Master Thesis

Reducing Waiting Lists for Mental Healthcare Patients with Data-Driven Decisions

by

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1 SUMMARY

The need for mental health care keeps increasing. Patients deal with long waiting times, and are placed on waiting lists. People with a severe mental health disorder need to be treated as soon as possible, but sometimes this isn't possible. The use of capacity management could help significantly. Capacity management is used frequently in other health care institutes, and is meant to reduce the waiting times and waiting lists by looking at the demand and capacity, and trying to figure out the right amount of care to help as many patients as quickly as possible. This thesis discusses a way of using the available data of the mental health institute Arkin, located in Amsterdam. Arkin deals with waiting lists longer than desired, and wishes to find a way to treat these patients as soon as possible.

The goal is to build a "what-if" tool, which is based on a simulation model. The simulation model can take input that represents a "what-if" question, such as: "What if the length of stay in each capacity decreases with 10%?". The simulation tool can compute the output, which represents the answer to this specific "what-if" question. The output consists of performance measurements such as the length of the waiting list over time, the waiting times of patients, and occupation rates of departments, making it possible to use the simulation tool for predicting the influences that certain factors have on these performance measurements.

The simulation tool is implemented in Python, with the help of the library SimPy. To build the model, Process Mining is used to provide visualizations of the patient flows between the different departments and clinics of Arkin. The length of stay for departments, and the number of arrivals in the system can be retrieved from the available data provided by Arkin.

This thesis gives the answer to five different "what-if" question. The most interesting result was the answer to the question: "What if semi-acute and acute patients can be considered the same?", which gave a big reduction in the overall waiting list, occupation rate, and waiting times.

Arkin can benefit a lot from this simulation tool. Using this tool, it can be concluded that reducing the length of stay by only a few percent has a big positive impact on the waiting times. The tool can also be used to make the future more plannable. If it is expected that the number of arrivals will rise, the input of the tool can be modified in order to represent an increase in arrivals, and see the impact of it on the performance predictions.

2 INTRODUCTION

2.1 Background: Mental health issues

Mental health is becoming a more and more important topic. The amount of mental health conditions are increasing worldwide [20], which leads to increasing demand for help [18]. A shortage of help may have severe consequences, such as unnecessary disability, unemployment, substance abuse, homelessness, inappropriate incarceration, and suicide [19]. The resources for treatment of mental disorders are limited. In the Netherlands, mental health patients have to deal with long waiting times before getting their treatment [17]. The pressure on the mental health institutes is high, as a lot of responsibility lays with the townships that have limited funding. There is little attention for recovery, which often results to clients being 'full time patient', there is less staff available and technological opportunities aren't sufficiently exploited [11]. These technological opportunities can lay in different areas. Capacity management could be the answer for reducing waiting times for patients [16]. Capacity management is used to make sure that the available recourses are used optimally in order to help as many clients as possible [9]. Many hospitals outside the mental health care make use of capacity management for many of its main processes and procedures [6]. Therefore, the use of capacity management in the mental health care could provide new and useful insights.

2.2 Background: Statistical methods

At a high level, the logistic process of a healthcare institute can be seen as a queuing system where patients arrive at a system and receive service for some amount of time. An important probability distribution that can represent the interarrival- and service times is the exponential distribution. The exponential distribution has the following probability density function:

$$f_X(x) = \begin{cases} \lambda e^{-\lambda x} & x > 0 \\ 0 & \text{otherwise.} \end{cases} \tag{1}$$

An example of an exponential distribution can be seen in Figure 1 [12]. The λ is the parameter of the distribution, often referred to as the rate parameter. This parameter represents the average number of occurrences per time interval, i.e. per hour, or per day. If the exponential distribution can represent the service times (length of stay) of the departments, or the inter-arrival times of the patients, then it can be used in the simulation by drawing random values from that distribution.

