Reducing Workload Fluctuations through Causal Forecasting

A Case Study in the Plaster Room of Sint Maartenskliniek

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June 2018

General information

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Management summary

Introduction

The employees and management of the plaster room in Sint Maartenskliniek in Nijmegen, The Netherlands, perceive high fluctuations of workload over the days resulting in overstaffed and understaffed days. Earlier research of Dijkstra (2017) and performance analysis over data from 2016 and 2017 confirm these workload fluctuations and show that the demand of walk-in patients, which consists of approximately 38 percent of the total treatment time, is highly variable over and on individual days.

The objective of this research is to minimize workload fluctuations over the days by creating a planning method that incorporates patient demand while maintaining patient service levels.

Approach

We develop a planning method that improves the match between capacity and demand by incorporating walk-in patient demand. This research provides a step-by-step guide to generate, select and validate causal forecasting models that can support outpatient clinic planning staff in making scheduling decisions. The input distributions are created using historical patient data from 2016 and 2017. Using discrete convolution, one output probability distribution per time period is created. Figure 1 shows the visual representation of the steps used to obtain the expected walk-in demand probability distribution.

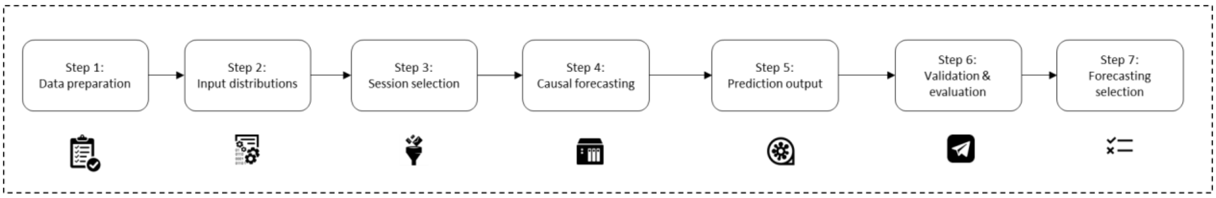


Figure 1: Overview of causal forecasting model

The best performing prediction is used to calculate the expected walk-in demand in March 2018 as shown in Figure 2. This prediction is used to create a new patient planning, where capacity is reserved for walk-in demand based on the mean expected output value obtained from the forecasting method. A patient planning simulation is used to evaluate the experimental patient planning and its performance is compared with the realization of the plaster room in March 2018.

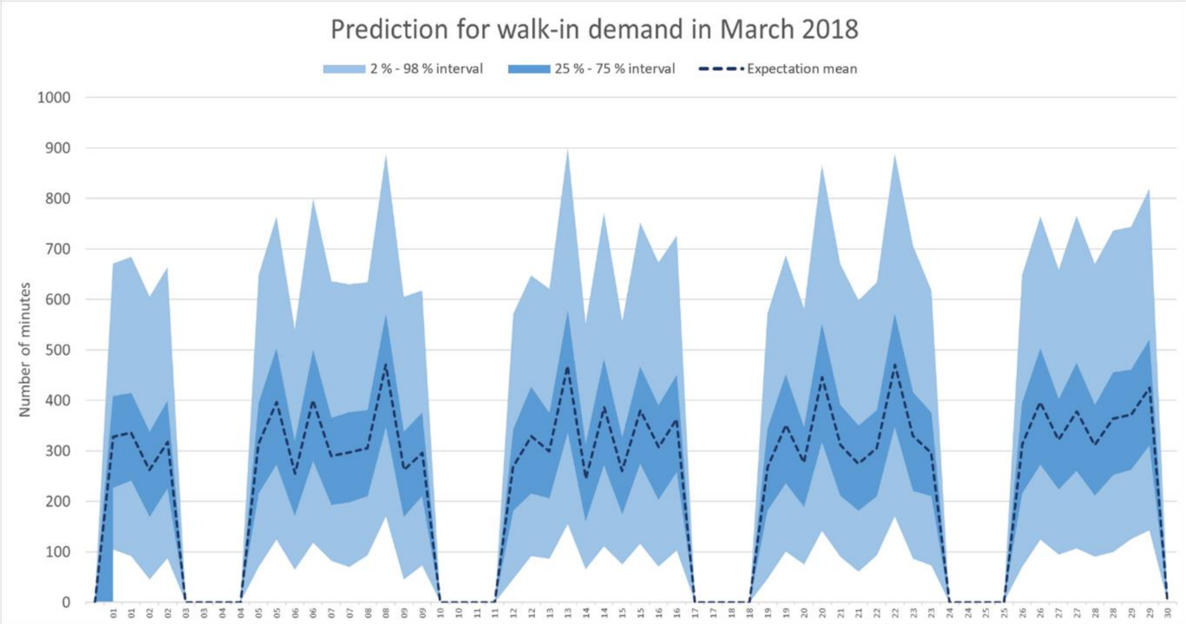


Figure 2: Expected plaster room walk-in demand per daypart in March 2018

Results

Table 1 shows the results of the simulation model, where the experimental interventions show to outperform the realized situation by a reduction of overstaffed days of 50%. We achieve a decrease in average capacity shortage of approximately 35%.

				If understaffed, then capacity shortage in minutes is:		
	Days overstaffed	Days correctly staffed	Days understaffed	Average	Minimum	Maximum
Current situation	4	10	7	-700	-275	-1075
Results using booked time	2	12	7	-468	-291	-768
Results using realized time	2	10	9	-453	-253	-801

Table 1: Results of patient planning simulation using expected walk-in demand

Conclusion

This research shows that the method to predict walk-in demand can increase the match between capacity and demand in the plaster room and minimizes workload fluctuations over the days. The methodology results in a model that can continuously create walk-in demand predictions and is implemented in the plaster room in the summer of 2018.

Recommendations & Further research

Our proposed forecasting model is validated and evaluated during a two-month period. We recommend evaluating the forecasting output on more data to ensure validity and captivate possible seasonal trends by including more (extreme) off-peak moments and peak-moments.

The results of this research create the opportunity to experiment with or implement more complex appointment rules in the plaster room. The information made available through this research offers the opportunity to create a better match between capacity and demand.

This research focuses on creating a walk-in demand predicting due to its high impact on workload and lack of insights. We recommend generating a probability distribution of the expected appointment-based demand to determine the required capacity per week.

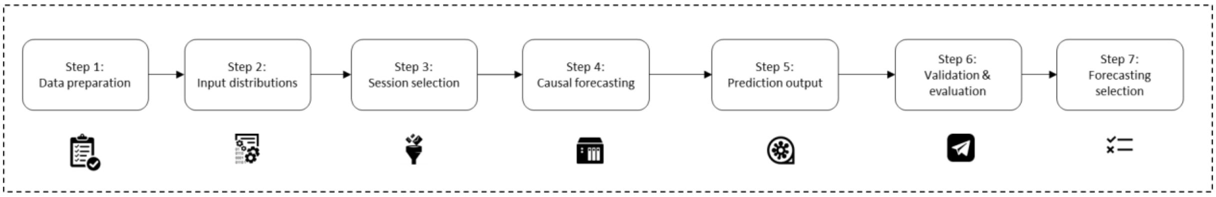
Samenvatting

Het management en de medewerkers van de gipskamer van de Sint Maartenskliniek in Nijmegen, Nederland, ervaren grote fluctuaties in de dagelijkse werkdruk. Dit resulteert in ongewenste onderbezette of overbezette dagen. Onderzoek van Dijkstra (2017) en performance analyse over de data van 2016 en 2017 bevestigen dit probleem. Bij het maken van de patiëntenplanning en het medewerkersrooster wordt geen rekening gehouden met de vraag van patiënten op inloop, terwijl deze groep verantwoordelijk is voor 38% de totale behandeltijd. Daarnaast is er een sterke fluctuatie van de vraag van inloop patiënten per dag, variërend van ongeveer 300 minuten (5 uur) tot 1400 minuten (23 uur) in 2016 en 2017.

Het doel van dit onderzoek is om de fluctuaties van de dagelijkse werkdruk te minimaliseren, door gebruik te maken van verwachte vraag in de planning van de gipskamer.

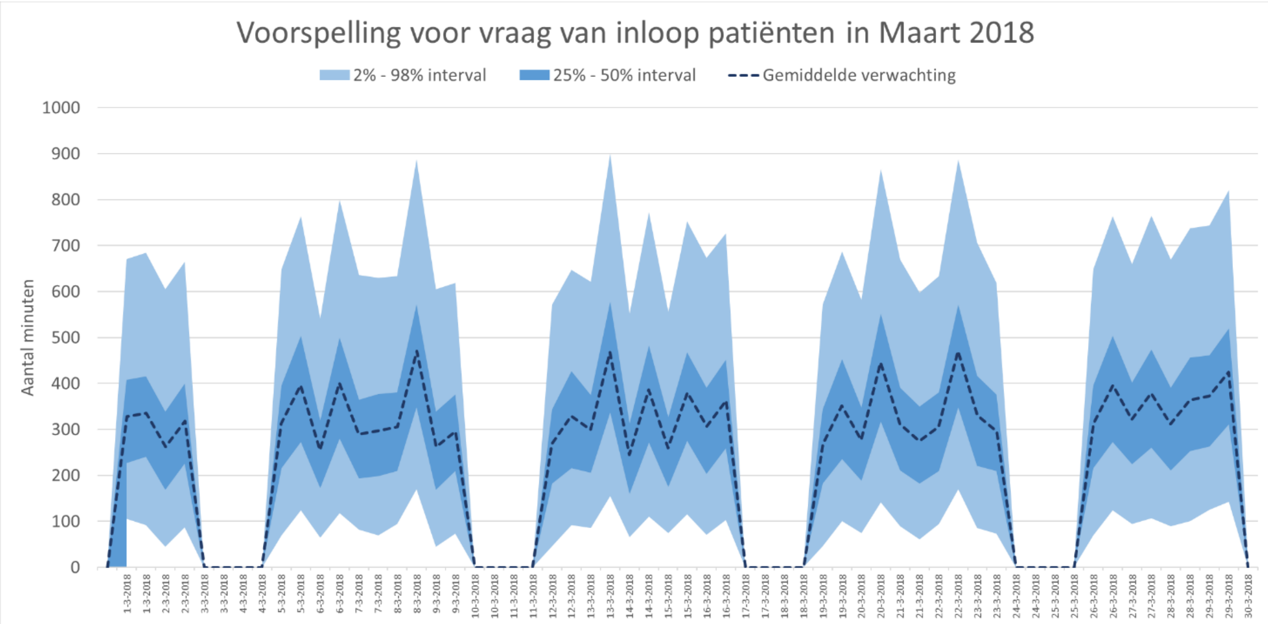
Aanpak

We ontwikkelen een planningsmethode die de vraag van patiënten en de capaciteit van de gipsverbandmeesters op elkaar afstemt. Door gebruik te maken van verwachte vraag (expected demand) van patiënten op inloop, creëren we de mogelijkheid om de capaciteit van gipsverbandmeesters beter te benutten en het personeel te ondersteunen in het nemen van planningsbeslissingen. Dit onderzoek verstrekt een handleiding waarmee een afdeling Causal Forecasting modellen kan genereren, selecteren en valideren. Figuur 1 geeft een globaal overzicht van de stappen waaruit het model bestaat. De benodigde input distributies in dit onderzoek bestaan uit de historische patiënten data uit 2016 en 2017. Door middel van convolutie wordt in stap 4 één output distributie gecreëerd in de vorm van verwachte vraag op inloop in minuten per dagdeel.



Figuur 1: Overzicht van het Causal Forecasting model

De output distributie die in stap 6 en 7 het beste presteert wordt gebruikt om de verwachte vraag van inloop patiënten in Maart 2018 te berekenen (zie Figuur 2). Deze voorspelling wordt gebruikt om een alternatieve patiëntenplanning te maken, waarbij er capaciteit gereserveerd wordt voor inloop patiënten op basis van de gemiddelde verwachte waarde. In een simulatiemodel vergelijken we de gerealiseerde prestatie met het door ons gecreërde alternatief op basis van verhouding tussen vraag en aanbod, en de bezettingsnormen.



Figuur 2: Verwachte vraag van inloop patienten per dagdeel in Maart 2018

Resultaten

De resultaten van de prestaties in Maart 2018 in alle situaties zijn te zien in Tabel 1. De alternatieve patiëntenplanningen presteren beter dan de huidige situatie: een afname van 50% is te zien in het aantal overbezette dagen en de gemiddelde ondercapaciteit in onderbezette dagen is afgenomen met ongeveer 35%.

				In geval van onderbezetting is het capaciteitstekort in minuten:		
	Aantal dagen overbezet	Aantal dagen juist bezet	Aantal dagen overbezet	Gemiddeld	Minimum	Maximum
Gerealiseerde situatie	4	10	7	-700	-275	-1075
Resultaat (bij gebruik van geboekte afspraaktijden)	2	12	7	-468	-291	-768
Resultaat (bij gebruik gerealiseerde afspraaktijden)	2	10	9	-453	-253	-801

Tabel 1: Resultaten van de verschillende patiëntenplanningen

Conclusie

Dit onderzoek laat zien dat de methode om de vraag van inloop patiënten te berekenen in staat is om vraag en aanbod beter op elkaar af te stemmen. Hierdoor worden fluctuaties in de werkdruk over de dagen verminderd en wordt de bezetting per dag van gipsverbandmeesters verbetert. Het Causal Forecasting model is in staat om autonoom voorspellingen voor de vraag op inloop te berekenen en wordt in de zomer van 2018 in gebruik genomen door de gipskamer van de Sint Maartenskliniek.

Aanbevelingen en verder onderzoek

Het Causal Forecasting model wordt gevalideerd en geëvalueerd over een periode van twee maanden. Onze aanbeveling is om de output distributies te evalueren over een langere periode om zo extremiteiten en seizoensgebonden trends mee te nemen.

De resultaten van dit onderzoek bieden de mogelijkheid om te experimenteren met complexe planningsregels voor de patiëntenplanning en de medewerkersplanning. Door gebruik te maken van de informatie uit dit onderzoek kan een betere afstemming worden gecreëerd tussen vraag en aanbod.

Door de hoge impact op de werkdruk en het gebrek aan inzichten van de vraag van inloop patiënten, is dit de focus geweest van dit onderzoek. Door het genereren van een voorspelling voor de verwachte vraag van patiënten op afspraak per week kan de benodigde wekelijkse capaciteit worden vastgesteld. Hiermee wordt de match tussen vraag en aanbod in de gipskamer verder verbeterd.

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List of Abbreviations

AA	Average Accuracy (evaluation measure)
AE	Average error (evaluation measure)
FTE	Full time equivalent
KPI	Key Performance Indicator
MAPE	Mean Absolute Percentage Error (evaluation measure)
OCT	Orthopedic cast technician
OR	Operating room
POA	Percent of Accuracy (evaluation measure)
SMK	Sint Maartenskliniek
xDemand	Predicted demand, estimated demand

1 Introduction

The focus of this research project is to map and evaluate the workload of the plaster room of the Sint Maartenskliniek in Nijmegen, the Netherlands. The goal of this research is to assess and map the internal processes and discover opportunities to improve the performance and quality of the delivered care.

This chapter provides background information regarding the Sint Maartenskliniek, the plaster room and Rhythm (Section 1.1), followed by the problem description (Section 1.2) and research objective and questions (Sections 1.3 and 1.4 respectively).

1.1 Brief context description

Sint Maartenskliniek

Sint Maartenskliniek (SMK) is a hospital in Nijmegen, the Netherlands, which specializes in movement and posture disorders. The hospital has four different facilities at distinct locations, where the facility located near Nijmegen is considered the main facility. This facility consists of multiple departments, one of which is the plaster room where this research is conducted. The three basic medical specialties are: orthopedics, rheumatology and rehabilitation techniques. In its field, the SMK is among the leading institutions in the Netherlands and Europe.

Plaster room

In the plaster room, the Orthopedic Cast Technicians (OCTs) provide patients with all kind of treatments, such as applying or removing plaster and caring for wounds.

The plaster room classifies their treatments into three groups: appointment, walk-in and patients that are treated in the operating room (OR). A treatment is defined as walk-in when the appointment was made less than 24-hour prior. Patient treatment demand between these groups vary in complexity, duration and desired expertise.

Rhythm

Rhythm is a spin-off of the University of Twente research group CHOIR, Centre for Healthcare Operations Improvement and Research, and ORTEC, specialist in optimization-based services and software. Rhythm supports the Sint Maartenskliniek in the logistical process and developed several algorithms and applications to support the departments. The research project is conducted under supervision and in cooperation with the logistics department consisting of Rhythm employees, in order to maintain consistency within the SMK.

1.2 Problem description

The management of the plaster room wants to align the supply (of OCTs) and the demand (of patients) to reduce workload fluctuations over the days.

Recent research of Dijkstra (2017) aimed to assess and benchmark the current practice of the plaster room in the SMK, as well as improve performance on individual days. The research strongly recommends investing in creating and implementing a method that predicts expected patient demand (xDemand), since this knowledge provides the base for more operational improvements. Dijkstra experimented with interventions to optimize operational performance over individual days, therefore this is excluded from this research.

The employees and management of the plaster room perceive a fluctuating workload over the days, which implies that capacity and demand are not balanced adequately. Approximately 53% of the patients planned their appointment in advance, where the other 47% are walk-in patients. The expected demand regarding the number of walk-in patients, treatment length and complexity is unknown to the staff of the plaster room.

