of a combination of surgeries per surgeon

In the example, the combination of protocols X-X occurs with an expected probability of 0.8 and the combination of protocols Y-Y occurs with an expected probability of 0.2 for surgeon A. The probability of a surgeon executing a combination of surgeries is calculated as follows. In Table 13 we see that surgeon A has executed the surgeries with protocols X-X once before, with weight 0.5. Surgeon A has also executed surgeries with protocols Y-Y with weight 0.125. This surgeon's total weight is therefore equal to $0.5 + 0.125 = 0.625$. The probability that surgeon A will execute a combination of surgeries with protocols X-X in the future is equal to $\frac{0.5}{0.625} = 0.8$.

4.3.4 Step 5: Extract the future OR schedule

In step five we extract the future OR schedule from the database and determine the reschedule probabilities of the scheduled surgeries. In this case we are at 20 days before the surgery date and two surgeries are scheduled for surgeon A. Patient 1 has physical therapy protocol X, belongs to specialism knee and has urgency category 1. From Table 12 it follows that the reschedule probability of a surgery with these characteristics is equal to 0.2. Patient 2 has physical therapy protocol Y and the reschedule probability is equal to 0.25. This is displayed in Table 14.

Days until surgery	Surgeon	Patient	Protocol	Specialism	Urgency	Reschedule probability
20	A	1	***X***	Knee	1	***0.2***
		2	***Y***	Knee	2	***0.25***

Table 14 - Matching the calculated reschedule probabilities to planned appointments

4.3.5 Step 6: Determine the probability of each combination of surgeries

In this step we determine the probability of each combination of surgeries that was executed in the past, to occur on the day of surgery, based on the scheduled surgeries and the corresponding reschedule probabilities. We remain at 20 days before the surgery date.

Reschedule matrix

First, we examine the reschedule probabilities. In the example two patients are planned, which can both either be rescheduled (1) or not rescheduled (0). This yields a binary matrix of $2^2 = 4$ possible combinations.

Second, we determine the probability of each combination of reschedules to occur. The probability that an appointment is not rescheduled (0), is equal to one minus the reschedule probability. For patient 1, the probability that he or she is not rescheduled is equal to $1 - 0.2 = 0.8$. The total probability for both appointments to remain scheduled is obtained by multiplying the respective probabilities $P(X = 0) * P(Y = 0) = P(X = 0 \cap Y = 0) = 0.8 * 0.75 = 0.6$. Table 15 present the results of those calculations.

Patient	**Combinations of reschedules**			
X	0	0	1	1
Y	0	1	0	1
Patient	**Probabilities**			
X	0.8	0.8	0.2	0.2
Y	0.75	0.25	0.75	0.25
Total probability	***0.6***	***0.2***	***0.15***	***0.05***

Table 15 - Calculating the probability of a combination of rescheduling events

This is calculated as follows:

$$P(X = x \cap Y = y) = P(X = x) * P(Y = y).$$

Probability of each combination of surgeries

In Table 16 we determine the probability of each historical combination of surgeries for surgeon A to occur again, based on the scheduled surgeries and the reschedule probabilities of the scheduled surgeries.

		Planned patients	**Combinations of reschedules**				
		X	0	0	1	1	
		Y	0	1	0	1	
		Total probability	***0.6***	***0.2***	***0.15***	***0.05***	
Surgeon	**Combinations**	**Probability**	**Probability of surgery combination, given reschedules (calculations)**				
A	X-X	0.8	N/A	(0.2/0.4)*(0.8/0.8)	N/A	(0.05/0.4)*(0.8/1)	
	Y-Y	0.2	N/A	N/A	(0.15/0.4)*(0.2/0.2)	(0.05/0.4)*(0.2/1)	
Surgeon	**Combinations**	**Probability**	**Probability of surgery combination, given reschedules (results)**				**Total probability of combination**
A	X-X	***0.8***	N/A	0.5	N/A	0.100	***0.6***
	Y-Y	***0.2***	N/A	N/A	0.375	0.025	***0.4***
							1.0

Table 16 - Expected output of the OR schedule in terms of physical therapy protocols

In the first combination of reschedules, $P(X = 0 \cap Y = 0)$, neither of the scheduled surgeries is rescheduled. However, there is no historical combination of surgeries that contains both X and Y, therefore this does not lead to a valid combination of surgeries. As a result the valid combinations of reschedules are restricted to a smaller set. For the other combinations of reschedules, a valid historical combination of surgeries exists. Thus, the valid combinations of reschedules that remain, add up to a total of $0.2 + 0.15 + 0.05 = 0.4$. We divide the probability of a combination of reschedules by the sum of probabilities of the valid subset. For instance, the probability that X is not rescheduled and Y is rescheduled ($P(X = 0 \cap Y = 1)$) is now equal to $\frac{0.2}{0.4} = 0.5$.

We do the same for the combinations of surgeries. In the case where X is not rescheduled and Y is rescheduled $P(X = 0 \cap Y = 1)$, Y-Y cannot be the final schedule. Therefore, the valid combinations of surgeries is limited to X-X in this case. This means, assuming X is not rescheduled and Y is rescheduled, the probability of ending with the schedule X-X is equal to 0.8/0.8 = **1**.

Previously, we calculated that the probability that X is not rescheduled and Y is rescheduled ($P(X = 0 \cap Y = 1)$) is equal to $\frac{0.2}{0.4} = \mathbf{0.5}$. Multiplying these values yields $\mathbf{1} * \mathbf{0.5} = \mathbf{0.5}$, where 0.5 is the probability that X-X is the combination of surgeries in the OR schedule on the day of surgery, given that X-Y was planned in the OR at 20 days before the surgery, X remains scheduled and Y is rescheduled.

Horizontally adding the probabilities for each combination of surgeries shows the total probability of that combination of surgeries to occur, given the currently planned surgeries and their reschedule probabilities. For instance, the probability that X-X is the combination of surgeries in the OR schedule on the day of surgery, given that X-Y was planned in the OR at 20 days before the surgery is equal to $0.5 + 0.1 = 0.6$.

4.3.6 Step 7 & 8: Determine demand for inpatient physical therapy

In this section we translate the probability distribution of expected surgeries to determine a probability distribution of demand for inpatients physical therapy per postoperative day.

Performing discrete convolutions

In step 6 we saw that the predicted output of the OR results in a probability distribution of historic combinations of surgeries. SMK currently utilises six ORs, which will result in six probability distributions of historic combinations of surgeries. To create a single probability distribution of the historic surgeries that will follow from the six ORs in total, we iteratively perform discrete convolutions. A convolution is a mathematical operation on two functions to produce a single function. In Figure 25 we present an example of iteratively performing discrete convolutions on the probability distributions of the historic combinations of surgeries, in the case of three ORs.

OR 1	
Historic combinations of surgeries	Probability
X-X	0.6
Y-Y	0.4

OR 2	
Historic combinations of surgeries	Probability
A-A	0.5
A-B	0.3
B-B	0.2

OR 1 + 2	
Historic combinations of surgeries	Probability
X-X & A-A	0.6 * 0.5 = 0.3
X-X & A-B	0.6 * 0.3 = 0.18
X-X & B-B	0.6 * 0.2 = 0.12
Y-Y & A-A	0.4 * 0.5 = 0.2
Y-Y & A-B	0.4 * 0.3 = 0.12
Y-Y & B-B	0.4 * 0.2 = 0.08

OR 3	
Historic combinations of surgeries	Probability
X-A	0.5
X-Y	0.5

OR 1 + 2 + 3	
Historic combinations of surgeries	Probability
X-X & A-A & X-A	0.3 * 0.5 = **0.15**
X-X & A-B & X-A	0.18 * 0.5 = 0.09
X-X & B-B & X-A	0.12 * 0.5 = 0.06
Y-Y & A-A & X-A	0.2 * 0.5 = 0.1
Y-Y & A-B & X-A	0.12 * 0.5 = 0.06
Y-Y & B-B & X-A	0.08 * 0.5 = 0.04
X-X & A-A & X-Y	0.3 * 0.5 = 0.15
X-X & A-B & X-Y	0.18 * 0.5 = 0.09
X-X & B-B & X-Y	0.12 * 0.5 = 0.06
Y-Y & A-A & X-Y	0.2 * 0.5 = 0.1
Y-Y & A-B & X-Y	0.12 * 0.5 = 0.06
Y-Y & B-B & X-Y	0.08 * 0.5 = 0.04

Figure 25 - An example of performing discrete convolutions

We can now say that, with a probability of 0.15, we expect three patients with inpatient physical therapy protocol X and three patients with inpatient physical therapy protocol A to be the output of the three ORs. We use the inpatient physical therapy protocols of the surgeries to determine the number of physical therapy treatments on each postoperative day. To determine demand for inpatient physical therapy on each day we add the number of physical therapy treatments on each postoperative day.