An important generalization of the exponential distribution is the gamma distribution. The probability density function of the gamma distribution is as follows:

$$f_X(x) = \frac{(\frac{x-\mu}{\beta})^{\gamma-1} e^{\frac{-x-\mu}{\beta}}}{\beta\Gamma(\gamma)} \tag{2}$$

The gamma distribution has a total of three parameters: the shape, the scale and the threshold [8]. The threshold parameter μ defines the smallest value in a gamma distribution. Another word for the threshold is the location. The values of the distribution must all be greater than the threshold. A common value for the threshold is 0, which lets the distribution only have positive value. Whenever the threshold parameter is set to 0, it is often referred to as a two-parameter gamma distribution.

Loosely speaking, the shape parameter γ specifies how many events are going to be modelled. This value has to be positive, but does not need to be an integer. An example is evaluating the probabilities for the elapsed time of three accidents. The shape parameter will be 3 in this case. When evaluating one accident, the shape parameter will be 1. When the shape value is

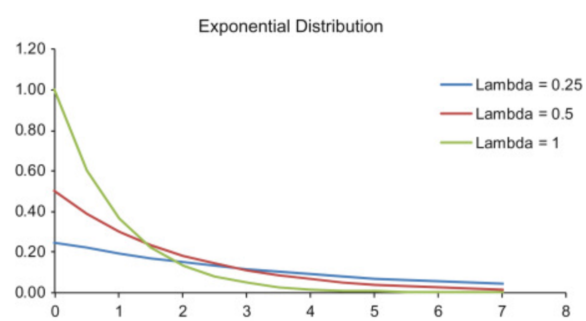

Figure 1: Examples of the exponential distribution with different values for Lambda

very high, the gamma distribution tends to approximate the normal distribution.

The scale parameter β represents the mean time between two events. For instance, the time between two accidents. If this time equals i.e. 4 days, the scale parameter will be 4. Instead of the scale parameter, the rate parameter can also be used. The scale parameter is the inverse of the rate parameter λ. The rate parameter is defined as the mean rate of occurrences during one unit of time (i.e. occurrences in one day). The relation between the scale parameter and the rate parameter is as follows:

$$\beta = 1/\lambda \tag{3}$$

$$\lambda = 1/\beta \tag{4}$$

Figure 2 illustrates how changing one of the parameters affects the distribution.

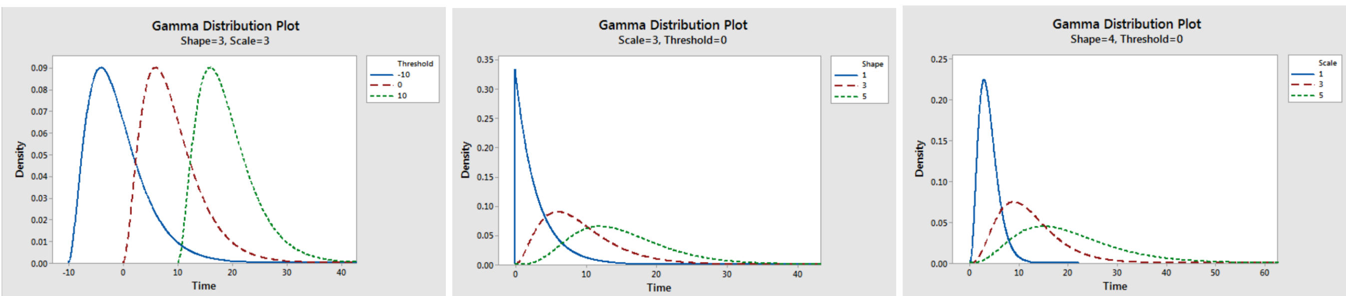

Figure 2: Examples of the exponential distribution (left) and gamma distribution

2.3 Arkin

Arkin is a mental healthcare institute based in Amsterdam, specialized in providing help to people affected by psychiatric disorders. Examples of disorders treated by Arkin are alcoholism, substance abuse, schizophrenia, psychosis, and depression [3]. Arkin has many different branches that can treat different types of patients. Examples of these branches are Arkin Jeugd Gezin (deals with mental ilnesses for youth and in families), Arkin ouderen (mental ilnesses for elderly people), Jellinek (treats patients dealing with substance abuse), and novarum (eating disorders and obesity). This thesis will focus on one specific branch, namely Mentrum. Mentrum has various clinics and staff focused on treating Serious Psychiatric Disorders (EPA). The severity of these disorders can be very high, and are considered dangerous for themselves and their surroundings. This is often caused by delusions, where i.e. a patient thinks that he or she can fly. Therefore, the need for care of these patients is high. Figure 3 shows the admission process for a patient arriving at Arkin.