The treatments in the plaster room are mainly requested by orthopedic physicians. All patients treated in the plaster room are under the responsibility of their primary physician.

Regarding patients with appointments, both the complexity and treatment length are increasing for patients that have appointments. The uncertainty in the type of treatment that is required is not known until after the first treatment in the plaster room.

Decisions regarding the staff planning and patient planning are made with little information from other departments, while these determine the plaster room patient demand. The current insights in the expected demand is too inadequate to create the desired intelligence and is not used when planning decisions are made.

The core problem is an inadequate match between capacity and demand, resulting in a fluctuating workload over and on individual days. The lack of insight in patient demand hinders the planning staff of the plaster room to achieve a more balanced match between capacity and demand.

1.3 Research objective

The objective of this research is *to minimize workload fluctuations over the days by creating a planning method that incorporates (walk-in and appointment based) patient demand while maintaining patient service levels.*

Since prior research focused on planning optimization during the day, this is not included in this research. More information on this subject is found in the research of Dijkstra (2017). This study focuses on optimizing performance over multiple days. Employee planning is subject to multiple restrictions and is regarded as fixed, in consultation with the management of the plaster room. Both walk-in and appointment-based patient demand is unknown for the plaster room, while both greatly influence workload. Walk-in patients should be treated on the same day, while patients with an appointment have their treatment planned by the plaster room staff. Quantifying the patient demand as input for the patient planning shows substantial potential for operational performance, for example by planning more treatments on suspected off-peak moments of walk-in demand.

Therefore, the scope of this research is *workload performance over multiple days*.

1.4 Research goals and questions

In line with the research objective, we define the following research goals and corresponding questions:

1. Describe current operational processes and performance indicators
   What are the relevant processes and corresponding performance indicators of the operational performance in the plaster room?
   What is the current operational performance of the plaster room?
   What is the patient demand of the plaster room and by what factors is it determined?
2. Literature review
   Which relevant solution methods can be found in the literature?
3. Solution design
   Concluding from the prior chapters, what are the most promising opportunities for improving operational performance in the plaster room of the Sint Maartenskliniek?
4. Model design
   What is the design of the model that offers potential regarding the presented solution?
5. Results
   What are the effects of the modeled interventions and how can we use these interventions to improve operational performance?
6. Conclusions and recommendations
   Which insights does this research provide and how does it benefit the plaster room?

Chapter 2 gives the answers to the research questions under goal number 1. In Chapter 3 the solution methods found in the literature are discussed. Chapter 4 presents the solution design based on opportunities found in the prior chapters. In Chapter 5 the design of the model is outlined, and the results obtained using this model are shared in Chapter 6. The conclusions and recommendations of this research are in Chapter 7.

2 Context analysis

This chapter provides the context analysis of the plaster room. Section 2.1 focuses on operational planning processes. Section 2.3 presents insights in the patient demand. Section 2.3 describes the current operational performance. Section 2.4 concludes this chapter.

2.1 Operational processes

This section gives an overview of the operational processes of the plaster room in the SMK. It starts with a description of the process and system and gives an insight in the current situation and organization.

2.1.1 Process and system description

The treatments in the plaster room involve multiple activities like the applying and removing plaster, wound treatment and making braces. Figure 3 shows a map of the plaster room department, showing the front desk, treatment rooms and waiting room. The opening hours of the plaster room are compliant with the hospital-wide opening hours, which are from 08:00 to 17:30. Recent developments in the hospital include extended opening hours for the operating room. Since the decision of when to accommodate this extension has been rescheduled multiple times during the project, this aspect is outside the scope of this research.

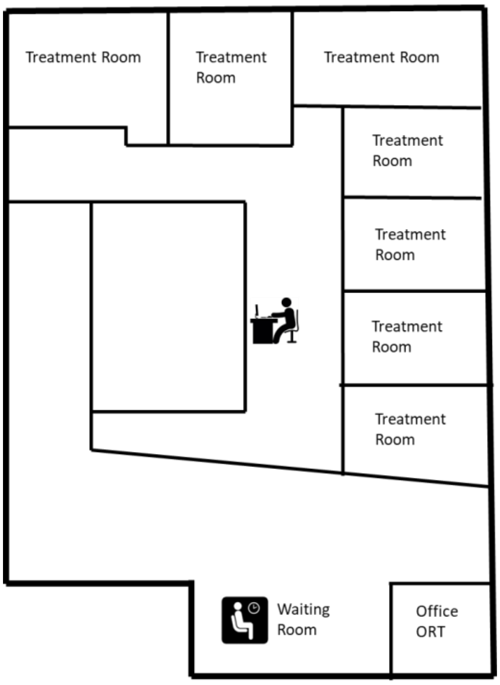

Figure 3. Map of plaster room department

The staff of the plaster room consists of Orthopedic Cast Technicians (OCTs), medical specialists, management, planning staff and support staff. A brief overview of these different actors and their roles is shown in the following section.

Orthopedic Cast Technicians

The OCTs are the specialized staff that treat the patients in the plaster room. These treatments are given in the plaster room, in the operating room or on the ward. In total there are 9 OCTs employed in the plaster room in Nijmegen. Each day, one of the OCTs is assigned as coordinator. The tasks of the coordinator include deciding on whether it is time for the lunch break and other ad hoc operational decisions. One of the OCTs is responsible for the employee planning in the plaster room, including the review of requested planned absence.

Medical Specialists

The medical specialists are the primary physicians of the treated patients and redirect the patients to undergo treatment in the plaster room. Special consultation hours for the specialties hand, foot and wound are planned in the plaster room in cooperation with the referring department. The physicians can require treatment of their patients during a surgery, after an outpatient clinic visit, during their stay in the hospital of in between other consultations. The production of the medical specialist determines most of the demand (and thus the fluctuations) in the plaster room.

Management

The management of the plaster room is responsible for the strategic and tactical planning. The management determines the required staff capacity. The management is responsible for the tactical planning of employees and is the key stakeholder in the entire process.

Planning staff

The planning staff member is responsible for the operational patient planning and the planning staff member is located at the front desk. The responsible planning staff member registers and schedules the patients. The planning staff is also responsible for several administrative tasks and is supervised by one of the OCTs.

Supporting staff

The supporting staff is responsible for inbound phone calls, cleaning the department and other supporting tasks.

Patients of all specialties (orthopedics, rehabilitation, rheumatism, internal medicine and sports) are treated in the plaster room, but nearly all patients (*95%*) are referred by the orthopedic department. With plaster room patient planning as focus, these patients can be subdivided into distinct categories based on plaster room patient planning; walk-in patients, appointment-based patients and OR patients. The patient paths are visualized in Figure 4. All patients who receive treatment in the plaster room are under treatment of a primary physician outside of the plaster room department, meaning the plaster room does not have their 'own' patients but treat the patients of the physicians that request plaster room treatment.

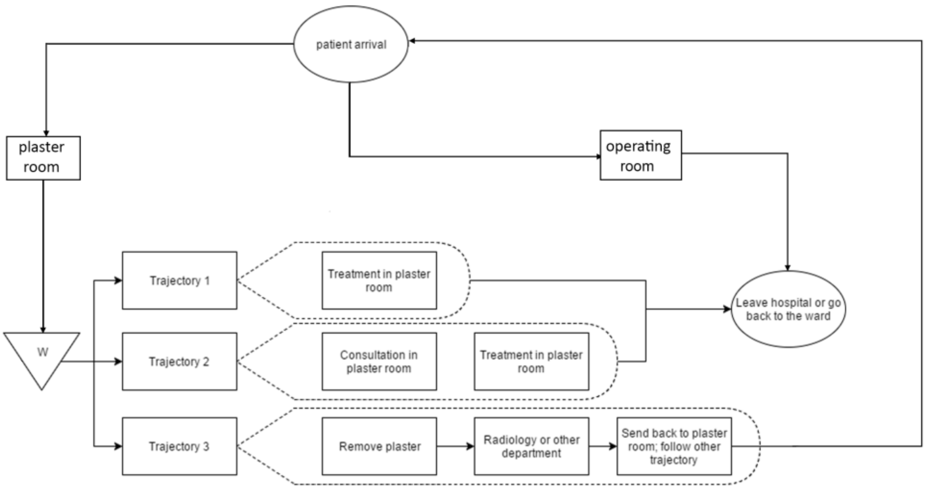

Figure 4: Overview of patient flow, by Dijkstra (2017)

Patients who request treatment in the plaster room register at the front desk. If the planned timeslot or the first available timeslot is within 30 minutes, the patients are send to the waiting room. Patients in the waiting room are generally treated on a first come, first served basis without priority rules. However, on busy moments the plaster room staff grants priority to patient with a scheduled appointment. This decision of prioritizing appointment-based patients is made by the employees and is rather based on experience than on policy.

Appointment-based patients

Patients that have an appointment scheduled more than *24 hours* prior to the appointment itself are considered appointment-based. These treatments are planned in by the plaster room in their agenda and include inpatient and outpatient treatments. Patients that need treatment at the OR are also scheduled in the plaster room agenda but are subject to the uncertainty of the OR schedule. Furthermore, there are occurrences of walk-in patients that receive an appointment for a following day; these treatments are considered too complex or time-demanding for walk-in (for example the creation of patient-specific braces which can take several hours).

Walk-in patients

The plaster room offers treatment for patients without an appointment. Most of these patients had an appointment at the Sint-Maartenskliniek and are referred to the plaster room for a same-day treatment. These patients can be considered unplanned, although walk-in is more descriptive. If the patients can be treated within thirty minutes, they are sent to the waiting room. If there is a timeslot available later on the day, they are asked to wait elsewhere in the hospital and return on the planned timeslot.

OR patients

Some patients that have undergone surgery need treatment from an OCT at the OR. If this is needed, the OCT leaves the plaster room to perform the necessary tasks at the OR. These treatments have priority over patients in the waiting room, as otherwise the OR schedule will be delayed.

2.1.2 Planning description

To gain insight in the planning processes, the framework provided by Hans, Van Houdenhoven, & Hulshof (2012) is used. In this framework, four hierarchical levels are distinguished. An example of the framework in multiple managerial areas is shown in Figure 5. The hierarchical components create a distinction between strategic, tactical, offline operational and online operational planning. The next sections describe the patient planning and employee planning following the given framework, focusing on the resource capacity planning managerial area. A summary of the described processes can be seen in Table 2.

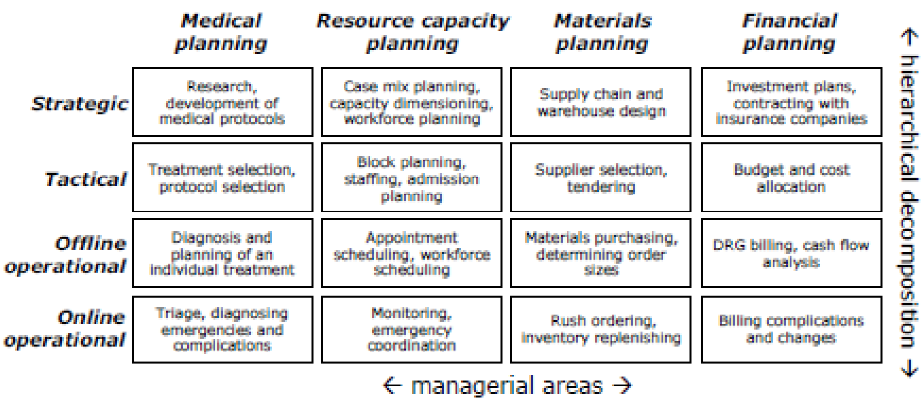

Figure 5: Application example of the framework according to Hans et al. (2012)

	Resource capacity and patient planning	Employee planning	Optimal moment
Strategic	Department lay-out, number of treatment rooms	Budget, number of FTEs, number of OCTs and support staff	~ 1 year
Tactical		Availability, planned absence, required staff capacity/occupation (week level)	>3 months
	Session planning: opening hours, number of sessions per day, asignment in type of sessions (planned, walk-in, OR), consultation hours (hand, foot, wound)	Required staff capacity/occupation (shift level), number of needed shifts	1-3 months
Offline operational	Patient appointment planning	Personnel planning (roster), planned educational moments, special leave of absence	28 days
Online operational	Walk-in patients, emergency patients	Absenteeism (unplanned)	

Table 2: Hierarchical planning overview

Resource capacity and patient planning

Strategic

The plaster room department consists of several treatment rooms as described earlier and is fixed within the hospital. The amount of treatment rooms is determined by the management and is planned at least one year in advance.

Tactical

The session planning method that the plaster room uses is static capacity reservation. The opening hours of the plaster room are fixed and the availability of the OCTs is known well in advanced. According to the orthopedic planning, day slots are designated for appointment planning, keeping in mind that walk-in patients could arrive. The number of slots and sessions is based on the available number of OCTs on that day. An example of the patient planning can be seen in Figure 6.

There are multiple groups of patients that require special attention, for example through a consultation of a medical specialist. Currently, there are three different consultation hours: foot, hand and wound. The frequency and recurrence of these consultation hours are determined by the patient demand. The tactical planning of these consultation hours is made in collaboration with the corresponding department and the plaster room but requested by the referring physician.

Offline operational

Appointments are scheduled at the first available appointment slot. Appointment slots start at 08:00 and each slot takes 15 minutes.

Patients that need to be treated on the OR are registered in 'treatment room 7' by a planner of a different department. This sometimes results in a situation where multiple OR patients are planned in the same timeslot. Since the OR planning is subject to last minute changes, flexibility of OCTs is required to meet this demand. Treatment room 6 is used for inpatient treatment.

Online operational

Patients present in the waiting room are called in via the first come, first serve principal based on time of registration at the central desk without priority rule for types of patients. On peak moments, patients with appointments are given priority based on employee experience. No patients are assigned to specific OCTs, the first OCT available treats the first patient in the queue.

When walk-in patients arrive at the plaster room, they are scheduled in the first available appointment slot. When there is a slot available within 30 minutes, patients are asked to wait in the waiting room. If there is no slot available within 30 minutes but somewhere later that day, the patient is asked to wait somewhere else in the hospital and welcome to come back at the discussed time. If there is no treatment slot available on that day, patients are scheduled for a different day or the patients are squeezed in other (already booked) timeslots.

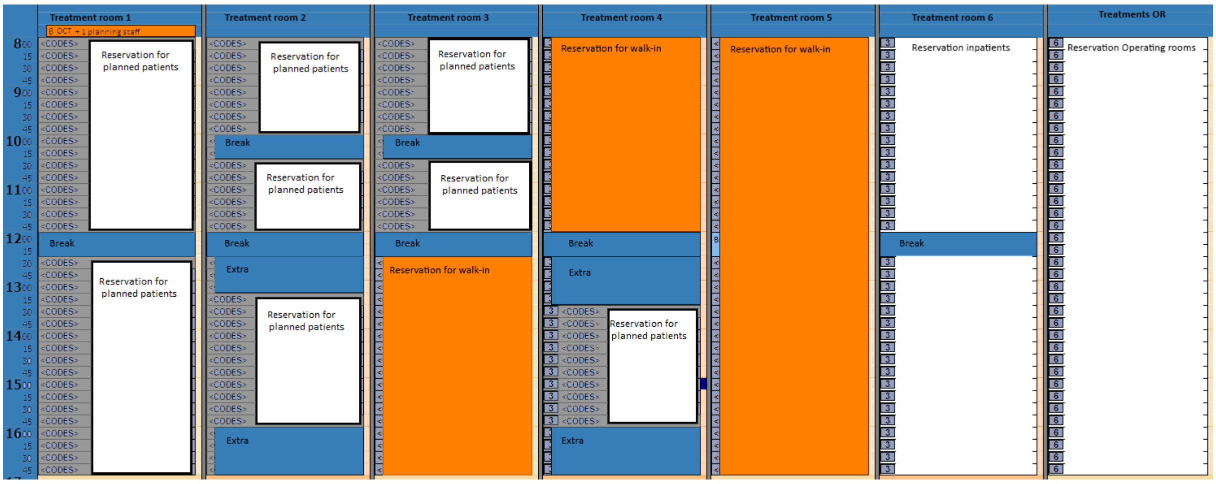

Figure 6: Example of the plaster room patient planning (Dijkstra, 2017)

Employee / Staff

Strategic

The number of FTEs and OCTs in the plaster room is decided by the management on the long term. The management makes a budget for the next year and determines how many OCTs and medical specialists are hired for the plaster room. This budget is crucial for the entire planning of the plaster room. The management requires an overview of expected demand to determine the budget, required qualifications and FTEs of these employees and staff.

Tactical

The planned absence is based on the staff occupation requirements and number of needed shifts. The number of required OCTs on regular days is fixed on five employees and in more quiet periods (e.g. summer holidays), four employees are planned. This required number of OCTs is set in advance (more than 1 year). The employees must request absence at least three months in advance. Exceptions are the (summer) holidays, where the employees must request absence approximately 7 months in advance. The planning department determines the absence of every individual based on mutual consent within the department. The request is either denied, approved or changed according to the number of required employees and availability of the rest of the staff.

Offline operational

The shifts of the employees are considered in full days, in accordance with the cyclic week schedule. Every employee has its own fixed week schedule with might include different start or stop times. Deviation only occurs on rare occasions and is most often prevented or avoided. The final planning is published 6 weeks in advance and the only alterations of this planning are because of absenteeism due to sickness or other unforeseen circumstances.

Educational moments are not planned, except for education on a different location. The execution of the educational moments is left to the initiative of the employees.

