# Optimizing operations at an orthopaedic hospital

Forecasting patient distributions and implementing strategies

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This report is intended for OCON Orthopedische Kliniek, as an advice on optimizing their operations, especially the process patients follow from their appointment at the outpatient clinic until their surgery.

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# Preface

Dear reader,

Before you lies my bachelor thesis ‘Optimizing the operations at an orthopaedic hospital’. The goal of this research was to find a way to assess the performance of the different departments at OCON and the process as a whole and simultaneously find options to improve this performance. To conduct this research, I worked at OCON from September 2020 until September 2021.

I would like to thank all people who assisted me during my research the past year. Firstly, I would like to thank Peter Schuur, my first supervisor from the UT, for all his time and interest to supervise this research. Our discussions encouraged me to approach the research from different angles and the constructive feedback pushed me to think more critically about the problems and solutions in this research. Secondly, I want to thank my supervisor from OCON, Rob Lindeman. During the past year, Rob has guided me in my research, proposing several problems that could be looked at and explaining their urgency. Rob’s critical thinking has also made me think twice about steps in my research, resulting in a well thought out research approach. Furthermore, I would like to thank the different employees at OCON that helped me over the course of this research, especially Erik Maartens and Feike de Graaff, who took extra time to provide different perspectives on my decision-making.

In particular I would like to thank everyone involved in this research, my friends and my family, for supporting me during the most difficult parts of last year. As a result of this support, I can now be proud to present this thesis. I hope that you may enjoy reading this thesis and that it generates new insights on combining theories to new theories and putting them to practice.

Kind regards,

Robbert Abbink

Enschede, September 2021

## Executive summary

OCON Orthopedische Kliniek (OCON) is a specialist hospital for orthopaedic and sports medical healthcare. OCON has departments in the hospitals in Hengelo and Almelo. Patients receive tailormade healthcare that is regularly adjusted following scientific developments.

OCON believes that alignment between the different departments within their organisation contributes to the improvement of healthcare. This way of working follows the protocols of enhanced recovery after surgery (ERAS) and is the motive for conducting this research. Optimizing the scheduling process at the preoperative screening (POS) and the surgery planning will reduce waiting times for patients, resulting in faster treatment. The faster patients receive treatment, the lower the chance of complications during and after the surgery. Thus, OCON and its patients benefit greatly from optimizing the scheduling process.

Currently, key performance indicators (KPIs) are in place to assess the performance of the scheduling process at both departments. Patients are assigned a patient category based on their progress in the process from outpatient clinic until surgery. Using these KPIs, strategies are implemented and departments are told to adjust their operations, with the aim to reduce the number of patients in unwanted patient categories. An example of an unwanted patient category is the patient category that includes patients that are screened and approved for surgery, but do not want to undergo surgery yet. These patients may have filled up a spot at the POS at the expense of a patient that wants to undergo surgery as soon as possible.

Unfortunately, these KPIs often lack goals and policies and often include various types of surgery, which blurs the image of the KPI and lets OCON implement strategies that are not well-founded. In order to solve this problem, the following central research question is formulated:

*What is the efficiency of the current scheduling process at the preoperative screening at OCON and how can it be improved?*

The research starts with mapping the whole process from outpatient clinic to surgery planning and identifying the way the tactical planning counsel (TPO) assesses the performance of the POS and the surgery planning, after which analysis of this process is conducted to find associated bottlenecks and problems. Furthermore, a data analysis is conducted to find proof for these bottlenecks and problems.

During a literature study, different modelling theories are discussed to find the best way to model the process at OCON. Combining the benefits of these theories results in a new model, which we call the Markov Interventions Model. Using transition probabilities, it is possible to forecast the transition of patients from one patient category to another. With this model, OCON can assess the current patient distribution and forecast it for the upcoming weeks. Based on historical data, OCON can alter the transition probabilities according to a strategy option and implement them in the Markov Interventions Model. The forecasting model will then show OCON whether or not the strategy has the desired effect on the patient distribution on the short and long term. Furthermore, seasonal fluctuations can also be implemented in the Markov Interventions Model, to ensure higher accuracy of the forecasting model. The validity of the model can be improved by utilizing a larger dataset than used in this research, for instance three years instead of one, and by observing permanent shifts in the transition probabilities and adjusting the model accordingly.

With this model, the central research question of finding the current efficiency of the scheduling process and identifying options to improve it is answered indirectly. While the model itself does not provide OCON with improvement options, using the model helps to identify strategies that will improve the efficiency of the scheduling process. Furthermore, this research shows that combining several modelling theories can result in new theories that may be more applicable to a specific situation.

The model that is designed in this research has not yet been implemented by OCON. For this, compatibility with the current hospital system HiX would be ideal but not necessary. When the model is implemented in the operations at OCON, KPIs can be implemented to keep track of the performance of the whole process and to further analyse the potential strategies at hand. Lastly, after more data analysis is conducted and OCON is satisfied with the results from the Markov Interventions Model, simulation or serious game could be the next step in improving the forecasting of patient distributions.

# Table of Contents

# Reader's guide

*Chapter 1: Problem Identification and Approach*
In this chapter, the company and its operations are introduced. The relevance of the problem is explained as well as the problem-solving approach. The research question and the sub-research questions are mentioned and the deliverables are discussed. Overall, this chapter explains why and how the research is carried out.

*Chapter 2: Current scheduling process*
In chapter 2, the current scheduling process at the POS and surgery planning is explained. Furthermore, the collaboration of the two departments and their performance assessment is discussed. This chapter elaborates on the introduction of the operations in chapter 1 in more detail.

*Chapter 3: Performance of the current scheduling process*
This chapter analyses the performance of the scheduling process in the current situation. Firstly, the current performance assessment is used, after which associated bottlenecks and problems are identified. Lastly, the performance is also analysed by conducting a data analysis.

*Chapter 4: Literature study*
The literature study provides us with a discussion on the different theories on modelling a process. Their advantages and disadvantages are mentioned and a conclusion is drawn to pick the best model.

*Chapter 5: Improvement options*
The new model created in chapter 4, is put into practise in chapter 5. In this chapter, the use of the model is discussed as well as the benefit of introducing it into the operations at OCON.

*Chapter 6: Solution*
In this chapter, the introduction of the new model is mentioned. This chapter concerns the necessary resources to successfully implement the new model. Furthermore, the long-term maintenance of the model is discussed.

*Chapter 7, 8 and 9: Discussion, Conclusion and Recommendations*
These three chapters answer the central research question. The discussion explains the limitations and assumptions in this research. The conclusion mentions what the result from this research is and why this result answers the central research question. In the last chapter, recommendations are made to further improve the operations at OCON and to give suggestions about additional research.

# Terminology

**ERAS (Enhanced Recovery After Surgery) (p. 9)**
Policy that states that every part of a patients' process influences the number of complications and the recovery time after the surgery.
**Perioperative (p. 9)**
Used to describe the alignment of different departments in the whole process leading towards and after the surgery.
**Postoperative (p.9)**
Concerns everything that happens after the surgery has taken place.
**POS (preoperative screening) (p. 9)**
The screening department that screens patients before they are approved to undergo surgery.
**Preoperative (p. 9)**
Concerns everything that happens before the surgery takes place
**EPR (Electronic Patient Records) (p. 10)**
Electronic files in which doctors can store information and data of a patient (for example appointments and health related information)
**HiX (p. 10)**
Computer system which holds the EPR and provides the option to extract and analyse data.
**TPO (tactical planning counsel) (p. 10)**
Meeting with associates of different departments to streamline the whole operation at OCON.
**ASA-classification (p. 18)**
Classification of patients based on their health, diet and the complexity of the surgery at hand. Based on the ASA-classification, different timeslots can be assigned to a patient. For more information on the ASA-classification, see appendix C.
**WL (p. 24)**
The amount of patients that want to undergo surgery but have not been scheduled for surgery yet (category 2 and 5).
**Transition probabilities (p. 32)**
The probability that a patient will enter a certain phase after one week. For example, a patient has not been screened by the POS this week. Transition probabilities will then show what the chance is that this patient will be screened next week.
**Flex-day (p.42)**
OCON operate a flex-day, which means that orthopaedic surgeon is either scheduled to perform surgery or to see more patients at the outpatient clinic. This way, OCON can influence the patient distribution over all departments of the process.

# 1. Problem identification and approach

This research has been carried out as a bachelor thesis for the study of Industrial Engineering and Management in the faculty of Behavioural, Management and Social Sciences at the University of Twente. The bachelor assignment has been formulated in collaboration with OCON Orthopedische Kliniek. In this chapter the company and the problem context are described in order to get a better picture of the day-to-day operations of OCON and the cause that let to this particular assignment.

## 1.1. OCON Orthopedische Kliniek

OCON Orthopedische Kliniek (OCON)is a specialist hospital in Twente that offers orthopaedic and sports medical healthcare. OCON has departments in the hospitals of Ziekenhuis Groep Twente (ZGT) in Hengelo and Almelo and focusses on the optimal treatment and individual healthcare of the patient. Patients receive tailormade healthcare that is regularly adjusted following scientific developments.

OCON believes that alignment between the different departments within their organisation contributes to the improvement of healthcare. The confluence of the different fields of knowledge and expertise makes sure that all important aspects of the patients' surgery are considered and results in a treatment with a lot of monitoring and finetuning to acquire the best possible care for every individual patient.

This way of working follows the protocols of enhanced recovery after surgery (ERAS), where a combination of multimodal evidence-based strategies is applied to conventional perioperative techniques, resulting in a reduction of postoperative complications and early recoveries (Moningi, Patki, Padhy, & Ramachandran, 2019). In other words, optimizing the whole process instead of the individual steps can result in a reduction of complications during and after surgery and a faster rehabilitation. In some cases, for instance colonic surgery, it is proven that ERAS also decreases the costs per surgery and patient, and consequently could result in lower treatment costs for patients (Sammour, Zargar-Shoshtari, Bhat, Kahokehr, & Hill, 2010). By implementing ERAS, OCON hopes to improve healthcare while reducing costs at the same time.

## 1.2. POS and surgery planning

Preoperative screening (POS) has an important role in the ERAS protocol. Monitoring cardiac behaviour, educating patients and ensuring a healthy diet before entering the operating room are all parts of the preoperative screening and reduce the number of complications during and after surgery. OCON has also implemented a POS-department but outsources treatments related to these screenings. For instance, when a test shows that the patient has cardiac problems, the patient is referred to a cardiologist that works for ZGT. Only when a patient has passed the screening, they are approved for surgery and surgery can be scheduled.

The surgery planning schedules timeslots with a certain type of surgery. For example, more complicated surgeries take longer for which a longer timeslot is necessary. For the first upcoming weeks these timeslots will be or have been filled with available patients. The surgery planning tries to schedule surgeries in their own type of timeslot but sometimes it is better to schedule another patient to fill gaps (i.e., gaps that have been created by other scheduling decisions or because no other patient is available that fits in that timeslot). Because scheduling is based on the type of surgery, it would be useful if the POS knew the open timeslots in order to prioritize patients with the corresponding type of surgery.

The surgery planning also schedules timeslots for emergency patients. These timeslots are reserved, but will be opened two days in advance if no emergency patients are available to fill the timeslots. The surgery planning then has some time to try to schedule another patient in that timeslot.

## 1.3. Problem introduction

OCON wants to schedule the surgeries as efficient as possible in order to be able to treat as many patients as possible and reduce costs in the meantime. Since September 2020 OCON has set up the tactical planning counsel (TPO) that meets every two weeks in order to streamline the POS and the surgery planning and to identify points of concern for the schedules of the next five weeks. The TPO uses data from the electronic patient records (EPRs) via HiX (the hospital system that holds the EPRs) and divides the patients in certain categories to assess the efficiency of the surgery planning. In order to understand these different categories, a flowchart is designed, which can be found in Appendix A and in figure 2 on the next page.

The process that concerns this research starts at the moment the orthopaedic surgeon decides that a patient needs surgery and ends when a patient has had its surgery. The type of surgery and potential wishes to hold off surgery until a better moment are recorded in the EPR at the start of the process. The type of surgery is then visible for the surgery planning in terms of surgery duration. For this reason, the measurements by the TPO are also made in surgery durations. The measurements are made every two weeks and concern the schedule for the upcoming five weeks. To make things clearer, the number of surgery hours per patient category is calculated and the patient categories are based on the availability to schedule them in the next five weeks. If a surgery has taken place, the data of that patient is excluded in the measurements of the TPO, as these patients are not relevant for the schedule of the upcoming five weeks. The categories can be found in figure 1, together with the corresponding percentage of surgery hours. The data in figure 1 is from the measurements on September 20th, 2020.

The first block in the diagram reads "total number of surgery hours". This number is the sum of all the surgery durations that have been requested by the orthopaedic surgeons and includes every patient that will get surgery somewhere in the future, whether the surgery has already been scheduled or not. The total amount is then divided into two groups: approved and not approved for surgery. The surgery hours that have been approved **only** include patients that have already had their screening and have gotten approval from the POS. The surgery hours that have not been approved include patients that still need to be screened **and** patients that have been screened but need additional appointments at another department (i.e., cardiology). The TPO does not know whether the screening has already taken place or not, which makes it hard to say anything meaningful based on this number.

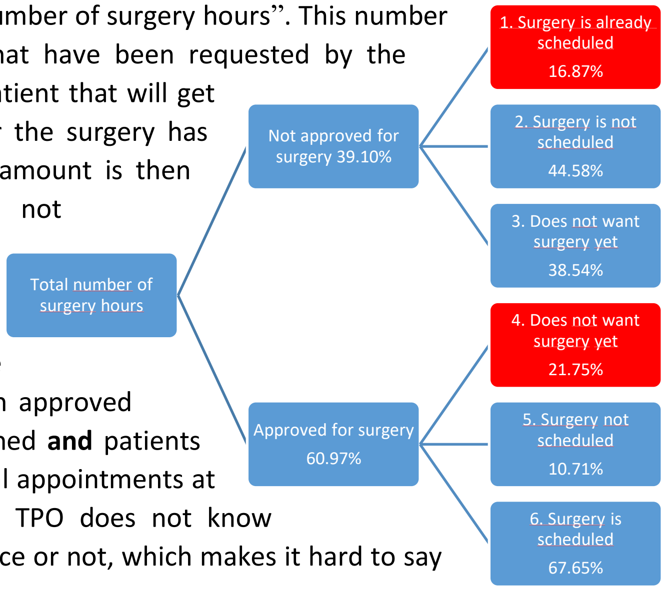



*Figure 1: Patient categories and their percentages on September 20th, 2020.*

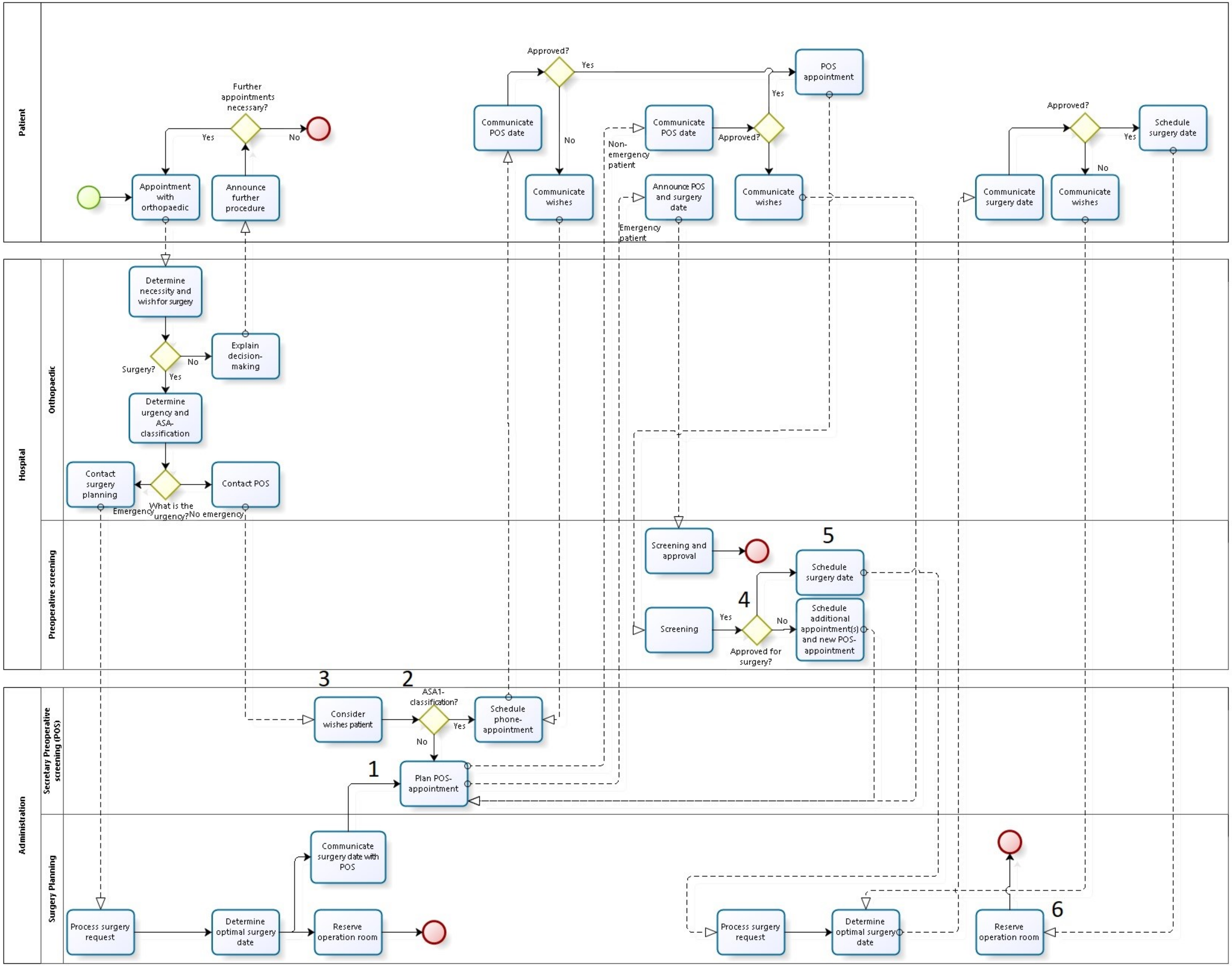

Patient
Hospital
Orthopaedic
Preoperative screening
Administration
Secretary Preoperative screening (POS)
Surgery Planning
Appointment with orthopaedic
Further appointments necessary?
Yes
No
Announce further procedure
Determine necessity and wish for surgery
Surgery?
No
Yes
Explain decision-making
Determine urgency and ASA-classification
Contact surgery planning
Contact POS
Emergency
What is the urgency?
No emergency
Process surgery request
Determine optimal surgery date
Communicate surgery date with POS
Reserve operation room
1
Plan POS-appointment
2
ASA1-classification?
Yes
No
3
Consider wishes patient
Schedule phone-appointment
Communicate POS date
Approved?
Yes
No
Communicate wishes
POS appointment
Non-emergency patient
Communicate POS date
Approved?
Yes
Emergency patient
Announce POS and surgery date
Communicate wishes
Screening and approval
Screening
Yes
4
Approved for surgery?
No
5
Schedule surgery date
Schedule additional appointment(s) and new POS-appointment
Process surgery request
Determine optimal surgery date
Communicate surgery date
Approved?
Yes
No
Communicate wishes
Schedule surgery date
6
Reserve operation room

*Figure 2 (on previous page): Flowchart of the process starting at the orthopaedic surgeon and ending when surgery has taken place.*

The above-mentioned categories are also further divided into six patient categories, as shown in figure 1, of which the corresponding number can be found in the flowchart in figure 2:

1. Not approved for surgery and surgery is already scheduled
   This category includes patients that already have a surgery date (because it is an emergency case or because OCON benefits from prioritizing this patient), but have not passed the screening yet. It is coloured red because patients that have already been scheduled but are not approved yet, need to be screened as soon as possible. Otherwise, the timeslots that are reserved for these patients will be lost.
2. Not approved for surgery and surgery is not scheduled
   Patients that either did not have their screening yet or did not pass their screening. As this is not visible from the data, it is not known where in the process these patients are at that particular moment. Patients might have had an appointment at the POS, an appointment can already be scheduled, but it is also possible that the patient is still waiting for the appointment to be scheduled.
3. Not approved for surgery and does not want surgery yet
   These patients have probably mentioned that they do not want surgery yet and have therefore not had their screening yet. However, it is still possible that they are already in the process of screening, which is a waste of resources and timeslots at the POS.
4. Approved for surgery and does not want surgery yet
   Patients that were already approved for surgery, but do not want surgery yet. Category 4 is coloured red as these patients have been screened while they do not want surgery yet, which is a waste of resources and timeslots at the POS. These timeslots could have been assigned to patients that do want their surgery as soon as possible.
5. Approved for surgery and surgery is not scheduled yet
   This category includes patients that want to have surgery in the upcoming five weeks and have been approved for surgery by the POS. The surgery planning can schedule surgeries for these patients. When this group and the variety of patients in the group are bigger, it will be easier to make an efficient schedule for the operating rooms.
6. Approved for surgery and surgery is already scheduled
   These patients have already been scheduled prior to the measurement of the TPO and they have also been approved. This category also includes emergency patients that have passed the screening before the measurements took place.