This figure shows three types of arrivals: *acute*, *semi-acute* and *regular*. Altough all patients that enter this branch are considered very severe, a distinction in urgency can still be made. Acute patients need to be admitted as soon as possible, and are of the highest urgency. Regular patients can wait a bit longer usually, and are, compared to the other two types of urgency, the least severe. These patients will be admitted to one of the EPA clinics when possible. The figure already shows one of the

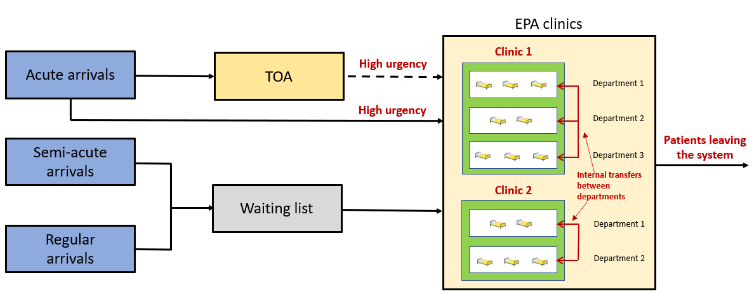

Figure 3: Illustration of the process of admitting patients

departments, the TOA. The TOA (Tijdelijke Overbruggings Afdeling, Temporal Bridging Department) admits patients that have to wait until there is a place in one of the clinics for them. Patients with a high severity that have to be admitted as soon as possible can be admitted here when there is no room yet in the clinics. More information about the TOA, urgency types, and the departments can be found in Chapter 6.

2.4 Research aim

As the number of people in need of healthcare is increasingly growing, the mental healthcare institutes desperately need to find ways in order to reduce its waiting lists. This paper will research the possibility of implementing capacity management for mental healthcare institutes by the use of process mining and simulation. The aim is to use process mining to give insights into their processes now, and use the simulation to calculate different outcomes of certain scenario's, leading to a more plannable future.

2.5 Research questions

To summarise, the goal of this thesis is to answer the following questions:

- What insights can be retrieved from the available data in health care institutes?
- How to develop a performance and capacity model for Arkin?
- How to use a performance and capacity simulation model to answer "what if" questions?

The process mining, along with some data analysis, is used to answer the first question. The simulation aims to answer the second and third question, by going through multiple scenarios and calculating what the impact is for the pressure on the available capacity.

2.6 Thesis overview

The report will start with a literature review in Chapter 3, describing how capacity management is used in hospitals. Next, Chapter 4 will go over the available data. It will highlight the most important data features, such as the urgency of patients. It will follow with data preparation for both the process mining and the simulation. Chapter 5 will explain the process mining part of thus report. It will start with an explanation of the term process mining, followed by the different tools that are used for it. After, the insights retrieved from process mining are discussed. In Chapter 6, the model design is shown and explained further. An explanation of the departments of Arkin is given, together with an explanation of the waiting lists. This chapter also gives the transition matrix, showing the probabilities of a patient moving from one department to another. Chapter 7 shows how the simulation can provide answers to different what-if scenario's. It starts with an explanation of the performance measures. The necessary input is explained after, following by a description of the researched what-if scenario's and the results of these scenario's.

3 LITERATURE REVIEW

This chapter focuses on available research regarding capacity management within the medical field. The use of capacity management in hospitals can be done in many ways. The chapter will go over various papers that describe the use of capacity management in different ways, i.e. simulation and queuing models.