Online operational

If there is unplanned absence most often nothing changes in the employee planning. On some occasions the manager helps on the floor. No absent employees are asked to come in.

Risks

Strategic

The number of required shifts/available employees per day is currently fixed based on the holiday season; either 4 or 5 OCTs must be present. Not only is planned absence decided on these fixed numbers, but also the number of sessions per day as in number of fixed blocks for appointment-based and walk-in patients. Most decisions follow from these numbers and have profound influence on the performance of the plaster room. Since the required number of available employees is based on experience in previous years, there is a significant risk of under- or overstaffing due to new circumstances.

Tactical

It is relevant to analyze under- and overstaffed days based on historical data. Another risk that is clearly seen in historical data is the (deviation in) production of the orthopedic department. Long-term sickness of one of the medical specialists caused a lengthy period of overstaffed days in the first two quarters of 2016. The required staff capacity is considered fixed and was not altered in this period, resulting in overcapacity.

Offline operational

The roster and session planning does not take production of other departments within the hospital into account, while almost all patients that are treated in the plaster room are referred by physicians from those departments. This could result in unexpected quiet or busy moments for the OCTs, as seen in per day, week or hour. The set KPI's for the patients, staff and management result heavily on the online operational activities. Research should indicate the optimal tradeoff between flexibility and availability based on the performance indicators.

Online operational

The fixed personal cyclic schedules of the OCTs create a situation with minimal flexibility. In case of unplanned absenteeism or unforeseen high patient demand no alterations are made as no OCTs are available upon request on busy days. This method of planning causes a substantial risk of fluctuating workload or increased work pressure.

2.2 Patient demand

This section elaborates on the historical patient demand, using patient treatment data from 2016 and 2017.

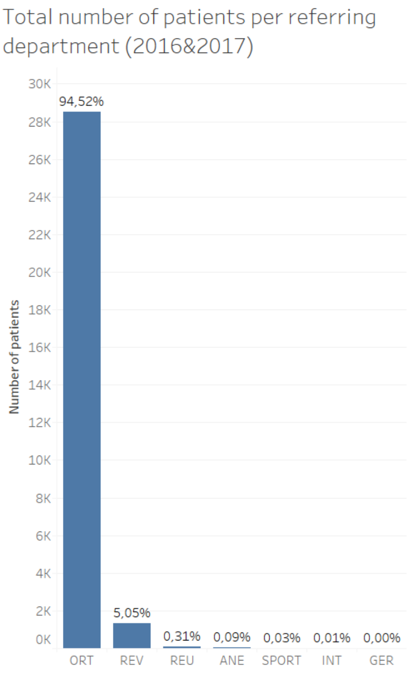

Figure 7: Patients per department (N=30192 patients, 2016&2017, source: database Sint Maartenskliniek)

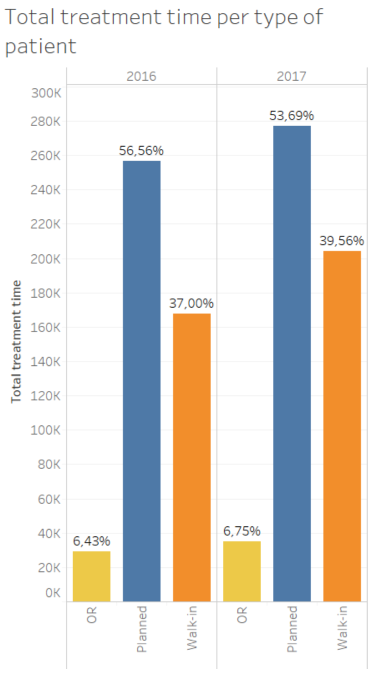

Figure 8: Treatment time per patient type (N=27580 treatments, 2016&2017, source: database Sint Maartenskliniek)

The plaster room treats patients who are referred by one of the SMK departments. Figure 7 shows that almost all patients (94%) are referred by physicians working within the orthopedic department (ORT). The departments rheumatology (REU), anesthesiology (ANE), sports (SPORT), internal medicine (INT) and geriatrics (GER) provide less than 1% of the patient population. The remaining 5% is referred by physicians of the revalidation department (REV). Since the most patients origin from the orthopedic department, a more extensive analysis of these patients is made.

Figure 8 shows the patient demand in treatment minutes per patient type. Within the group of patients referred by the orthopedic department, the demand in terms of treatment time is predominantly generated by appointment-based patients.

Noteworthy is the increase in demand over the years for all type of patients. When comparing 2017 to 2016, total treatment time of OR patients increased with more than 80 hours, walk-in treatment time increased with almost 635 hours and planned patients almost 350 hours. This corresponds with the hospitals increase in orthopedic production.

As stated before, all patients treated in the plaster room are referred by physicians from different departments. Since the plaster room treats specific conditions, it is expected that the majority of the patients are referred by specialists on these conditions and therefore patient demand in the plaster room is predominantly influenced by the production of these physicians. Figure 9 shows the number of treatment request and corresponding total treatment time per physician. Physician 84 and 152 ordered more than 10.000 treatments in 2016 and 2017. Their production created approximately 35% of the patient demand in the plaster rooms in those two years.

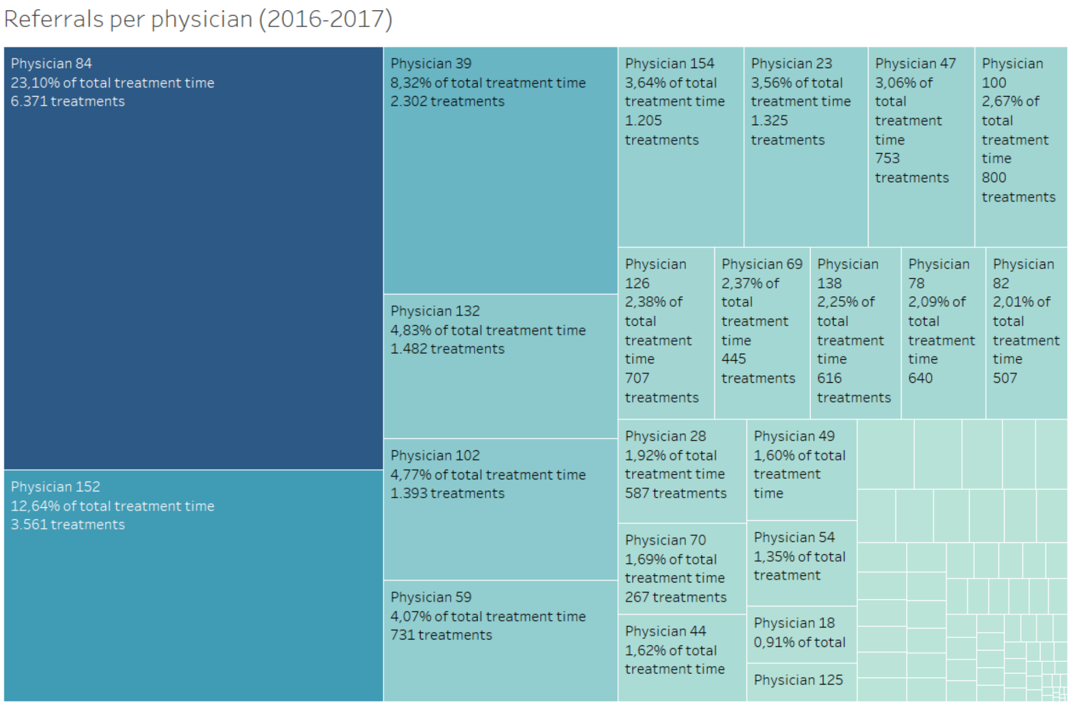

Figure 9: Patient demand per referring physician (N=27580 treatments, 2016&2017, source: database Sint Maartenskliniek)

Fluctuations in treatment time over the days is highly influenced by the demand of walk-in patients. The boxplot of Figure 10 shows the demand per day per type of patient. The difference between the upper whisker and lower whisker of walk-in demand per day is 1139 minutes, almost 19 hours. Since this demand is unknown to the planning staff, the consequences of peak moments and off-peak moments of walk-in demand cannot be underestimated.

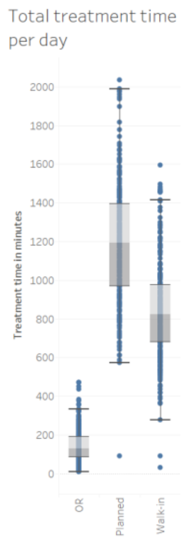

Figure 10: Patient type total treatment time per day (N=27580 treatments, 2016,2017, source: database Sint Maartenskliniek)

2.3 Operational performance

Before the performance of the plaster room can be measured, the performance indicators need to be defined. All definitions are defined in cooperation with the management of the plaster room and the logistics department of the SMK.

2.3.1 Definition of performance indicators

Table 3 gives an overview of key performance indicators (KPIs). The selected KPIs are subdivided into distinct categories dependent on the corresponding stakeholders: patient, staff or management.

Before the definitions of the KPIs are given, we first present the employability structure that is used in the definition of the performance indicators. This employability structure is used by multiple departments and constructed in cooperation with the hospital management.

	KPI	Definition
Patient	Waiting time	Average waiting time per day per patient type
		Service level: percentage of patients of type per day with waiting time under set target
	Correct treatment date	Percentage of patients that receive treatment on the preferred treatment day
	Accessibility walk-in	Percentage of walk-in patients that receive treatment without appointment
Staff	Correctly staffed	Percentage of days that are not under- or overstaffed; days where the measured workload is within target values.
	Overtime occurrence	Percentage of days where overtime occurs
	Average overtime	If overtime occurs, the average number of minutes overtime
Management	Productivity	Ratio between patient treatment related activities and net employability
	Employability (gross-net ratio)	Ratio between net employability and gross employability

Table 3: KPI overview per stakeholder

Employability structure

The Sint-Maartenskliniek uses the employability structure, developed by Rhythm, to give a clear insight in the activities of individual employees. Figure 11 shows the visualization of this model for OCTs. The model determines the net employability and shows the direct time that an OCT can spend on their patients. The net employability divides the working hours of an OCT at the office into direct time, indirect time, idle time and facilitating activities. The available patient-related time consists of the direct time, indirect time and idle time. These definitions are used in the calculation of the KPIs.

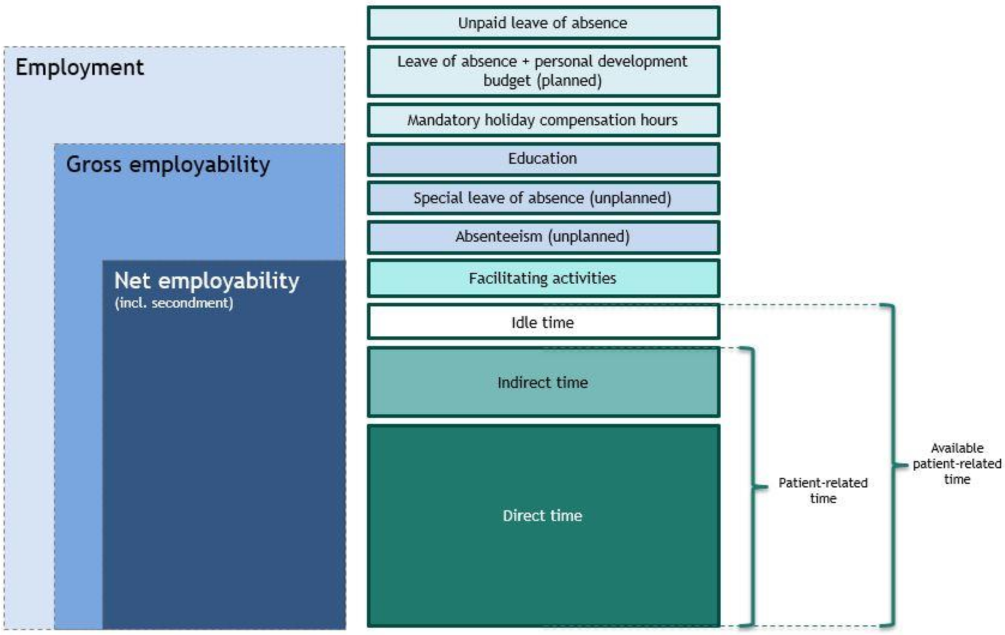

Figure 11: Employability model of the SMK (Rhythm, 2018)

Waiting time

The waiting times for patients are significant to all stakeholders. The waiting times are measured in separate ways: average waiting time and service level waiting time.

Since the patient paths of walk-in patients and patients with an appointment differ tremendously, the waiting time is measured per type of patient.

Let us define the time variables for individual patients:

$$T_{arrival} = time\ of\ registration\ at\ front\ desk$$
$$T_{call\ in} = start\ time\ of\ treatment$$
$$T_{appointment} = time\ of\ planned\ appointment$$
$$T_{departure} = time\ of\ departure$$
$$i = patient\ type = \{planned, walk\ in, OR\}$$

Now, waiting time per patient can be calculated as:

$$T_{waiting|planned} = T_{call\ in} - (biggest\ of\ arrival\ or\ appointment\ time)$$
$$T_{waiting|walk\ in} = T_{call\ in} - T_{arrival}$$

To obtain average waiting time (per patient type) per day, let:

$$N_i = \sum all\ patients\ of\ type\ i\ per\ day$$

Then

$$W_{planned} = average\ waiting\ time\ per\ day\ for\ planned\ patients = \frac{\sum T_{waiting|planned}}{N_{planned}}$$
$$W_{walk\ in} = average\ waiting\ time\ per\ day\ for\ walk\ in\ patients = \frac{\sum T_{waiting|walk\ in}}{N_{walk\ in}}$$
$$W_i = average\ waiting\ time\ per\ day\ for\ patient\ type\ i = \frac{\sum T_{waiting|i}}{N_i}$$

To obtain the service levels regarding waiting time, targets need to be determined by the management. The current targets selected by the management are 15 minutes for patients with an appointment and 30 minutes for walk-in patients. Service level waiting time is defined as:

$$Service\ level\ T_{waiting|planned} = \frac{number\ of\ patients\ where\ (T_{waiting|planned} < Target_{planned})}{N_{planned}} * 100\%$$

$$Service\ level\ T_{waiting|walk\ in} = \frac{number\ of\ patients\ where\ (T_{waiting|walk\ in} < Target_{walk\ in})}{N_{walk\ in}} * 100\%$$

$$Service\ level\ T_{waiting|i} = \frac{number\ of\ patients\ where\ (T_{waiting|i} < Target_{i})}{N_{walk\ in}} * 100\%$$

Correct treatment date

To assure optimal care for patients, access times for appointments are significant. When a treatment is given on the preferred date, this contributes to optimal recovery. The plaster room management aims to schedule these patients on the preferred treatment day with minimal exceptions.

$$Service\ level\ treatment\ date = \frac{\sum Patients\ where\ |Preffered\ date\ - actual\ date\ | < 1\ day}{\sum Patients}$$

At this moment, it is impossible to measure the correct treatment date due to absence of this data. We advise to register preferred date for all patients.

Accessibility (walk-in patients)

The strategy of the plaster room clearly states that they want to treat walk-in patients on the same day. Unfortunately, there are situations wherein patients register at the front desk and are given an appointment at a different day. To gain insight in what extend this occurs, the performance indicator accessibility is assessed:

$$Accessibility = \frac{\sum N_{walk\ in}(treatment\ on\ day\ of\ registration)}{\sum N_{walk\ in}}$$

At this moment, it is impossible to measure the accessibility due to absence of this data. We advise to register preferred date for all patients.

Correctly staffed

One of the key issues pointed out by the management and employees of the plaster room is the fluctuating workload and the number of days that are under- or overstaffed.
To determine the daily workload, we first define the following variables:

$$Patient\ demand = \sum\nolimits_{N} Treatment\ time\ in\ minutes$$

where $Treatment\ time = T_{departure} - T_{call\ in}$.

If at least one of these values is unavailable, the estimated treatment time is used.

$$OCT\ capacity = \sum\nolimits_{OCTs} Available\ patient\ related\ time$$

Where

$$\begin{aligned} &Available\ patient\ related\ time \\ &\quad = Net\ employability\ in\ minutes\ per\ day \\ &\quad - minutes\ spend\ on\ facilitiating\ activities \end{aligned}$$

The management of the plaster room and the logistics department decided the optimal staffing per day.

The Sint Maartenskliniek uses alike definitions for correct staffing over other departments in the hospital and applies to the plaster room due to the company-wide policy. This definition is determined in close collaboration with the logistics department.

To determine if a day is correctly staffed, understaffed or overstaffed, the boundaries of daily workload need to be selected. The method used to determine the lower boundary and upper boundary in this context is added in Appendix F.

The boundaries selected by the management are:

$$Lower\ boundary = -4\ hours$$
$$Upper\ boundary = +3.5\ hours$$

A day is correctly staffed, if the available capacity is within the boundaries as visualized in Figure 12. For example, if the patient demand is 20 hours, that day is categorized as correctly staffed if the OCT capacity is between 16 hours and 23.5 hours. The patient demand and the selected boundaries decide what the OCT capacity on that day should be. The difference between the lower boundary and upper boundary is chosen in such a way that it equals one full OCT shift.