Translating the expected surgeries to demand for inpatient physical therapy

In this example, postoperative treatment protocols take no longer than four days. We determine demand for inpatient physical therapy per day for the next four days. Therefore, we need data from three days ago to three days from now. In a single graph we see the number of physical therapy treatments per postoperative day as a result of the performed surgeries on that day. This is determined by matching the expected surgeries with the associated treatment protocols.

In the bottom graph we take the sum of the demand on each postoperative day, to determine the total demand for inpatient physical therapy. Because treatment protocols can take up to four postoperative days in the example, the first three days and last three days are not based on complete datasets and should be excluded from the result.

4.4 Conclusion

With a statistical analysis we showed that there is a significant difference in the percentage of rescheduled appointments per combination of urgency category and specialism of an orthopaedic appointment. Furthermore, we developed an approach to forecast demand for inpatient physical therapy, based on currently scheduled surgeries and their reschedule probabilities. In the case of multiple ORs, we have shown that we can iteratively perform discrete convolutions to find a probability distribution of the total demand for inpatient physical therapy per day.

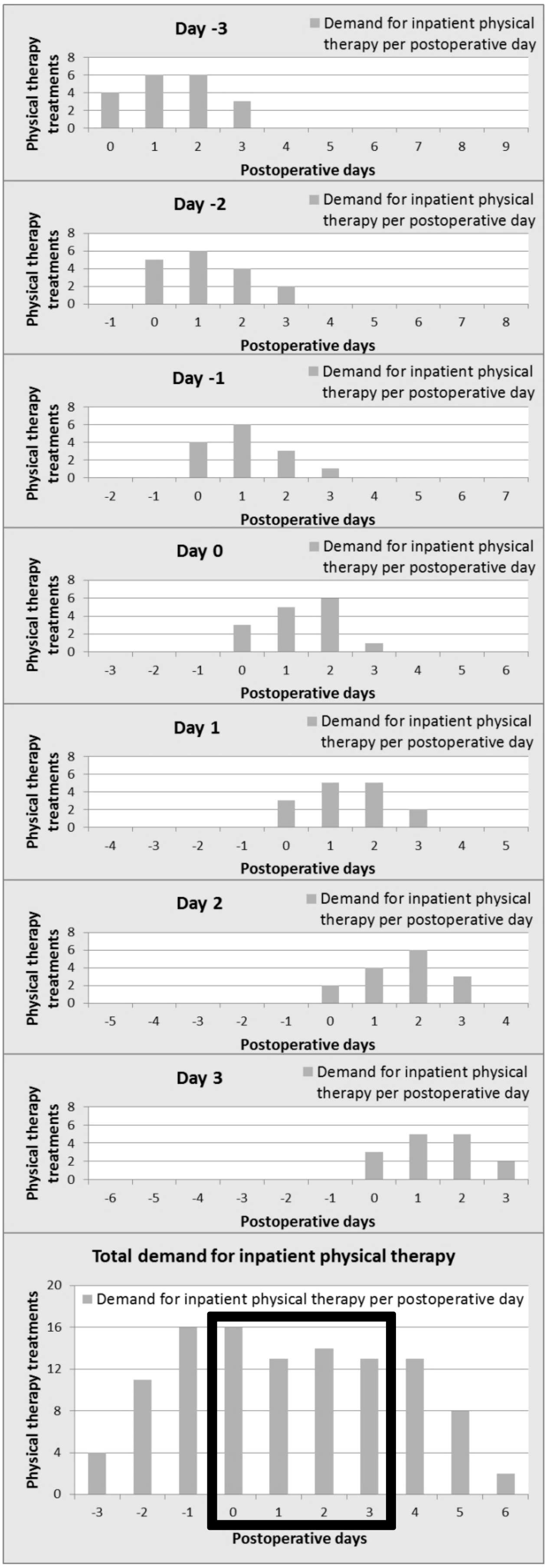


Figure 26 - An example of the expected demand for inpatient physical therapy

5. Results

In this chapter we present the results of the designed forecast. In 5.1 we evaluate the results of the forecast. In 5.2 we discuss the forecast in terms of validity. In 5.3 we finish the chapter with a conclusion.

Contents

5.1 Results of the forecast

In this section we examine the results of the forecast. In 5.1.1 we discuss the output of the forecast. In 5.1.2 we explain the variability in the output of the forecast. In 5.1.3 we discuss the level of accuracy in the forecast and in 5.1.4 we compare the forecast to the forecast that is currently utilised to forecast demand for inpatient physical therapy.

5.1.1 Output of the forecast

We executed the forecast on the 15th of October 2015. The output is a probability distribution of demand for inpatient physical therapy per day for the next three months. In Figure 27, we translated this to a confidence interval of demand for inpatient physical therapy in number of treatments per day. Figure 27 also shows the protocolised demand, which is the actual demand on each day when physical therapy inpatients are treated according to protocol. Due to time restrictions we were only able to observe the protocolised demand until the 23rd of November 2015.

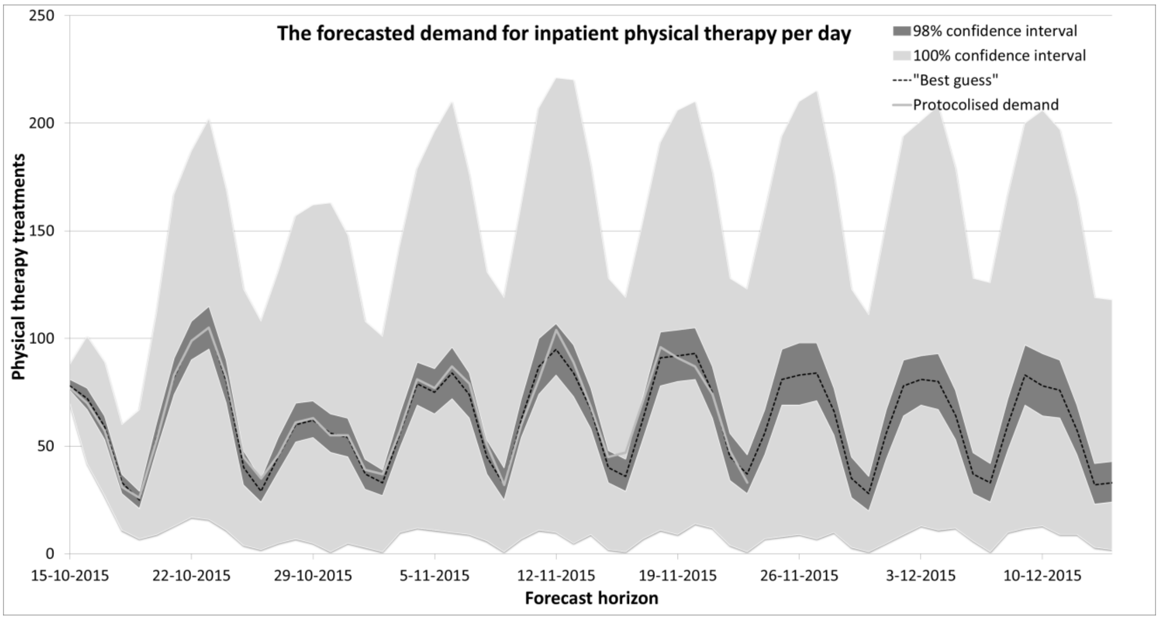


Figure 27 - The actual and forecasted demand for inpatient physical therapy per day

One of the aspects that catches the eye is the size of the 100% confidence interval. This can be explained as follows. In the forecast, scheduled surgeries in future OR sessions can be rescheduled according to their calculated reschedule probabilities. When we forecast demand for inpatient physical therapy for the next day, it is possible to reschedule all the scheduled surgeries and fill the OR schedule such that the minimum output seen in the historical data is scheduled. One day before the surgery date, reschedule probabilities are very small. Thus, the probability of rescheduling all scheduled surgeries is very small as well, but not zero. Therefore, this event is included in the 100% confidence interval.