## 1.4. Problem cluster

The action problem of this research is defined as: the performance of the surgery planning is not optimal and can be more efficient. Figure 3, on the next page, shows the underlying causes of the action problem in a problem cluster. The action problem is shown in red and the orange boxes present the causes that cannot be influenced. As a lot of branches of the cluster end in "screening patient not compliant to demand" a separate cluster is made for this problem, which can be found in figure 4. Screening patients that are not compliant to demand are the patients that fit category 4 in figure 1. However, these patients can also be categorized as category 5, where patients have been approved but do not fit the timeslots that are still available at the surgery planning and cannot be scheduled for surgery at this moment. One branch ends with "few patients or patient-timeslot mismatch". This branch continues in the top two branches with the same names, which is shown in green.

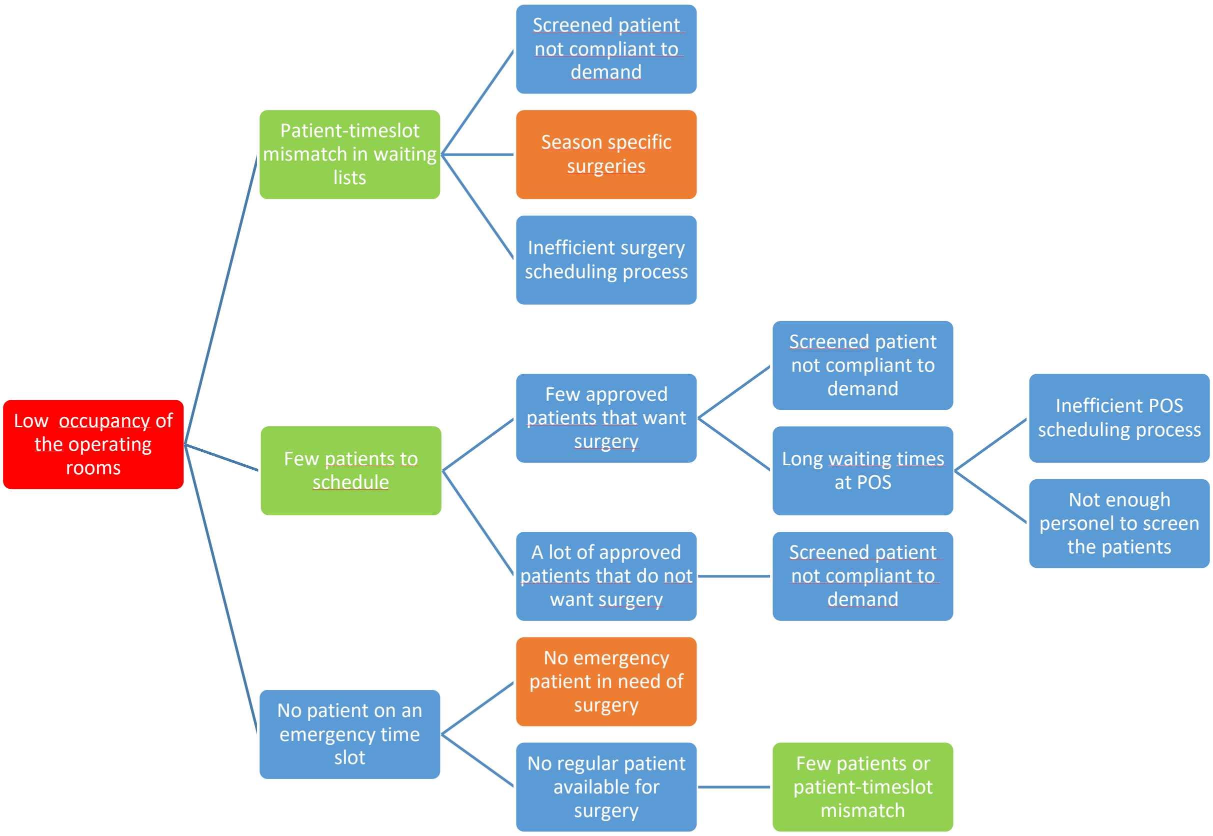



*Figure 3: Problem cluster.*

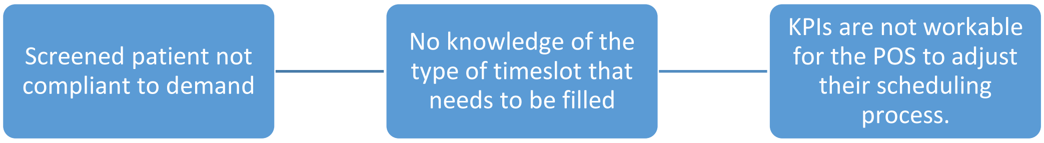



*Figure 4: Problem cluster continued from figure 3.*

## 1.5. Core problem

In order to find the core problem in this problem cluster, the steps that are defined in the book Geen Probleem were followed (Heerkens & van Winden, 2012). Firstly, Geen Probleem mentions that the core problem can only be a problem that is not caused by something else. In the problem clusters from figures 3 and 4, the following potential core problems can be found.

a) Inefficient surgery scheduling process
b) Inefficient POS scheduling process
c) Key performance indicators (KPIs) are not workable for the POS to adjust their scheduling process.

The boxes in orange are not listed as these cannot be influenced and are therefore also no potential core problem. After discussing the remaining potential core problems with some employees at OCON a) and b) were eliminated as OCON uses the scheduling system of ZGT and needs to keep using this to ease patients through the whole process of their treatments. Furthermore, adjusting the forecasting methods for emergency patients and adjusting the scheduling of time slots in a more efficient way is an assignment that is hard to succeed in 10 weeks. According to the last step in Geen Probleem, this means that a) and b) do not score well in the cost-benefit analysis and as a result c) is the core problem for this action problem: KPIs are not workable for the POS to adjust their scheduling process.

## 1.6. Norm and Reality

The difference between norm and reality determines the improvement that is possible with a solution to the above-mentioned core problem and should therefore be identified.

In order to determine the occupancy of the operating rooms, TPO carries out a few measurements every two weeks. In the table below you can find the relevant measurements for the 31st of August until the 12th of October 2020.

*Table 1: Measurements by TPO*

| Date | 31-08-20 | 14-09-20 | 28-09-20 | 12-10-20 |
|---|---|---|---|---|
| **Total number of surgery hours** | 1466 | 1380 | 1443 | 1414 |
| **Total number of hours approved for surgery** | 312 | 840 | 800 | 814 |
| **Total number of hours approved for surgery and available within 5 weeks** | 235 | 169 | 169 | 343 |
| **Total time available for surgeries** | 422 | 298 | 307 | 608 |
| **Total shortage of available surgery hours** | 187 | 129 | 138 | 265 |

To exemplify this table, suppose we consider the measurements from August 31st, 2020.
The total number of surgery hours corresponds with the same block in figure 1 and includes every patient for which a surgery has been requested somewhere in the future (i.e., next week or in two years).

The total number of hours approved for surgery also corresponds to the same block in figure 1.

The third row, total number of hours approved and available within five weeks, includes patients of category 5 (patients that have been approved for surgery, but surgery is not scheduled yet). These patients will be scheduled for surgery in the upcoming five weeks.

The total time available for surgeries excludes surgeries that have already been scheduled. To clarify, after a measurement has taken place, the surgery planning starts scheduling patients in timeslots within five weeks, which overlaps with the measurements of the next TPO meeting. Therefore, when the measurements take place, there is already a certain number of surgeries scheduled.

The total time available for surgeries only includes timeslots that have not been assigned to a patient yet. The difference between the surgery hours available for scheduling (third row/category 5) and the available timeslots results in timeslots that cannot be assigned to patients yet, as there are no patients left to schedule. This number can be found in the row ‘total shortage of available surgery hours’. This shortage needs to be filled with patients that have been approved for surgery and want their surgery to be scheduled within five weeks. This can only be done by screening category 2 patients (not approved for surgery and surgery not scheduled yet) to obtain more category 5 patients.

With the current data, there is no exact knowing what actions to undertake. The total shortage of available hours is an indicator that the POS should screen more patients that want to undergo surgery within five weeks (category 2), but it is not known what the type of surgery is for which timeslots are still available. Consequently, the POS decides to screen more patients without knowing if that patients' type of surgery satisfies the open time slots at the surgery planning. Moreover, there is no monitoring of previous performance. Actions undertaken by the POS in previous months is not monitored for its effect on the surgery schedules and the occupancy of the operating rooms is not measured in terms of open time slots that could possibly be prevented by prioritizing the patient with the corresponding type of surgery. Lastly, it is not clear from the current KPIs in table 1 whether it is even necessary to screen more patients. A shortage of available surgery hours should not be a problem when the current shortage is below the number the POS normally screens and approves. In other words, there is no reference to the performance of the POS and conclusions based on this KPI are not made with a complete overview of the process.

The arguments above form the reality of the operation.

The norm is that the POS can steer on KPIs in order to prioritize the screening of patients with the type of surgery that is needed to fill open timeslots. This would make it easier for the surgery planning to fill every time slot in their schedule and consequently increase operating room occupancy. Furthermore, the healthcare and service provided by OCON improves as the patients that want their surgery as soon as possible, will be able to have them.

In conclusion, the gap between the norm and the reality is the absence of clear and workable KPIs to help the POS in scheduling patients with the type of surgery that fits the available timeslots. The aim of this research is to fill this gap.

### 1.7. Research approach

In this section, the research approach is described. First, the central research question is introduced. After that the research methodology is explained. The activities, sub research questions, data gathering methods and the deliverables are described for every step in the research. Lastly, a reader's guide is given to show what question will be answered in which section.

#### 1.7.1. Central research question

As mentioned in section 1.5, the core problem is defined as: KPIs are not workable for the POS to adjust their scheduling process. In order to solve this core problem, the following central research question is formulated:

What is the efficiency of the current scheduling process at the preoperative screening at OCON and how can it be improved?

#### 1.7.2. Sub research questions

In order to solve the central research question, the central research question is further divided into a set of sub research questions. These questions are categorized according to the Ist-Bottleneck-Soll method. Ist-questions are relevant to what is happening now with respect to the problem setting. Bottleneck-questions deal with problems and barriers and Soll-questions deal with the desired state.

***Ist***

1. How does the POS secretary currently schedule its appointments?
    a. What methods and/or principles are used?
    b. Who are the stakeholders involved?
2. What are the key performance indicators (KPIs) that are currently in place?

To understand the current scheduling process, interviews are conducted with the POS secretaries. There have also been interviews with other stakeholders in the scheduling process who are known to the supervisor at OCON and who have been mentioned during the other interviews. To answer question 1.a, a detailed description of the process is given, combined with a process flow chart to support this description. In this flowchart, the stakeholders of the scheduling process will also be included. Question 2 has been answered by reading the relevant parts of the minutes of the TPO meetings and by looking into the presentations that are made for these meetings.

***Bottleneck***

3. How is the performance of the POS in terms of KPIs?
    a. What bottlenecks can be found?
4. What are the problems associated with the current POS scheduling?

By interviewing the problem owners and stakeholders, the bottlenecks and problems have been identified. Since this often leads to subjective results, the bottlenecks and problems have been checked to verify whether it was real, whether it was an important problem and whether it could be solved. In addition, the process flow chart from the Ist-phase was used to identify problems that were not mentioned by the stakeholders. As a result, a list of important problems and bottlenecks is given.

***Soll***

5. What literature is available on POS scheduling?
    a. What literature is available on priority scheduling at the POS?
    b. What literature is available on cooperation mechanisms between surgery planning and the POS?
6. What factors do influence the planning of operating rooms?
7. What KPIs are useful in addition to existing ones?
8. What improvement options can be distinguished?
    a. What modifications are required to achieve these?
    b. What are the pros and cons to the chosen improvement options?
9. What is the best possible solution out of the chosen options?
    a. What are the financial implications involved in trying to do this?
    b. What are other benefits apart from possible cost savings?
10. How can the solution be implemented?

By conducting a literature study, possible improvement options can be identified. These are options that might work for other hospitals in another situation, but not for OCON or not for this situation. Therefore, question 8 aims to find the improvement options that are suitable for OCON. In order to find the options for OCON, it is necessary to know the factors that influence the planning of the operating rooms and whether this influence should be promoted or prevented. Furthermore, additional KPIs might be necessary to improve the performance of the POS scheduling process. After the Soll-phase, there will be one or more solution(s) that can be recommended to OCON. The recommendations will be accompanied by a step-by-step approach for OCON to implement the solution(s) and which factors to consider.

### 1.7.3. Reader's guide

| Section title | Related sub-research questions | Content |
|---|---|---|
| **2. Current scheduling process** | 1 | Lay-out of the scheduling process at the POS and surgery planning, their decision-making and collaboration. |
| **2.4. Current performance assessment** | 2 | Introduction of the KPIs currently in place. |
| **3.1. Current Key Performance Indicators** | 3 | Assessment of the usefulness of the current KPIs. |
| **3.2. Associated bottlenecks and problems** | 4 | Introduction of the bottlenecks and problems associated with the scheduling process at the POS and surgery planning. |
| **3.3. Data analysis** | 3, 4 and 6 | Analysis of the current performance of the scheduling process using a dataset acquired by OCON. |
| **4. Literature study** | 5 and 8 | Explanations of different approaches and their (dis)advantages. |
| **5. Improvement options** | 7 and 9 | Implications and benefits of implementing the proposed approach. |
| **6. Solution** | 10 | Description of how the proposed approach can be implemented at OCON. |

# 2. Current scheduling process

In order to make recommendations that fit the situation at OCON, the current situation has been analysed. This chapter discusses the whole process that patients follow when they need to undergo surgery. As mentioned in the previous chapter, there are different patients that follow different paths in the process. This is also further explained in this section. As the POS scheduling process is an influencing factor on the surgery planning, the collaboration between these departments is described as well. Lastly, it is mentioned how OCON assesses the performance of the POS scheduling in the current situation.

## 2.1. Patient flows at POS

For this research, the start of the process is defined as the moment an orthopaedic surgeon requests surgery for a patient. The process ends at the moment a patient has had its surgery. In this process, a sub-process is identified at the POS. This sub-process has the same start, but ends at the moment a patient is approved for surgery. This section elaborates on this sub-process and focuses on its position within the whole process.

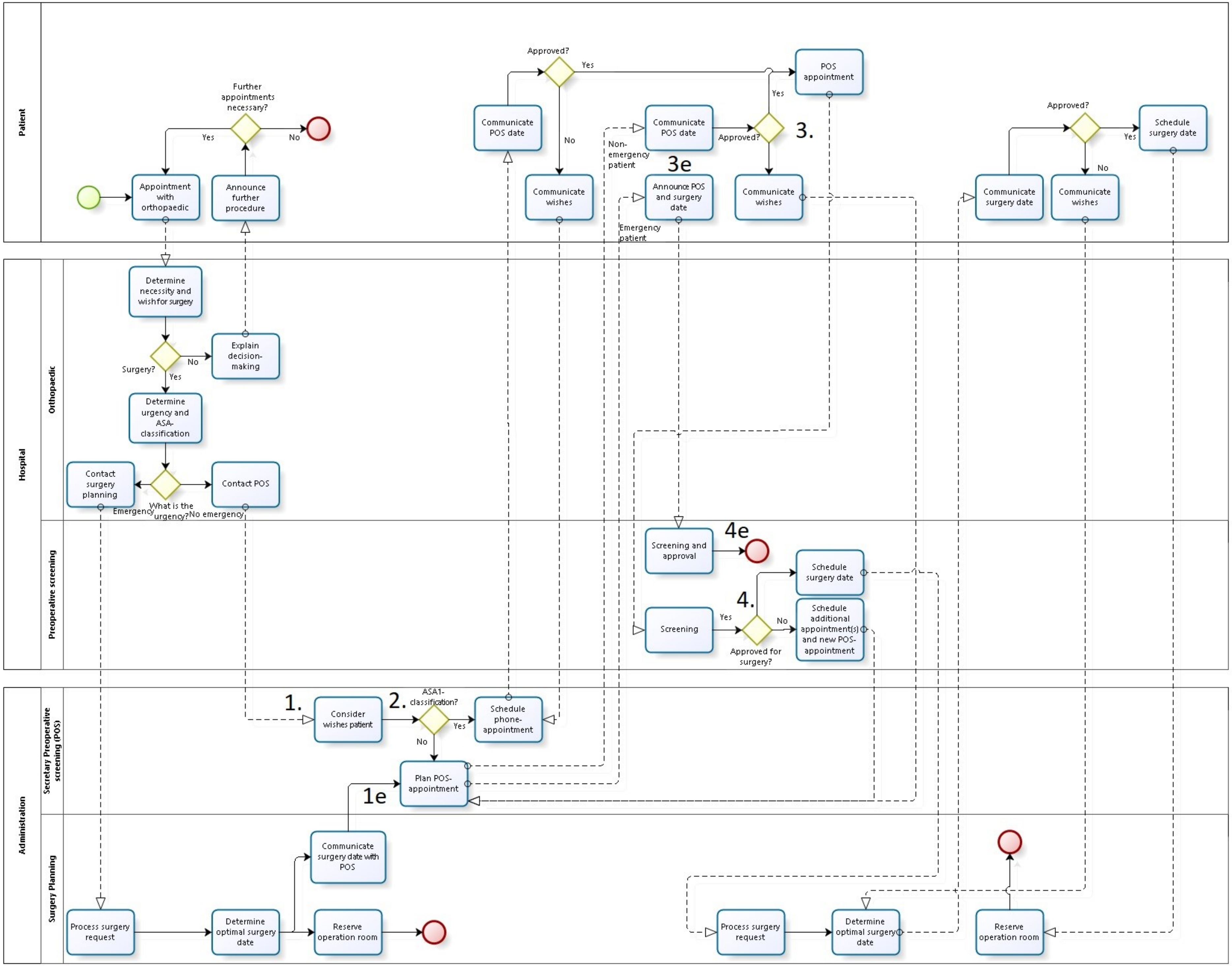
The sub-process of the POS involves both regular and priority patients. Later in this section, we define what makes a priority patient. The numbers that indicate different steps in this process can be found in figure 5 on the next page and in appendix B. First, the flow of regular patients through the POS process (1-4) is explained after which the process of the priority patients (1e-4e) is clarified.

**Regular patients**

1. This number indicates the entrance of a patient into the POS process. The orthopaedic surgeon estimates the ASA-classification based on the available patient information. This classification is necessary to assign a type of timeslot for a screening appointment. The ASA-classifications, their screening durations and validities can be found in appendix C.
2. The POS secretary checks if a patient is ready to be screened, based on the patients' wishes. Patients often decide to hold off surgery until a better moment (i.e., after their vacation or when there are family members available to help them during rehabilitation). In case a patient has been found that can be screened, the POS secretary schedules an appointment based on the ASA-classification. ASA-1 type patients can be screened over the phone. All other ASA types need to come to the hospital. All patients receive a date for their appointment by mail.
3. Patients get the chance to reschedule the appointment if it does not fit their schedule. The POS then schedules another appointment over the phone until an appointment date can be determined. The patient will then have their screening.
4. After the screening, the anaesthesiologist determines whether the patient can be approved for surgery or if additional appointments are necessary (i.e., cardiology, nutrition). In case of approval, the POS communicates this with the surgery planning, whose process is explained in the next section. When additional appointments are necessary, this is communicated with the specific department(s). A patient will then be approved for surgery by the department(s) (as other aspects of the screening did not cause any problems) and it is communicated to the surgery planning that the patient is available to be scheduled.