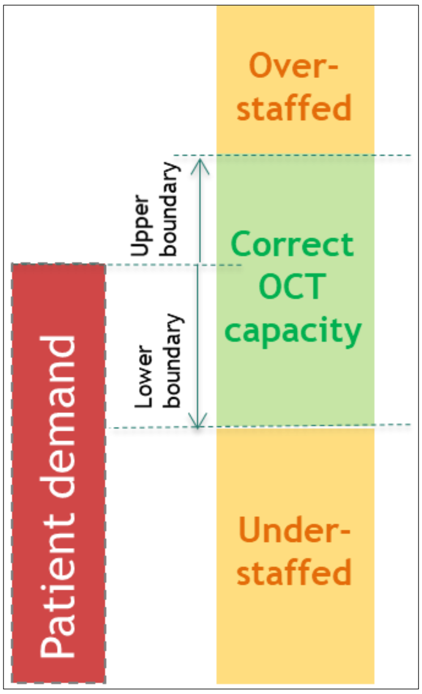

Figure 12: Visualization of calculation of KPI 'Correctly staffed'

Overtime

The management wants to prevent having too many instances of overtime. For balancing the workload, overtime is measured with two KPIs: days per year without overtime and average overtime if overtime occurs. We define overtime as working time after opening hours on workdays plus a deviation of 30 minutes, so patients being treated after 18:00 on regular work days. The definitions are:

$$Overtime\ occurence = \frac{Number\ of\ workdays\ where\ overtime\ occurred\ (per\ month?)}{Total\ number\ of\ workdays\ (per\ month?)} * 100\%$$

$$Average\ overtime = \frac{\sum minutes\ working\ in\ overtime}{Number\ of\ workdays\ where\ overtime\ occurred}$$

The management of the plaster room declared the maximum overtime occurrence should be 5 percent and average overtime should not exceed 30 minutes.

Productivity

When an OCT works in the hospital, they perform a broad range of activities. To assure patient care delivery and treatment quality, the productivity levels should be between the desired boundaries. Productivity for the OCTs is calculated as follows:

$$Productivity = \frac{\sum_{\#\ of\ OCTs} Patient\ related\ time}{Net\ employability}$$

The boundaries are defined by the management of the SMK, and productivity levels should be around 80 percent. The definitions of the patient related time and net employability are visualized in Figure 13.

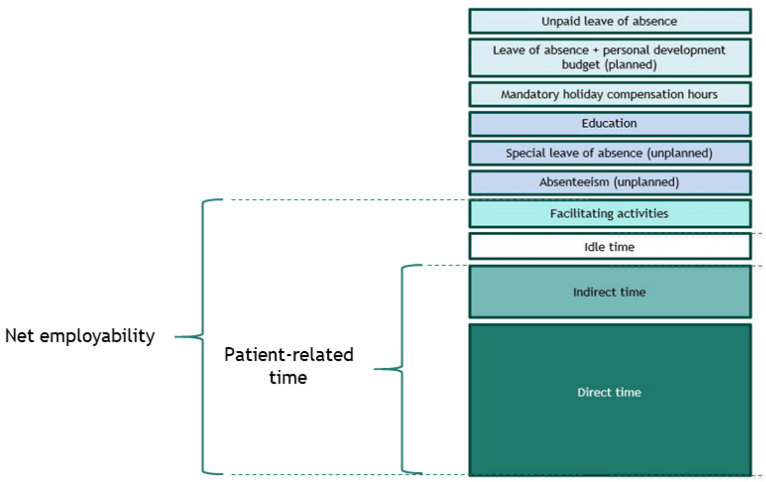

Figure 13: Input for KPI 'productivity'

Employability (gross-net ratio)

Personnel costs are a substantial part of the available budget. Therefore, it is key to monitor (and guard) the utilization of the OCTs. Utilization is calculated as:

$$Employability\ (ratio) = \frac{Net\ employability}{Gross\ employability}$$

The target within the hospital for employee utilization is 80%. The definitions used for gross employability and net employability are visualized in Figure 14.

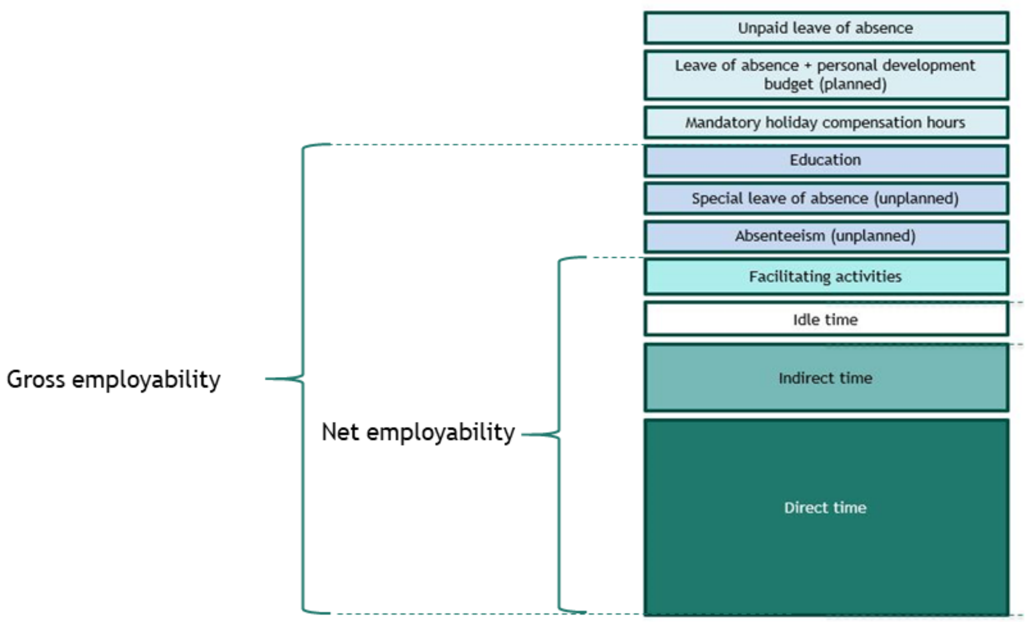

Figure 14: Input for KPI 'employability ratio'

2.3.2 Zero-measurement of performance

Waiting time

Figure 15 shows the average waiting time per patient in 2016 and 2017. The waiting time before treatment not be calculated in 22.69% of the treatments due to missing or incomplete data.

The maximum average waiting time of all patients was measured in May 2017, showing an average of 10 minutes. Planned patients have a lower average waiting time than walk-in patients, which corresponds with the plaster room incentive to treat planned patients within 15 minutes and walk-in patients within 30 minutes. Even though the minimum average waiting time (7.0 minutes in March 2016) and the maximum average waiting time is three minutes, the plaster room management determined these values as acceptable.

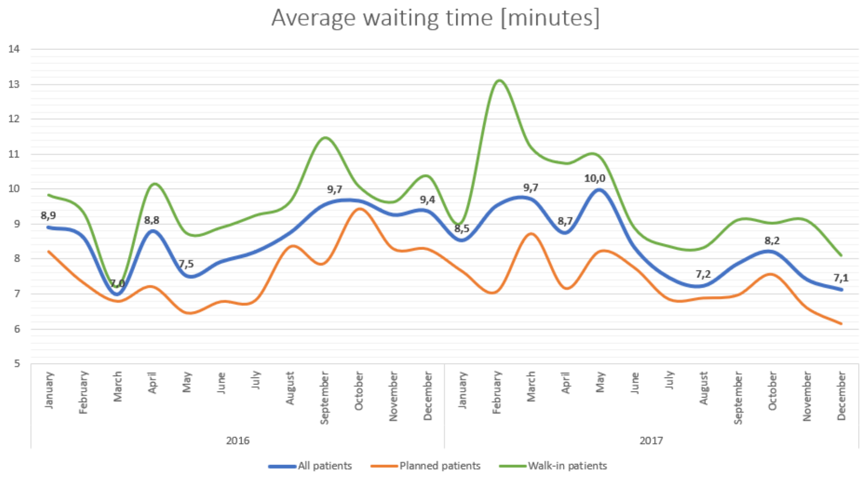

Figure 15: Average waiting time per month (N=13 patients, 2016&2017, source: database Sint Maartenskliniek)

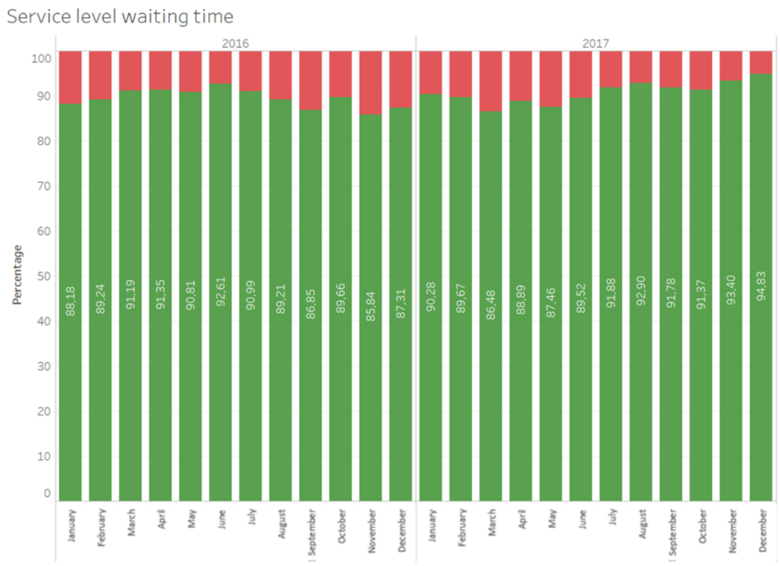

Figure 16: Service level waiting time per month (N=14937 patients, 2016&2017, source: database Sint Maartenskliniek)

The waiting time service level indicates the percentages of patients that waited less than the norm, which is 15 minutes for planned patients and 30 minutes for walk-in patients. Figure 16 shows the results of the service level waiting time in 2016 and 2017. The highest percentage of patients within the waiting norm, 94.83%, is achieved in the last month of 2017. The service level measured in 2016 and 2017 never drops below 85%. In 2017, a service level above 90% is achieved in 7 out of 12 months. Plaster room management considers these values as acceptable.

Correct treatment date & Accessibility walk-in

The performance indicators 'Correct treatment date' and 'Accessibility walk-in' could not be determined in this research because of insufficient data. Recommendation for future monitoring of these indicators is given in Section 7.2 on page 71.

Correctly staffed

Figure 17 shows that the goal of 70% of the days correctly staffed is only met in September 2016. All months up to and including June 2016 show that less than 50% of the days the staffing was within the desired boundaries. The management has only set a hard boundary for the percentage of days that may be understaffed, which should be under 5%. Unfortunately, only 8 out of 24 months meet this condition. Considering the high amount of days that are overstaffed, these results imply opportunities to improve the number of days that are correctly staffed, or at least reduce the occurrence of understaffed days.

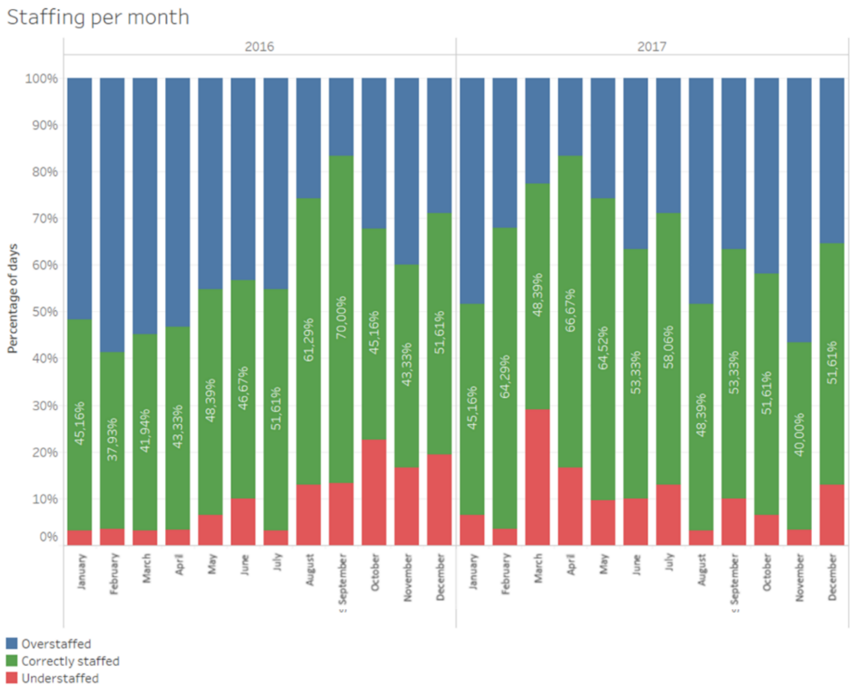

Figure 17: KPI 'staffing' per month (N=311 days, 2016&2017, source: database Sint Maartenskliniek)

Overtime occurrence & average overtime

In the patient data of 2016 and 2017, no patients were recorded leaving after 17:30. This means, with the information we had at our disposal, no overtime occurred. Therefore, the overtime occurrence for both years is zero, which automatically puts the average overtime at zero minutes.

Productivity

In this research, productivity is defined as the ratio between the net employability and the patient related treatment time. The net employability is calculated by using the personnel roster in excel, where the availability of student OCTs or the management is not considered. There have been multiple students in 2016 and 2017 who were able to treat patients but are not taken into account when calculating the productivity. This means that the (average) productivity can rise above one, while in regular situations this cannot happen.

The total patient treatment time is calculated by measuring the treatment time of all patients. This number represents the direct patient treatment time, while indirect treatment time is not considered in these calculations. If the data is unavailable, we use the expected treatment time (N=12702 treatments, 42% of all treatments in the dataset in 2016 and 2017).

Figure 18 shows the average daily treatment time and available OCT minutes. The net employability varies per month, but even when we keep in mind that not all months have an equal amount of working days, these variations are substantial. Comparing the employability and patient treatment time, we see that they do not follow a similar pattern. This implies that capacity and demand are not balanced and shows potential for improvement by synchronization of capacity and demand.

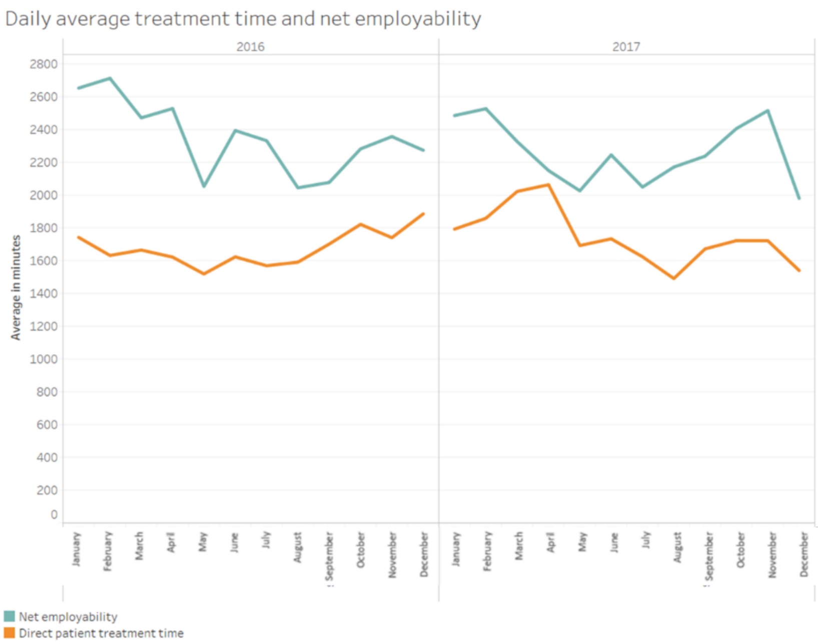

Figure 18: Average treatment time (N=29985 treatments) & net employability per day (N=311 days), 2016&2017, source: database Sint Maartenskliniek)

This results in the productivity as seen in Figure 19.. The total yearly average in 2017 was 0.76, while 2016 showed an average productivity of 0.72. The months where the recorded productivity reached its highest value is march and April 2017. Looking at the net employability and patient demand, we can see that in those months the demand increased (compared to the months before) while net employability was decreasing. In an optimal situation, net employability would be determined based on the patient demand and base its fluctuations on the fluctuations in patient demand.