3.1 Capacity management in healthcare

As mentioned (2), hospitals outside the mental healthcare domain are already making use of capacity management. This term became more important because of COVID-19. Hospitals around the world had to innovate their processes in order to separate COVID-19 patients from non-COVID-19 patients. Alban e.a. [1] developed a simple patient simulation model, called icu-covid-sim. This model supports hospital and regional planning decisions, using queing theory and patient flow simulations. The model describes the maximum rate of COVID-19 patients that can be handled with the available number of ICU beds for COVID-19 patients. For this simulation, the input needed to compute the number of patients that can be treated are the length of stay distribution, the arrival rate of COVID-19 patients and the number of ICU beds dedicated to COVID-19 patients. This simulation tool gives insights in the waiting time performance within hospitals, providing information about the amount of patients that can be handled. For a regional level, Alban e.a. suggest that it might be useful using the tool to anticipate the amount of referrals to a central hospital for any given demand level for COVID-19 recourses.

Gunal [14] describes a guide for building hospital simulation models. He states that Operational Research and Management Science methods have an essential role in improving both the planning and management of hospitals. Two views are discussed and shown how they support each other: a conceptual view, where issues like framing and speciication are discussed, and a technical view, which evaluates three simulation methods. These three different simulation methods are Discrete Event Simulation (DES), System Dynamics (SD) and Agent-Based Simulation (ABS). Gunal states that DES is a powerful method, and especially useful for systems with a strong queing structure. SD can be described as a useful forward strategic-level thinking, as it does not look at individuals but at the changes in cohorts of patients. ABS is a method with great potential. It is fairly new compared to the other two methods, being driven by self-deciding agents. Lastly, Gunal also mentions the possibility of hybrid models, combining different simulation methods in order to further improve the simulation.

Bae K. et al [4] describe the increase in the demand for Long-Term Care (LTC) amongst elderly people. The paper discusses a simulation model that simulates the patient flow to gain insights in the relationship between capacity and demand and investigate the impacts on several performance measures, such as the average waiting times for LTC patients. Bae K. et al. integrate various health care providers, such as hospitals, nursing homes, and home care. The simulation model results include the increase / decrease in the average waiting times for several ADD (Area Development Districts). The expectation of implementing the simulation model that Bae et al. has is that it will benefit both the LTC providers as the LTC patients. Decision making based on the model will help healthcare providers to make sure the needed recourses to help the patients are provided at the right time, resulting in a reduction of an unnecessary excess in resources while the patients still get the care that they need.

In the paper of McCaughey et al. [15], an extensive literature search was conducted with the use of several search engines and scholarly databases. Articles that were found were identified by keywords. The retrieved articles were later reviewed, and a selection was made to be included in this literature study. This study goes specifically about the emergency department, and is focused on improving the capacity management. In total, twenty two articles were selected, based on their relevance to the emergency department and having a focus on operations management concepts. McCaughey et al. distinguished the articles into four different groups: problems, solutions, outcomes, and metrics. McCaughey concludes that there exist a wide variety of operations literature that healthcare managers could implement. An important insight is that electronic and technological solutions to capacity management problems have a great potential, resulting in an improved quality of patient care and patient satisfaction.

Green [13] discusses the use of queuing models in healthcare, mostly due to the many delays that exist in this field. Queueing models described in this article are the Poisson process, the M/M/s model with some extensions, and the M/G/1 and GI/G/s models. The paper illustrates that some service systems are very complex, as it has both predictable and unpredictable sources of variability, both in the demand for service and the service times. Green explains that queuing theory is a very powerful and practical tool, mostly due to the fact that these models require relatively little data, and are simple and fast to use. The main advantages of queueing models is that they can be used to quickly evaluate and compare different possibilities for providing service. A downside to queueing models however, is that the operational data needed for the input of these models is sometimes unavailable in the healthcare.

3.2 Capacity management within the mental healthcare field

The previous papers were all written for health institutes like normal hospitals, not for mental health institutes. In order to find out what different approaches are used for mental health institutes, two papers are discussed that describe tackling the waiting times for these institutes.