The surgery planning does not schedule regular patients if they have not received approval by the POS. However, it can also be the case that a patient has been approved for surgery but that too much time has passed. In some cases, these times will be exceeded and a new approval is necessary. In those situations, the patient will enter the POS process again and a new appointment will be scheduled.

*Figure 5 (on the next page): Flowchart of the process for both regular and priority patients.*



Patient
Hospital
Orthopaedic
Preoperative screening
Administration
Secretary Preoperative screening (POS)
Surgery Planning
Appointment with orthopaedic
Announce further procedure
Further appointments necessary?
Yes
No
Communicate POS date
Approved?
Yes
No
Communicate wishes
POS appointment
Communicate POS date
Approved?
Yes
3.
Non-emergency patient
3e
Announce POS and surgery date
Emergency patient
Communicate wishes
Communicate surgery date
Approved?
Yes
No
Communicate wishes
Schedule surgery date
Determine necessity and wish for surgery
Surgery?
No
Yes
Explain decision-making
Determine urgency and ASA-classification
Contact surgery planning
What is the urgency?
Emergency
No emergency
Contact POS
Screening and approval
4e
Schedule surgery date
4.
Screening
Yes
No
Approved for surgery?
Schedule additional appointment(s) and new POS-appointment
1.
Consider wishes patient
2.
ASA1-classification?
Yes
No
Schedule phone-appointment
Plan POS-appointment
1e
Communicate surgery date with POS
Process surgery request
Determine optimal surgery date
Reserve operation room
Process surgery request
Determine optimal surgery date
Reserve operation room

**Priority patients**
We define this type of patients as priority patients instead of emergency patients, as it does not only involve emergency patients. For instance, OCON would like to minimize the chance of patients going to competitors that are present in some of the speciality fields of OCON. For example, close to the hospital in Hengelo there is an orthopaedic clinic that specializes in hand surgeries. In order to gain competitive advantage, OCON prioritizes hand surgeries, consequently decreasing the waiting times for this type of surgery. A priority patient follows a slightly different route in the POS process.

1e. A priority patient enters the process after or at the same time a surgery date has already been scheduled. This patient needs to be screened as soon as possible in order to decrease the risk of not having approval on the surgery date.
3e. An emergency patient receives a date for screening with no opportunity of rescheduling. The patients that provide competitive advantage will be scheduled with priority over regular patients, after which the patient can still reschedule.
4e. The priority patient has had its approval for surgery and the surgery date is already scheduled, so no further actions are necessary.

## 2.2. Surgery planning

The surgery planning is responsible for scheduling the surgeries of all types of patients for OCON. The moment that the surgery is scheduled differs per type of patient.

**Regular patients**
Regular patients are only scheduled when they have been approved for surgery by the POS. In HiX, the surgery planning can see the number of patients that need to be scheduled and which type of surgery they need to undergo. Sometimes, patients prefer to have a later surgery date, which can also be seen in their EPR. The surgery planning can then schedule these patients in available timeslots. These timeslots are based on the surgeons and resources that are available. Moreover, there are some timeslots reserved for emergency patients that cannot be filled with regular patients. What is left are intervals that can provide one or more surgeries. For instance, when an interval is six hours long, the surgery planning can schedule one surgery of six hours or two surgeries of three hours.

The time left in an interval by scheduling a surgery is considered while scheduling that surgery. If one hour would be left in an interval, the surgery would probably not be scheduled as this gap in the schedule cannot be filled with another patient. It would be more efficient to schedule a surgery in this interval that takes one hour longer, or shorter, so that the interval can be filled with two surgeries. As this is a manual process, it can take up a lot of time, but it is necessary to be able to schedule patients as soon as they have gotten approval.

**Priority patients**
As mentioned in the previous section, surgeries for priority patients have already been scheduled before they are screened. However, there is a different approach for the two types of priority patients. For emergency patients, special timeslots are reserved so that they can be scheduled directly, regardless of other surgeries. The number of emergency timeslots that have to be reserved, has been calculated by forecasting the probability of an emergency patient entering the process. Emergency patients are scheduled on these timeslots and will be screened in the period before the surgery. Two days before the surgery, the surgery planning will check whether the emergency patient has passed the screening. If not, the surgery planning will schedule a new date for the emergency patient and try to find a new regular patient that has been approved for surgery to fill the timeslot that has opened up.

The patients that provide a competitive advantage for OCON follow a different procedure as there are no reserved timeslots for these patients. However, the surgery planning must give priority to these patients. In order to do so, the surgery planning will already schedule these patients in the earliest timeslots possible (while taking into consideration that the patient still needs to be screened). As a result, the patients will have their surgery earlier than a regular patient, even though they might have entered the process at a later point in time.

## 2.3. Collaboration between the POS and the surgery planning

As can be imagined from reading the sections above, the POS and the surgery planning are quite dependant on each other. In some cases, clear communication is necessary to ensure a good and efficient flow of patients. For instance, when a priority patient receives a surgery date, the surgery planning calls the POS to make sure that this patient is also prioritized in the screening process. The POS can then schedule a screening appointment for this patient, following the same procedure as the surgery planning (emergency timeslots or priority scheduling).

In some cases, the POS calls the surgery planning to make sure that a surgery is scheduled. This is often the case when a patient has a higher ASA-classification and thus approval is valid for a shorter period. For instance, a patient with a known heart condition passes the screening today, but its physical condition can rapidly change. As this occurs more often with patients with a higher ASA-classification, the period that the approval is valid is shorter. When it took a lot of time and effort for a patient to pass the screening, this is also communicated to avoid even more delay before the patient undergoes surgery. In these cases, the surgery planning knows that these patients have priority over the other regular patients and directly schedules the surgeries (when possible).

It is necessary that the POS and the surgery planning collaborate extensively to ensure that all patients are treated as soon as possible. This does not only decrease the chance of complications during or after a surgery, but it also decreases the costs for resources and labour. A good collaboration is thus profitable for both the patients and OCON.

## 2.4. Current performance assessment

To assess the performance of aforementioned process, OCON has set up the tactical planning council (TPO), which consist of employees of different departments within OCON and members of the management. The TPO not only assesses the performance of the POS and the surgery planning, but also the other departments within OCON. In this section, only the performance assessment of the POS and the surgery planning is discussed.

Every two weeks, one member of the TPO analyses the data from HiX and extracts the relevant data for the next five weeks. These measurements and an explanation on the data can be found in section 1.6. and provides the TPO with the necessary data to assess the performance of the POS and the surgery planning. The measurement results in a number of operation hours that needs to pass the screening to fill the surgery schedule of the next five weeks. If this number is relatively low, the POS has screened a good amount of the right type of patients (previously category 2, now categories 5 or 6) and when this number is relatively high, the POS should screen more patients in the upcoming weeks to make sure that the surgery planning can fill the schedule of the next five weeks.

## 2.5. Conclusion current scheduling process

From the analysis of the current scheduling process, the following conclusion can be drawn. Collaboration and communication between the POS and surgery planning is very important to achieve the highest occupancy of the operating rooms. This applies to both regular and priority patients and goes both directions: the surgery planning communicates the surgery dates of the priority patients so that the POS can schedule their screening appointments and the POS in turn communicates that regular patients have gotten their approval for surgery.

# 3. Performance of the current scheduling process

In this chapter, the performance of the current scheduling process is analysed. First, the performance in terms of the current KPIs is described. Then, associated bottlenecks are identified both by interviews and observations. Afterwards, a data-analysis has been carried out to identify other bottlenecks. At the end of the chapter, a conclusion is drawn on the performance of the current scheduling process based on the three different approaches.

## 3.1. Current Key Performance Indicators

As mentioned in the previous chapters, TPO assesses the performance of the current scheduling process according to measurements that can be found in table 1. With these measurements, TPO calculates a shortage of available surgery hours. This can be explained as open timeslots after scheduling all patients that have been approved for surgery and want surgery in the next five weeks. In other words, this is the number of surgery hours that still has to pass the screening in order to fill the schedule of the next five weeks. This KPI is important as the POS now knows what is asked from them in the next five weeks.

However, the KPI has to be seen in perspective to a goal, in order to say something about the performance of the POS. To exemplify this, suppose we consider the measurement of August 31st, 2020. A shortage of 187 available surgery hours could sound low, perfect or too high. Once it is placed in perspective, we can see that the number is around the average of all four measurements. Still, you can say nothing about the performance with respect to the desired state. For this, a goal is necessary. For instance, TPO could set a goal that they want a maximum shortage of 150 available surgery hours on average. This goal should be set while considering the resources and abilities of the POS. If in the upcoming weeks there are less employees working at the POS, the goal is harder to achieve than when they are all working. Therefore, the goal is also dependent on the situation at the POS. On the other hand, it can also be possible for the surgeons to be short on staff. In this case, the total time available for surgeries will be lower, resulting in a lower shortage of available surgery hours. The goal should then also be adjusted accordingly to see if the performance is satisfying, regarding the current situation. For these reasons, this KPI does not provide enough knowledge for the POS to adjust their operations accordingly.

***Table 1: Measurements by TPO.***

| Date | 31-08-20 | 14-09-20 | 28-09-20 | 12-10-20 |
|---|---|---|---|---|
| **Total number of surgery hours** | 1466 | 1380 | 1443 | 1414 |
| **Total number of hours approved for surgery** | 312 | 840 | 800 | 814 |
| **Total number of hours approved for surgery and available within 5 weeks** | 235 | 169 | 169 | 343 |
| **Total time available for surgeries** | 422 | 298 | 307 | 608 |
| **Total shortage of available surgery hours** | 187 | 129 | 138 | 265 |

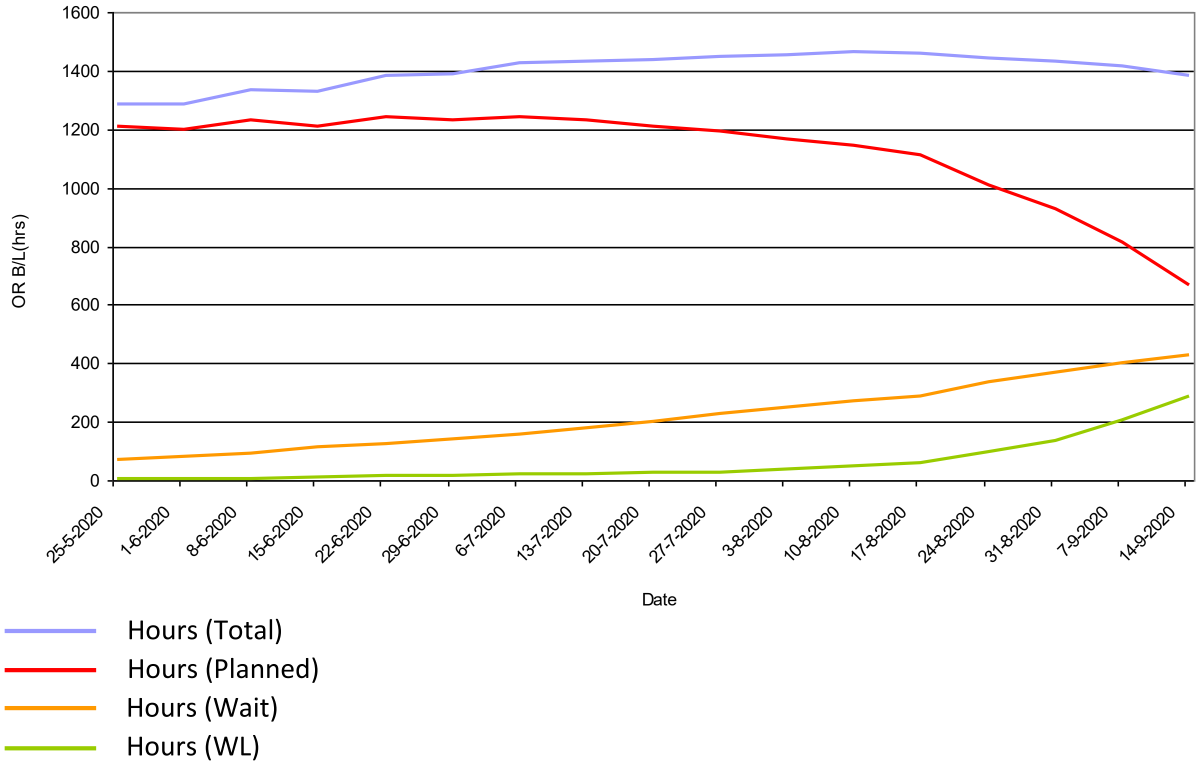



*Figure 6: Graphical visualisation of the waiting list at the surgery planning on September 14th, 2020.*

TPO also discusses other KPIs. In figure 6, a visualisation of the waiting list at the surgery planning can be found. The blue line indicates the total number of surgery hours, corresponding with the same number in table 1 for September 14th, 2020. The red line shows the total number of surgery hours that have already been scheduled (categories 1 and 6). The orange line indicates the number of surgery hours that waits for their surgery voluntarily (categories 3 and 4). The green line shows the number of surgery hours that wants their surgery as soon as possible, but have not been scheduled yet (categories 2 and 5) and is indicated by WL for “waiting list”. It is important to not confuse this waiting list with the patients that are waiting voluntarily as the waiting list should be scheduled for surgery.

Note that this graph is updated every week, so data of older dates in this graph will be different than the measurements on that day. This is also the reason that the measurements of August 31st in table 1 are not the same as the data in the graph. To clarify, if you look at the datapoints of May 25th in the graph, we can see that the difference between the red and the blue line is exactly the same as the number of voluntary waiting patients. This means that there are patients that entered the system before May 25th who still do not want surgery and thus these patients are also included in the data of September 14th.

These KPIs are relevant to a certain extend. The total number of surgery hours (blue line) is interesting as it indicates the result of input and output of the process. When more new patients need to undergo surgery than patients that undergo surgery, this number will be growing in that period. A high total number of surgery hours is not desirable as this will result in longer waiting times for patients. However, a low number is also not ideal as the surgery planning then has fewer patients to fill their schedule with. An optimum is not yet identified by the TPO nor by OCON.

The number of surgery hours that have already been scheduled is only relevant in order to calculate the number of surgery hours that still need to be screened and approved by the POS. Comparing these numbers with each other can tell something about the performance of both departments. When the red line is relatively low, this could mean that the surgery planning is behind on scheduling patients. On the other hand, if the number of patients in category 5 is low as well, this could mean that the POS is not screening effectively. A higher number of surgery hours that have already been scheduled, could be the consequence of too many patients in the process and could indicate a shortage of resources at the surgery planning or OCON in general, resulting in long waiting times. For this KPI an optimum is not identified yet.

The number of patients that are waiting voluntarily is an interesting number to keep track of, however, it does not say anything about the performance of the POS or the surgery planning. It would be more interesting to calculate the number of approved surgery hours where patients still choose to hold off their surgery. This number should preferably be (near) zero, as these patients fill the appointment slots at the POS, while patients that do want their surgery as soon as possible are not scheduled. Therefore, the way the current KPI is designed is not effective to draw conclusions on the performance of the POS.

The last KPI that the TPO discusses, is the number of surgery hours that have been approved by the POS. These numbers can be found in table 2 below and include categories 4, 5 and 6, which makes it hard to assess the performance of the POS. The percentage could be built up for the biggest part by patients of category 4. As mentioned before, this is not desirable and thus the performance of the POS is not optimal. On the other hand, if the percentage is built up entirely of categories 5 and 6, the performance would be outstanding (when the percentage is high). In addition, like the other KPIs, this KPI lacks a goal or aim and does not compare to the results of the previous week(s).

***Table 2: Percentage of the total number of surgery hours that has been approved by the POS.***

| | 31-08-20 | 14-09-20 | 28-09-20 | 12-10-20 |
|---|---|---|---|---|
| **Total number of surgery hours** | 1466 | 1380 | 1443 | 1414 |
| **Total number of surgery hours that have been approved by the POS** | 953 | 840 | 800 | 814 |
| **Percentage** | 65% | 61% | 56% | 58% |

The KPIs also have one other flaw in common: they include every type of surgery. For instance, when we look at the first KPI, the total shortage of available surgery hours, this includes all types of surgery. As a result, the POS does not know which patient to screen in order to fill the schedule of the surgery planning. Another example is the percentage of surgery hours that have been approved by the POS. This percentage could be realized by only screening patients that need to undergo the same type of surgery. This is a result of misunderstanding the KPIs and could have big negative consequences on the scheduling of the surgery planning.

In conclusion, the KPIs that the TPO has set up to assess the performance of the POS and the surgery planning, do not satisfy their purpose yet. Mostly, the relationships between the KPIs need to be considered before a clear assessment can be made. An overview of the KPIs and their flaws can be found in table 3. In some cases, the KPI should be divided into smaller KPIs that makes it easier to distinguish different patient categories and surgery types. This can be a hard process as it will result in a lot more KPIs and may cause an even less understandable KPI dashboard.

***Table 3: Current KPIs and their flaws.***

| KPI | No relation to other KPIs | No goal | Not effective | No continuity | Every type of surgery |
|---|---|---|---|---|---|
| **Total shortage of available surgery hours** | X | X | | | X |
| **Total number of surgery hours** | | X | X | | X |
| **Number of surgery hours that have already been scheduled** | X | X | | X | X |
| **Number of surgery hours waiting voluntarily** | X | X | X | | X |
| **Number of surgery approved by the POS.** | X | X | | X | X |

## 3.2. Associated bottlenecks and problems

During interviews, additional bottlenecks were identified, some related to the existing KPIs and others were problems that are associated to the POS scheduling process. Since these bottlenecks were found during individual interviews with employees in different departments, they may be based on personal experiences and opinions. Nevertheless, they are all discussed to get a clear picture of the concerns regarding the POS scheduling process.

First, the preoperative screening, as its own department, was introduced at OCON in January 2020. Until then, the orthopaedic surgeons and the surgery planners worked closely together to plan the surgeries. This direct line between orthopaedic surgeons and surgery planners should have been interrupted by the secretaries at the POS in order to streamline POS appointments and surgery planning. However, because orthopaedic surgeons were used to the old way of working, they still sometimes surpass the POS and communicate directly with the surgery planning. The surgery planner in its turn then makes decisions based on that conversation without checking the POS for availability. As a result, these patients are often not approved for surgery before their surgery takes place and if they are, this has cost a lot of time and work from the secretaries at the POS to schedule a screening appointment in time.

This inserting of patients also happens in another way when a timeslot in the surgery planning is not filled yet. When this happens, the surgery planning often calls the POS to prioritize the screening of a patient that would fit in this timeslot. Just like the previously mentioned situation, this costs a lot of work and time to realize and often it is not realized in time or patients do not want to undergo surgery under such short notice. The effort by the employees at the POS can therefore be seen as sunk costs and it would probably be better to leave the timeslots empty.

Another bottleneck is a direct effect of the conclusions communicated by the TPO. One of the conclusions is the shortage of available surgery hours to plan for the operating rooms. Indirectly, the message is that the POS should screen at least that number of surgery hours in order to maximize operating room efficiency. However, it does not state which type of timeslot needs to be filled. For instance, the shortage of available surgery hours may be high, while it is a cumulative of many short timeslots. This requires the POS to focus on patient with a type of surgery that fits those short timeslots instead of patients with surgeries that take longer. The POS cannot see this from the current KPI and thus a lot of effort is lost in screening patients with the "wrong" type of surgery.

Related to these bottlenecks is the idea that every department serves to obtain the highest possible efficiency at the surgery planning. Considering the ERAS-principle this could be a misconception, meaning that peak efficiency at the surgery planning does not necessarily mean the best performance by OCON in general and that it may be profitable to decrease efficiency at the surgery planning to improve the performance at, for instance, the POS.

These associated bottlenecks are difficult to test on validity, which is mainly the result of the way the KPIs are set up. As mentioned, the KPIs focus on the planning of the operating rooms for the upcoming five weeks and based on the KPIs, the best approach for the upcoming two weeks is decided. In order to check whether the approach has worked, it is necessary to reflect on the previous period and the effect of the approach on the efficiency of the surgery planning. This way, OCON can rule out or validate the before mentioned bottlenecks and come up with approaches that work once the KPIs show certain values for the next five weeks. For example, when the shortage of surgery hours to plan for the operating rooms is very high and the approach is chosen to screen a lot more patients, regardless of surgery type, the TPO can see if this approach has worked by reflecting on the past period and see if desired outcome was realised.

## 3.3. Data analysis

In order to get a broader picture of the performance of the POS, that excludes bias from interviews and OCONs own KPIs, a data analysis was carried out using historical data extracted from the EPR database. The fields that were extracted include dates on which the patient goes to another step in the process. To clarify these dates, a simplified process flow is used, which can be found in figure 7.