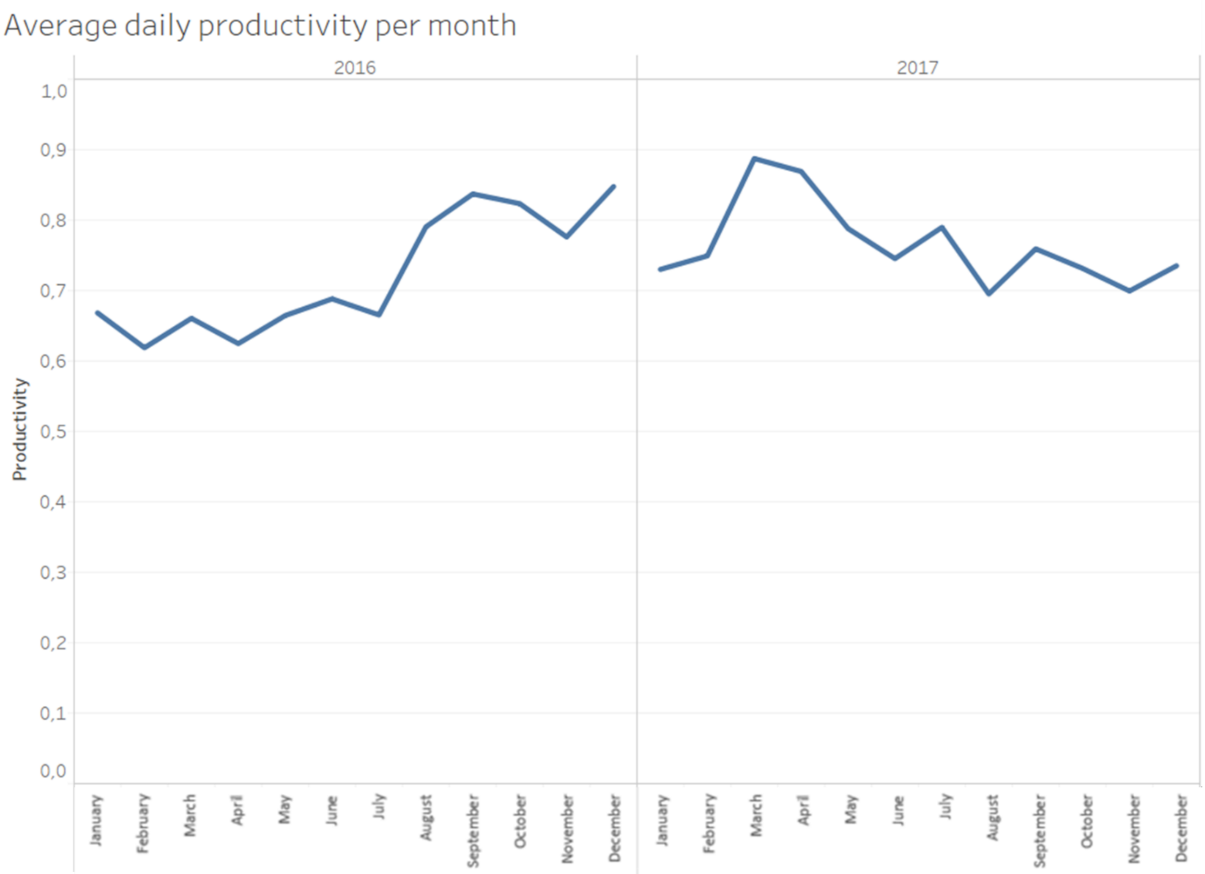

Figure 19: Average productivity (N=311 days, 2016&2017, source: database Sint Maartenskliniek)

Employability (gross-net ratio)

Employability is measured per year. Gross employability is calculated using the budgeted number of FTEs while net employability is calculated using the personnel roster. The theoretical employability resulted in a value of 0.94. The employability measured in 2016 was 0.90 and 0.87 in 2017.

2.4 Recapitulation and considerations

The planning department barely looks at other departments in the hospital, while we see that the plaster room is extremely dependent on the production of other departments. The other departments refer their patients to the plaster room and the OCTs are often required to work on the OR of other departments.

The personnel planning lacks flexibility. The working hours of all employees are fixed, and their available hours are predetermined at least six weeks in advance. It is important to find a way to predict the demand, which allows the planning department to get a better occupancy planning. In the current situation, it is harsh to cope with the huge amount of flexibility during different days. It could be interesting to see if there are minimal adaptations possible that increase the flexibility while keeping the current structure. One way could be to use the availability of the orthopedic department in the personnel planning of the plaster room, as the orthopedic department is accountable for 95 percent of the demand.

The fixed blocks show most room for improvement, as they are made by the insights of the planning staff members. If the planning staff could get more insights of the expected demands, by evaluating the expected number walk-ins and expected time per patient, the patient planning can be adjusted. The OR availability of the OCTs has a priority over the patient support at the plaster room, which complicates the task to make an adequate schedule.

Another difficult aspect for patient planning is the required days between the appointments. Some patients must visit the plaster room at least once a week, which also indicate an opportunity as these meetings are plannable.

The plaster room has the goal to help all walk-in patients the same day. This research does not focus on the planning per day as we do not look at the time of the walk-in. It is possible that a patient walks in in the morning, gets a meeting in the afternoon and is considered positive as he is helped on the same day.

Most room for improvement is a proper prediction and more insights in the previous appointments of the patients. If this information is gathered, it can be turned into a useful tool for the planning staff. In the optimal situation, this information is gathered eight weeks in advance so that the personnel planning can be adjusted to this information. This can help the planning staff with scheduling meetings according to the expected walk-in and OR patients.

This information is also useful to the most important departments and medical personnel. If they have better insights in the consequence of their work on the plaster room, better communication lines can be set up to collaborate better.

The employees of the plaster room are eager to have more and better information for planning purposes. There is no fixed system for planning at this moment. The plaster room performs well but is subject to the quality of the individual planning staff members. This includes the risk as the planning knowledge is available in the minds of the planning staff. Having set up guidelines can help the planning department to make choices and evaluate the consequences of these planning guidelines.

2.5 Conclusion

The content analysis shows that most of the patient demand originates from the orthopedic department (94.52%). The percentage of total treatment time per patient type in 2017 is 6.75% for OR patients, 53.69% for patients with an appointment and 53.69% for walk-in patients. Treatment in the plaster room is requested by physicians. In 2016 and 2017 two physicians were accountable for approximately 35% of the total patient demand.

The framework of Hans et al. (2012) is used to gain insights in the employee planning and patient planning. Multiple planning decisions are not taken on the optimal moment, some are even considered fixed. The capacity requirements are currently fixed on five OCTs per day on regular workdays and four OCTs in the holiday season. No appointment rules based on the production in other departments are used in the plaster room.

The zero measurement of the operational performance showed acceptable waiting times and waiting time service level. No overtime was recorded in the data. Productivity is highly variable over 2016 and 2017, originating from the fluctuating patient demand and varying employee capacity. The amount of days correctly staffed per month in 2017 varies from 40.0% to 66.7%. These results confirm the statements of the management and employees regarding the fluctuating workload.

3 Literature research

This chapter gives an overview of existing research found in literature. Section 3.1 focuses on prior research on operational performance in plaster rooms in the Netherlands. Section 3.2 contains research on solution methods that aim to optimize outpatient planning. Section 3.3 concludes this chapter. The search strategy used to obtain the literature can be found in Appendix B.

3.1 Plaster room

Research on operational performance, scheduling or planning in plaster rooms is scarce. Research aiming to improve workload in plaster rooms is conducted by Dijkstra (2017), Hoogwout (2010) and van de Vrugt (2016). While van de Vrugt (2016) conducted her research as part of her PhD thesis, both Hoogwout (2010) and Dijkstra (2017) conducted research as part of their MSc theses, all performed at the University of Twente.

Van de Vrugt (2016) investigated both workload of staff and waiting time for patients in the Jeroen Bosch hospital throughout and over the day. An implementation-oriented case study is presented where insight in workload and alternative appointment scenarios are suggested. The plaster room in the Jeroen Bosch hospital treats both appointment and walk-in patients, indicating that the varying workload is a consequence of an inefficient appointment schedule (van de Vrugt, 2016). The focus of the research is to balance the workload throughout each day by designing an appointment schedule. A simulation model with several parameter settings is constructed, where results show that the best operational performance achieved is a decrease of overtime. None of the suggested appointment scenarios can prevent peaks in patient demand. Recommendations to reduce waiting time are queuing priority rules or offering walk-in patients an appointment at peak moments. No results regarding optimization over multiple days is presented.

The research performed by Hoogwout (2010) focuses on improving the interaction between patient flow and capacity of the plaster room in the Academic Medical Center in Amsterdam. A simulation model is used to evaluate multiple interventions including; improved communication between OCTs and doctor assistants (1), redesigning the patient planning within shifts (2), alterations in slot duration and adjustment in the department capacity (3). Hoogwout (2010) concludes that the best performing intervention (a combination of intervention 1,2 and 3) offers limitations regarding implementation but recommends implementing in intervention 1 and 2 when possible mainly due to reduced waiting times. The interventions that reduce workload is scheduling appointments on the beginning and end of each shift, scheduling treatments with long durations at the end of the day and more day-specific alterations. No results regarding workload over multiple days is presented.

Dijkstra (2017) focused on improving performance in the plaster room in the Sint Maartenskliniek on individual days. In Section 1.2: Problem description, the main recommendations were stated and formed the basis for our research. Main conclusions and findings of Dijkstra (2017) were to implement dynamic capacity reservation, improved estimation of appointment length and investment in expected demand to improve capacity reservation for patient planning.

Unfortunately, all three research papers focus on improving daily operational performance. The main recommendations regard the optimal patient planning per day when walk-in is present and on how to minimize fluctuations over the days.

3.2 Outpatient planning considering walk-in patients

To get a better understanding of outpatient planning considering walk-in patients, multiple articles are discussed to get insights on best practices in other scientific research. Multiple research papers originate from Asia and most research includes a case study and/or simulation model of patient planning.

Literature review carried out by Cayirli, Veral, & Global (2003) on outpatient scheduling in healthcare describes that effective scheduling systems should aim to match demand with capacity in order to increase utilization of capacity and minimize patient waiting time. According to Cayirli et al. (2003) main decisions when scheduling patients in outpatient clinics are: appointment rules, patient classification and inclusion of effects of walk-ins, emergency patients and no-shows.

Kortbeek et al. (2014) present a methodology on designing appointment systems in outpatient clinics. Treatment of both walk-in and pre-scheduled patients are researched and a general method that balances access time and waiting time is provided. The model schedules appointments when expected walk-in demand is low, while in high demand periods the walk-in patients are given an appointment. To achieve this Kortbeek et al. (2014) developed a cyclic schedule that maximizes the number of walk-in patients treated on the same day, where the unscheduled arrival pattern is one of the main inputs.

Multiple research papers originating from Asia were found in the literature search (Lu, Tsai, & Chu, 2014; Morikawa & Takahashi, 2017; Su & Shih, 2003; Wu, Khasawneh, Yue, Chu, & Gao, 2014).

The research by Morikawa & Takahashi (2017) is conducted in Japan and proposes a scheduling method for clinics or departments that serve both walk-in and pre-scheduled patients. They aim to reduce waiting times for all patients by using a model that assigns walk-in patients to slots within blocks, where each session consists of different blocks. The best result achieved by Morikawa (2017) resulted in shorter waiting times, while the total idle time for the physicians increased. This intervention included reserving the last part of each appointment block for walk-in patients and assigning an appointment time to a patient when they arrive.

Wu et al. (2014) conducted a simulation study in China on an outpatient clinic that aims to decrease waiting time and to improve staff utilization and equipment utilization by experimenting with multiple appointment scheduling rules. Experiments to determine the optimal proportion between walk-ins and fixed appointments resulted in a ratio of 70%-30%. The scheduling rule where pre-scheduled patients were treated in one hour and walk-in patients in the successive hour resulted in the shortest waiting time and highest utilization according to (Wu et al., 2014).

Research in Taiwan by Su & Shih (2003) includes a case study where the percentage of walk-in patients was approximately 72%. The objective was to analyze scheduling solutions by using a simulation that evaluates different mixed-registration-type appointment systems. The appropriate arrival time interval for preregistered patients had consequential impact on the queuing problems and none of the selected interventions obtained an overall performance increase for all patient types (Su & Shih, 2003).

Lu et al. (2014) aimed to reduce waiting time for an orthopedic outpatient clinic by introducing an agent-based collaborative model for scheduling. Their model uses different software agents to dynamically adjust scheduling rules to adapt to the real-time situation, by letting the agents of different departments communicate with the main scheduling agent. Implementation of this model would require multiple investments in both time and money, while the assumption is made that the queue is never empty and idle time of caretakers is zero. While if the idle time is zero, workload is always at a peak level.

The phenomenom of seasonal walk-ins and their influence on outpatient appointment scheduling is the topic of the research of Cayirli & Gunes (2014). Access rules, appointment-scheduling rules and combinations of the two are examined by using heuristic solutions and simulation optimization. The main challenge is formulated as “to balance the trade-offs in serving walk-ins promptly without increasing the wait times of scheduled patients and overtime”. They strive to answer the question “how to refine capacity and appointment-scheduling decisions to accommodate walk-ins” (Cayirli & Gunes, 2014). Access rules are described as the amount of patients that are scheduled in a given period determining the capacity for walk-in treatment, where the appointment scheduling rules decide the start time for every treatment based on the daily booking limit. The least fluctuations in the performance were achieved by including monthly and weekly seasonality of walk-in demand, resulting in the recommendation of Cayirli & Gunes (2014) of determining the case-specific demand model prior to experimenting with interventions. When the walk-in demand model of an outpatient clinic is known, their general heuristics for calculating reservation levels and for appointment rules can be used to determine slot positions and daily booking limits.

The effect of reserving slots for urgent patients (those who must receive same-day care) is examined in the research of Dobson, Hasija, & Pinker (2011) by using a stochastic model which optimizes on multiple quality measures. These quality measures are: number of patients that are not helped within opening hours, the average queue of pre-scheduled patients and converted to financial consequences. Demand of both the pre-scheduled and urgent patients is assumed to be Poisson distributed and treatment times of all type of patients are assumed constant. Dobson et al. (2011) did not use a case-study to test and validate their model and therefore do not present conclusions of results in practice.

3.3 Conclusion

Most research discussed focused on how to accommodate walk-in treatment by adjusting the appointment schedule. Almost all research objectives were to decrease the patient waiting time (Cayirli & Gunes, 2014; Kortbeek et al., 2014; Lu et al., 2014; Morikawa & Takahashi, 2017; Su & Shih, 2003; van de Vrugt, 2016; Wu et al., 2014). Although some research included minimization of workload or workload fluctuations (Dijkstra, 2017; Hoogwout, 2010; van de Vrugt, 2016; Wu et al., 2014), all research does consider matching demand and capacity in some way. Some researchers include this component by measuring overtime (Cayirli & Gunes, 2014; Dobson et al., 2011) while others measure idle time of the physicians (Lu et al., 2014; Morikawa & Takahashi, 2017). Planning optimization over multiple days in scientific literature is scarce, most research found strove to optimize planning on individual days. The main subject all discussed research has in common, is that they all assume (walk-in) demand to be known. Optimization using simulation models is used, where one of the input parameters is the expected demand. Since the SMK plaster room demand is not known to the planners at the time of decision making, this is considered as the first step towards (operational) improvement.

4 Solution design

In this chapter we discuss the most promising opportunities for improvement of the operational performance in the plaster room. In section 4.1 we propose a new timeline with planning decisions and discuss the most promising opportunities within this new framework. Section 4.2 elaborates on the forecasting model currently used by Sint Maartenskliniek in other departments. Section 4.3 concludes this chapter.

4.1 Proposition of planning decisions based on available information

The decision-making process in the plaster room regarding the tactical patient planning and employee planning is currently based on experience, while useful information could be made available for the plaster room. Optimization of the patient planning and employee planning to match capacity and demand shows great potential, given the expected demand is known beforehand and used as input. Since walk-in demand has fluctuations over multiple time periods, using an average could result in undesirable fluctuations in workload.

We propose a model in which the decision-making process of the planning is dynamically changed, based on available information and data intelligence. The timeline in which the current planning decisions are made is visualized in Table 4. Since demand of walk-in patients is unknown beforehand, planning slots for walk-in and appointments or deciding on the required number of OCTs is challenging and has impact on the volatility of workload and work pressure. Table 4 also shows our proposition for planning decisions, where planning decisions are allocated to the moment where relevant information is available. The weekly capacity requirements are allocated to 3 months and the session capacity requirements to 8 weeks in advance. The draft session plan is moved from 3 months to 8 weeks in advance.

	Year	3 months	8 weeks	6 weeks	4 weeks	2 weeks
Available Information	Budget physicians OR and polyclinical production plan available	Availability physicians known	Employee roster, OR roster, polyclinical roster available		Update rosters	OR patients known
Current situation						
Patients & capacity	Rooms, opening hours	Session plan (appointments / walk-in)	Update session plan			
Employees	Number of FTE (OCTs, support), workdays and -hours, occupancy requirement (5 per day / 4 per day)	Attendance schedule (holidays), based on occupancy requirements	Update roster (requested absence based on occupancy requirement)			Session specific activities (education, projects, facilitating activities)
Proposed situation						
Patients & capacity	Rooms, opening hours		Draft Session plan		Publication of updated session plan	
Employees	Number of FTE (OCTs, support), workdays and -hours	Weekly capacity requirements (based on availibility physicians) Attendance schedule (holidays) based on ocupancy requirement	Session capacity requirements (approval of absense , flexible work days and work hours)		Publication of updated session plan	Session specific activities (education, projects, facilitating activities)

Table 4: Timeline of current and proposition of planning decisions

To use expected patient demand (xDemand) as an input variable in decision making, information regarding this demand should be known beforehand. That is why xDemand is calculated eight weeks in advance, when the information regarding the planning of the orthopedic department is known. The information can be used to decide on required capacity. The model assumes that the employee planning will not change during these 8 weeks. The objective of the model is optimization of patient planning.

4.2 Causal forecasting model

The logistic department of the Sint Maartenskliniek is currently implementing expected demand in the radiology department. They use causal forecasting, based on historical data and the production of the orthopedic department. This model is based on the research of Kortbeek, Braaksma, Smeenk, Bakker, & Boucherie (2015) and Vanberkel et al. (2011). Both researchers use a model that projects the workload for downstream departments and is based on probability distributions with historical data as input. T Vanberkel et al. (2011) describe the analytical approach and application at the Netherlands Cancer Institute-Antoni van Leeuwenhoek Hospital in the Netherlands. Kortbeek et al. (2015) build upon the model of Vanberkel et al. (2011) and is applied in the Academic Medical Center in Amsterdam, the Netherlands. Both models were created to determine the number of occupied beds in the wards as a function of the Master Surgery Schedule (MSS) and emergency patients. The walk-in demand in the plaster room is not a function of the MSS but rather of the outpatient clinic schedule of the orthopedic physicians. Most patients that request walk-in treatment are referred by these physicians after consultation during their outpatient clinic sessions. Therefore, the outpatient clinic session schedule is used as input rather than the MSS.