The mental healthcare field is new to capacity management. There are not a lot of papers written for this topic. Robotham D. et al [21] evaluate the implementation of the Choice and Partnership Approach (CAPA). CAPA is a clinical system, that aims for an improvement in managing demand and capacity within child and adolescent mental health services. Robotham et al investigates how CAPA is implemented within these mental health services in England, researching the benefits and drawbacks of the system. The paper concludes that, if the model is well managed and implemented, demand and capacity models such as CAPA can provide teams with structured, and formal planning mechanisms. However, the paper also states that if the model is implemented poorly, it can cause confusion and overworking amongst staff.

Williams M. et al. [22] evaluates a successful mental health center to eliminate the wait for psychiatric services for adults. It managed to reduce the waiting times for a psychiatric appointment from 13 days to 0 days, and reduce the no-show rate from 52% to 18%. Williams et al. built a quality improvement model. This model came out in two phases. The first phase reorganized a group of staff into a centralized intake program, in order to improve efficiency and consistency across programs. It improved access to schedule appointments during the initial call, and more intake slots were made available. The second phase consisted of monitoring supply and demand, and develop a "continuous flow" system designed to match demand. This model reduced the no-show rate and crisis hospitalizations, and help increase office efficiency.

4 DATA

Capacity management requires data from the organization to work properly. This report puts focus on analyzing patient flows with process mining (Chapter 5) and the use of simulation (Chapter 7) to examine the impact of several scenarios on the waiting times and waiting lists. Both the process mining and the simulation part require data in order to work accurately. This chapter describes the available data from the organization, explaining the different and most useful features. Next, the modification of the data needed for process mining is described. Lastly, the data that is needed for use in the simulation is discussed.

4.1 Available data

The data provided by Arkin came together in different files. The first file was a data set that contained data ranging 2018 until 2020. The data set contained information about 3207 different clients. The features contained information about the client (i.e. birth date, gender, region, urgency) and about the admission itself (i.e. Start- and end date of admission, clinic, institute, etc). An important column in this data set is the key column. This column is unique for every patient, and is used for all available data sets within the mental healthcare institute. This makes it that other data sets can be added to the original data set, providing more information about different clients.

Later, another data set was provided that included data from the years 2017 until the beginning of 2022. The data set contained information about 2494 patients, but had less features than the previous data set. The most important features were the start- and end date of the admission, the clinic that the patient was admitted to, and the urgency.

Together with these data sets, data about the waiting list was also provided. The data set ranged from 2 October 2020 until 28 February 2022 and contained the dates that patients were put on the waiting list, the urgency of the patients, and the dates that the patients were admitted to the system (i.e. removed from the waiting list).

4.2 Urgency of patients

Patients can have different urgencies. In this data set, five different types of urgency were included. The urgency column consisted of regular, semi-acute, and three different types of acute urgency. The three different types of acute urgency were grouped together, resulting into the urgency column consisting of either acute, semi-acute or regular. The urgency is important, as patients with a different urgency are in need of a different type of bed. These beds lay in different departments, which means that knowing the urgency leads to knowing in which department a patient has to be placed in. An overview of all the departments within Arkin is given in Chapter 6.

4.3 Data preparation for Process Mining

For the Process Mining tool to work properly, the data needs to include three main pillars [7]. These pillars are the following: Case ID, Activity (or event), and Timestamp. The timestamp is already included in the data; the starting date of admission. The Case ID and Activity were not correctly included in the data yet. This subsection will go over how the data was modified in order for it to be ready for process mining.

The activity pillar will consist of the type of department that a patient was admitted to. The data already included the exact name of the department, but not the type (i.e. open, closed, IC). First, the department names are put into categories, with each category representing a different type of department. This is done based on information given by Arkin. Next to the different types of department, a distinction is made on the clinic. For example, the closed departments in the 1e Constantijns Huygensstraat are put into a different category (CH closed) than the closed departments in the Kliniek Nieuwe Meer (KNM closed). After the departments are put in their corresponding categories, a new column is created based on the category types. Using this column together with the timestamp gives information about when a patient was admitted in which department type.