We advise to consider the 98% confidence interval instead. The meaning of this interval can be interpreted as follows. In 1% of the cases, the number physical therapy treatments will be higher than the maximum of the 98% confidence interval. Similarly, in 1% of the cases, the number of physical therapy treatments will be lower than the minimum of the 98% confidence interval. In Figure 27, the dotted line represents our “best guess”.

5.1.2 Variability

The variability in Figure 27 is explained by several factors. First, there are no surgeries in the weekend, which causes a dip in demand for inpatient physical therapy in the following days. Second, during several weeks there is a reduced number of ORs available. This is for instance the case during holidays. The variability shows us that the forecast model reflects the effect of the OR schedule on demand for inpatient physical therapy.

5.1.3 Level of accuracy

Figure 28 presents the difference between the maximum and minimum of the forecasted 98% confidence interval of the forecast in Figure 27. Similar to Figure 27, the variability in the graph is explained by the fluctuating utilisation of ORs.

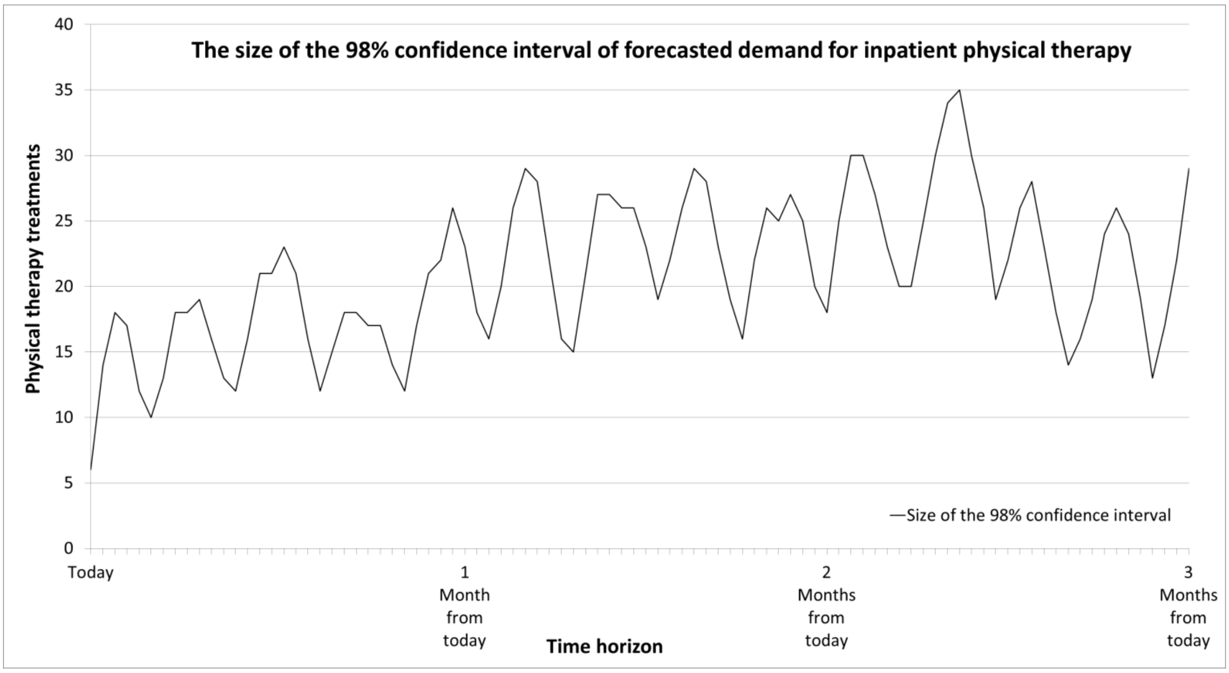


Figure 28 - The size of the 98% confidence interval of the designed forecast

We can see that, generally speaking, the size of the interval increases as we attempt to forecast demand further in time. This makes sense, because the percentage of filled OR capacity decreases and the reschedule probabilities increase as we forecast further in time, which both cause the output of the OR to be more uncertain. This uncertainty translates to a wider confidence interval. Figure 29 displays the average planned capacity of the ORs and the average reschedule percentage per day. During the weekends we maintain a smooth line by using the average value of the previous three days.

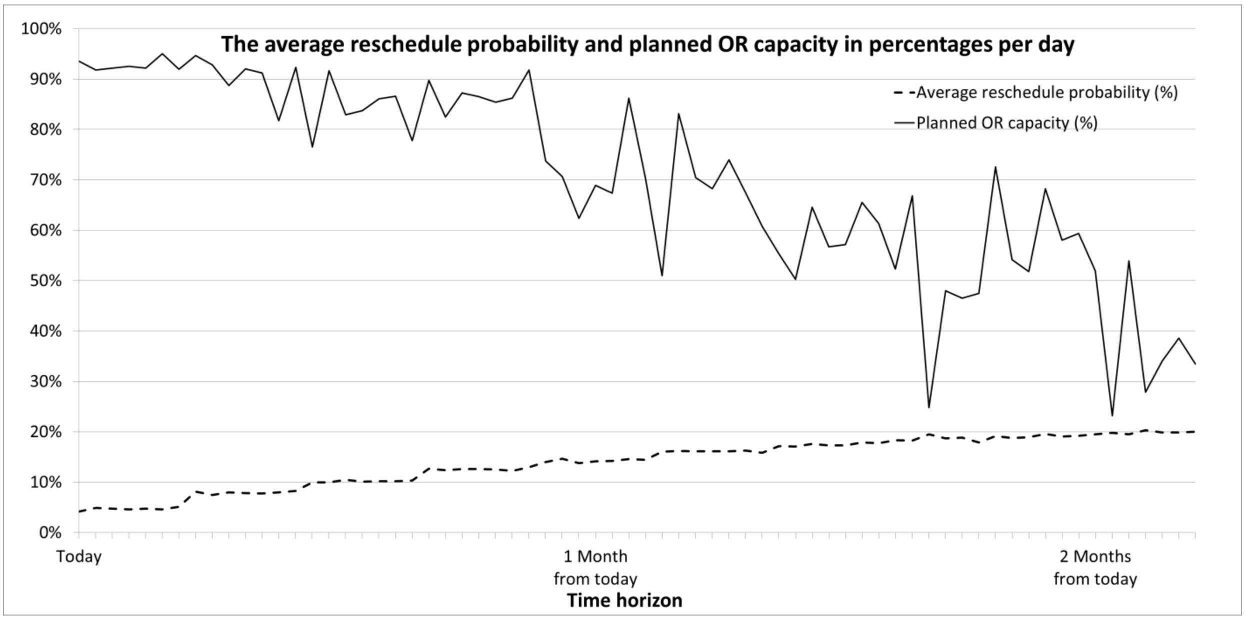


Figure 29 - The average reschedule probability and planned OR capacity per day

5.1.4 Comparison with the current forecast

In Figure 30 we compare the size of the 98% confidence interval of the designed forecast to that of the current forecast over the same period.