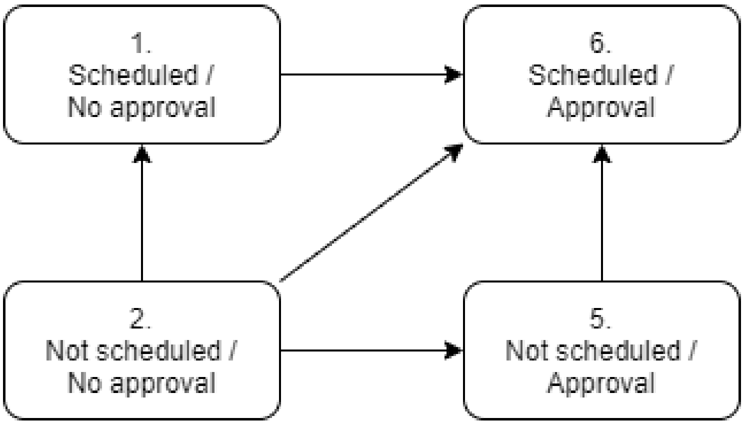



*Figure 7: Simplified process flow.*

The first date that was extracted is the registration date. On this date, the orthopaedic surgeon has decided a surgery is necessary and registered the patient and the type of surgery in the database that concerns the process in this research. The patient enters the process in category 2, as it does not have a surgery date or approval for surgery yet. The next date is the date of approval. On this date, the patient enters category 5. Then, the date of surgery is extracted, which shows when the surgery will take place. When this date has passed, the process of this patient is terminated and it leaves category 6.

From the paragraph above, it becomes clear that the data does not allow to determine whether a patient enters category 1 and 6. Moreover, data fields were often left empty or incorrect data was inserted. For example, some patients would undergo surgery on their birth date, according to the dataset. In order to get some indication and usefulness from this extraction, some assumptions have been made. When the date of approval was left empty or was appointed incorrectly, we assume that the approval would have been given 5 days after registration. For the surgery date, this was harder to fabricate, therefore patients with an incorrect or empty surgery date were deleted from the dataset.

In order to fabricate a surgery date for categories 1 and 6, the assumption was made that patients know their surgery date 10 days before the actual surgery. With these assumptions and generated data, it is possible to look at the different categories and the number of patients in them.

Considering the effects of the corona crisis, the analysis starts at June 1$^{st, 2020,}$ and a graph is made for the following 6 months. Since the current KPIs are all extracted on Mondays, we also use Mondays in this data analysis. The period includes the summer holiday. From the interviews we learned that the employees think that the holidays result in a lower number of patients that is willing to undergo surgery, because they want to go on holiday or because their family members are on holiday and cannot take care of them during rehabilitation. In figure 8, we can see that the number of patients in category 2 increases over the summer (1/6/2020-1/8/2020) and decreases afterwards. At the same time, the number of patients in category 6 decreases until the end of the holidays and increases afterwards. From the historical data we now know for certain that the holidays have an effect on the patient distribution.

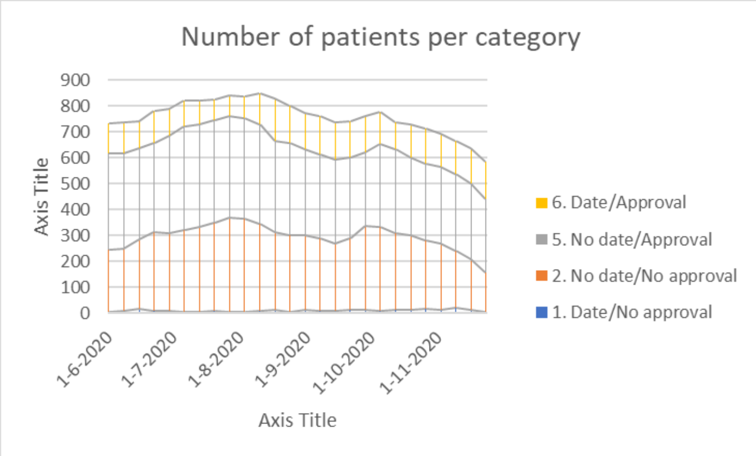



*Figure 8: Number of patients per category, starting from June 1st, 2020 (simplified version).*

Unfortunately, there are more limitations to this data analysis than the assumptions already mentioned. First of all, the POS is only part of OCONs operations since January 2020, which is visible in figure 9. On January 6th the dataset was empty as patients' information was still included in the records of the ZGT. From that point onwards, the dataset fills with patients, which leads to the second limitation in this analysis. The corona crisis had a big effect on "regular" healthcare. As a result, a change in patient distribution is visible in March and April. Category 6 decreases, as patients cannot be scheduled for surgery and as a result, category 5 increases. This effect is still visible until the end of May.

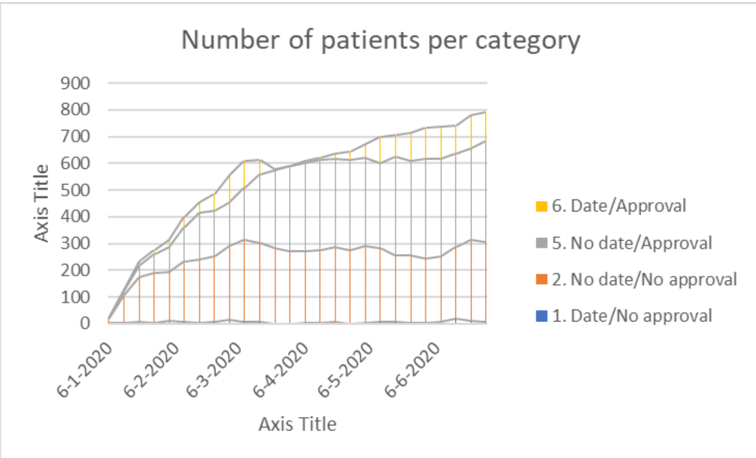



*Figure 9: Number of patients per category, starting from January 6th, 2020 (simplified version).*

Finally, starting the data analysis on the 1st of June excludes the corona crisis but this shows another limitation in the last part of 2020. As is visible in figure 8, the graph shows a decline from October onwards. Looking at the end of the year in figure 10, we see that this decline ultimately results in a dataset that does not include any patients. This can be explained by looking at the way the data is extracted. Only patients that have had their surgery are included in the dataset and thus patients that are still in categories 1,2 and 5 at the end of the extraction period are excluded. Since the extraction was carried out in January, the dataset excludes all patients that are still in categories 1,2 and 5, even though they were registered a lot earlier.

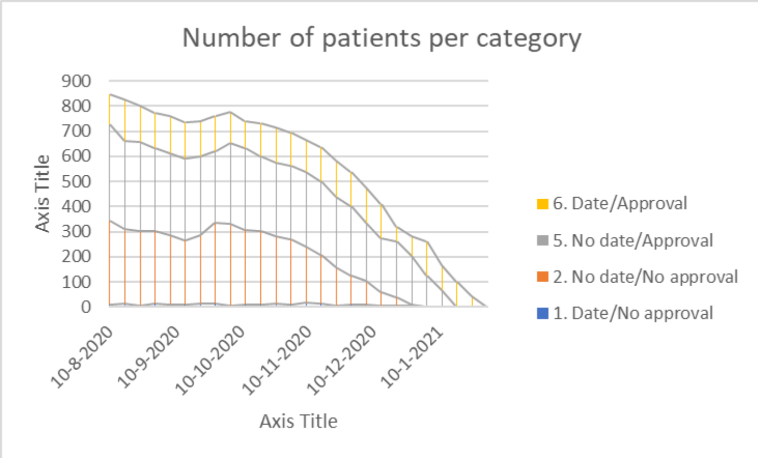



*Figure 10: Number of patients per category, starting from August 10th, 2020 (simplified version).*

Since the surgery planning and the TPO base their calculations on the surgery hours instead of number of patients, we use surgery hours in the following paragraphs.

**Wish to delay surgery**

As mentioned, the above is true for the simplified model of patient clusters. The same is possible for the two categories (3 and 4) where patients wish to delay their surgery for personal reasons. The data that is necessary to distinguish these patients from the rest can be extracted from the data field that determines when a patient is available to be scheduled. However, since this field can be changed multiple times over time and we rely on historical data that does not include these changes, there is no knowing if the date in this field was a wish or a necessity or that the patient wanted to delay surgery but changed its mind. Therefore, we disregard this data field and assume that patients wish to delay surgery when they have not changed categories in three weeks. In other words, in case a patients' status has not changed within three weeks, the patient will be included in categories 3 or 4, depending on their previous category (2 and 5 respectively). In the following sections, these categories are referred to as absorption states, as they absorb patients from categories 2 and 5 respectively. In figure 11, the process flow used in this part of the data analysis is shown.

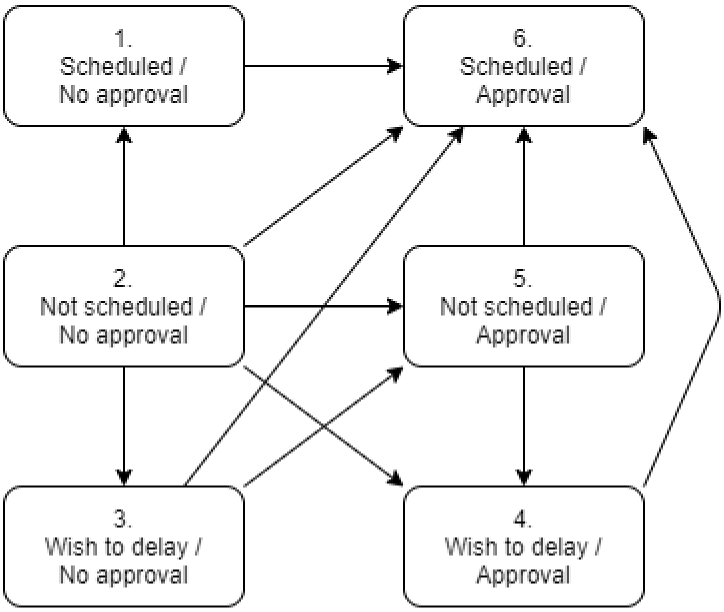
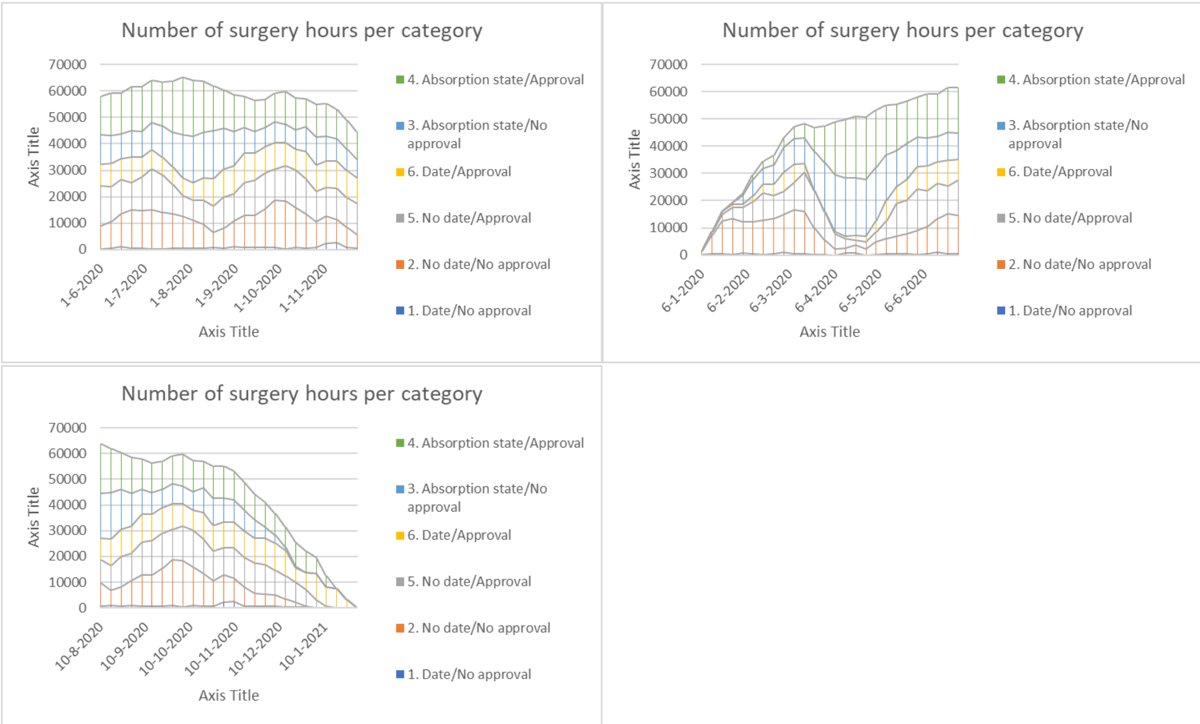



*Figure 11: Elaboration on the simplified process flow.*

As expected, the change in design of the process flow does not have a significant effect on the graphs. However, it gives a better picture of the underlying patient distribution. For instance, when we look at the first graph from the first model, we see that categories 2 and 5 grow during the summer holiday. In the first graph from the second model, it becomes clear that the underlying cause is the number of patients that choose not to undergo surgery yet (categories 3 and 4). This is a relevant insight, because it shows that for OCON there is not much to do about this and they can better focus on dealing with this fact. Even though we already predicted this, it is important to keep track of underlying causes to see if the assumption is still correct or that there is a flaw somewhere in the process.




*Figures 12-14: Number of surgery hours per category, starting from June 1st, January 6th and August 10th, clockwise (elaborated process flow).*

## 3.4. Conclusion performance of the current scheduling process

Comparing the different KPIs that OCON has in place, we see that they have a few flaws in common: they often lack perspective to draw the right conclusions, there is no aim or goal that the POS or the surgery planning can try to accomplish and KPIs include different types of surgery and multiple patient categories, which makes it hard to get a clear picture of the performance. This also came to light during the interviews with employees. Most associated bottlenecks and problems have to do with the fact that it is not clear what the actual performance of both departments (POS and surgery planning) is and how this affects the performance of OCON in general. KPIs that may be clear for the surgery planning do not provide a plan of action for the POS and as a result efforts by the POS to satisfy the demand by the surgery planning do not always work. In conclusion, it is necessary that the current KPIs provide a clearer picture or that new KPIs are set up, in order to steer and apply strategies to the operations of OCON.

# 4. Literature study

There are a few different possibilities to obtain a clearer picture of the whole process and its flow of patients. In this chapter the different options of modelling the process are discussed and the best option is chosen from the information found in the literature. The following five options will be discussed: Event-driven process chains, Markov Chains, Markov decision processes, Simulation and Markov Interventions Model. This order is chosen as it increases complexity, the ability to operationalise and the relevance for this research.

## 4.1. Event-driven process chains

An event-driven process chain (EPC) provides a model for the general process flow of an organisation. According to the literature, EPC focusses "on representing domain concepts and processes rather than their formal aspects or their technical realization" (Weske, 2012). The EPC shows the possibilities and decisions that have to be made during the process, but does not give technicalities about the decision-making process or the reason behind a certain event in the process. An EPC can be set up in various different ways and in their own designs. In this research such an EPC is already shown. Figures 2 and 5 show the EPC of the process from orthopaedic surgeon until surgery. These figures show the general process flow and the decisions that are made during that process. However, the figures do not show how decisions are made. For instance, the part of the process where the POS appointment is scheduled does not show the rules for the scheduling. It is unknown to the reader whether the POS secretaries schedule patients based on a first come, first serve policy or that other factors are weighted to come to the surgery schedules. For this reason, an EPC is often considered as a first step in data analysis and forecasting. It provides a clear picture of the operations, but does not provide any numerical analysis. To realise this, the following options are more suitable.

## 4.2. Markov Chains

Markov chains are a type of stochastic process that can be modelled for various types of processes. A stochastic process is a system which evolves in time while undergoing chance fluctuations (Coleman, 1974). For example, the number of customers in a queue of a larger process or in our case, the number of surgery hours in one category. Changing from one state to another is called a transition and the probability that this happens is called the transition probability. Mapping these transition possibilities gives us paths and nodes in a similar way as the process flow in figure 11 from section 3.3. A distinction can be made between discrete- and continuous-time stochastic processes. Discrete-time stochastic processes follow state changes on fixed points in time. In a continuous-time stochastic process, the state of the system can be viewed at any point in time (Winston & Goldberg, 2004). Although our process can be viewed at any time theoretically, the TPO carries out measurements every Monday, which makes the process a discrete-time stochastic process.

Markov chains have the additional characteristic that the "probability distribution of the state at time *t+1* depends on the state at time *t* and does not depend on the states the chain passed through" (Winston & Goldberg, 2004). The process in this research follows patients that need to undergo surgery. Ultimately, patients will leave category 6, but the path they take does not affect the further process flow of that patient. For example, one patient enters the process at category 2 in week 1 and goes to category 5 in week 2 while another patient enters the process at category 2 but wants to delay surgery and enters category 3. After a few weeks, the second patient decides to make a screening appointment and is approved for surgery. Both patients are now in category 5, following different paths. However, the surgery planning is not concerned with their paths through the process. The surgery planning sees that they have entered category 5, which is enough knowledge to know that they are ready to be scheduled for surgery.

The last assumption we make for Markov chains is that the probability distribution does not depend on the point of time. For instance, the probability of leaving category 2 and entering category 5 in week 1 is the same as the probability for that same transition in week 10 or 100. This is called the stationary assumption, which is obviously not true for the process in this research, as follows from the conclusions in section 3.3. However, following the assumption, we can calculate the average transition probability and assume that the process is a stationary Markov chain. Later on in this chapter, the effect of relaxing this assumption is discussed.

Other classifications can be made for our process, which is that every category is a transient state. This means that one category can be reached from another but not the other way around. From the process flow in figure 11 in section 3.3, we can see that this is the case. As mentioned, the transition probabilities can only be made using an average over a longer period of time, which means that the process will be modelled as a steady-state or equilibrium distribution. As a result, the patient distribution will ultimately end in following a certain limit for all categories and does not, or hardly, change approaching that limit.

The transition probabilities and the fact that we can assume a stationary assumption help us to create a model to run our process. We can give the model an input of patient hours or use an existing state, e.g., the current patient distribution, and it will show us the patient distribution for next week and onwards. On the other hand, the stationary assumption is a huge disadvantage of this type of modelling. We know for a fact that transition probabilities can differ throughout the year as a result of holidays and seasonal injuries. For this reason, a stationary Markov chain is not the best option to model the process.

### 4.3. Markov decision process

In Markov decision processes (MDPs), the process considers the effect of strategies and decisions made by the organisation on the transition probabilities. By changing strategies, transition probabilities can change, resulting in a different outcome. MDPs work with an infinite horizon length. For instance, when a company would like to maximise their turnover on the long term, they can use a MDP to calculate the expected rewards based on the different strategies the company can implement. In Markov chains, transition probabilities are set up as $P(j|i)$ or $P_{ij}$ where $i$ is the state on time $t$ and $j$ the state on time $t+1$. To illustrate this, suppose we have a transition probability as follows: $P(5,2)=0.2$. This means that the probability of leaving category 2 and entering category 5 in one week is 0.2. Applying this probability to the whole group of patients in category 2, we know that on average 20% of them will be in category 5 next week. In MDPs, the transition probabilities are shown as $P(j|i, d)$ or $P(j|i, \delta)$, where d and δ indicate the decision that is chosen. *P(5,2|one anaesthesiologist on holiday)*, shows the probability that one patient leaves category 2 and enters category 5, considering that there is one anaesthetist on holiday that week. There are often a lot of strategies or decisions that can be chosen from. Once the transition probabilities of every strategy are known, the organisation can calculate the best strategy to implement. Often a combination of strategies is applied. In that case, the decision is referred to as the policy.

As the aim of the research is to provide a clearer picture in order to apply strategies to the operations, this would be a viable option to model our process. Changing the transition probabilities based on the policy gives a clearer picture of the process and how the decision affects it. However, as MDPs use an infinite horizon length, it is not possible to assess the performance on distinct points in time. Moreover, the transition probabilities are set for the whole horizon length. So, when you decide to apply a certain strategy this week, a MDP will apply this strategy forever, which will make it impossible to assess the effects of the strategy.