The research by Vanberkel et al. (2011) presents an analytical approach to determine expected workload for downstream departments. The workload is determined by aggregating tasks associated with surgical patients who are in recovery and assumes an infinite server system. This means that demand can be higher than capacity (Vanberkel et al., 2011). The main output is the distribution of number of patients that is anticipated in that time period. More information regarding the steps taken, input and output of the model is added in Appendix E. Since the plaster room only offers treatment that takes less than a day and the outpatient clinic schedule does not show corresponding cyclical features as the used Master Surgery Schedules, the steady-state distribution is not relevant in our situation. Only the first two steps are of importance in this context: determining the individual probability distributions per physician, specialty or day and using convolution methods to aggregate these probability distributions into one function that describes the workload per time period.

In the remainder of this research we develop an adjusted version of the model to determine the walk-in demand in the plaster room. Further explanation and implementation of this model is described in Section 5.1.

4.3 Conclusion

The most promising opportunity for operational improvement in the plaster room is the incorporation of expected walk-in demand in the planning. A new timeline for both the patient planning and employee planning is proposed, that offers the opportunity to take information on production of other departments into account.

The trade-off between available information on production and the proposed planning timeline results in calculating the expected demand 8 weeks in advance.

5 Model design

This chapter describes the prediction model and patient planning simulation model. Section 5.1 elaborates on the causal forecasting model used to create a valid prediction of walk-in demand. Section 5.2 explains the simulation model that integrates the walk-in demand prediction in the patient planning.

5.1 Prediction model

5.1.1 Causal forecasting: predicting walk-in demand

The model constructed to predict walk-in patient demand in the plaster room eight weeks in advance consists of 7 steps and can be subdivided in the categories input, output and validation and evaluation. The different steps are visualized in Figure 20.

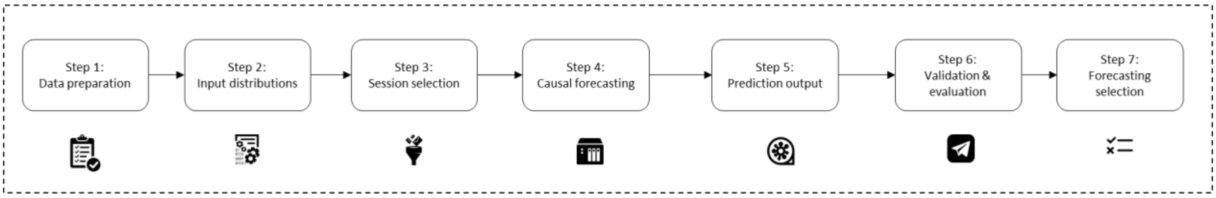

Figure 20: Overview of forecasting model

Step 1 to 3 focusses on creating the correct input parameters and distributions, where step 5 to 7 are based on the generated predictions. Step 4 of this process consist of the causal forecasting calculations, using convolution to create one output distribution. These queries are currently used by Rhythm to predict the demand for the radiology department. We create an adapted version for the plaster room for this research and future use. Collaborating with Rhythm on building this model ensures consistency for the plaster room department. In the following sections we describe each step of the forecasting model.

5.1.1.1 Input

Step 1: Data preparation

To create the input distributions, preparation of multiple data sets is performed. For the preparation of these data sets, we use Pentaho Data Integration (Kettle). These datasets are:

- Outpatient clinic schedule
- Outpatient activities
- Plaster room activities

All relevant variables in the datasets are attached in Appendix A.

All data sets are filtered on the following criteria: location Nijmegen, specialty: orthopedics, outpatient, date between January 1st, 2016 and the 31st of December 2017. In the plaster room activity data set we also exclude all appointment-based treatments.

The historical demand is divided in three groups.

a. Patients with a treatment in the plaster room on the same day as an outpatient clinic visit
b. Patients with a treatment in the plaster room on the same day as an unscheduled meeting with a doctor
c. Patients without any other treatment in the SMK on the same day

The model assumes that patients visit the doctor and the plaster room on the same part of the day. The care demand of the plaster room is therefore planned at the daypart on which the patient had an outpatient clinic visit.

Step 2: Create input distributions

We use the historical demand to generate probability distributions per session category by aggregating the historical demand. The outpatient clinic sessions can be categorized in multiple ways and is aggregated over the data originating from group a. The following distributions are created:

- Outflow per physician per daypart *[e.g., doctor A morning]*
- Outflow per physician without daypart differentiation *[e.g., doctor A]*
- Outflow per orthopedic specialty per daypart *[e.g., specialty foot morning]*
- Outflow per outpatient clinic session without physician or orthopedic specialty differentiation *[e.g., generic]*

The generic outflow per outpatient clinic session can be used to predict outflow of outpatient clinic sessions of physicians that are unknown in the historical data set.

The data of group b and c is used to create a distribution that aggregates the data per daypart (Monday morning) since those could not be linked to outpatient clinic sessions.

Step 3: Session selection

We combine the obtained distributions in four different input sessions. The sessions created all include the distribution created from group b and c. The distinction between the sessions regard the classification of outpatient clinic sessions (physician, specialty, daypart).

This results in the following combined input distributions:

xDemand1	per doctor per daypart, general outpatient information, basic outflow per daypart
xDemand2	per specialism per daypart, general outpatient information, basic outflow per daypart
xDemand3	generic outpatient information, basic outflow per daypart
xDemand4	per doctor, generic polyclinical information, basic outflow per daypart

Step 4: Causal forecasting

In step 4 of the process, we alter the causal forecasting model. The forecasting model is implemented in the radiology department of Sint Maartenskliniek. The model is adapted to make it applicable to use in the plaster room. The scientific research underlying this model is described in Section 4.2. The outpatient clinic schedule contains the scheduled physicians, which is linked to their historical outflow distribution. By using discrete convolution all outflow distributions are be combined per daypart, resulting in one probability distribution per daypart. The expected demand is calculated for January, February and March 2018. Both the input and the output are treatment time in minutes.

5.1.1.2 Output

Step 5: Prediction output

The output provided by model produce an output containing the following variables:

$$D_2 = 2\%\ boundary$$
$$D_{25} = 25\%\ boundary$$
$$D = Mean\ estimate$$
$$D_{75} = 75\%\ boundary$$
$$D_{98} = 98\%\ boundary$$
$$R = Realization$$

Figure 21 shows an example of the output variables over multiple time periods. The output consists of a mean value and two confidence intervals: a 25%-75% confidence interval and a 2%-98% confidence interval. Suppose that physician A and physician B have an outpatient clinic session scheduled on Monday morning, then we expect their mean outflow to the plaster room to be around 365 minutes. Considering all dayparts where the outpatient clinic schedule is equal, we expect that the realized mean walk-in demand of these dayparts falls within the boundaries of the 25%-75% interval with a certainty of 50%.

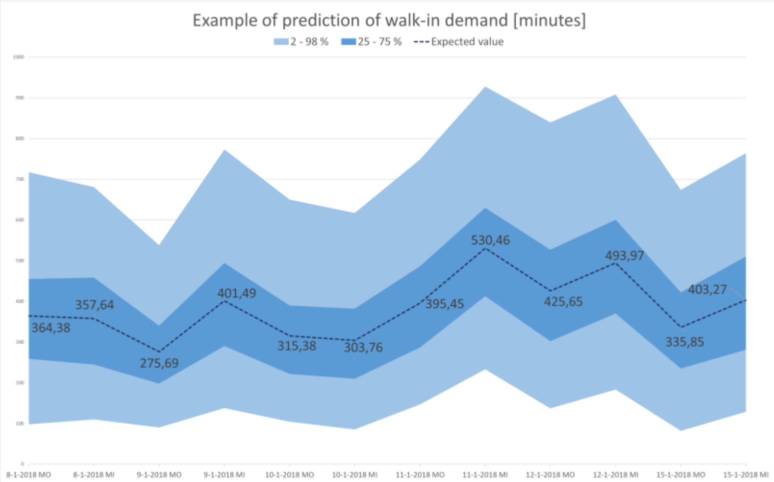

Figure 21: Example of visualization of the causal forecasting output

5.1.1.3 Validation and evaluation

Step 6: Validation and evaluation.

The forecasting distributions are validated and evaluated with the data from January and February 2018. The evaluation methods are:

$$Average\ Error\ (AE) = \frac{\sum_{dayparts} D - R}{\sum_{dayparts}}$$

$$Mean\ Absolute\ Percentage\ Error\ (MAPE) = \frac{\sum_{dayparts} \left|\frac{R-D}{R}\right|}{\sum dayparts} * 100$$

$$Percent\ Of\ Accuracy\ (POA) = \frac{\sum_{day} R}{\sum_{day} D} * 100\%$$

$$Average\ Accuracy\ (AA) = \frac{\sum_{dayparts} (\ |D-R| < 90\ minutes\ )}{\sum dayparts}$$

To gain additional insights in how often the forecasting distribution over- or underestimates the walk-in demand, the number of times the realization is between D_2 and D_{25}, D_{25} and D, etc. to get insight are counted.

Step 7: Forecasting selection

Based on the evaluation measures in step 6, the most accurate and promising forecasting distribution is selected. This prediction is used in the second part of the model as if the plaster room were to use it when making patient planning decisions. Possible inaccuracies or deviations from realization are analyzed to determine errors in the causal forecasting method or give recommendations on how to implement the selected forecasting distribution.

5.2 Simulation model

5.2.1 Incorporating walk-in demand in a weekly appointment schedule

With an estimation of the expected walk-in demand, the plaster room can make decisions in their employee planning and patient planning to better match demand and capacity. To evaluate the forecasting distribution, a possible patient planning is created. For this experiment, the data from March 2018 is used. Although the expected demand is calculated 8 weeks in advance and the employee schedule is still subject to changes at that time, we assume the employee schedule to be fixed. We develop an alternative patient planning and compare this planning to the realized performance to determine if using expected demand when scheduling appointments leads to lesser workload fluctuations over the days.

5.2.1.1 Input

The input for the patient planning simulation model is the forecasting distribution created in the method described in Section 5.1.1 and the employee roster. Although the expected demand distribution offers an estimate per daypart, the workload is determined per day. The number of employees and available patient-related time per day determines the amount and length of the session in the patient planning. This is visualized in Figure 22.

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	Number of OCTs present	Available patient-related time [hours]
Monday	5	36
Tuesday	6	40
Wednesday	6	45
Thursday	5	37
Friday	5	37

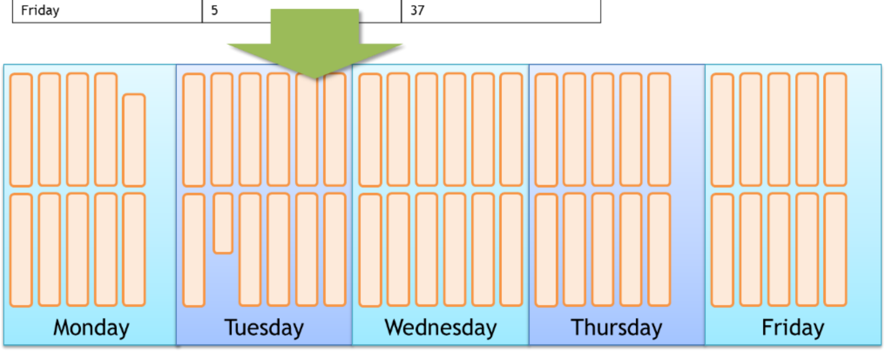

Figure 22: Example of session selection based on employee schedule

Now the number and length of the sessions is established, sessions for walk-in treatment can be reserved based on the predicted demand as shown in Figure 23. We use the expected mean of the output distribution for reserving sessions or blocking slots.

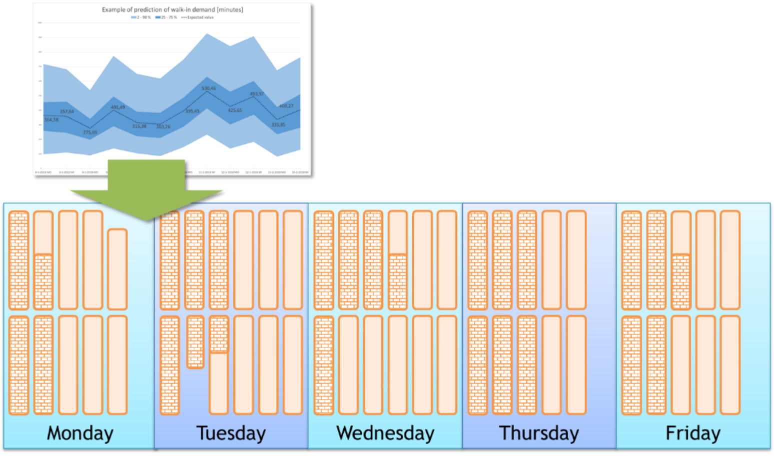

Figure 23: Reserving sessions and/or slots for walk-in treatment (orange blocks)

Since there are appointments or treatments that cannot be transferred to another day, for example inpatient treatment or OR treatment, at least one full daypart should be available for appointments. If this is filled in in the proposed patient planning, we obtain Figure 24.

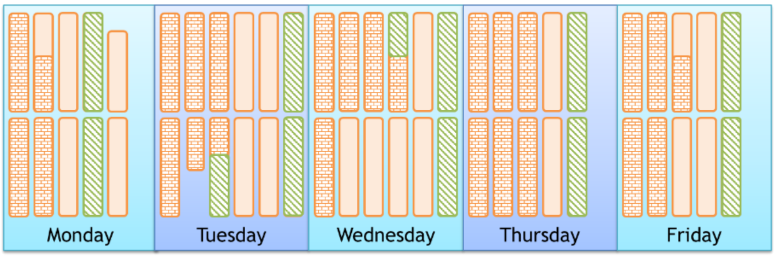

Figure 24: Reserving sessions and/or slots for inflexible treatments (green)

The environment this model operates in is a simplified version of reality, one where we assume all requested appointments are known at the time of patient planning and patients always accept the offered timeslot for their treatment. No further restrictions or limitations regarding patient planning are implemented or executed in this model and we assume appointments can be shifted within that week but must be executed in that same week.

5.2.1.2 Output

Now the total OCT capacity is known and estimated walk-in demand and inflexible treatments are implemented in the schedule, the remaining capacity can be determined. We calculate the total number of treatment minutes per day and the percentage of remaining capacity in that week.

To determine where to plan the remaining appointments, we use the percentages of remaining capacity. If the percentage of remaining capacity on Wednesday is 25%, then one quarter of the treatment time that has to be scheduled, is scheduled on Wednesday. We assume the scheduling staff is capable of optimally spreading workload on individual days.

5.2.1.3 Performance

When the proposed session planning is completed, we use the realization of walk-in treatment to measure the total workload per day. The fictional workload obtained by this planning is compared to the actual performance in March 2018 to determine the relative performance. The main output parameter is the KPI 'Correctly Staffed' and if a day is classified as understaffed, the extend of under capacity in minutes is quantified.

6 Results

This chapter presents the results obtained by executing the model described in Chapter 5. Section 6.1 provides the results of the causal forecasting model, evaluates the obtained probability distributions and concludes with the best performing prediction. Section 0 gives the results of the patient planning simulation model that uses the selected prediction as input and compares the fictional performance to the actual performance achieved by the plaster room.

6.1 Causal forecasting

All data is prepared to create all distinct individual probability distributions. The input per session type is altered to the specified scenario and an example is added in Appendix C. The output variables are collected and analyzed in Microsoft Excel. Realized walk-in demand for validation and evaluation are determined following the methods described in Section 2.3.1.

6.1.1 Results

Figure 25 shows the visual output of the forecasting model per daypart for all four scenarios developed, as well as the realized walk-in demand. The width of the confidence intervals of the predicted time is shown in Table 5. The minimum width obtained within the 2% - 98 % confidence interval is over 9 hours which makes the data unusable for implementation in the patient or employee planning, since one OCT shift equals approximately 225 minutes or 3.75 hours. This means that the interval results in a range of capacity of 2.6 to 2.7 OCTs. The 50% confidence interval ranges from 3.1 to 3.3 hours which can be interpreted as 0.83 to 0.87 OCTs present which we consider as acceptable since it is less than one shift.

	WIDTH INTERVAL 2% - 98 %	WIDTH INTERVAL 25% - 75%
XDEMAND1	579 min / 9.6 hours	187 min / 3.1 hours
XDEMAND2	585 min / 9.8 hours	189 min / 3.2 hours
XDEMAND3	607 min / 10.1 hours	193 min / 3.2 hours
XDEMAND4	607 min / 10.1 hours	195 min / 3.3 hours

Table 5: Width of confidence intervals of prediction probability distributions

On multiple dayparts the realized walk-in demand shows high peaks that none of the forecast distributions were able to predict. Notable differences on individual days between the morning and afternoon are also frequent. Therefore, a visualization of the sum of the expected means per day and sum of the realized walk-in treatment time per day is shown in Figure 26. Although the maximum values are still not completely accounted for, the highest fluctuations are accounted for and of the predicted values in both smoothened out when merging the values to daily averages (for example: comparison of the last week of the predicted values in both Figure 25 and Figure 26 shows more consistent values in the latter).