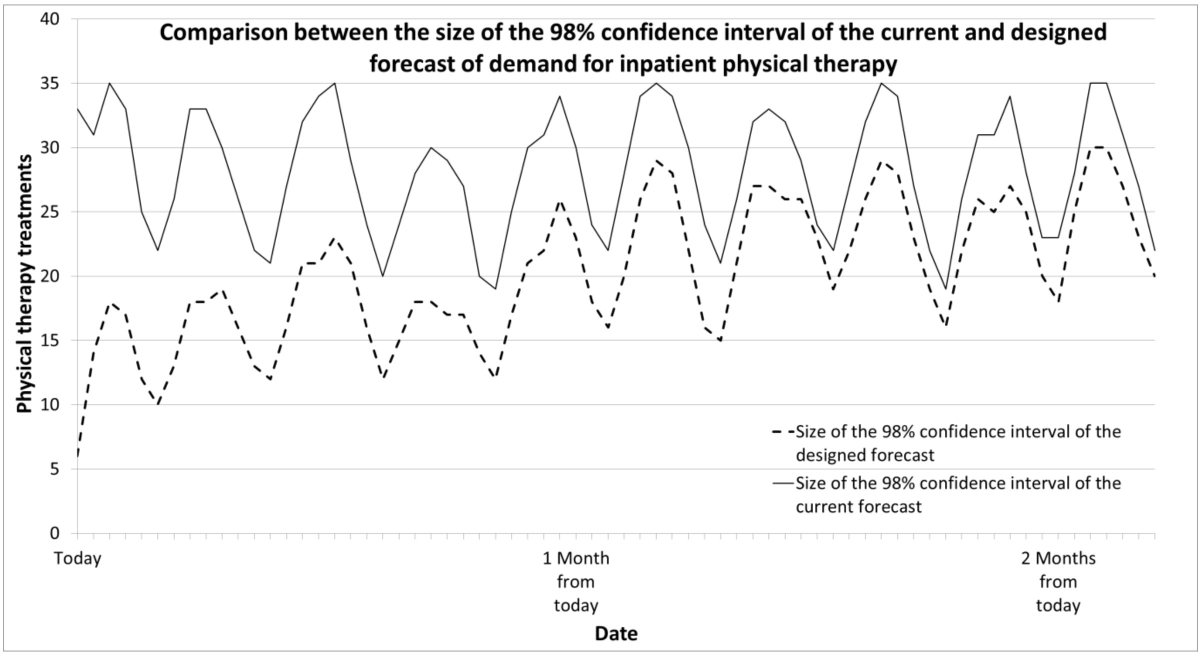


Figure 30 - A comparison between the size of the confidence interval of the designed forecast and the current forecast

We can see that in the first month, the size of the 98% confidence interval of the designed forecast is, on average, approximately 40% smaller than the 98% confidence interval of the current forecast. As we forecast further into the future, the size of the intervals become more similar. This can be explained by the high percentage of planned OR capacity and low reschedule probabilities in the first month. In Figure 31 we combine Figure 29 and 30 to emphasise the relationship between the number of scheduled surgeries and the reschedule probability, and the difference in the size of the confidence intervals.

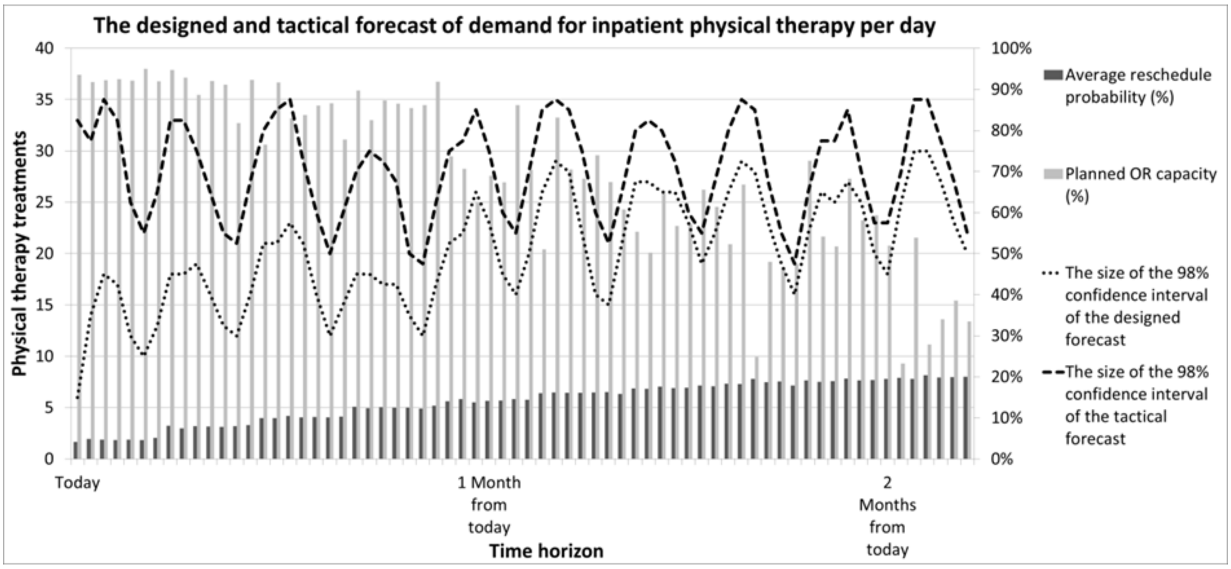


Figure 31 - A comparison between the designed and current forecast

The results indicate that the physical therapist department can use the designed forecast to schedule their personnel more efficient on the short-term.

5.2 Validity

To validate that the designed forecast provides accurate results, we performed several actions. We briefly discuss the different validation methods used.

- We analysed the VBA-code step-by-step in debug mode to check for errors.
- We discussed the more complex aspects of the algorithm to minimise the possibility of overlooking any errors.
- We compared the output of the forecast to the actual protocolised demand. However, due to time constraints we were only able to do this for a restricted amount of data.
- We compared the output of the forecast to the output of the current forecast.

5.3 Conclusion

On the short-term, the results of the designed forecast indicate a significant improvement compared to the forecast that is currently utilised. We saw that in the first month the size of the 98% confidence interval of demand for inpatient physical therapy of the designed forecast is, on average, approximately 40% smaller than the 98% confidence interval of the current forecast. The forecast has been validated; however, we recommend to continue to monitor the accuracy of the forecast to ensure its validity.

6. Conclusion

The physical therapist department struggles to accurately determine demand for inpatient physical therapy and is experiencing cases of over- and understaffing as a result. In this research we developed a prototype tool to forecast demand for inpatient physical therapy per day for the next three months.

The forecast predicts which surgeries will follow from an OR schedule, based on the scheduled surgeries in the OR schedule and the related reschedule probabilities. The forecast then translates this to demand for inpatient physical therapy with the treatment protocols, which defines the number of physical therapy treatments a patient receives during his or her postoperative stay. With this additional information, the designed prototype tool forecasts approximately 40% more accurate during the first month than the current forecast tool.

We conclude that the prototype forecast tool is accurate on the short-term, however more time and effort should be invested to validate the output and improve its accuracy on the longer term.

Because the forecast model first predicts which surgeries will follow from an OR schedule, the designed forecast can be used for multiple departments besides physical therapy. With some modifications the forecast can, for instance, be used to predict the bed occupation in the ward. Moreover, the algorithm used to forecast demand for inpatient physical therapy, can also be used in other hospitals. However, the prototype tool will have to be modified to cope with a different data structure.

In 6.1 we discuss the limitations of this research. In 6.2 we provide recommendations for SMK. In 6.3 we advise on the implementation of the prototype tool and in 6.4 we argue topics for further research.

Contents

6.1 Limitations

We discuss the limitations of the research in this section.

6.1.1 Incongruence of treatment protocols

The first limitation of this study is that patients are currently not treated according to the predetermined treatment protocols. As a result, the forecasted demand, which is based on the treatment protocols, differs from the number of treatments that will be performed. Therefore, the forecast should be used with caution.

6.1.2 The historical combinations of surgeries

Second, the forecast assumes that a surgeon will always perform a combination of surgeries he or she has performed in the past. This makes the model vulnerable to changes in the future. The exponential smoothing weights partly counters this vulnerability by providing heavier weights to more recent surgeries. In the case where a new surgeon is hired and no data is available on the surgeries he or she has performed in the past, we advise to use a historical combination of surgeries of a surgeon who performs similar surgeries.

6.1.3 Forecast error

Third, we were unable to execute a thorough validation and determine a forecast error, due to a lack of available data. We advise to observe the results of the forecast for a certain amount of time to ensure its validity.

6.2 Recommendations

In this section we provide recommendations. We mainly recommend to professionalise the prototype tool that was designed in this research. More specific advice on how to implement the forecast tool is provided in 6.3.

Furthermore, we recommend to utilise the forecast to support decision-making at a tactical level in the planning of physical therapists and whenever the current forecast provides insufficient information. Below we name the factors that may contribute to a more accurate forecast and provide advice.