## 4.4. Simulation

A simulation is an "experimentation with a simplified imitation of an operations system as it progresses through time, for the purpose of better understanding and/or improving that system". (Robinson, 2014) As you might notice, this definition is also true for the Markov chain. In this section, we discuss simulation as a more sophisticated tool, where software is used to program unpredictability and randomness. For this, data analysis should provide enough information to program probability distributions, for example the probability of a patient entering the process at a certain point in time.

Simulating has the benefit of controlling the variability within a process. Once a simulation is set up, its variables can be altered according to the strategies of the company. This way changing strategies can be done by changing the variables accordingly, instead of building a new simulation every time.

As we know, transition probabilities can fluctuate over time and are based on averages within a given dataset. A simulation can be set up in such a way that new data can be implemented and transition probabilities are recalculated based on the old and new data, without completely changing the simulation.

Another advantage of simulating is the fact that it requires fewer assumptions and simplifications, as the possibilities to model are almost endless. Probability and randomness may apply to a process but cannot be modelled in a Markov chain or other queuing model. For this reason, simulating would benefit this research by being able to adjust probability based on seasons (i.e., the holiday period). Of course, probability and randomness in this research is based on the (limited) dataset present. Without a larger dataset it is impossible to calculate these probabilities and randomness accurately.

The last benefit of simulating is transparency. Simulating often provides an organisation with a more visual and intuitive result. A simulation regularly includes a miniature set up of the organisation. In queuing simulations, this is often done by showing the different departments, the paths and relations between them and the persons and queues are simulated as well. This way the simulation represents the process more accurately and as a result, the organisation has a better understanding of the simulation and its outcome and is more eager to acknowledge the outcome.

There are disadvantages as well. As there are many possibilities in simulating, the process of setting up a simulation is often time-consuming and expensive. Simulation software needs to be bought and an expert (team) needs to set up the simulation, validate it using real data and adjust it accordingly. Furthermore, a lot of data is necessary to validate probabilities and distributions, more than in Markov chains for instance. Currently, this data is not available as we are limited to a dataset from only one year that was also different from other years because of the corona crisis. Lastly, as mentioned, simulating provides an organisation an appearance of reality. The danger lies in over confidence in the simulation and directly acknowledging every outcome, without considering the validity, assumptions and simplifications made by the programmer. Because simulating can be very time-consuming and expensive and a small dataset is available, simulation would not be a preferred option in this research.

## 4.5. Markov Interventions Model

When looking at the literature, all options to model the process in this research have major disadvantages. EPC is too basic and does not involve data analysis, the stationary assumption in Markov chains does not comply with the changing transition probabilities in our process, MDPs use an infinite horizon length, which makes us unable to assess the patient distribution on the short term and simulation is too expensive and time-consuming to carry out in this research. However, combining the advantages of each of these models and eliminating their disadvantages, provides us with a better approach. Let us call this model "Markov Interventions Model". It relies on the programmer or data analyst to adjust certain variables in the model, according to the situation at hand.

As the name of the model might suggest, it follows the basic principles of the Markov chain. It uses transition probabilities and bases them on averages over a longer period of time. To eliminate the stationary assumption, the model provides the possibility to adjust the transition probabilities during certain weeks or periods, for instance the holiday season, according to the same principle used in simulation. "Regular" transition probabilities are based on their average in weeks outside the "irregular" periods and the adjusted transition probabilities are based on their average in the distinct periods.

Lastly, we want to be able to see the effect of changing strategies to improve the decision-making, as is the case in MDPs. As mentioned in section 4.1.3, the transition probabilities can change accordingly, but we need to eliminate the use of an infinite horizon length to be able to see the short-term effects. This can be done by changing the transition probabilities in the weeks that a certain policy is applied. Of course, applying a strategy in week 3 affects the patient distribution forever, but the change in transition probabilities is limited to week 3 and maybe a few surrounding weeks. Therefore, the programmer can decide to only implement the change in transition probabilities in those weeks and applying the "regular" transition probabilities in the following weeks.

Implementing parts of the four different process modelling approaches, has provided us with a simplified simulation model that accurately follows the reality. It gives us a clear picture of the process, which allows OCON to steer and apply strategies based on the results of the model.

## 4.6. Conclusion literature study

In this chapter, multiple process modelling approaches were discussed. Event-driven process chains give a clear indication of the relations between different parts of the process and how a patient flows through it, but it does not use data to support or analyse this process. Markov chains use transition probabilities to forecast the path a patient will take. It assumes that these probabilities will not change on a specific point in time, which neglects our analysis that patient flows change during holiday seasons. Markov decision processes provide models to see the effect of a certain strategy or decision that is made. Transition probabilities depend on the chosen policy and remain the same during an infinite horizon length. Therefore, the implications for the upcoming weeks are still uncertain. Simulation would provide a platform to model the process and forecast more accurately. However, this would cost a lot of time and resources. Besides, a simulation nears reality but does not guarantee it. Following a simulation could therefore result in over-confidence and ultimately a lower working morale.

Combining the advantages and eliminating the disadvantages of these different approaches, we obtained a model called Markov Interventions Model. Programmers or data analysts can adjust the transition probabilities in certain weeks instead of forever, resulting in a simplified simulation model that provides OCON with a clearer picture of the process, which allows them to steer and apply strategies based on the outcome of the model.

# 5. Improvement options

The model from the data analysis in section 3.3. can be altered in such a way that it functions as a Markov Interventions Model, which can be used to gain more insight in patient clusters and patient flows. In future decision-making, this model can help to foresee the effects of the different options on hand. In this chapter, the Markov Interventions Model is described, the functions of the model are explained and theoretical examples of the functions are given.

## 5.1. Markov Interventions Model

The Markov Interventions Model is set up using the dataset of section 3.3. This dataset provides us with historical data on which to base our transition probabilities and input values. However, this means that the same assumptions and limitations are true, which are summarized below:

- Some data is incomplete or faulty and thus some data fields have been fabricated.
- Absorption states have been designed for patients with long waiting times instead of patients that wish to delay their surgery.
- The dataset includes the corona crisis and the summer holiday, both resulting in fluctuations in supply and demand of surgeries.
- The dataset starts and ends empty, resulting in incorrect data at the beginning and end of 2020.

Considering these assumptions and limitations, we conclude that the Markov Interventions Model will not be a perfect representation of reality. For this, real-time data is necessary to acquire the current state of the process and more data is required to define more accurate probabilities and averages. On the other hand, the current dataset provides a model to explain certain dynamics, which in turn provides important insight leading up to a model that is more accurate, as well as an image of what OCON benefits from implementing a Markov Interventions Model in their operations and the possibilities this implementation provides them.

### 5.1.1. Transition probabilities

Using the elaborate process flow from section 3.3, we can calculate transition quantities for each state and patient category. Again, measurements are done every week on Monday. Therefore, we calculate how many patient hours went from one patient category to another, how many patient hours stayed in the same category, how many patient hours entered the process and how many patient hours left the process every week before Monday morning. Dividing the transition quantities over the number of patient hours that were in the original category one week ago, provides us with the percentage of patient hours that followed the various transitions. For example, at the beginning of week 1, we counted 20 patient hours in category 2. At the beginning of week 2, 10 of them received approval by the POS and are now classified as category 5. We now know that 50% of the patient hours in category 2 went to category 5 in one week.

Of course, this is only true for that specific week, which is why we also look at the fluctuations over time and the average per week over 25 weeks. The separate calculations and their averages are then put into a graph to show the fluctuations. The data period chosen for these graphs, includes measurements from July 6$^{th}$, 2020. However, when looking for other effects (i.e., the corona crisis), other data periods can be chosen. To clarify the function of the transition graphs, suppose we consider the graphs from category 5.

In figure 15, we can see the graph showing the percentage of patient hours in category 5 that were in category 5 last week as well. In the graph, the upper control limit (UCL) and lower control limit (LCL) are plotted as well. To understand their meaning, we have to explain what a control limit is and how it was set up in this case.

Control charts are used to monitor the number of conformities on a unit or units of a process based on samples taken from that process at given times. Their strength comes from their ability to detect sudden changes in a process (NCSS, 2021). In other words, control charts let us determine an interval in which fluctuation is expected and a rule that guides us to determine when there is a shift in the process average or that a process is out-of-control. There are several types of control charts, depending on the nature of the process. In this case, we use U charts as these are used when a number of units will be sampled at each time point (instead of one) and our process concerns multiple patients. The limits of the U chart are determined by the following formula: $UCL/LCL = \bar{u} +/- m\sigma$.

In this equation $\bar{u}$ refers to the average of the sample, $\sigma$ refers to the standard deviation of the sample and $m$ is a multiplier that is chosen by the analyst. The value of the multiplier depends on the process and the likelihood of false-alarms (i.e., out-of-control signals when the process is in control). In this research the multiplier is chosen to be 1, as there is only a slim chance that the process becomes out-of-control. Out-of-control in our case, would mean that patients are not guided through the process and do as they will. Of course, this would never be possible, which is why the lowest multiplier was chosen.

Now that we have determined how to calculate the UCL and LCL, and implemented them in the graph, we can explain their use. The upper and lower control limit show the maximum variance that a graph could show when not considering seasonal effects. When the graph exceeds these limits for one or two data points, we know that there is either a systematic mistake or that the data is corrupt. When it exceeds the limits for multiple data points in a row, it could indicate a seasonal effect or corrupt data. In this graph, we see that at some points it exceeds the limits but not by far, for a long time or regularly in the same way. Therefore, we can assume that this is caused by data corruption, following the assumptions mentioned before.

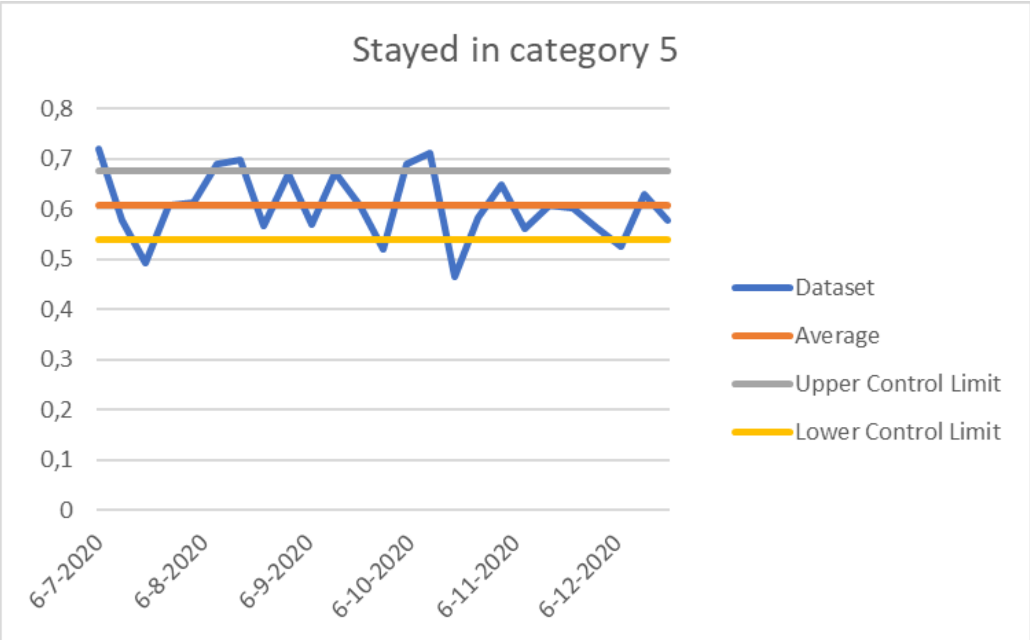



*Figure 15: Graph of the percentage of patient hours in category 5 that were in category 5 last week as well.*

Now that we know how to spot seasonal effects, figure 16 shows an interesting image. Starting from July 6th 2020, the graph peaks, exceeding the upper control limit by far and for a longer period of time. From section 3.3, we know that this is caused by the holiday period. As more patients wish to hold off their surgery, more patients transition from category 5 to category 4 and the transition probabilities increase.

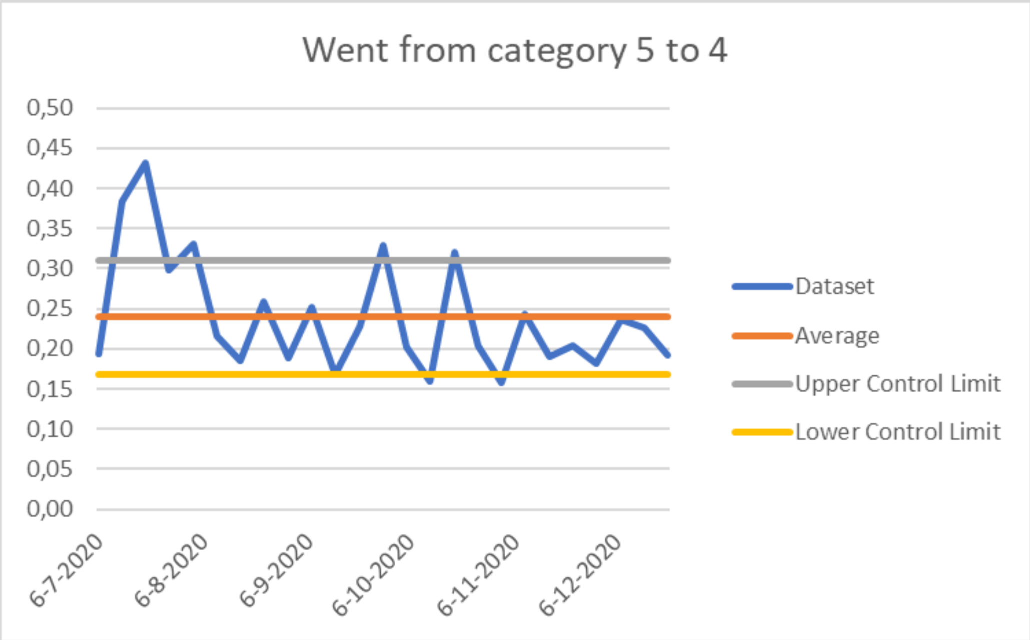



*Figure 16: Graph of the percentage of patient hours in category 4 that were in category 5 last week.*

In figure 17, the effect of the holiday period on transition probabilities is also visible. In the same period as figure 16, the transition probability of patient hours going from category 5 to category 6 decreases below the lower control limit. During the holidays, fewer patients wish to undergo surgery when they can choose to hold it off until after their vacation and thus fewer patient hours are assigned a surgery date in this period.

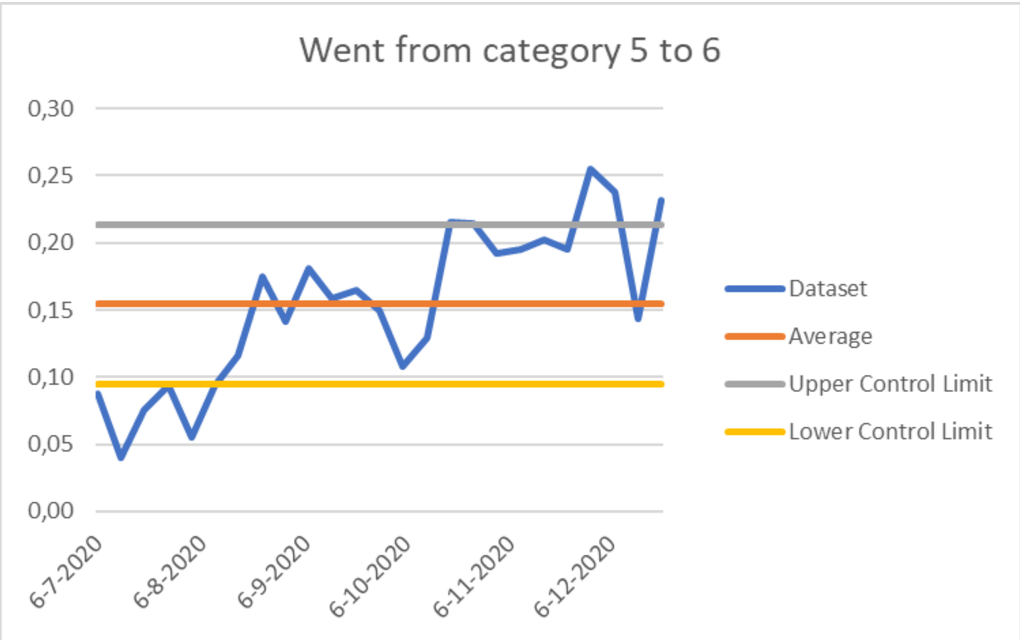



*Figure 17: Graph of the percentage of patient hours in category 6 that were in category 5 last week.*

The averages in these graphs can be used as transition probabilities for that transition in that specific period. For instance, when we look at figure 15, the probability that patient hours in category 5 will be in category 5 next week as well, equals the average from that period, which is 60%. This can be done for every transition which helps to make a forecasting model.

### 5.1.2. Forecasting model

At this point in the research, the forecasting model forecasts 25 weeks in the future, using the patient distribution from a given date and the transition probabilities from the same period as explained in section 5.1.1. To make this process clearer, we use the same example as in the previous section. The transition probability for patient hours staying in category 5 is 60% and will be 60% during the whole 25 weeks of the forecast starting at the 6th of July 2020. On this date, we know that 15405 patient hours were present in category 5 and thus 9243 patient hours will also be present in the next week. Using the same strategy, we can figure out the transition probability of patient hours entering category 5 (from category 2 or 3) and forecast the number of patient hours in category 5 next week. It is possible that patients enter the system on Monday afternoon (missing the data extraction of that Monday) and have their screening appointment on Friday. These types of cases result in several different input probabilities. In our example, the patient will suddenly appear in category 5 instead of category 2. Therefore, it is necessary to forecast the input of the different categories as well.

This process can be done for all categories and their transition probabilities to forecast the patient distribution for the next 25 weeks, resulting in the graph in figure 18.

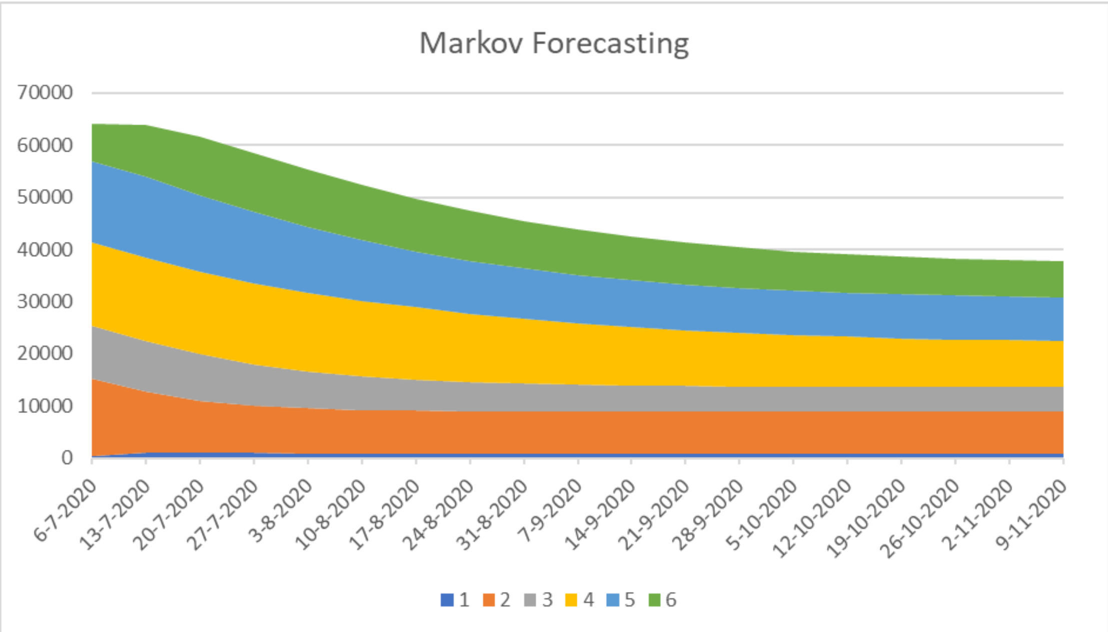



*Figure 18: Forecasting model starting on July 6th, 2020.*

As the transition probabilities are based on averages, the forecasting model does not show fluctuations or seasonal effects and ends in a state that hardly changes over time. Thus, the Markov equilibrium distribution is reached. The model gets more accurate when the input of patients is adjusted to real demand. To show this effect, the input of the dataset is used, resulting in a forecasting model with known demand. Of course, OCON will never know the demand beforehand, but predictions can be made. One example that was given by employees at OCON was the increase of patient input during and after the spring holidays as a result of skiing and snowboarding injuries. Another example of fluctuating demand is the summer holidays. Implementing a known demand into the model results in the graph in figure 19 on the next page.