The only pillar left now is the Case ID. The data set already included a key, distinguishing the different patients. This however is not the same as a case ID that is needed for process mining. Patients that leave the system but are re-admitted after a while get the same key. For process mining, using this key as case ID will result in paths from the department where the patient first left the system to the first department that the patient is readmitted to. To prevent this, a new column had to be made. This column is called case_number, and includes a unique number for every time a patients is (re-)admitted to the system.

4.4 Data preparation for simulation

The simulation part needed some data analysis for the input. Chapter 7 will explain the further details of this input. For now, it is important to know that the simulation needs the distributions of the service times (or length of stay) from the departments and the inter-arrival times of the patients. The service times differ per department. To determine what kind of distribution the service times have, an exponential and a gamma distribution were fitted and plotted with the data of each department. The plots for the departments within the 1e Constantijn Huygensstraat can be seen in Figure 4.

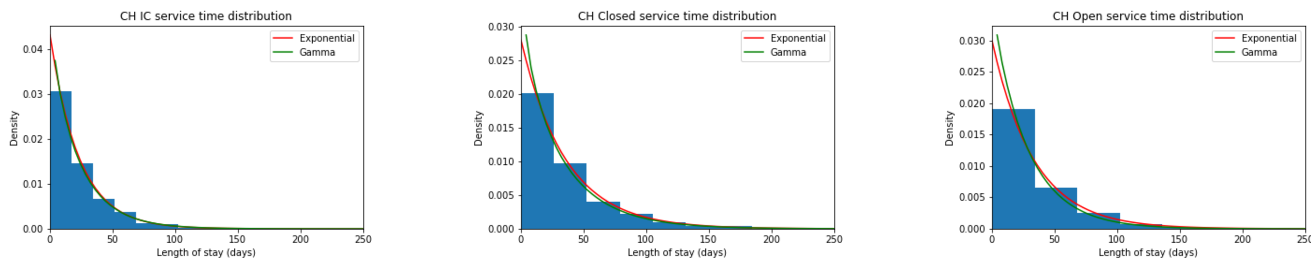

Figure 4: Service time distribution of the CH IC, CH Closed, and CH Open departments

In the plots, both the exponential and the gamma distribution seem to come very close to the actual data. Both distributions could be used to draw the service times from.

For the inter-arrival times, first a new column had to be created. This column represents the time until the next arrival. For this feature, the data of patients arriving in the TOA is used. This decision is made based on the fact that a large percentage of patients enter via the TOA. Also, using the data of the TOA alone ensures that it is only data of patients entering the system, not transferring to another department within the system. The TOA does not have incoming transfers from other departments, only new clients are admitted.

To compute this new feature, a copy of the arrival times was made. These values were shifted by one place, i.e. the last value of the orignal column was deleted and the first value of the column. Then, the shifted copy column was added back to the dataframe, and the original arrival dates column was subtracted from the copy. This resulted into inter-arrival times, representing the amount of days between two arrivals. The distribution of the inter-arrival times are shown in Figure 5.

This plot shows that on average 2.85 patients arrive per day in the system.

4.5 Waiting list and -time analysis

The last data set contained information about the waiting list, including the date of being added to the waiting list, the urgency, and the date when the patient was removed from the waiting list. From these features, a waiting list for each urgency separately

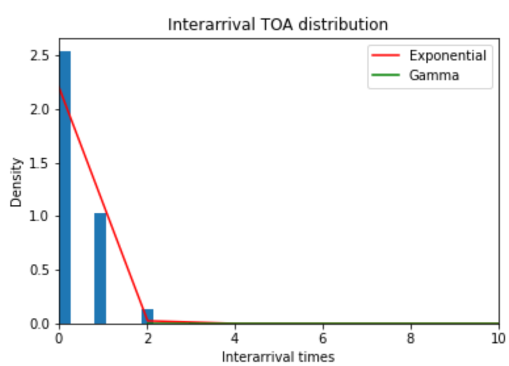

Figure 5: Inter-arrival time Distribution of the TOA

can be constructed. This is done by looping through the dates, starting from the 2nd of October until the 28th of February. By adding 1 to a variable whenever a patient is put on the waiting list and removing 1 whenever a patient is removed from the waiting list, a plot can be made for each type of urgency. These plots are seen in Figure 6.