- If the amount of remaining capacity in the OR schedule is lower when the forecast is performed this reduces the uncertainty in the output of the OR schedule. We advise to schedule orthopaedic patients as soon as possible.
- The scheduled appointments serve as a valuable information source to the forecast. When there are more modifications in the planning, this information becomes less reliable and thus less valuable. We recommend to minimise the number of modifications in the OR schedule.

- Currently, there is no standardised procedure to schedule the patients, which causes this process to be uncertain. We recommend to automate the scheduling of patients in the ORs.
- The physical therapy department is currently not treating all of its patients according to the established protocols. We advise to treat patients according to protocol. This improves the coordination between departments, clarifies the treatment process for the patient and makes it easier to benchmark results.
- The physical therapy department employs 47 unique treatment protocols. We recommend to consider the list of unique protocols and reduce the number of unique protocols to a medically sound minimum. This will decrease the number of possible treatment trajectories and therefore reduce the uncertainty in demand for inpatient physical therapy.
- The current physical therapist staff schedule is based on a fixed roster. The physical therapy department will only benefit from an accurate forecast if the staff schedule can be adjusted to match the forecast. We therefore advise to explore more flexible ways of personnel scheduling.

6.3 Implementation

In this section we elaborate on using the forecast. Furthermore, we provide recommendations to successfully implement the prototype forecast tool.

6.3.1 Using the forecast

Below we present the steps that are involved in creating the forecast. For a more detailed guide we refer to Appendix C.

1. Update Excel-file on cancellations

The historical reschedules are stored in an Excel-file, which is linked to a Microsoft Access database. First, this Excel-file needs to be updated to the most recent data.

2. Execute the SAS Query

Second, we need to execute the SAS Query designed to extract the required input data.

3. Execute the forecast

Finally, we execute the forecast by running a VBA macro. Creating the forecast may take up to 25 minutes of computation time.

6.3.2 Graphical user interface

We recommend to professionalise the prototype forecast tool and design a simple and clean graphical user interface to ensure physical therapy planners will be able to use the forecast tool autonomously.

Settings

Currently, the forecast produces a probability distribution of demand for inpatient physical therapy per day for the coming three months, based on historical data of the past 24 months. An interface that allows to adjust the following settings may improve the ease of use and accuracy of the forecast.

- *Exponential smoothing factor*

The exponential smoothing factor determines to what extent older data is discounted. In a stable situation a low smoothing factor is more appropriate, where a higher smoothing factor is more appropriate in a dynamic environment.

- *Historical data*

In certain situations part of the historical data may be unrepresentative of the current situation and should be disregarded completely. In such cases it is desirable to be able to adjust the length of the interval of historical data that is used in the forecast.

- *Forecast horizon*

To avoid a superfluous supply of information, we advise to include an option to adjust the length of the forecast horizon. If the planners are only interested in the forecasted demand for inpatient physical therapy for a specific day, it is inefficient to create a forecast for three months.

The output and its users

The output of the forecast may be interesting for more employees than the planners of physical therapy. For instance, the physical therapist department can use it to estimate the required budget and track its performance. We recommend to display the forecast in a dashboard. The dashboard can show the predicted demand, track how accurate the forecast is compared to the actual demand and to which extent patients are treated according to protocol on a daily basis. This encourages continuous improvement through striving for a better alignment of supply and demand. Moreover, physical therapists may be willing to work more flexible if they see this directly contributes to the number of patients that is able to receive treatment according to protocol.

6.3.3 Software

We advise to use R[12] to professionalise the forecast tool. R is a free software environment for statistical computing and graphics. This means no investments are required to utilise R. Furthermore, R is, through its extensive statistical capabilities, well-equipped for forecasting. Moreover, R's programming language is known within the logistics department of SMK and would therefore not require additional schooling efforts. Besides R, a SAS query is required to extract the relevant input data.

6.4 Further Research

In this section we discuss the topics that may be interesting to examine in the future. In 6.4.1 we discuss research topics that are related to integrally optimising the OR schedule. In 6.4.2 we discuss research that may lead to an improvement of the forecast that is designed in this research.

6.4.1 Integral optimisation

It might be interesting to examine whether there is a feasible OR schedule that leads to a more consistent demand for downstream resources. Additionally, it may be interesting to examine whether working with OR-slots leads to a more consistent demand for downstream resources. The forecast can be used to experiment with different OR schedules to find a more consistent demand pattern for inpatient physical therapy.

6.4.2 Improving the forecast

In this section we discuss multiple aspects that may improve the accuracy of the forecast.

Additional causal relationships

The forecast may be improved by researching additional causal relationships between the OR schedule and the OR output. One aspect that may be interesting to include is the different types of ORs that exist. At SMK, two ORs are referred to as orthopaedic intervention centres (OICs), which are designed for less complex surgeries. Including this additional information further restricts the feasible combinations of surgeries that may occur and therefore leads to a more accurate forecast.

Availability of medical equipment

Another aspect that can be considered is the limited availability of certain medical equipment. If all the equipment needed for a surgery is already reserved, this surgery cannot be planned.

[12] R is a programming language and software environment for statistical computing and graphics (https://en.wikipedia.org/wiki/R_(programming_language))

Horizon length

The forecast predicts demand for inpatient physical therapy per day for the coming three months, based on historical data of the past 24 months. Experimenting with the length of the historical data horizon, may improve the accuracy of the forecast and its responsiveness to changes.

Exponential smoothing

In the prototype forecast tool, the option is available to apply exponential smoothing weights to historical data to discount older data proportionally. Experimenting with different smoothing factors to determine a proper value may lead to a more accurate and more responsive forecast.

Scheduling probabilities

We advise to examine how surgeries are scheduled in the ORs and incorporate this in the forecast. There are several questions that should provide insight in this matter: what happens to an OR schedule where two patients with protocol A are planned at 20 days in advance? How often is an additional surgery planned and which surgery is this? If we can answer these types of questions, we can determine a schedule probability of additional surgeries, given current scheduled surgeries and the days left until surgery. We will then be able to devaluate combinations of surgeries that require an additional surgery. By incorporating a scheduling probability, i.e. the probability that an additional surgery will be scheduled, we can reduce the size of the 98% confidence interval of demand for inpatient physical therapy even further. This concept is discussed in more detail in appendix D.

On a more abstract level, we could consider the OR schedule and examine to what extent the OR schedule changes at a specific number of days before the surgery date. If we, for instance, know that 90% of the OR schedules remain unchanged at 1 week before the surgery date, we can devaluate the final OR schedules that require a modification proportionally. This concept excludes a reschedule and schedule probability and may therefore be simpler to design. However, we believe that this approach will be less successful, due to a lower level of causality.

References

[1] Adan, I., Bekkers, J., Dellaert, N., Vissers, J., & Xiaoting, Y. (2009). Patient mix optimisation and stochastic resource requirements: A case study in cardiothoracic surgery planning. Health Care Management Science, 12(2), 129-141.

[2] Afdeling Communicatie SMK. (2014, January). Retrieved from www.maartenskliniek.nl.

[3] Alaeddini, A., Yang, K., Reddy, C., & Yu, S. (2011). A probabilistic model for predicting the probability of no-show in hospital appointments. Health Care Management Science, 12(1), 146-157.

[4] ARC. (2015). Ambulant Reuma Centrum SMK Nijmegen.

[5] Archer, B. (1980). Forecasting Demand: Quantitative and intuitive techniques. International Journal of Tourism Management, 1(1), 5-12.

[6] Armstrong, J., Green, K., & Graefe, A. (2015). Golden Rule of Forecasting: Be Conservative. Journal of Business Research.

[7] Bonnet, D. G. (1990). Significance tests and goodness of fit of covariance structures. Psychological Bulletin, 88(3), 588-606.

[8] Bradley, D., & Martin, J. (1991). Continuous personnel scheduling algorithms: a literature review. Journal of the Society for Health Systems, 2(2), 8-23.

[9] Brusco, J., Jacobs, L., Bongiorno, R., Lyons, D., & Tang, B. (1995). Improving personnel scheduling at airline stations. Operations Research, 43(5), 741-751.

[10] Burke, E. K., De Causmaecker, P., Vanden Berghe, G., & Van Landeghem, H. (2004). The State of the Art of Nurse Rostering. Journal of Scheduling, 7(6), 441-499.