Figure 25 shows that the probability distributions follow a similar pattern, although the amplitudes visually differ in high demand dayparts. Especially the resemblance between xDemand1 and xDemand2 is easy to notice: apparently differentiating physicians or their orthopedic specialties does not result in distinct predictions.

The days where walk-in demand is relatively low (less than 500 minutes) are never accurately predicted since the minimum values found in the average predicted values of all distributions are between 510 and 580 minutes. All workdays where the realization of walk-in demand is determined to be less than 500 minutes will not be estimated accurate. If the probabilities are aggregated to daily average estimates, they show to overestimate the demand in most of the days. Underestimation only occurs when walk-in demand reaches maximum values (over 1000 minutes). xDemand4 results in the least underestimation when peak walk-in demand is present.

All four probability distributions seem to capture part of the trend displayed, although some deviations are not accounted for by any of the created distributions. This implies some part of the walk-in demand is not caused by the outpatient clinic roster but has a different origin that is not accounted for within the used model. Possible factors could be emergency patients, physicians in training or OCTs giving assistance to their coworkers. Further research could determine the causes of this walk-in demand and implement these in the models used.

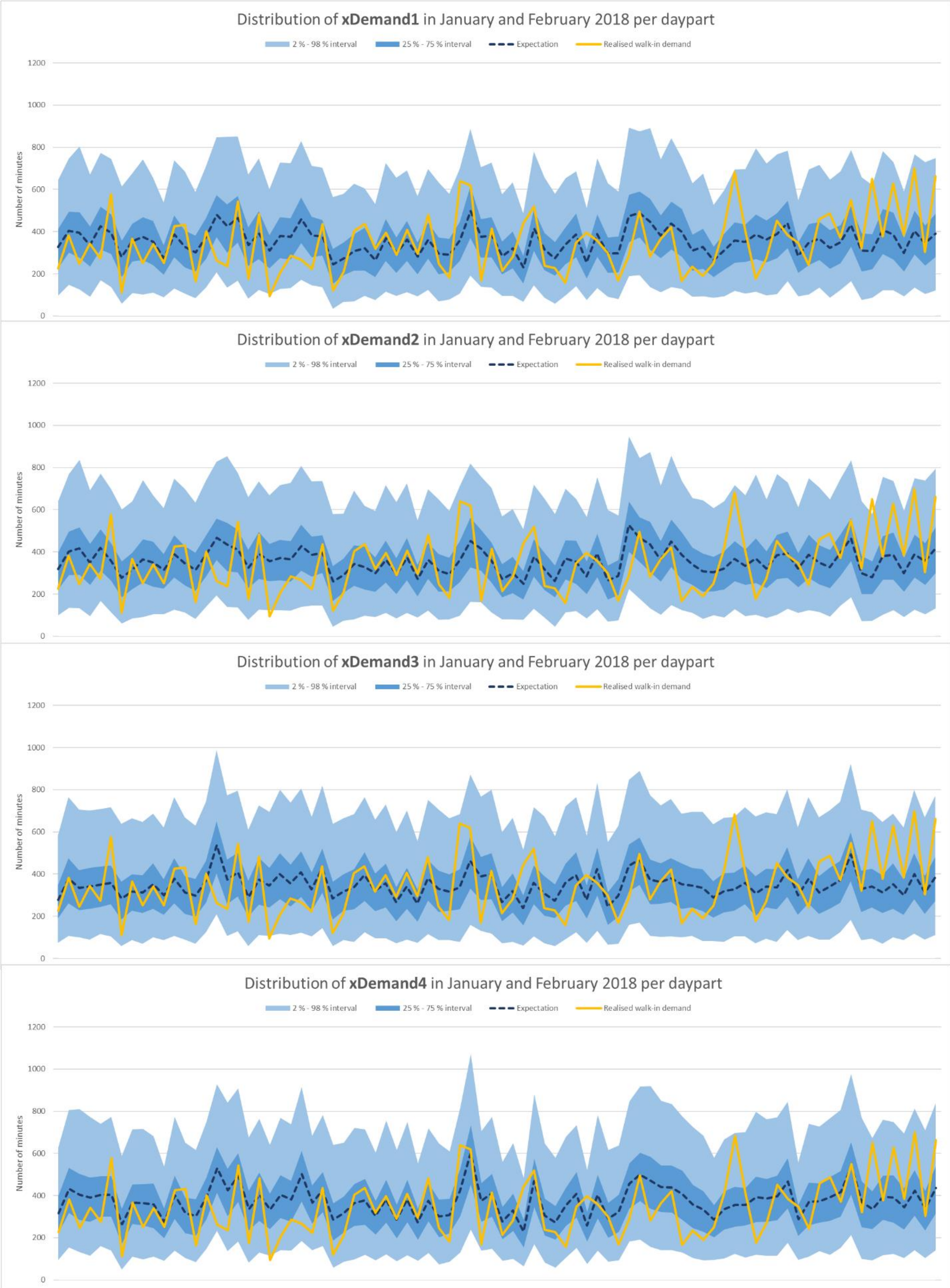

Figure 25: Output distributions for xDemand 1, 2, 3 and 4

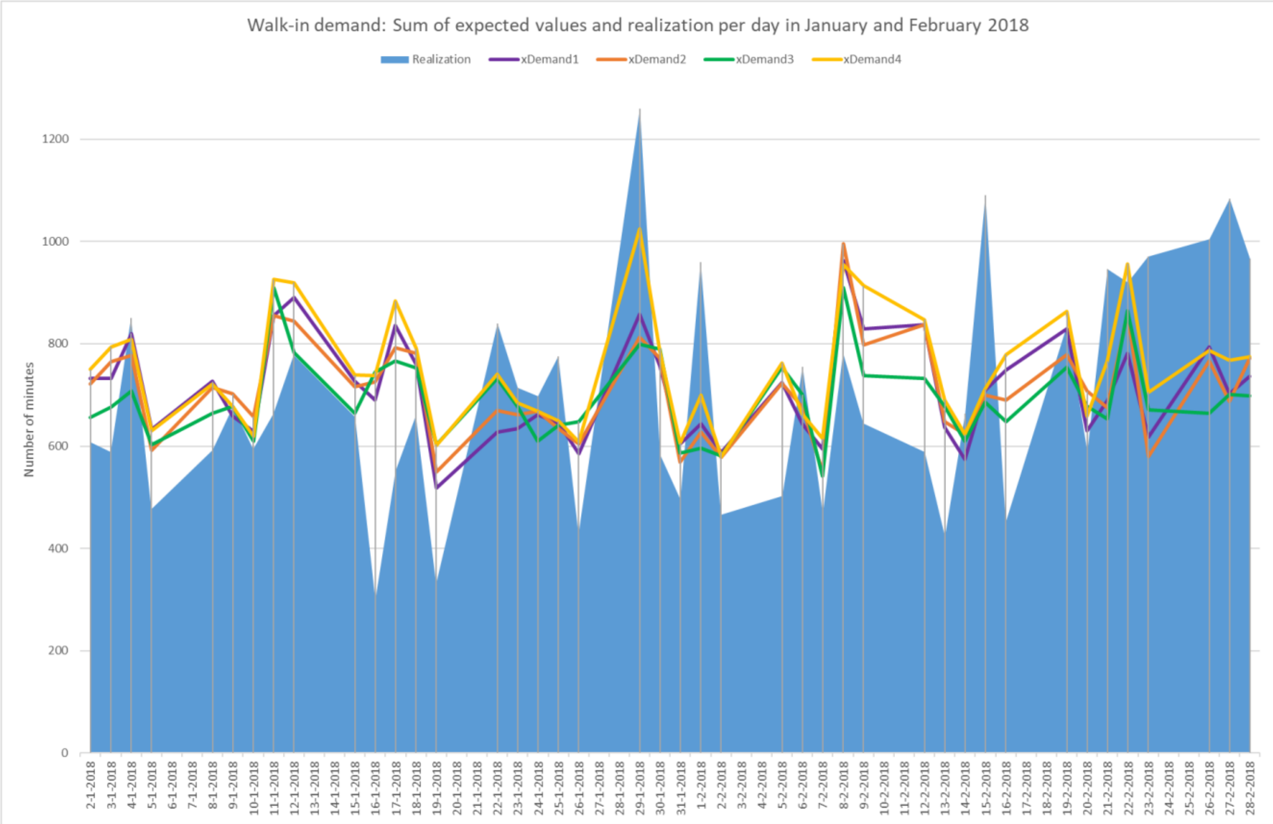

Figure 26: Sum of mean expected demand per workday and sum of realized demand per workday in January and February 2018

6.1.2 Evaluation and selection

The performance measures regarding the probability distributions per scenario as defined in Section 5.1.1.3 are shown in Table 6. Regarding the counting of the realized demand per boundary or confidence interval, only the 50% confidence interval is considered since the 2 - 98 % confidence interval turned out too wide to be functional for further use.

	xDemand1	*xDemand2*	*xDemand3*	*xDemand4*	***Optimum***
AE	7,376	7,429	-0,894	26,749	**0**
MAPE	39,17%	40,24%	38,34%	39,95%	**0,00%**
POA	0,982	0,983	1,005	0,929	**1**
AA	45,78%	49,40%	51,81%	53,01%	**100,00%**
50%-CI	48,19%	48,81%	51,19%	54,22%	**100,00%**

Table 6: Results of performance measure per forecast distribution

The notion of xDemand1 and xDemand2 to be nearly identical is confirmed by the outcomes of the evaluation measures; the only distinguishable outcome is calculated in the average accuracy where xDemand2 outperforms xDemand1 by almost 4%.

xDemand3 shows the best performance regarding average error with an average value close to zero, while the worst value is obtained by xDemand4. The performance of xDemand4 can be explained since it is the distribution that seems to predict higher overall demand. The mean estimated demand for xDemand4 is 374 minutes, while xDemand1 and 2 have mean estimations of 355 minutes and xDemand3 shows to be lowest with a mean average estimate of 347 minutes. The realized mean value per daypart was measured a little over 400 minutes. Although the mean average value of xDemand4 is closest to the realized average value, it shows the highest average error.

The mean average percentage error measure varies little between all four distributions: the difference between the best and worst outcomes is less than 2%.

The measure percent of accuracy aims to be as close to 1 as possible, which is achieved by xDemand3 with a difference of only 0.005.

xDemand1 scores worst regarding average accuracy, with only 45% of the dayparts correctly predicted. Both xDemand3 and 4 score over 50% showing that half of the dayparts the average estimate was within 90 minutes of the realized walk-in demand. When counting the number of dayparts that fall within the 50% confidence interval, again both xDemand3 and 4 score over 50% correct. xDemand1 and 2 have corresponding outcomes of 48%.

Concluding from all evaluation measures, xDemand1 and xDemand2 show similar poor-quality outcomes. Comparison between xDemand3 and xDemand4 turns out in favor for xDemand3, especially since the percent of accuracy scores impressively and the average error of almost zero. xDemand4 shows potential but tends to overestimate low-demand periods although it performs slightly better regarding the average accuracy and 50% confidence interval. Since xDemand3 also scores above 50% in both measures, we conclude this probability distribution is most accurate and has most potential for promising implementations.

6.2 Incorporating walk-in demand in a weekly appointment schedule

To execute the simulation model for the patient planning, we must first obtain the desired input. We used the input distributions of xDemand3 to determine the expected walk-in demand for March 2018. The average expected mean value on workdays is 334,5 minutes with a standard deviation of 61 minutes.

Figure 27 shows that the most walk-in demand is expected on the afternoons of 8, 13, 20 and 22 March. The mean and 50% confidence intervals are respectively; 470 minutes [348-572], 468 minutes [337-578], 445 minutes [318-552] and 470 minutes [348-572]. The lower limits all exceed 300 minutes.

The lowest expected walk-in demand is on the mornings of March the 6th and 15th. These mornings measure a mean expected value and 50% confidence interval of 254 minutes [172-319] and 260 minutes [175-325].

Looking at the confidence intervals of both the lowest and highest predicted values, the lower limits of the expected peak demand have similar values as the higher limits of the expected off-peak demand: both are approximately 5.5 hours. We therefore conclude that this probability distribution is useful input for making planning decisions. The mean expected value is used to determine the amount and length of session blocked for walk-in demand.

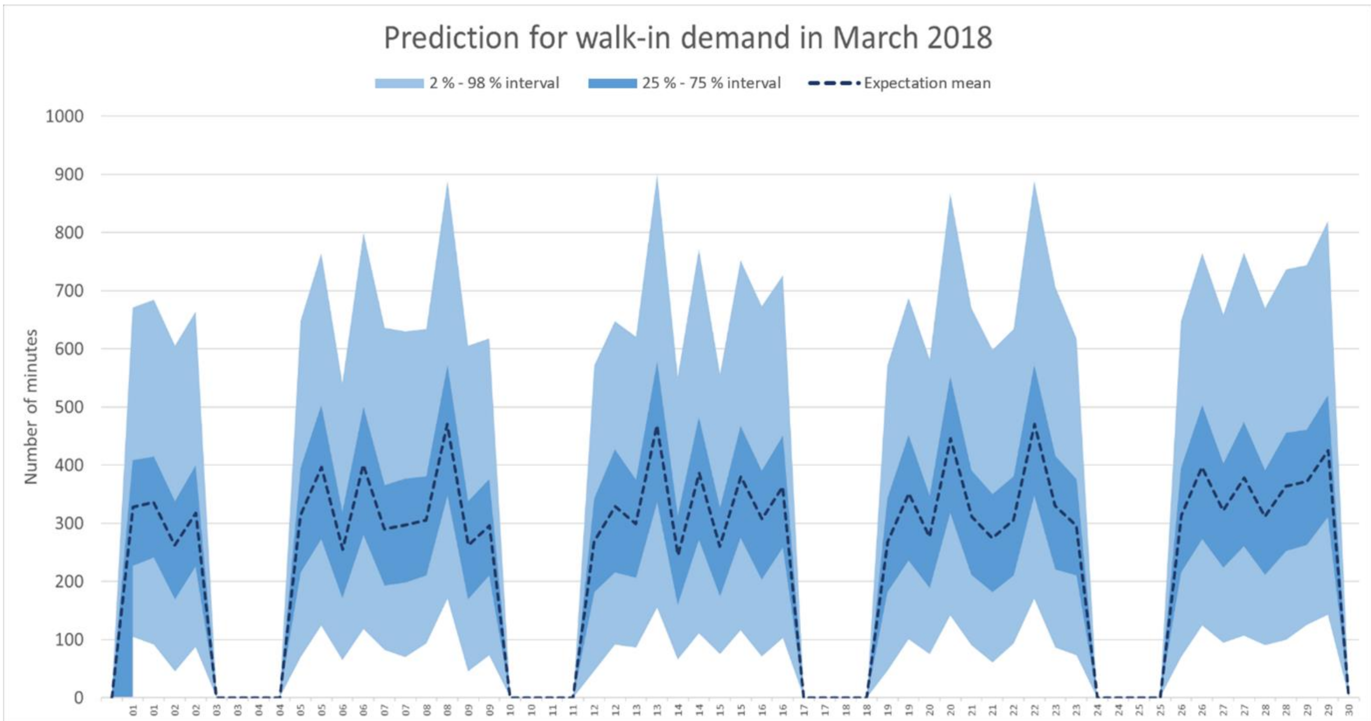

Figure 27: Predicted walk-in demand per daypart in March 2018

The necessary input from the employee planning was extracted from their schedule and the required input for the total amount of treatment time of appointments was obtained via the database of the SMK. Since the realized appointment treatment time and booked treatment time can differ slightly per appointment, both were used to calculate the fictional performance.

The total treatment time or workload per day is added in Appendix D. The outcomes of the KPI 'Correctly staffed' using the results from the model and gathered data can be seen in Table 7. If a workday is classified as understaffed, the shortcoming capacity is shown in minutes. The borders represent the 'workweek', for example the 1st and 2nd of March were in the same workweek. Table 8 gives an overview of the total amount of days per category.

	Current situation		Results using booked time		Results using realized time	
01-03	Over		Over		Over	
02-03	Over		Over		Over	
05-03	Correct		Correct		Correct	
06-03	Under	-767	Correct		Correct	
07-03	Over		Correct		Correct	
08-03	Correct		Under	-449	Under	-419
09-03	Correct		Correct		Correct	
12-03	Correct		Under	-349	Under	-359
13-03	Under	-275	Correct		Correct	
14-03	Correct		Correct		Correct	
15-03	Correct		Correct		Correct	
16-03	Correct		Correct		Correct	
19-03	Correct		Under	-361	Under	-400
20-03	Under	-879	Correct		Correct	
21-03	Correct		Under	-637	Under	-707
22-03	Correct		Correct		Correct	
23-03	Under	-928	Under	-768	Under	-801
26-03	Under	-367	Under	-421	Under	-483
27-03	Under	-606	Under	-291	Under	-329
28-03	Over		Correct		Under	-330
29-03	Under	-1075	Correct		Under	-253

Table 7: Staffing performance results

In all three situations, the first week (of March 1 and 2) are overstaffed. This indicates a high demand that could not be subdivided over the week.

In the second and third week, all three situations have one day understaffed. The modeled results in week 2 show less workload on the understaffed days (449 and 419 minutes short) compared to the current situation that was 767 minutes understaffed. In the third week, the current situation had the least capacity shortage with 275 minutes versus approximately 350 minutes in the modeled situations.