A histogram is made from the waiting times of acute patients, and is shown in Figure 7. This histogram shows that most acute patients do not have to wait for admission. There are some outliers, as some patients had to wait over 45 days. This is considered highly unlikely and assumed to be a mistake in the data. For completion, they are included in the plot.

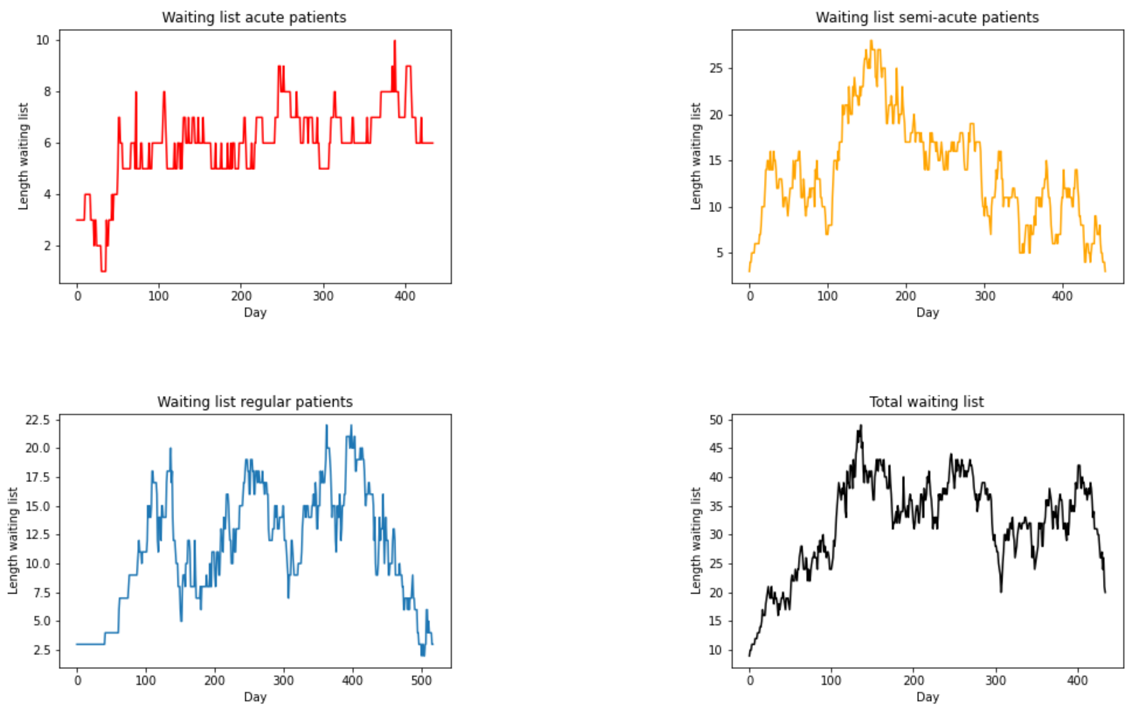

Figure 6: Waiting lists according to data provided by Arkin

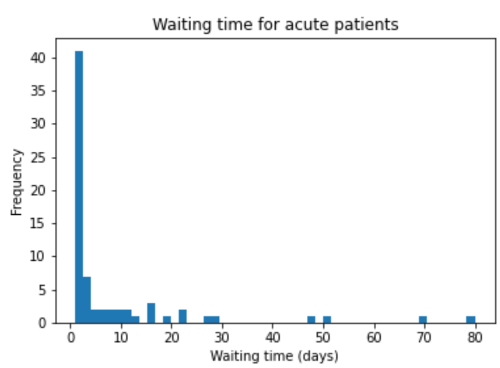

Figure 7: Wachttijden voor acute patiënten

5 PROCESS MINING

Process Mining is a powerful technique used to gain insights in the current patient flows and model of the mental healthcare institute. This chapter will start with an explanation of Process Mining, describing how it works and what kind of data it needs. After that, two different Process Mining tools are discussed and compared with each other. Lastly, various insights retrieved from the process mining are examined.