[11] Cardoen, B., Demeulemeester, E., & Beliën, J. (2010). Operating room planning and scheduling: A literature review. European Journal of Operational Research, 3(201), 921-932.

[12] Castillo, M. d. (2012). Modelling patient length of stay in public hospitals in Mexico. University of Southampton.

[13] Chen, H., & Boylan, J. (2008). Empirical evidence on individual, group and shrinkage indices. International Journal of Forecasting, 24, 525-543.

[14] Chipsoft. (2015). Database of SMK.

[15] Cote, M., & Tucker, S. (2001). Four methodologies to improve healthcare demand forecasting. Healthcare financial management: journal of the Healthcare Financial Management Association, 55(5), 54-58.

[16] De Causmaecker, P., Demeester, P., Vanden Berghe, G., & Verbeke, B. (2004). Analysis of real-world personnel scheduling problems. Proceedings of the 5th international conference on practice and theory of automated timetabling, (pp. 183-197). Pittsburgh.

[17] Dormann, C., Elith, J., Bacher, S., Buchmann, C., Carl, C., Carré, G., . . . Lautenbach, S. (2013). Collinearity: a review of methods to deal with it and a simulation study evaluating their performance. Ecography, 36(1), 27-46.

[18] Erdogan, S., Denton, B., Cochran, J., Cox, L., Keskinocak, P., Kharoufeh, J., & Smith, J. (2011). Surgery Planning and Scheduling. Wiley Encyclopaedia of Operations Research and Management Science, 1-13.

[19] Ernst, A., Jiang, H., Krishnamoorthy, M., & Sier, D. (2004). Staff scheduling and rostering: A review of applications, methods and models. European Journal of Operational Research(153), 3-27.

[20] Escabias, M., Aguilera, A., & Valderrama, M. (2004). Principal component estimation of functional logistic regression: Discussion of two different approaches. Nonparametric Statistics, 16(3), 365-384.

[21] Finarelli Jr, H., & Johnson, T. (2004). Effective demand forecasting in 9 steps. Healthcare Financial Management: Journal of Healthcare Financial Management Association, 58(11), 52-58.

[22] Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation. Journal of Marketing Research, 18(1), 39-50.

[23] Fügener, A., Hans, E., Kolisch, R., Kortbeek, N., & Vanberkel, P. (2014). Master surgery scheduling with consideration of multiple downstream units. European Journal of Operational Research, 239(1), 227-236.

[24] Guinet, A., & Chaabane, S. (2003). Operating theatre planning. International Journal of Production Economics, 1(85), 69-81.

[25] Gujarati, D. (2003). Basic Econometrics. New York: McGraw-Hill.

[26] Hans, E. W., Van Houdenhoven, M., & Hulshof, P. J. (2011). A Framework for Health Care Planning and Control. Enschede: University of Twente.

[27] Hosmer, J., David, W., & Lemeshow, S. (2004). Applied logistic regression. John Wiley & Sons.

[28] Hulshof, P. J., Kortbeek, N., Boucherie, R. J., & Hans, E. W. (2011). Taxonomic Classification of Planning Decisions in Health Care: a Review of the State of the Art in OR/MS. University of Twente, Department of Applied Mathematics. Enschede: Memorandum 1944.

[29] Jack, E. P., & Powers, T. L. (2009). Volume Flexible Strategies in Health Services: A Research Framework. Production and Operations Management, 13(3), 230-244.

[30] Jebali, A., Hadj Alouane, A. B., & Ladet, P. (2006). Operating rooms scheduling. International Journal of Production Economics, 1-2(99), 52-62.

[31] Jones, S., Thomas, A., Evans, R., Welch, S., Haug, P., & Snow, G. (2008). Forecasting daily patient volumes in the emergency department. Academic Emergency Medicine, 15(2), 159-170.

[32] Kleinbaum, D., & Klein, M. (2002). Logistic regression a self-learning text. New York: Springer.

[33] Kortbeek, N., Braaksma, A., Smeenk, H., Bakker, P., & Boucherie, R. (2012). Integral resource capacity planning for inpatient care services based on hourly bed census predictions. University of Twente, Department of Applied Mathematics. Enschede: Memorandum 1990.

[34] Lee, H. L., Padmanabhan, V., & Whang, S. (1997). Information Distortion in a Supply Chain: The Bullwhip Effect. Management Science, 43(4), 546-558.

[35] Min, D., & Yih, Y. (2010). Scheduling elective surgery under uncertainty and downstream capacity constraints. European Journal of Operational Research, 206(3), 642-652.

[36] ORchestra. (2012). *Twente, Devoloped by Center for Healthcare Operations and Improvement Research (CHOIR) at the University of*. Opgehaald van http://www.choir-ut.nl

[37] Przasnyski, Z. H. (1986). Operating Room Scheduling: A Literature Review. AORN Journal, 1(44), 67-82.

[38] Rais, A., & Viana, A. (2011). Operations Research in Healthcare: a survey. International transactions in operational research, 18(1), 1-31.

[39] Ryan, T. (1997). Modern Regression Methods. John Wiley & Sons.

[40] Smith-Daniels, V. L., Schweikhart, S. B., & Smith-Daniels, D. E. (1988). Capacity Management in Health Care Services: Review and Future Research Directions. Decision Sciences, 19(4), 889-919.

[41] TSM Business School. De Algemene Bedrijfskundige Probleemaanpak.

[42] Van den Bergh, J., Beliën, J., De Bruecker, P., Demeulemeester, E., & De Boeck, L. (2013). Personnel scheduling: A literature review. European Journal of Operational Research, 226, 367-385.

[43] Vanberkel, P. T., Boucherie, R. J., Hans, E. W., Hurink, J. L., Van Lent, W. A., Harten, V., & H., W. (2011). An exact approach for relating recovering surgical patient workload to the master surgical schedule. Journal of operational research society, 62(1), 1851-1860.

[44] Witt, S., & Witt, C. (1995). Forecasting tourism demand: A review of empirical research. International Journal of Forecasting, 11(3), 447-475.

[45] Wonnacott, T. H., & Wonnacott, R. J. (1990). Introductory statistics for business and economics. John Wiley & Sons.

[46] Zagier, D. (1997). Newman's Short Proof of the Prime Number Theorem. The American Mathematical Monthly, 104(8), 705-708.

Appendix A – Literature search methodology

In this section we discuss the methodology used to find literature.

Search strategy

We used Google Scholar as a search engine for our literature study. Additionally, we consulted the online literature database ORchestra [36]. Some articles have been obtained through recommendations of professors and fellow students. To increase the scope of our search, we intermittently used forward and backward search on articles.

In the Table below, we provide the search terms we used in Google Scholar, the initial number of hits and the sources we used in this research. Due to the limited available time to perform a literature study, we chose to focus on articles with a high number of citations. To not exclude recent articles we also considered the publication date in relation to the number of citations. We assume that a high number of citations is positively related to the quality of the analysis in the source or the insight it provides. By focussing on these articles we get a grasp of the fundamental literature in the studied areas. We further limited our search by using Google Scholar's sort by relevance and we limited our study to the articles on the first ten pages with full-text availability.

Search engine	Search terms	Initial hits	Sources
Google Scholar	No-show probability	5690	[3]
Google Scholar	Forecasting demand	1.100.000	[5; 15; 44]
Google Scholar	Forecasting seasonal factors	196.000	[6]
Google Scholar	Chi-square significance	2.550.000	[7; 22]
Google Scholar	Personnel scheduling	356.000	[8; 9; 10; 16; 19; 42]
Google Scholar	Operating room scheduling	143.000	[11; 24; 30; 37]
Google Scholar	Dealing with collinearity	36.800	[17]
Google Scholar	Surgery scheduling	82.000	[18]
Google Scholar	Demand forecasting healthcare	43.400	[21; 38]
Google Scholar	Demand uncertainty healthcare	138.000	[26; 29; 40]
Google Scholar	Logistic Regression	1.300.000	[27]
Google Scholar	Forecasting patient demand	36.800	[31]
Google Scholar	Bullwhip effect	20.000	[34]
Google Scholar	Regression methods	3.500.000	[39]

Besides searching with Google Scholar to find literature, we also used other methods. In the Table below, we provide an overview of the other methods we used to find literature and list the sources we used.