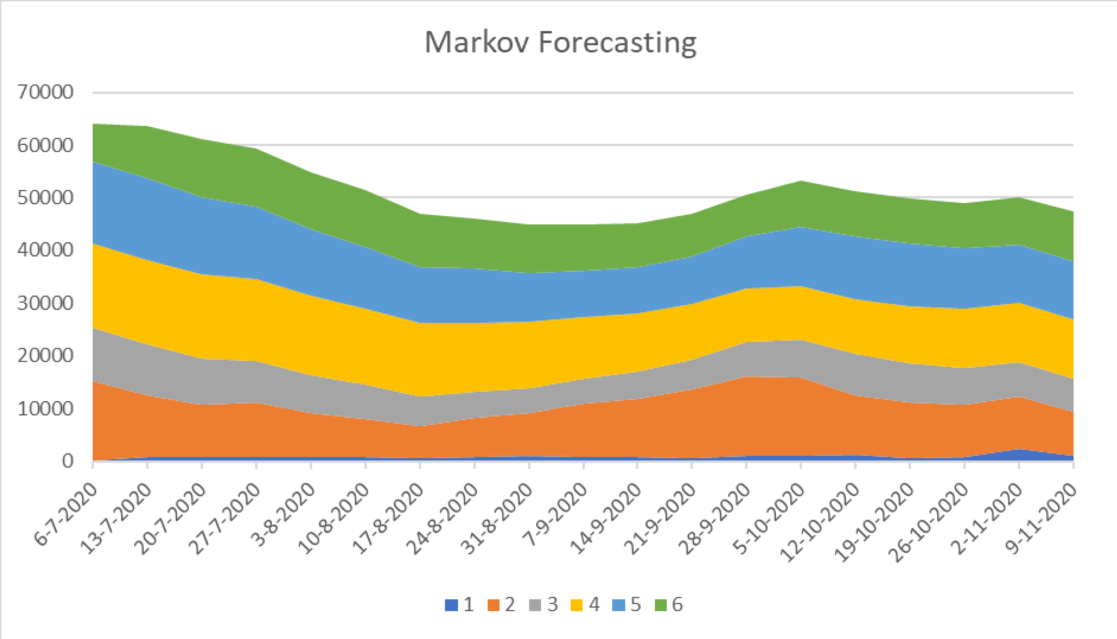



*Figure 19: Forecasting model starting on July 6$^{th}$, 2020, using known demand from the dataset.*

Figure 19 shows a decrease in total patient hours during the holiday period, as demand is lower (patients do not want to undergo surgery so they postpone their appointment with an orthopaedic surgeon) but transition probabilities are still the same for this period because they are based on averages over the whole period and not just the holiday period. From section 5.1.1, we know that the transition probabilities of the holiday period differ from other periods of the year. The transition probabilities can be changed manually for different periods of the year. Based on historical data and the conclusions we can draw from the transition graphs, manually altering the transition probabilities can be done in a very accurate way.

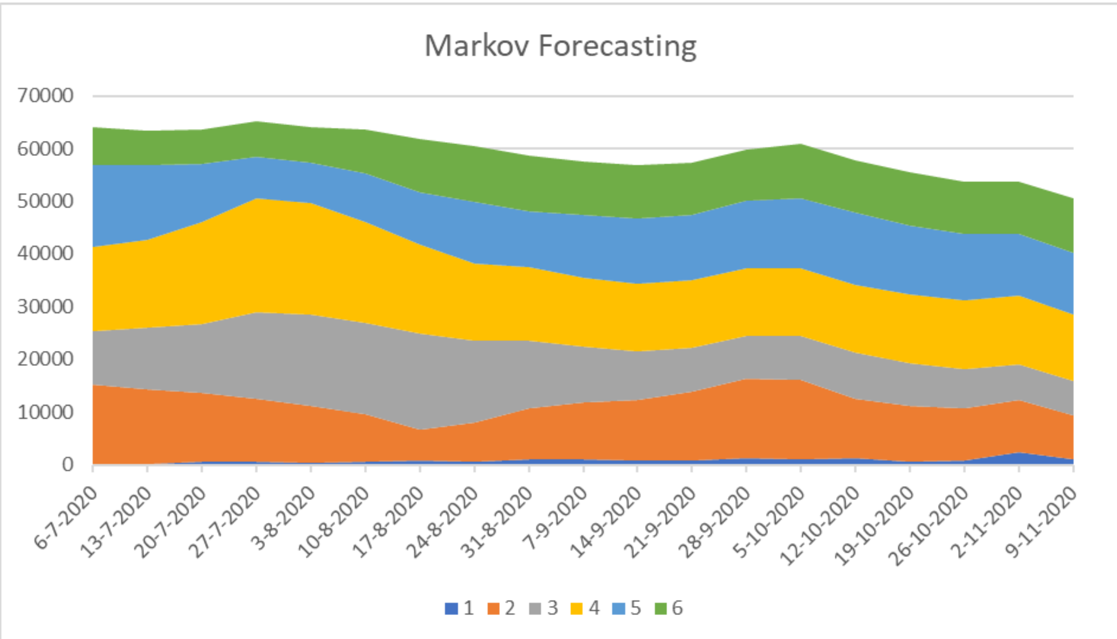



*Figure 20: Forecasting model starting on July 6$^{th}$, 2020, using known demand and manual transition probabilities during the holiday period (until August 31$^{st}$, 2020).*

The forecasting model in figure 20 follows from manual transition probabilities in the first period until August 31st, 2020, after which the average of the transition graphs is used again. This graph follows a more accurate line due to the manual transition probabilities. Notice the increase of categories 3 and 4 which follows from manually implementing the effects of the holiday period. Categories 3 and 4 include the type of patients that wish to hold off their surgery and are thus expected to increase during the holiday period.

Even when the demand is unknown, this gives an accurate prediction of the following weeks, as is visible in figure 21.

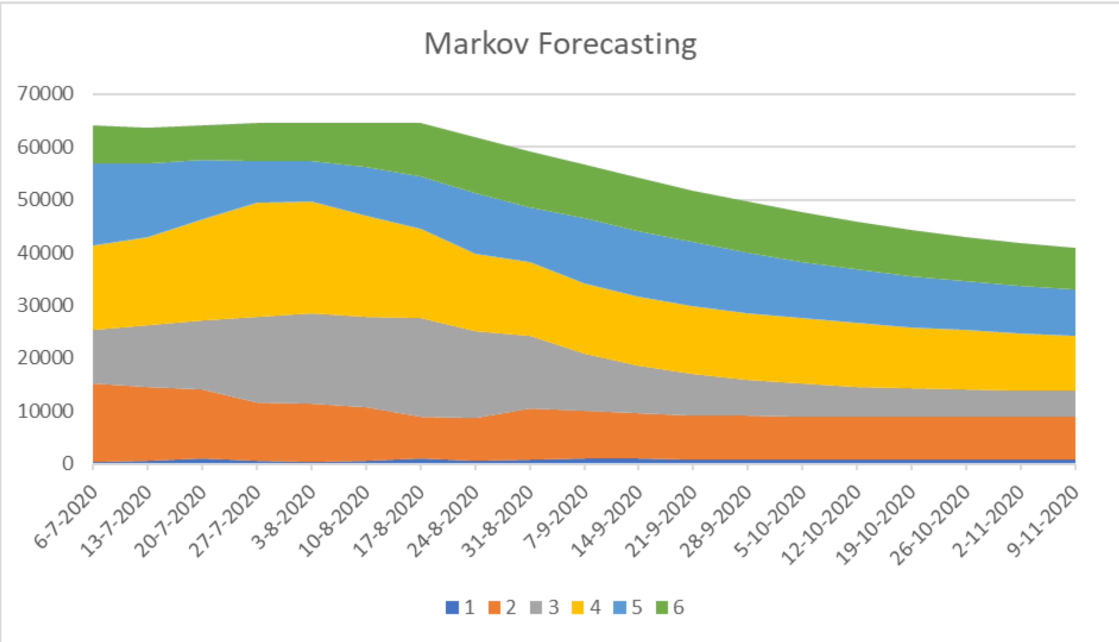



*Figure 21: Forecasting model starting on July 1st, 2020, using manual transition probabilities during the holiday period (until August 31st, 2020).*

The interventions must be done considering their validity. From the data, we know that the intervention in figure 20 is valid, but the same may not be true for other interventions. Taking this into account results in a Markov Interventions Model that forecasts patient distribution with great accuracy. In the following sections the necessity and further use of this model is explained.

## 5.2. Process insight

During this research, it came to light that certain aspects of the process are not visible or not monitored yet. Different departments have questions about the patient categories and whether that affects their operations. To answer these questions, it is necessary to provide an accurate measurement of the patient distribution and have a forecasting model that can show the effects on the process in the next few weeks. In the existing data analysis by the TPO, only the number of surgery hours in one patient category is mentioned. The flow of patients from one patient category to another is not discussed and as a result, it is not possible to forecast the patient distribution in the upcoming weeks. Hence, it is impossible to forecast the effects of the current distribution on the various departments in the process.

As mentioned in the previous section, the Markov Interventions Model solves this problem. The Markov Interventions Model is set up in such a way that the data of the current situation can be implemented. The transition probabilities are measured based on the average over a long period of time and forecasts a new situation for the next week(s). These probabilities can differ depending on the time of year. In the previous section, manual transition probabilities were implemented to show the effect of the holiday season on the forecasting model. However, there are other effects on the process that can be implemented using manual transition probabilities; the strategy of OCON for example.

OCON operates a so-called flex-day, that can be scheduled in two different ways. Either the orthopaedic surgeon is scheduled to perform surgery that day, or the orthopaedic surgeon will see more patients at the outpatient clinic. This decision is made by the TPO and is dependent on the data the TPO has. The two ways to schedule the flex-day have different effects on the transition probabilities. Scheduling more surgeries will lead to higher transition probabilities from category 5 to category 6 (as more surgery hours can be scheduled), increases the output of category 6 (as more surgeries take place) and decreases the input for category 2 (as fewer patients can visit the out-patient clinic). This way of scheduling the flex-day is further referred to as flex 1. Scheduling a day on the outpatient clinic increases the input for category 2, decreases the output of category 6 and lowers the probabilities from category 5 to 6. This makes sense since this is the exact opposite effect of flex 1. This type of flex-day is further referred to as flex 2. For the next four weeks, OCON already knows which way the day will be filled and thus the transition probabilities in these weeks can already be changed accordingly, which will give a better forecast for the patient distribution in the upcoming weeks. To explain this effect on the forecast, the following example is given.

The current forecasting model does not consider the effects of flex-days. Therefore, we can assume that it follows the average flex-day strategy, being half of the flex-days is used as flex 1 and the other half as flex 2. Suppose TPO chose to implement a full flex 2 week in the fourth week, after which it returns to the average strategy. Figure 22 shows the forecasting model without this implementation. Changes to this forecasting model due to flex 2 in the fourth week are:

- Input of category 2 increases in week 4.
- Output of category 6 decreases in week 4.
- Transition probabilities from categories 5 and 4 to category 6 decrease in the first three weeks.

The last change is due to less timeslots that can be filled by the surgery planning. As a result, fewer patients can be scheduled and thus transition probabilities decrease.

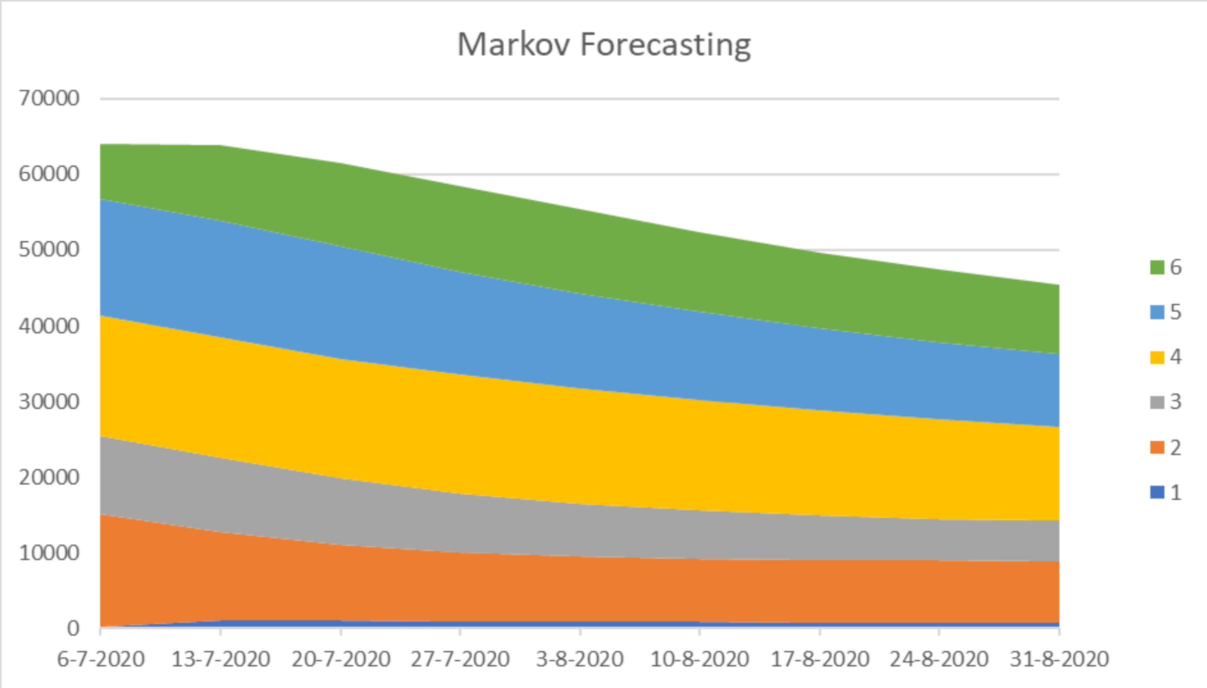



*Figure 22: Forecasting model starting from July 6th, 2020, assuming data includes weeks of both flex 1 and 2.*

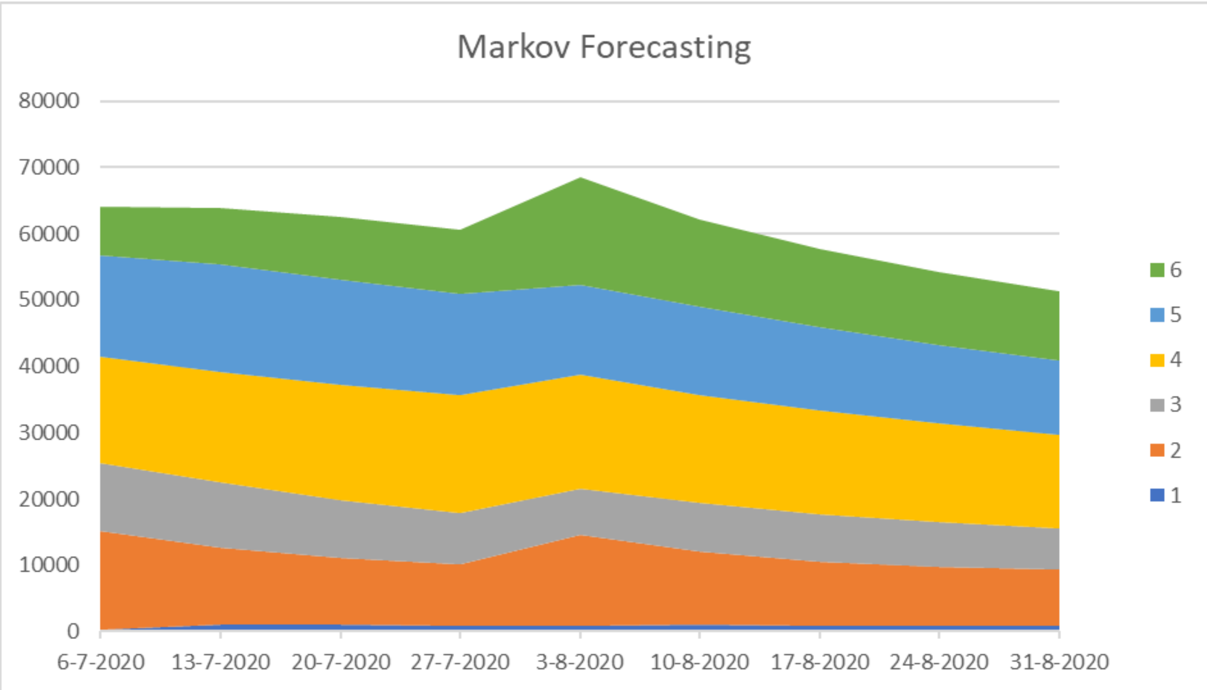



*Figure 23: Forecasting model starting from July 6th, 2020, implementing flex 2 in the fourth week (August 3rd)*

From figure 23, we can conclude that the strategy of implementing flex 2 in the fourth week (August 3rd) does not show big effects on the short term. In the fourth week however, we see that categories 2 and 6 increase due to the flex 2 strategy. Both categories take about three weeks to be back on the normal level. Furthermore, the total amount of patients in the process increases. These effects on the forecasted situation on the long term can provide OCON with a strategy to reduce these effects, implementing a flex 1 day for example. This decision-making is explained in the next section.

### 5.3. Decision-making

As mentioned, the Markov Interventions Model can forecast the distribution of patients for a long period of time. In the previous section, we discussed a forecasting method that helps to determine the patient distribution on the short and long term. Manually changing the transition probabilities makes these forecasts more accurate, but it can also help to determine the right strategy. TPO determines the strategy for the fifth week from their meeting. The different scheduling of the flex-day changes the transition probabilities and shows the effect of the strategy. This can help TPO to determine whether their chosen strategy will have a positive effect or that another strategy is necessary. To explain this process, we elaborate on the example in section 5.2. Suppose a flex 1 week in the fifth week is something that the TPO would like to consider. This would result in the following changes in transition probabilities for strategy 1.

- Input of category 2 increases in week 4.
- Output of category 6 decreases in week 4.
- Transition probabilities from categories 5 and 4 to category 6 decrease in the first three weeks.
- Input of category 2 decreases in week 5.
- Output of category 6 increases in week 5.
- Transition probabilities from categories 5 and 4 to category 6 increase in the second, third and fourth week.

In the second and third week, the changes in transition probabilities from categories 5 and 4 to category 6 overlap each other. As a result, they cancel each other out and the regular transition probabilities are in force. TPO could also implement strategy 2: a flex 2 week in the fifth week. In that case the following changes should be implemented in the forecasting model:

- Input of category 2 increases in week 4 and 5.
- Output of category 6 decreases in week 4 and 5.
- Transition probabilities from categories 5 and 4 to category 6 decrease in the first three weeks.
- Transition probabilities from categories 5 and 4 to category 6 decrease in the second, third and fourth week.

In this case, lower transition probabilities from categories 5 and 4 to category 6 in the second and third week add up and become even lower. Both forecasts can be found in figure 24 and 25, respectively.