The fourth and fifth week are the most remarkable ones: the current situation shows only three days correctly staffed and five days understaffed, while one of the days in this seemingly busy period is overstaffed. The results from the model differ in these weeks. The results obtained using the booked time include 4 days correctly staffed and 5 days understaffed, while the results using realized time only classifies two days as correctly staffed and all others understaffed. This raises the question, if capacity for these weeks is too little anyway, what would be more desirable? Since the objective is to realize less fluctuation in perceived workload we take a better look at the days that are classified as understaffed. Table 8 shows per scenario that when a day is overstaffed what the average, minimum and maximum capacity shortage is in minutes. Even though the results obtained using realized appointment times show that more days are understaffed, the average capacity shortage is less than in de current situations. Looking only at the last week in this scenario where all days were understaffed, we see an average capacity shortage of 350 minutes and total shortage of almost 1400 minutes or 23 hours. The current situation shows one day overstaffed and an average under capacity of 683 minutes over 3 days resulting in the total shortage that week of almost 2050 minutes or 34 hours.

				If understaffed, then capacity shortage in minutes is:		
	Days overstaffed	Days correctly staffed	Days understaffed	Average	Minimum	Maximum
Current situation	4	10	7	-700	-275	-1075
Results using booked time	2	12	7	-468	-291	-768
Results using realized time	2	10	9	-453	-253	-801

Table 8: Staffing performance overview in all scenarios

Depending on whether the plaster room wants to minimize the understaffed days or to minimize fluctuations when weekly workload exceeds the weekly capacity, either the results using booked appointment time or realized appointment time can be favored. Both scenarios achieve a better performance in the KPI ‘correctly staffed’ than the plaster room realized in March with their current planning if the extend of capacity shortage is considered. We therefore conclude that implementing expected demand, even if this probability distribution still under- or overestimated the realized demand influences the workload fluctuations in a positive way.

6.3 Conclusion

The best performing expected demand distribution, xDemand3, uses input distributions that do not distinguish between type of orthopedic outpatient clinic sessions but was based on generic outpatient clinic information. The input used for xDemand3 was aggregated per outpatient clinic session without differentiation between morning or afternoon, or (type of) orthopedic physician. The two distributions that performed poor, xDemand1 and xDemand2, both included differentiation per daypart.

We use xDemand3 to make an alternative patient planning for March 2018. Simulation shows that the alternatives created outperform the current situation: overstaffing is reduced with 50% and the average under capacity on understaffed days is lowered with 232 to 247 minutes.

7 Conclusion and recommendations

This chapter provides the conclusions of this research as well as the final recommendations for practice and further research. Section 7.1 presents the conclusions of this research. Section 7.2 elaborates on the limitations and assumptions of the research, as well as providing recommendations for practice and scientific research.

7.1 Conclusion

The objective of this research is to minimize workload fluctuations over the days. We develop a planning method that improves the match between capacity and demand by incorporating walk-in patient demand. To accomplish the objective, research questions were formulated. Section 7.1.1 contains the answers to the research questions. Section 7.1.2 and Section 7.1.3 present the conclusion regarding the contribution to practice and the contribution to science respectively.

7.1.1 From this research

The motivation for this research was that both the management and the employees of the plaster room in Sint Maartenskliniek perceive a fluctuation workload over the days, resulting in understaffing and overstaffing.

Operational processes and operational performance

The OCTs in the plaster room treat patients that are referred to the treatment room by physicians of other departments. The context analysis shows that most of the patient demand of the plaster room originates from the orthopedic department (94,52%). Patients can be categorized in three categories: patients who are treated on the OR, patients with an appointment and walk-in patients. In 2017 the percentage of total treatment time was 6.75% for OR patients, 53.69% for patients with an appointment and 39.56% for walk-in patients.

The zero measurement of the operational performance showed acceptable waiting times for patients: in 2017 the average waiting time per month varies from 7.1 to 10 minutes for all patients. The minimum service level regarding waiting times of 2017 occurs in March, when 86.48% of the patients waited less than the norm of 15 minutes (for patients with appointments) or 30 minutes (for walk-in patients). In all other months in 2017 the service level achieved was between 87% and 94%, where in seven months the service level was above 90%. No overtime occurred in 2016 or 2017. The data analysis confirmed and quantified the statement of the management and employees regarding fluctuating workload. The productivity levels per month fluctuate significantly which is visualized in Figure 19 on page 40. The cause of these fluctuations are the patient demand fluctuations and capacity fluctuations. Figure 18 on page 39 shows the OCT capacity per day and treatment time per day are not balanced throughout the year. This results in understaffing and overstaffing: the amount of days correctly staffed per month in 2017 varies from 40.0% to 66.7%. The outcomes of these performance indicators confirm the statement of the OCTs and management regarding fluctuating workload and shows room for improvement.

To gain insight in the employee planning and the patient planning, we use the planning framework of Hans et al. (2012). We conclude that multiple planning decisions are not taken on the optimal moment and some are even considered fixed, such as the weekly capacity requirements and session capacity requirements. There are no appointment rules or planning rules based on the production of other departments within the hospital, while almost all patients are referred by physicians of other departments. This results in unexpected peak moments or off-peak moments for the OCTs per day, week or hour, as confirmed by the zero-measurement of the performance indicators.

Scientific research

Literature containing a similar objective turned out to be scare, since most research is focused on optimization of performance on individual days (Cayirli & Gunes, 2014; Dijkstra, 2017; Dobson et al., 2011; Hoogwout, 2010; Lu et al., 2014; Morikawa & Takahashi, 2017; Su & Shih, 2003; van de Vrugt, 2016; Wu et al., 2014) and on decreasing patient waiting time (Cayirli & Gunes, 2014; Hoogwout, 2010; Kortbeek et al., 2014; Lu et al., 2014; Morikawa & Takahashi, 2017; Su & Shih, 2003; van de Vrugt, 2016; Wu et al., 2014). The literature review of Cayirli et al. (2003) emphasizes that effective scheduling systems should aim to match demand with capacity. This component is present in all research discussed, but all researchers consider the demand to be known beforehand.

Solution design

The most promising opportunity for operational improvement in the plaster room is the incorporation of expected walk-in demand in the plaster room planning. A new timeline for both the patient planning as well as the employee planning is proposed, which offers the opportunity to incorporate information on production of other departments when making planning decisions.

The trade-off between available information on production and the proposed planning timeline results calculating the expected walk-in demand 8 weeks in advance. The causal forecasting model used to calculate expected demand for the radiology department in Sint Maartenskliniek is altered to determine the expected walk-in patient demand for the plaster room.

Model design

We use causal forecasting to generate four probability distributions based on different session types from the orthopedic outpatient schedule. We provide a step-by-step guide (see Figure 28) to implement, select and validate forecasting models that can determine the optimal forecasting model. The required input for the model includes historical plaster room patient demand, historical orthopedic outpatient clinic patient demand and the historical and future orthopedic outpatient clinic schedule. The historical patient data is used to create input probability distributions and based on the orthopedic outpatient clinic schedule, an output distribution is created using discrete convolution. These output distributions are evaluated using multiple evaluation measures.

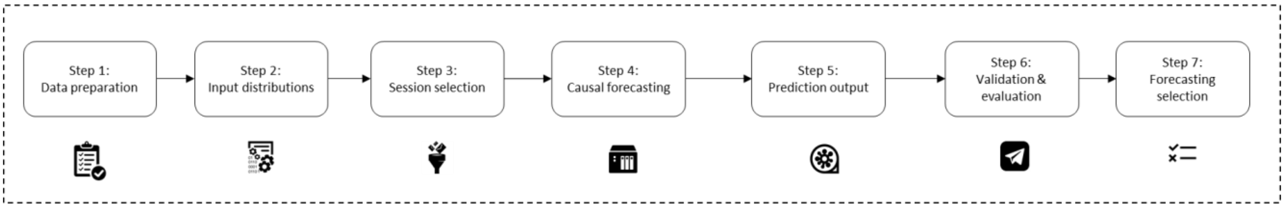

Figure 28: Overview of the causal forecasting model

We use the best performing probability distribution for expected walk-in demand to derive a new planning template, which we evaluate in a patient planning simulation model to determine operational performance in March 2018. Employee planning is considered as fixed in this simulation and is not used as experimental factor.

The model design offers a valuable contribution to future research and implementation when the context permits causal forecasting.

Model results

The best performing expected demand distribution uses input distributions that does not distinguish between type of orthopedic outpatient sessions. Implementation of the probability distribution of expected walk-in demand in a patient planning simulation leads to an increase of the days that were staffed correctly and indicates a more evenly distributed workload by lowering the average minute of under capacity in understaffed days as shown in Table 9. The number of days that are overstaffed decreased in both interventions with 50%.

				If understaffed, then capacity shortage in minutes is:		
	Days overstaffed	Days correctly staffed	Days understaffed	Average	Minimum	Maximum
Current situation	4	10	7	-700	-275	-1075
Results using booked time	2	12	7	-468	-291	-768
Results using realized time	2	10	9	-453	-253	-801

Table 9: Results of patient planning simulation

The results of this research show that the method to estimate walk-in demand for the plaster room based on the outpatient clinic schedule has added value in creating the patient planning and improves the balance between capacity and demand.

The research is innovative in the perception of optimization over multiple days and the possibility to include flexible employee planning. The results of the model show that operational performance can be increased when expected walk-in demand is incorporated in the patient planning. The generated expected patient demand can improve the match between demand and capacity in more ways than simulated in this research. Further research should focus on improving the estimated demand probability distributions, as well as implementation and simulation of both the patient and employee planning. The designed model provides a guideline for situations where causal forecasting is a possibility to create and determine the optimal probability distribution.

7.1.2 Contribution to practice

The research impacts the plaster room planning in several ways. The methodology results in a model that can continuously create walk-in demand predictions based on the orthopedic outpatient schedule. At the time of writing the plaster room is working on using the prediction to determine the planning for the summer period in 2018. Making this information available to the planners in sufficient time, even without using appointment rules, will most likely increase the performance of the plaster room due to additional information in the orthopedic production and patient flow.

The proposed planning decision timeline offers the opportunity for the plaster room to take even more information into account when making planning decisions. Room for improvement can be found in both the session planning and capacity requirements for both weeks and individual sessions. For the plaster room, peak moments of walk-in demand are essential to know beforehand. These moments are predicted by the offered probability distribution, even though it seems to underestimate the peaks.

The plaster room can match capacity and demand better and therefore improve operational performance when the methodology is applied correctly. The results show that with straightforward and uncomplicated planning methods we managed to decrease the fluctuations in daily workload.

The average capacity shortage in understaffed days decreases with more than 3 hours in the simulated situation. In the week where overall demand is at its maximum, the realized situation shows a day that was overstaffed which did not occur in the simulated situations. We conclude that experimenting with interventions that use appointment rules based on the expected demand has enormous potential for improving the performance of the plaster room in the future.

7.1.3 Contribution to science

7.1.3.1 Healthcare

In contrast to methods found in literature, we aim to optimize workload over multiple days. Most literature discussed in this research focuses on reducing patient waiting times while our focus was on improving workload fluctuations. In general, demand was known before optimization and used to match capacity and demand. Since our situation offered no quantification of expected demand, we offer a solution that includes creating an expected demand probability distribution. This research provides a guideline to determine and evaluate expected demand in other settings.

This research combines the opportunity to optimize both the patient planning and employee planning. The proposed timeline for planning decisions gives an overview of optimal moments to make planning decisions and reflect on current approaches regarding flexibility and consistency.

7.1.3.2 Other disciplines

The setting of this research is a plaster room in a Dutch hospital, but the presented solution can be applied in other settings. Not only outpatient clinics that offer both walk-in treatment and treatment on an appointment basis can benefit from the outcomes, but many other disciplines face similar difficulties like unknown demand and fluctuating workload. The methodology can be altered to offer solutions in markets that experience of fluctuating ‘walk-in’ demand, such as the entertainment industry or public transport. By using expected demand in timely matter, adjustments to capacity or precautions can be made to meet this demand. Sint Maartenskliniek has gathered lots of (relevant) data in the past years. Even though in most situations access to these amounts of data is still limited, innovations such as Internet of Things can provide the necessary data for causal forecasting methods making this method even more applicable in the near future.

7.2 Discussion and recommendations

This section discusses the limitations of the method and forthcoming recommendations. Section 7.2.1 describes the recommendations for the plaster room in the Sint Maartenskliniek. Section 7.2.2 describes the consequences of the scope and section 7.2.3 elaborates on the recommendations for further research.

7.2.1 Recommendations to practice: implementation in Sint Maartenskliniek

The results of the research show an improvement in workload fluctuations over the days. We advise the plaster room management to make the walk-in demand prediction available for the planning staff as soon as possible. At the time of writing, efforts to create insights in the expected walk-in demand for the summer of 2018 use the methodology of this research.

Even without using the expected walk-in demand in the planning decisions of the plaster room, improvements can be achieved by providing insights in other departments. By quantifying the consequences of the productivity in terms of outflow, opportunities for influencing the demand can be created. Increasing the level and frequency of outer-department communication can be achieved by convincing the relevant stakeholders of the impact of their outflow to the plaster room.

7.2.1.1 Data: assumptions and limitations

The data collection in Sint Maartenskliniek is taken seriously and is done extensively. Still, improvements regarding the data collection can improve the monitoring of performance.

We define walk-in patients as treatments that are booked on the same day in this research. Alterations in the patient planning can therefore result in treatments being classified as walk-in while they are not. One of the tasks of OCTs is aiding a co-worker, which is often also classified as 'walk-in'. Since these treatments do not directly originate from the outpatient clinic schedule, they will not be accurately predicted by our method. The data also classifies emergency patients as walk-in, while these can be considered a new patient type. We therefore recommend expanding the patient data gathering with a field where the type must be selected, creating the opportunity to distinguish walk-in patients, emergency patients, OR patients, patients with an appointment and unexpected activities. Enrichment of the data with this information helps to create more accurate insights and predictions.

The data collection of the plaster room could be enriched by listing the desired treatment date; the performance indicators 'correct treatment date' and 'accessibility walk-in' could not be measured due to this missing data. Access times can be monitored and evaluated when this information is available.

This research uses the realized treatment times when available by calculating the difference between time of arrival and departure, the booked treatment time is used when this data was not available. Even though registration of the arrival time and departure time has increased tremendously over the years, we were often compelled to use booked treatment time instead of realized time. Improvements in registering the realized duration of assistance of an OCT are necessary since the workload of these activities cannot be derived accurately from the data. This could result in imprecise outcomes of the performance indicators, since the assistance activities have a considerable impact on the workload.

7.2.1.2 Model: assumptions and limitations

The forecasting model creates variables per part of the day. The input distributions assume that the treatment in the plaster room takes place on the same part of the day as the outpatient appointment. The accuracy of the prediction per daypart can be improved by creating input distributions that incorporate the opportunity to visit the daypart before or after the outpatient clinic appointment.

The probability distribution that is created with the causal forecasting model includes several variables, of which two of them are unusable now: the confidence interval between 2% and 98% is almost 10 hours which is too inaccurate for our purposes. Increasing the sample size or simplifying the possible inputs could result in a narrower interval, but we strongly advise to investigate this in further research since the 25%-75% and mean predicted value have shown to be useful in practice.

The simulation patient planning model in our research includes many assumptions, including optimal patient planning on the day itself and that appointments can be rescheduled within that same week but not in another. Many simulation models for testing and evaluating patient appointment planning are available in literature and have already been applied to hospital departments. Research aiming to create a patient planning simulation model that resembles the current situation of the plaster room can test appointment rules or planning decisions based on the expected demand. More complex appointment rules can subsequently be tested before implementation to assure performance improvement, offering the opportunity to experiment with 'what if' situations. An example can be the effect of appointment rules on overtime or patient waiting times or aiming to empty the schedule of an employee in weeks with overcapacity.

The results of this research show four different predictions for walk-in demand. The evaluation and validation are executed over two months. Although this seems to be sufficient, a longer time period for evaluation and validation would have our preference. The patient planning simulation consists of one month which is limited. By expanding the time frame of the simulation, more extreme off-peak and peak moments can be included.

7.2.2 Scope

The scope of this research is defined as *workload performance over multiple days*. The first part of the research considers both the employee planning and the patient planning, where the models only include the patient planning. We are convinced that the results of this research can have a positive impact on the employee planning based on the suggested timeline. The current employee planning offers little flexibility which complicates the goal of matching demand and capacity. Research by Mulder (2016) presents a decision support model that supports the staffing of physical therapist on a tactical level in the Sint Maartenskliniek. Not only does this model use expected demand as main input variable, the model has been improved and is currently in use in Sint Maartenskliniek. Implementation of such models is often without difficulties, therefore a successful case within the same hospital should create learning possibilities and opportunities to convince all stakeholders to create more flexibility in the capacity.

7.2.3 Recommendations to science: further research

In this research we present a model design that can be used to create, select and validate forecasting models. Unfortunately, as mentioned earlier in this chapter, the 2%-98% confidence interval of the output prediction is too wide. Further research can offer opportunities to make this interval narrower and therefore more useful.

We chose to predict walk-in demand due to its high impact on workload and the lack of insights in the walk-in demand. It can be useful to research the added value of appointment-based demand. We recommend analyzing the historical demand of planned treatments, and if possible, to calculate the expected patient demand. This could, for instance, help to determine the required capacity per week.

When validating the expected walk-in demand probability distributions, we noticed some peak moments of walk-in demand that were missed by all four distributions. Since we use a causal forecasting method, it is possible these peaks are not created by outflow of outpatient sessions of orthopedic physicians and are therefore missed by our predictions. Further research can explain these peaks, determine its origin and adjust the expected demand accordingly.

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