Other search methods used	Sources
Master Thesis of Bas Kamphorst	[1; 33; 35]
Backwards search on [6]	[13]
CHOIR meeting	[23; 43]
Via colleague	[28]
Backwards search on [3]	[32]
Consultation with a statistics professor	[45]

Appendix B – Logistic regression iterations

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	UpperExtremity	,085	,057	2,219	1	,136	1,089
	Emergency	-1,336	,162	67,687	1	,000	,263
	Hip	-,042	,060	,491	1	,484	,959
	Spine	,180	,072	6,194	1	,013	1,197
	TwoMonths	-,616	,097	40,478	1	,000	,540
	Constant	-1,157	,032	1313,858	1	,000	,314

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	Knee	-,106	,054	3,923	1	,048	,899
	Elective	,879	,084	109,369	1	,000	2,408
	Spine	,114	,075	2,345	1	,126	1,121
	UpperExtremity	,039	,060	,428	1	,513	1,040
	OneMonth	,044	,149	,087	1	,768	1,045
	Constant	-1,956	,086	517,019	1	,000	,141

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	Knee	-,201	,057	12,443	1	,000	,818
	Elective	1,059	,101	109,170	1	,000	2,883
	UpperExtremity	-,063	,063	1,004	1	,316	,939
	TwoMonths	,411	,136	9,081	1	,003	1,508
	Hip	-,179	,065	7,498	1	,006	,836
	Constant	-2,038	,106	370,306	1	,000	,130

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	Hip	-,143	,064	5,043	1	,025	,867
	TwoMonths	,409	,136	8,991	1	,003	1,505
	Knee	-,165	,055	8,975	1	,003	,848
	Feet	,025	,066	,149	1	,699	1,026
	Elective	1,060	,101	109,543	1	,000	2,887
	Constant	-2,075	,104	394,572	1	,000	,126

Appendix C – Instruction manual to the forecast

In this section we provide a basic manual to perform the forecast. For a more detailed step-by-step manual in Dutch we recommend to consult the file “Handleiding voorspellingstool”, which can be found in my shared folder.

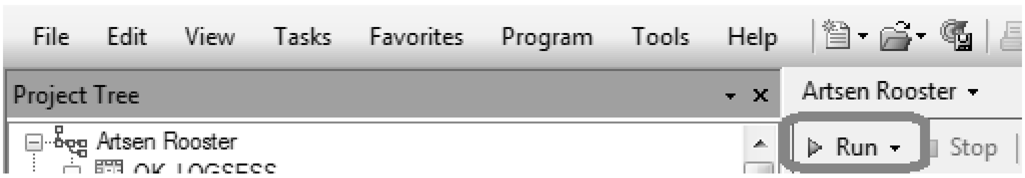
Update the reschedule data

1. Open the file “Annuleringen”
2. Update the data
    a. Go to “Gegevens”
    b. Click on “Alles vernieuwen”

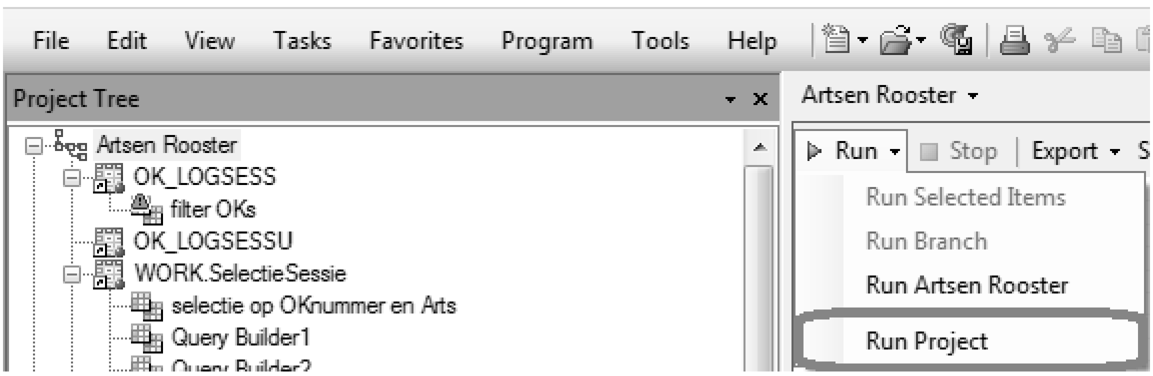
3. Save and close the file

Run the SAS query

1. Open the file “SAS Query”
2. Go to “Run”



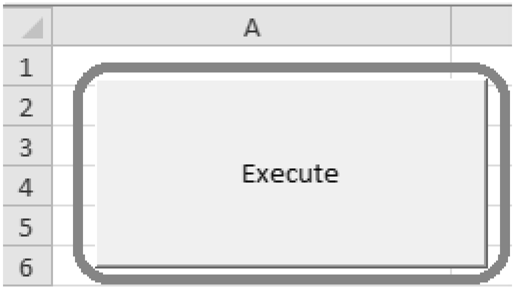
3. Click on “Run Project”



4. Close the file

Execute the forecast

1. Open the file “Forecast”
2. Click on the button “Execute” in the sheet “Control Sheet”



3. Excel will compute for about 25 minutes
4. The results are projected in the sheet “Results”
5. Close the file afterwards without saving

Appendix D – Devaluation of OR schedules

The forecast model uses the reschedule probability of a scheduled surgery to devaluate final OR schedules that require a reschedule of a currently scheduled surgery. However, the forecast model does not devaluate final OR schedules that require the scheduling of additional surgeries. We elaborate on this below.

The Prime Number Theorem shows that higher numbers are more likely to have a positive divisor other than 1 and itself, and are therefore less likely to be a prime [46]. Similarly, final OR schedules that consist of more surgeries are more likely to contain the inpatient physical therapy protocols in the tentative OR schedule and thus do not require a reschedule. OR schedules that consist of more surgeries often contain more demand for inpatient physical therapy. As a result, the final OR schedules that contain relatively more demand for inpatient physical therapy are devaluated less. We illustrate this concept with an example.

In the example there are three possible surgeries that can be performed: X, Y and Z. These surgeries can be performed in any combination, with a maximum of three surgeries. Below we show that this adds up to a total of 19 different OR schedules, excluding an empty OR schedule. Here:

k = the number of surgeries in the combination,

k = {1, 2, 3},

n = the number of unique surgeries {X, Y, Z},

n = 3.

In the case of one scheduled surgery in the OR (k = 1, n = 3) this results in:

$\binom{k+n-1}{k} = \binom{1+3-1}{1} = 3$ combinations.

In the case of two scheduled surgeries in the OR (k = 2, n = 3) this results in:

$\binom{k+n-1}{k} = \binom{2+3-1}{2} = 6$ combinations.

In the case of three scheduled surgeries in the OR (k = 3, n = 3) this results in:

$\binom{k+n-1}{k} = \binom{3+3-1}{3} = 10$ combinations.

$3 + 6 + 10 = 19\ combinations.$

We present the possible combinations of tentative OR schedules and the combinations of final OR schedules in Table 17.