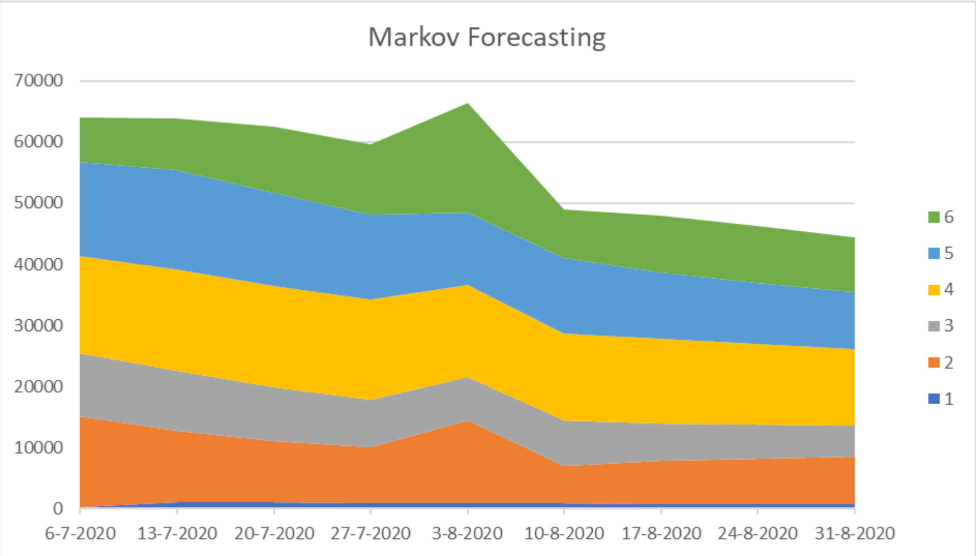



*Figure 24: Forecasting model for strategy 1.*

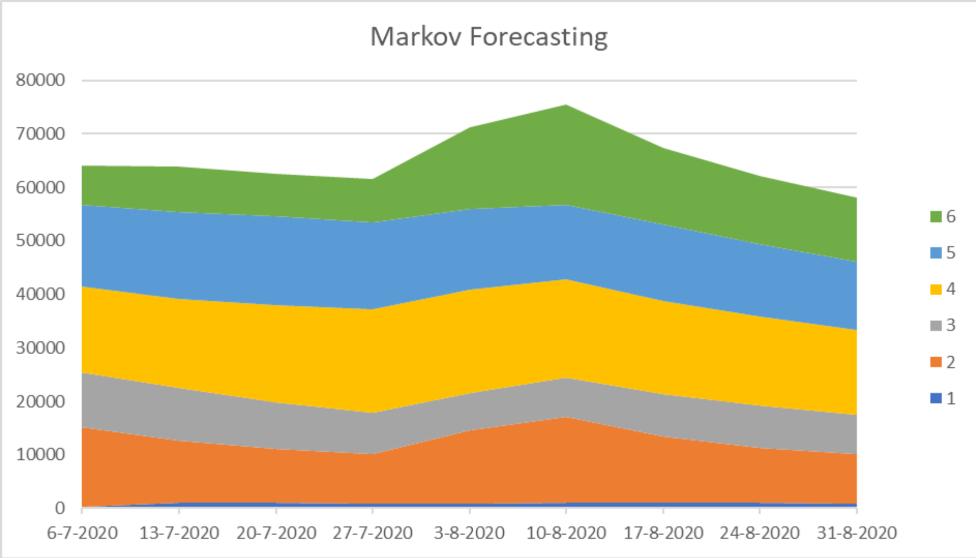



*Figure 25: Forecasting model for strategy 2.*

In both figures, we get a clear picture of the effects of the strategy on the patient distribution. In figure 24, the number of patient hours present in the process, decreases drastically, returning to the trend of the forecast model without interventions. In figure 25, categories 2 and 6 keep increasing, resulting in a higher number of patient hours present in the process. Both strategies can be profitable for OCON, regarding the situation of that moment and in perspective with the total number of patient hours present in the process. Comparing to the capacity at the different departments can provide this perspective. When the total number of patient hours present in the process is much lower than the number OCON is able to manage, strategy 2 is a great way to increase this number and be able to work on full capacity. However, when the process is overloaded with patients, this will result in long waiting times and strategy 1 is necessary to decrease the number of patients waiting for their surgery.

Besides the flex-day, OCON can implement strategies such as opening an extra operating room or hiring another employee at the POS. By changing the capacity in different parts of the process, the transition probabilities change and the effect of the strategy can be visualised by the forecasting of the Markov Interventions Model. For this reason, the Markov Interventions Model provides a flexible forecasting method for OCON, resulting in better decision-making. Combining the implementation of decision-making and the seasonal effects gives an even more accurate forecast for the next few weeks. For instance, performing more surgeries just before a holiday period would not be beneficial when these patients can also undergo surgery during the holidays. This way, operating rooms will be empty or emptier during the holidays, which is a waste of resources. Hence, taking these seasonal effects into account provides more insight to make the most profitable decisions.

## 5.4. Conclusion improvement options

In conclusion, thanks to the historical dataset, it was possible to set up a Markov Interventions Model with transition probabilities and input and output data. The Markov Interventions Model provides OCON with a flexible tool to gain more insight in their own operations and forecast the patient distribution for the next few weeks by implementing season effects and strategies. This helps OCON in identifying bottlenecks or problems in the process and applying strategies to solve them.

# 6. Solution

A clear description of the short- and long-term actions to undertake are required to implement the Markov Interventions Model successfully. In this section a short manual is given to explain the different steps that are necessary. First, the setup of the model is described, after which the use of the model in practise is explained. Lastly, the model needs to be updated so, the maintenance of the model is also mentioned.

## 6.1. Setup

Currently, the Markov Interventions Model uses transition probabilities based on historical data and forecasts using the current patient distribution. It is recommended to run this model another time for a more representable period (excluding the corona crisis and the holidays) to obtain more accurate averages for the transition probabilities. Excluding the holidays results in incorrect data for these periods. Therefore, it is necessary to analyse the holiday periods separately and calculate the corresponding averages. This way, the transition probabilities for the holidays can be setup and implemented when the holidays take place. This can be programmed to be implemented automatically, for instance using a starting date of the holiday period. When this date is reached, the model will implement the transition probabilities of the holidays. The same is true for the implementation of the flex day strategies. For the flex day strategies, the model needs to recognise their effects in every upcoming week. Figure 26 explains this situation more clearly. In week 1, the data of week 1 until week 4 is used to determine the strategy in week 5 (yellow). In week 2, the data of week 2 until week 5 is used to determine the strategy in week 6 (blue). From figure 26, it becomes clear that the effect of the chosen strategy in week 1, has its effects on the decision-making in week 2, as week 2 until 4 are affected by the chosen strategy in week 1 and is used in the decision-making in week 2 (overlap of yellow and blue).

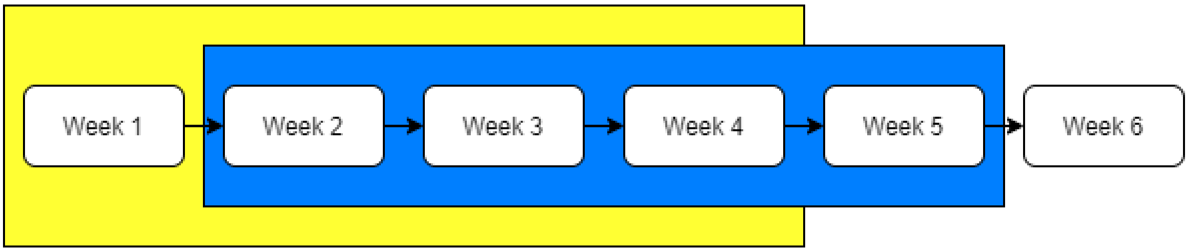



*Figure 26: Overlap in analyses of the first and second week.*

Once the above-mentioned actions have been realized, the only thing that is left is to insert the current patient distribution and the model can be used. It is important that the patient distribution is updated every week, as the model provides a forecast and not a certain result. So, the outcome of previous week can differ from reality. The patient distribution can automatically be inserted by linking the model to the dataset or software.

## 6.2. Using the model in practise

The core problem of this research is: KPIs are not workable for the POS to adjust their scheduling process. Although this research has not provided OCON with new or adjusted KPIs, from section 5.3, we have learned that the Markov Interventions Model enables OCON to see the effects of their decision-making and strategies. Consequently, the scheduling process at the POS and other departments within OCON can be adjusted accordingly.

Currently, the TPO discusses the strategy that needs to be implemented and communicates this with the different departments. This way of working is efficient because only a select group is concerned with the decision-making. However, because it is a select group, the employees do not know why certain decisions are made and only hear the conclusion of the meeting. This decreases the trust in the decision-making and consequently, decreases the willingness to cooperate under a certain strategy. Sharing the outcome of the Markov Interventions Model or by sharing the changes in the transition probabilities, increases awareness and clarity of the current or upcoming situation. This way, employees will trust the decision-making process and become more compliant.

## 6.3. Maintenance

As mentioned in the previous sections, there are some limitations to the Markov Interventions Model as well as a few assumptions that were made. These limitations and assumptions can be loosened in the years to come by undertaking the following actions:

**Some data is incomplete or faulty and thus some data fields have been fabricated.**
The data fields that employees fill in for every patient in their EPD can be adjusted in such a way that faulty and incomplete data is not possible. For instance, in the current situation, a surgery date can be scheduled in the past (going back as far as 1900). Implementing a simple rule in this data field can stop people from entering faulty data.

**Absorption states have been designed for patients with long waiting times instead of patients that wish to delay their surgery.**
In this case, new data fields may be necessary. At this time, employees can fill in a data field called "Oproepbaar vanaf" or available from date. This data field is sometimes used to communicate an expected approval date. In order to differentiate between patients that wait for approval and patients that wish to delay their surgery a simple tick box can be added called "wish to delay". These patients can then be excluded from the relevant part of the Markov Interventions Model.

**The dataset includes the corona crisis and the summer holiday, both resulting in fluctuations in supply and demand of surgeries.**
In section 6.1, we have discussed the importance of recalculating the transition probabilities using a more accurate and representative dataset, excluding the corona crisis and holidays. In order to implement different transition probabilities for the holiday periods, they have to be calculated separately.

**The dataset starts and ends empty, resulting in incorrect data at the beginning and end of 2020.**
This limitation can also be solved by recalculating the transition probabilities using a more accurate and representative dataset.

Another important aspect to keep in mind is the gradual changes in transition probabilities. It is possible that, as a result from implementing the Markov Interventions Model, operations at OCON change in such a way that transition probabilities also change. Therefore, it is important to keep an eye on the transition probabilities and adjust them when a permanent shift is visible.

A permanent shift in the transition probabilities can be observed by looking at the upper and lower control limits as mentioned in section 5.1.1. To exemplify this, suppose a transition probability shifts to a higher average permanently. The shift can be made visible in two ways: using the old or the new average, UCL and LCL. In the first case, we can see that the data points of the transition probabilities will consequently exceed the old UCL. In the second case, new average, UCL and LCL are calculated. In the graph it will become visible that old data points will be situated below the new LCL. Both situations show the data analyst that the transition probability has shifted permanently and indicate that the new transition probability should be used in future decision-making.

# 7. Discussion

This research finds that there are several options to consider when trying to answer the central research question: What is the efficiency of the current scheduling process at the preoperative screening at OCON and how can it be improved? In the literature study in chapter 4, the options were discussed. The result of this research is to combine the advantages of the different options and eliminate their disadvantages. Consequently, a model was found that can assess the efficiency of the performance at the preoperative screening and that provides a tool to determine beneficial strategies.

Currently, the Markov Interventions Model proves to be a great solution to the central research question and tackles both the assessment of the current performance of the POS as well as the improvement of said performance. The data used in this research must, however, be interpreted with caution because there are quite a few assumptions that were made during the setup of the Markov Interventions Model. Moreover, the dataset is so limited that direct implementation of the model should be done with care for validity. Even though efforts have been made in this research to minimise this risk, it is still possible that the solution in this research does not comply to the rules that apply to reality. For this reason, section 6.3 provides us with actions to undertake on the long term to ensure the validity of the Markov Interventions Model for OCON.

The model that is designed in this research has not yet been implemented by OCON. For this, compatibility with the current hospital system HiX would be ideal but not necessary. Another option would be to manually insert the current data in the model (currently designed in Microsoft Excel). Unfortunately, this can become difficult when the actions in section 6.3. are carried out. Therefore, it would be wise to assign a data analyst who will update and format the model in such a way that data can easily be inserted in the model.

# 8. Conclusion

This research aimed to assess the efficiency of the POS at OCON and to find improvement options. By analysing the current way the efficiency is assessed and by conducting interviews, the problems and bottlenecks of this process were found. The main finding of this analysis was that the key performance indicators often do not satisfy the goal for which they were set up. Mostly, they lack perspective towards each other and their desired value is not determined. This makes it hard to steer on the KPIs and adjust the operations accordingly. Moreover, the employees of the different departments have no idea what the strategies and decisions are based on, resulting in a lower motivation to cooperate in the chosen strategy.

To assess the efficiency of the POS, a data analysis was carried out. Interesting findings were the effect of the holidays and the corona crisis. In the holiday periods, patients often choose to postpone their surgery until after the holiday, because of their own or their relatives' holidays. The effect on the POS and surgery planning is clearly visible as these patients accumulate and fewer surgeries can be performed. As a result, at the end of the holidays, there is an over-abundance of patients that want to undergo surgery. To ensure an efficient use of the capacity of the operating rooms, it is important to identify and acknowledge this effect and adjust the operations at OCON accordingly. The corona crisis was also clearly visible in the data analysis. Corona related healthcare was prioritised at the cost of regular healthcare. Consequently, fewer patients had an appointment at the outpatient clinic, were screened at the POS and did undergo their surgery. The data analysis already provided OCON with a better insight of the patient distribution and its effect on the long term.

On the other hand, the data analysis only provides insight in the process based on historical data. In order to make better decisions and apply suitable strategies, a model was necessary to show the effect of the strategy for the operations in the upcoming weeks. A literature study was carried out to find options to develop such a model. The various models that were found in the literature study all had their benefits but flaws as well. Therefore, to suit the process from this research, the types of models were combined into a new type of model, which we call the Markov Interventions Model.

The Markov Interventions Model provides OCON with a tool to gain more insight in the current patient distribution and its effect on the operations in the upcoming weeks. In addition, the model enables OCON to try out different strategies and see their effects. This way, OCON can see if the strategy that they want to apply has the desired effect, resulting in a better decision-making process. The model also makes it easier to justify the chosen strategy and communicate it with the employees of the different departments.

Combining the benefits of several existing models can be beneficial for more situations in which the available literature does not provide a potential solution. Different processes in different organisations do not always follow the rules of existing models in literature. In this research, creating a new model using parts of existing models, gives a better representation of reality and enables OCON to forecast patient distributions while implementing different strategies. Choosing another existing model, would mean a compromise on either the accuracy of the model or the option to forecast using different strategies. This shows the importance of designing models based on existing ones.

Although there were no new KPIs that were introduced, the Markov Interventions Model will provide OCON with a clearer picture of the current situation of the patient distribution and enables them to see the effects of implementing different strategies. This way, OCON has a model that, when implemented in the operation at OCON, offers a tool that assesses the efficiency of the scheduling process at the preoperative screening and that can be used to find options to improve it.

# 9. Recommendations

This research resulted in designing a Markov Interventions Model, which may be used to determine a strategy. In this research we have not mentioned to use the Markov Interventions Model to set up KPIs. For further improvement of the decision-making at OCON, KPIs can be set up using the model to optimize operations. For instance, a KPI and accompanying goal can be set up for the desired number of surgery hours in category 6 (or one of the other categories). Implementing this KPI in the Markov Interventions Model, will enable OCON to see whether a strategy option satisfies the goal of this KPI during or at the end of the upcoming weeks. Choosing a strategy based on KPIs, results in the optimization of the scheduling process and ultimately a better use of the capacity at the different departments at OCON.

Secondly, it is beneficial to execute the mentioned maintenance work in section 6.3. The conclusion from this section is that the current data fields do not have rules to prevent impossible situation, for instance, the possibility of entering a birth date in the field of the surgery date. Moreover, the dataset lacks certain data fields that are necessary for the accuracy of the Markov Interventions Model, for example, a data field to indicate patients that wish to delay their surgery. When better data accuracy is realised, it will be possible to update the Markov Interventions Model accordingly to ensure a more accurate model.

Continuing on this, it is recommended to implement the Markov Interventions Model into the hospital system HiX. This way data does not have to be inserted manually and data is already compliant with the model that needs to use the data. As the hospital ZGT is already investigating further use of HiX, it is preferable to directly incorporate the model in HiX.

Lastly, OCON could look into the other modelling options such as simulation or serious game. In these models it will be easier to implement strategies and update changes is the model. However, a higher data accuracy is necessary to run a simulation or serious game and probability distributions need to be known beforehand. The Markov Interventions Model can be used to find these probability distributions provided that the input, throughput and output follow such a distribution. A simulation or serious game may seem to be profitable but as mentioned in this research, they can be expensive and time-consuming and may cause the user of the model to blindly trust the outcome of the model. Therefore, OCON should decide whether this is an investment that is necessary for the optimization of their operations or not.

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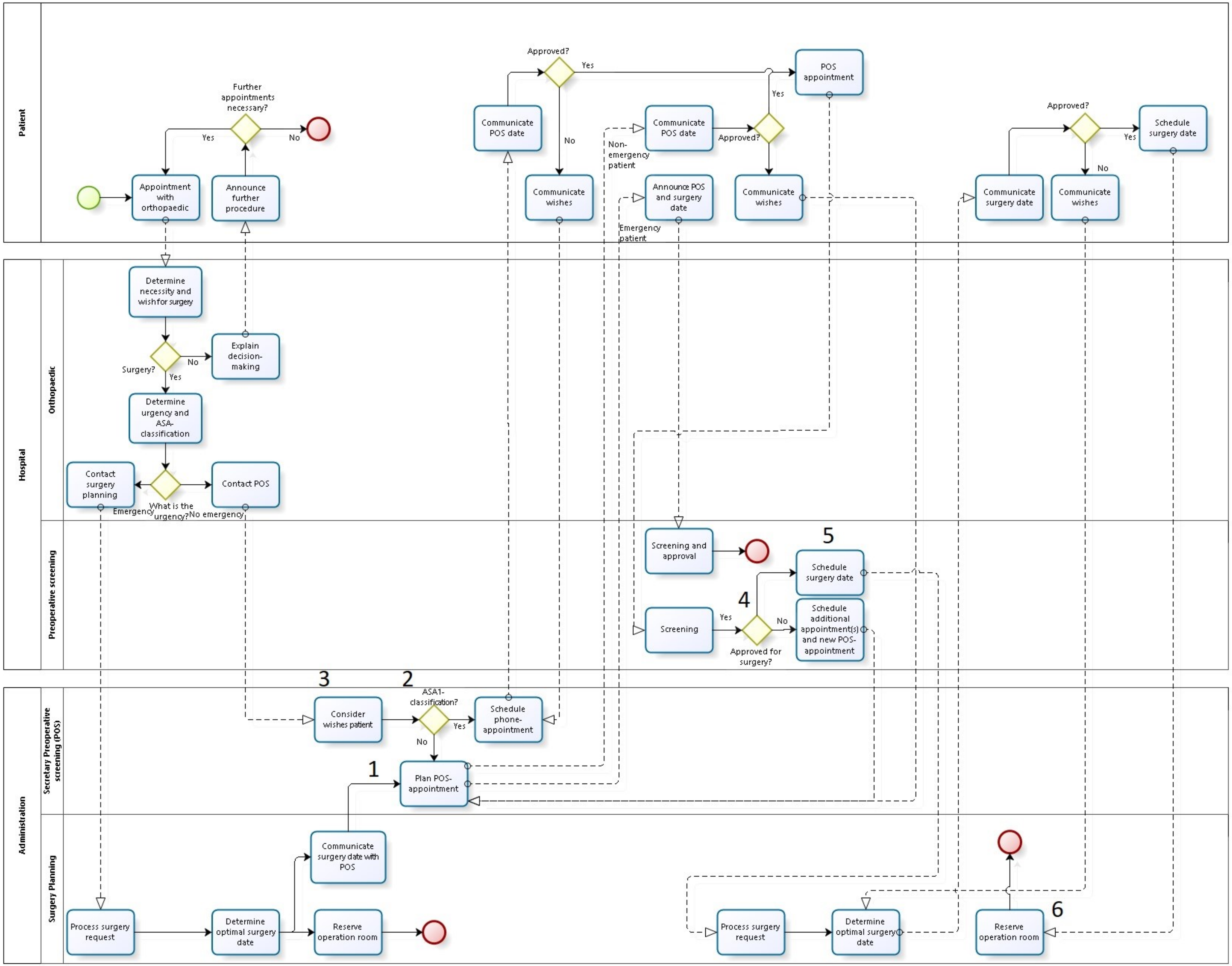
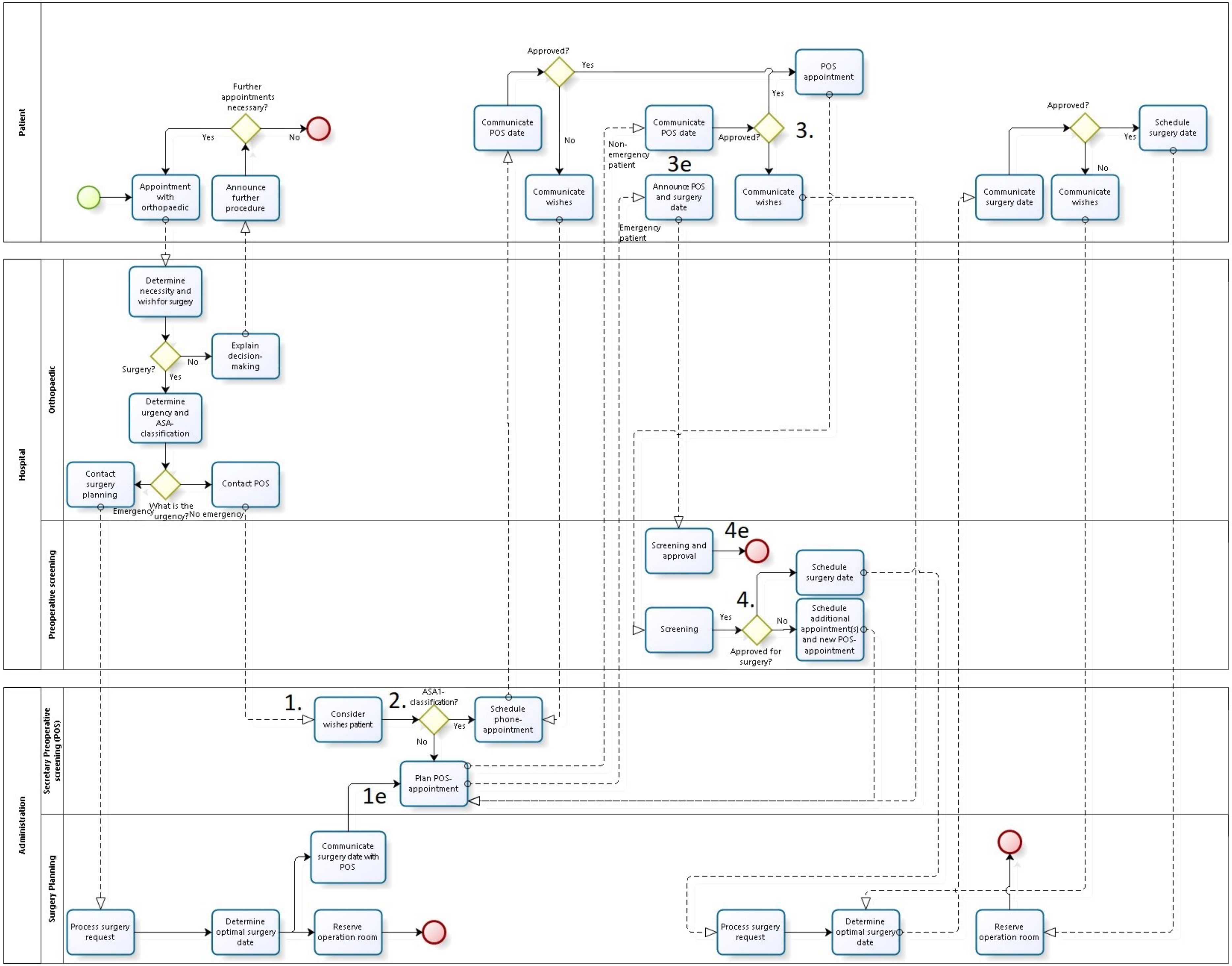
# Appendices