		Final OR schedules																		
		X	Y	Z	X-X	X-Y	X-Z	Y-Y	Y-Z	Z-Z	X-X-X	X-X-Y	X-X-Z	Y-Y-X	Y-Y-Y	Y-Y-Z	Z-Z-X	Z-Z-Y	Z-Z-Z	X-Y-Z
		Required number of reschedules																		
Tentative OR schedules	X	0	1	1	0	0	0	1	1	1	0	0	0	0	1	1	0	1	1	0
	Y	1	0	1	1	0	1	0	0	1	1	0	1	0	0	0	1	0	1	0
	Z	1	1	0	1	1	0	1	0	0	1	1	0	1	1	0	0	0	0	0
	X-X	1	2	2	0	1	1	2	2	2	0	0	0	1	2	2	1	2	2	1
	X-Y	1	1	2	1	0	1	1	1	2	1	0	1	0	1	1	1	1	2	0
	X-Z	1	2	1	1	1	0	2	1	1	1	1	0	1	2	1	0	1	1	0
	Y-Y	2	1	2	2	1	2	0	1	2	2	1	2	0	0	0	2	1	2	1
	Y-Z	2	1	1	2	1	1	1	0	1	2	1	1	1	1	0	1	0	1	0
	Z-Z	2	2	1	2	2	1	2	1	0	2	2	1	2	2	1	0	0	0	1
	X-X-X	2	3	3	1	2	2	3	3	3	0	1	1	2	3	3	2	3	3	2
	X-X-Y	2	2	3	1	1	2	2	2	3	1	0	1	1	2	2	2	2	3	1
	X-X-Z	2	3	2	1	2	1	3	2	2	1	1	0	2	3	2	1	2	2	1
	Y-Y-X	2	2	3	2	1	2	1	2	3	2	1	2	0	1	1	2	2	3	1
	Y-Y-Y	3	2	3	3	2	3	1	2	3	3	2	3	1	0	1	3	2	3	2
	Y-Y-Z	3	2	2	3	2	2	1	1	2	3	2	2	1	1	0	2	1	2	1
	Z-Z-X	2	3	2	2	2	1	3	2	1	2	2	1	2	3	2	0	1	1	1
	Z-Z-Y	3	2	2	3	2	2	2	1	1	3	2	2	2	2	1	1	0	1	1
	Z-Z-Z	3	3	2	3	3	2	3	2	1	3	3	2	3	3	2	1	1	0	2
	X-Y-Z	2	2	2	2	1	1	2	1	2	2	1	1	1	2	1	1	1	2	0
		Frequency																		
Required number of reschedules	0	1	1	1	2	3	3	2	3	2	3	5	5	5	3	5	5	5	3	7
	1	5	5	5	7	8	8	7	8	7	6	8	8	8	6	8	8	8	6	9
	2	9	9	9	6	7	7	6	7	6	6	5	5	5	6	5	5	5	6	3
	3	4	4	4	4	1	1	4	1	4	4	1	1	1	4	1	1	1	4	0
Sum product		35	35	35	31	25	25	31	25	31	30	21	21	21	30	21	21	21	30	15

Table 17 - An example of the required number of reschedules per final OR schedule, given a tentative OR schedule

For all of the possible tentative OR schedules, we calculate the number of reschedules required to reach a final OR schedule. In the case of the tentative OR schedule with scheduled surgeries X-Y-Z, the surgeries Y and Z need to be rescheduled to reach final OR schedule X-X. Therefore, the required number of reschedules is equal to two in this case.

Next, we determine the frequency of the number of required reschedules per final OR schedule. In the case where the final OR schedule consists of surgery X, we observe a required number of one reschedule five times. Finally, we take the sum of the required number of reschedules per final OR schedule. The resulting number shows the total number of surgeries that need to be rescheduled to reach a final roster, given all the tentative OR schedules. A relatively higher number shows that this final roster requires relatively more reschedules, given the tentative schedules. Because we use a reschedule probability to devaluate final OR schedules that require a reschedule, a higher required number of reschedules results in a higher devaluation and thus a lower probability in the outcome of the forecast.

We see a clear pattern in Table 17, where final OR schedules with more protocols are devaluated less than final OR schedules that consist of fewer surgeries. Final OR schedules that contain more surgeries often contain more demand for inpatient physical therapy. As a result, the designed forecast is able to increase the 1% minimum of the current forecast by devaluating final OR schedules with a lower amount of demand for inpatient physical therapy. However, the designed forecast is unable to decrease the 99% maximum of the current forecast, because final OR schedules that require additional schedules are not devaluated appropriately. In Figure 32 we show how the designed forecast is affected by this phenomenon.

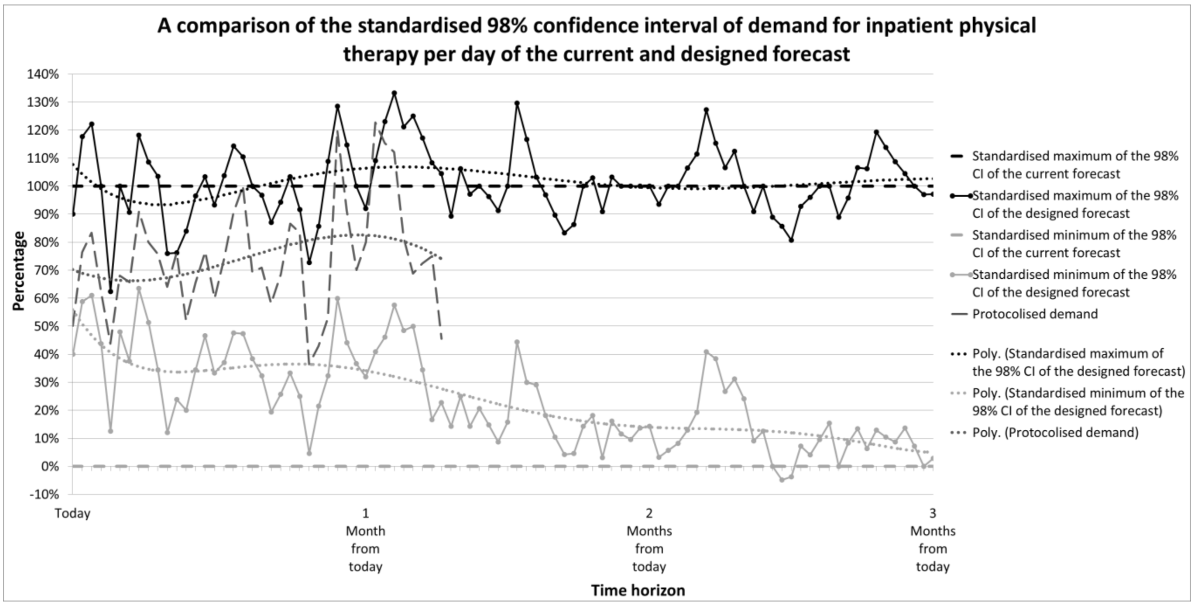


Figure 32 - A comparison of the standardised 98% confidence interval of demand for inpatient physical therapy per day of the current and designed forecast on the 15th of October 2015

In Figure 32 we standardise the upper and lower bounds of the 98% confidence interval of the current forecast and show how the 98% confidence interval of the designed forecast changes compared to this interval. The dashed horizontal lines represent the maximum and minimum of the 98% confidence interval of the current forecast. We present these values as 0% and 100% and show the relative change of the 98% confidence interval of the designed forecast with lines that have a circle on each observation point. The dotted lines are a fitted polynomial. We elaborate on Figure 32 with an example.

	Current forecast	Standardised
98% max	80	100%
98% min	70	0%
size of interval	10	100%

	Designed forecast	Standardised
98% max	81	(81 - 70) / 10 = 110%
98% min	72	(72 - 70) / 10 = 20%
size of interval	9	90%

Table 18 - Standardising the confidence intervals

In the example, the maximum of the 98% confidence interval of the current forecast is equal to 80 inpatient physical therapy treatments. The minimum of the 98% confidence interval of the current forecast is equal to 70 inpatient physical therapy treatments. In Figure 32 we standardise these values to 100% and 0%. The size of the 98% confidence interval of the current forecast is equal to 80-70 = 10.

In the example, the maximum of the 98% confidence interval of the designed forecast is equal to 81 inpatient physical therapy treatments. The minimum of the 98% confidence interval of the designed forecast is equal to 72 inpatient physical therapy treatments. We standardise these values as follows:

1. We take the 98% maximum or 98% minimum of the designed forecast and subtract the 98% minimum of the current forecast.
2. We divide the result by the size of confidence interval of the current forecast.

For the maximum of the 98% confidence interval of the designed forecast this results in $\frac{(81-70)}{10} = 110\%$. A similar calculation for the 98% minimum results in 20%. These values should be interpreted as follows. The 98% minimum of the confidence interval of the designed forecast lays 20% closer to the 98% maximum of the current forecast. Similarly, The 98% maximum of the confidence interval of the designed forecast lays 10% further from the 98% minimum of the current forecast. In this case the 98% confidence interval of the designed forecast is 10% smaller and we notice a shift upwards.

In Figure 32 we can see that the designed forecast is able to increase the minimum of the 98% confidence interval of the current forecast. To decrease the 98% maximum we propose to incorporate a schedule probability, i.e. the probability that a specific surgery is added to the OR schedule, to devaluate combinations of surgeries that require an additional surgery. We discuss the concept of a reschedule probability in more detail in 6.4.2.