## Appendix A: Flowchart of the process starting at the orthopaedic surgeon and ending when surgery has taken place.

## Appendix B: Flowchart of the process for priority patients.


Patient
Hospital
Orthopaedic
Preoperative screening
Administration
Secretary Preoperative screening (POS)
Surgery Planning
Appointment with orthopaedic
Announce further procedure
Further appointments necessary?
Yes
No
Communicate POS date
Approved?
Yes
No
Communicate wishes
POS appointment
Communicate POS date
Approved?
Yes
Non-emergency patient
Announce POS and surgery date
Emergency patient
Communicate wishes
Communicate surgery date
Approved?
Yes
No
Communicate wishes
Schedule surgery date
Determine necessity and wish for surgery
Surgery?
No
Yes
Explain decision-making
Determine urgency and ASA-classification
Contact surgery planning
What is the urgency?
Emergency
No emergency
Contact POS
Screening and approval
5
Schedule surgery date
4
Screening
Yes
No
Approved for surgery?
Schedule additional appointment(s) and new POS-appointment
3
2
Consider wishes patient
ASA1-classification?
Yes
No
Schedule phone-appointment
1
Plan POS-appointment
Communicate surgery date with POS
Process surgery request
Determine optimal surgery date
Reserve operation room
Process surgery request
Determine optimal surgery date
6
Reserve operation room


Patient
Hospital
Orthopaedic
Preoperative screening
Administration
Secretary Preoperative screening (POS)
Surgery Planning
Appointment with orthopaedic
Further appointments necessary?
Yes
No
Announce further procedure
Determine necessity and wish for surgery
Surgery?
Explain decision-making
Determine urgency and ASA-classification
What is the urgency?
Emergency
No emergency
Contact surgery planning
Contact POS
Communicate POS date
Approved?
Communicate wishes
POS appointment
Communicate POS date
Non-emergency patient
Emergency patient
3.
3e
Announce POS and surgery date
Communicate wishes
Communicate surgery date
Communicate wishes
Schedule surgery date
Screening and approval
4e
Screening
4.
Approved for surgery?
Schedule surgery date
Schedule additional appointment(s) and new POS-appointment
1.
Consider wishes patient
2.
ASA1-classification?
Schedule phone-appointment
Plan POS-appointment
1e
Communicate surgery date with POS
Process surgery request
Determine optimal surgery date
Reserve operation room
Process surgery request
Determine optimal surgery date
Reserve operation room

## Appendix C: ASA-classifications and validities

**ASA-1 (valid for 6 months)**

Healthy patients younger than 60 years old. Patients fill in a form after which they get an appointment for a screening over the phone.

**ASA-2 (valid for 6 months)**

Patients older than 60 years old and patients for whom an appointment is necessary (based on the form). ASA-2 patients will get a screening appointment of 15 minutes in the hospital.

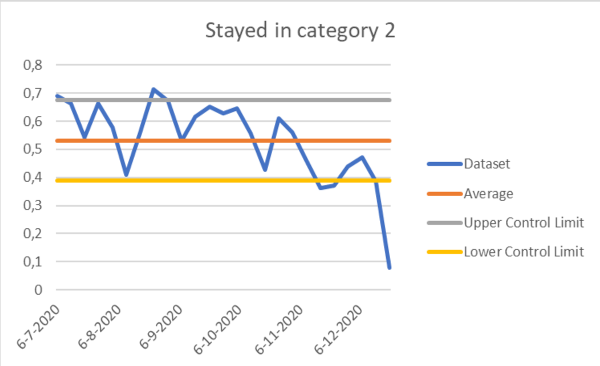
**ASA-3 or ASA-4 (valid 3 months)**

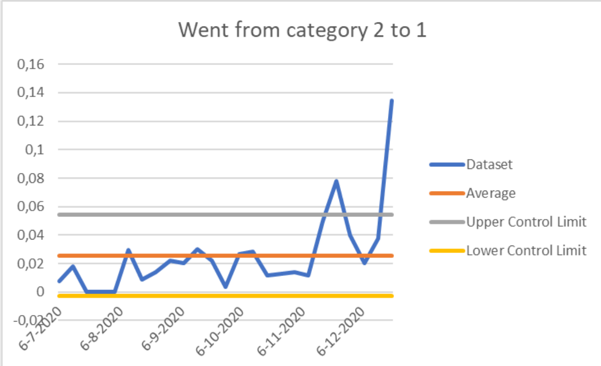
Based upon risks that were identified by the orthopaedic surgeon or by filling in the form, patients can receive an ASA-3 or even an ASA-4 qualification. The screening appointments for these patients take longer, often 30 minutes.

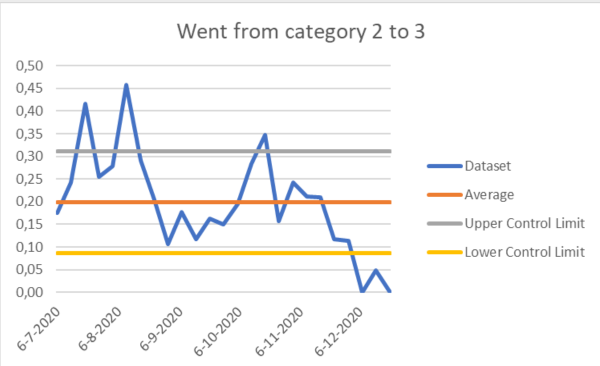
**ECG (in addition to ASA-qualification)**

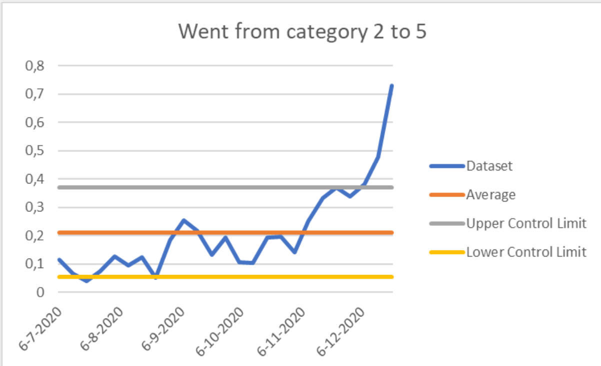
Sometimes it is clear that a patient needs to have an ECG before the appointment is scheduled. When this is the case, extra time is scheduled to fit the ECG within the same appointment.

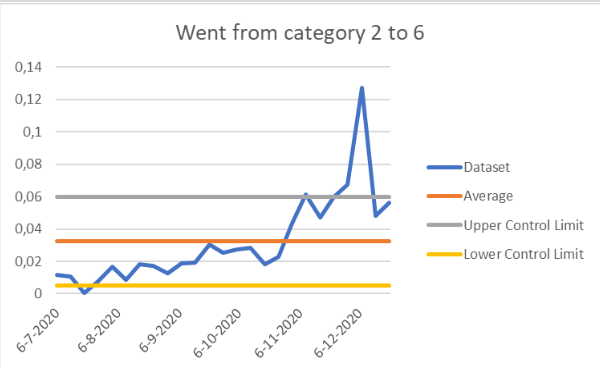
## Appendix D: Transition graphs starting from July 6th, 2020

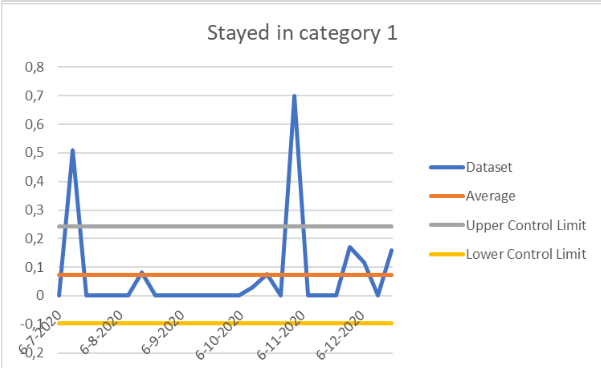


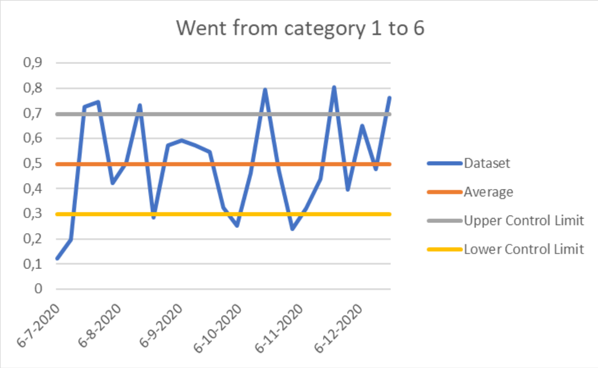



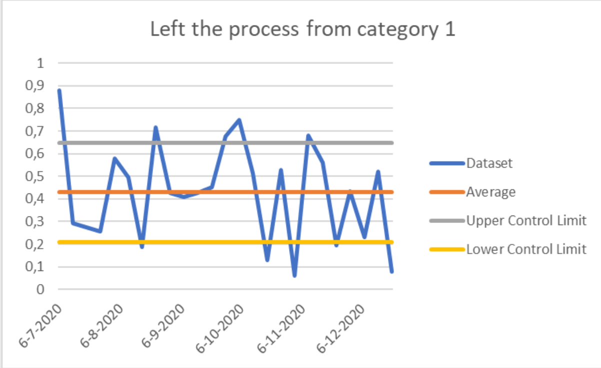



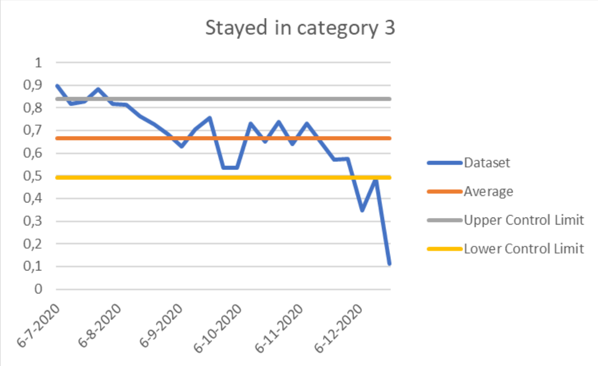



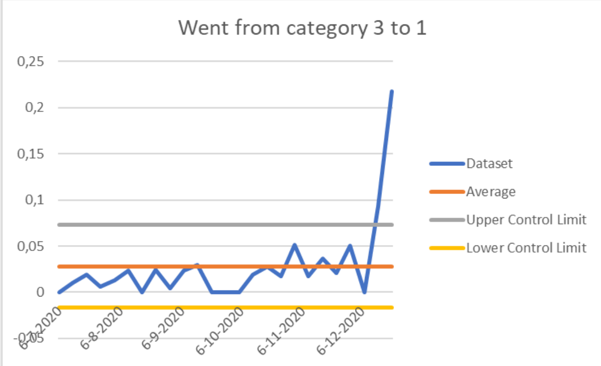



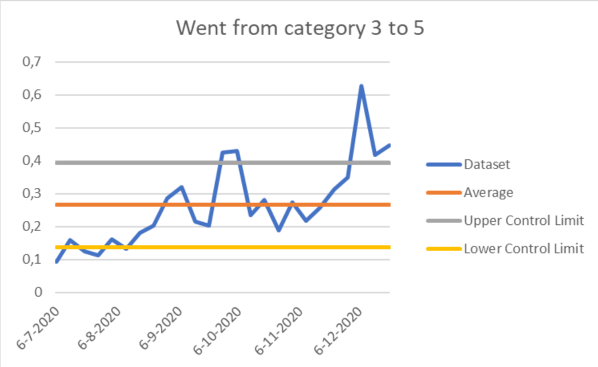



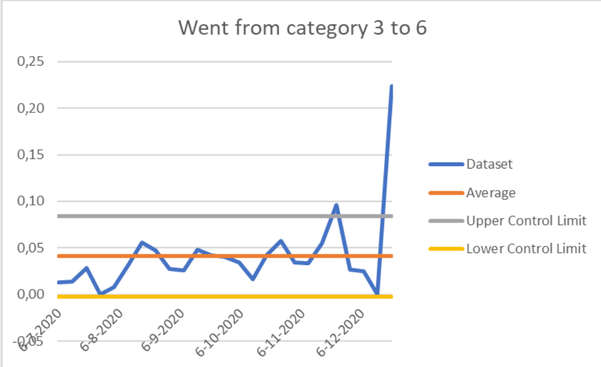

Went from category 1 to 6
Dataset
Average
Upper Control Limit
Lower Control Limit

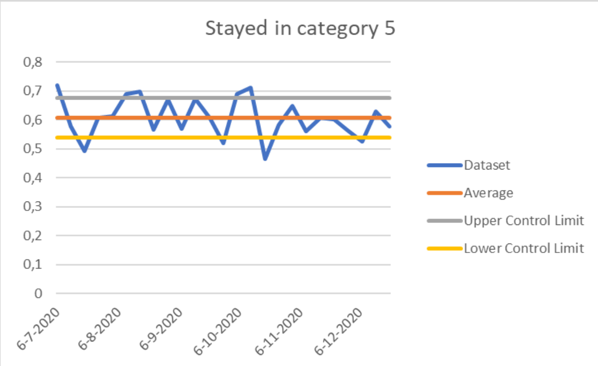

Left the process from category 1
Dataset
Average
Upper Control Limit
Lower Control Limit

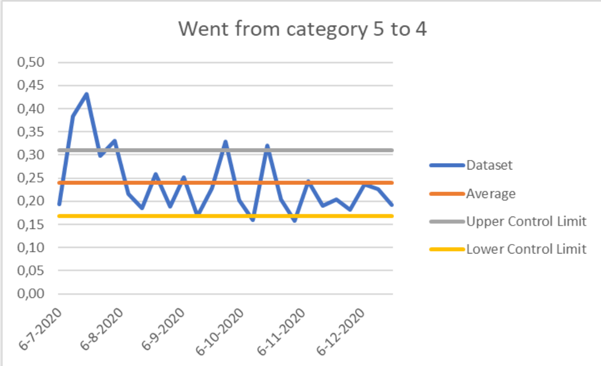

Stayed in category 3
Dataset
Average
Upper Control Limit
Lower Control Limit

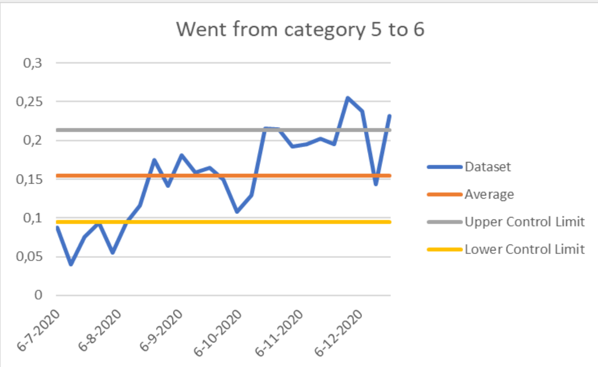

Went from category 3 to 1
Dataset
Average
Upper Control Limit
Lower Control Limit

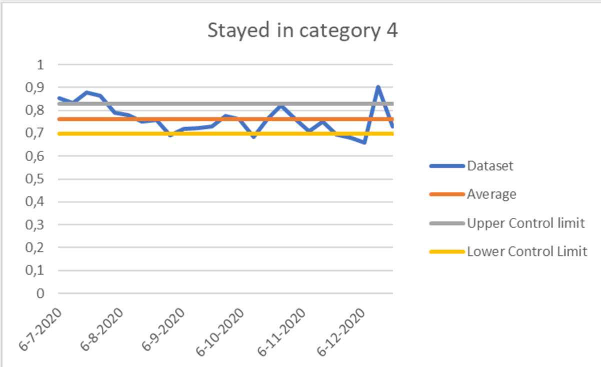

Went from category 3 to 5
Dataset
Average
Upper Control Limit
Lower Control Limit

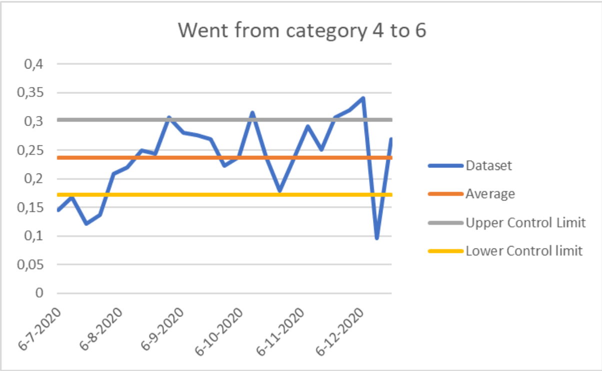

Went from category 3 to 6
Dataset
Average
Upper Control Limit
Lower Control Limit


Stayed in category 5
Dataset
Average
Upper Control Limit
Lower Control Limit


Went from category 5 to 4
Dataset
Average
Upper Control Limit
Lower Control Limit


Went from category 5 to 6
Dataset
Average
Upper Control Limit
Lower Control Limit


Stayed in category 4
Dataset
Average
Upper Control limit
Lower Control Limit


Went from category 4 to 6
0,4
0,35
0,3
0,25
0,2
0,15
0,1
0,05
0
6-7-2020
6-8-2020
6-9-2020
6-10-2020
6-11-2020
6-12-2020
Dataset
Average
Upper Control Limit
Lower Control limit