5.1 What is Process Mining?

The goal of Process Mining is to improve real business processes of a company. Process Mining aims to give insights into a company's process by visualizing the process using event data. As mentioned in Chapter 4, the key components of the process mining data are the date, the event and a unique key to distinguish the different cases. The aim of process mining is to give insight to the user of the current process performance, identify areas of improvement (i.e. by exposing bottlenecks within the system), and assess the results of process improvements.

One of the main advantages of process mining is its ability to transform many rows of data into an appealing visualization. This visualization shows how an item, or in the case of Arkin a patient, flows through the process. This can help with finding an "optimal" path for an item to go through the process as a factor of time, or costs. It can also be used in an organizational perspective, with the purpose of coming up with an optimal structure for organizational units. This thesis uses a case perspective. With the help of process mining, different cases can be analyzed, and relations between departments can be defined with probabilities of a patient moving from one department to another.

Creating a process mining visualization is done with the following steps:

- **Record activity**: When a patient is admitted to a department, it has to be recorded in the database)
- **Create event log**: Event logs are created by having the three key attributes needed for process mining as described in Chapter 4 (Case ID, event, timestamp)
- **Create visualization**: When the event logs are created, the process mining tool can automatically create a visualization of the process. Important for this thesis is that this visualization includes the volume of patients that walked a certain path.

Usually, people assume process goes differently than in reality. When asking a person how his or hers process works, it usually sounds relatively simple ("First X, than Y, etc."). In reality, processes are way more complex. Causes for this complexity can be that things have to be done over, special situations, or the possibility that the same process can be done in many ways. Figure 8 [7] shows the discrepancy between an ideal process that many people assume is happening, and the process in reality.

The reason for the difficulty of having an overview of the process are the following [7]:

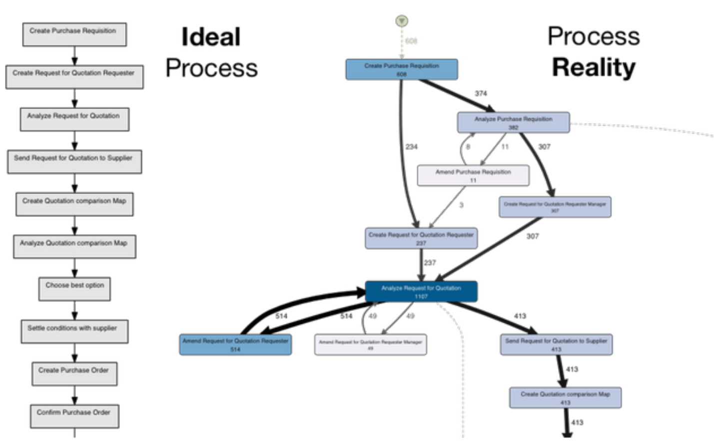

Figure 8: Example of discrepancy between a process assumption and reality

- **Subjectivity**: Usually, different people have different pictures of a process, depending on the role and perspective of that person. This makes it so difficult to get a clear overview, as it is hard to piece all these subjective views together into one objective picture.
- **Partial view**: There isn't one person that takes care of the whole process, but multiple people that take care of part of the process. Sometimes, even different companies can work on different parts of the same process. In Arkin, this can be seen as people working at a department, that only know where the patient will be sent to. They only treat the patient for a part of his or hers full treatment, and have no full image of his or hers process.
- **Change**: Processes change all the time. Whenever an analysis is done, it is most likely going to be outdated over time. It is important to have the documented processes maintained.
- **Invisibility**: Sometimes, customer cases can be missed, or lost. This could lead to missing a path in the process, or forgetting possibilities of certain routes.

Process mining fills the gap between the assumption of a process and the reality of a process, that is based on actual data. If there actually is a big gap between the assumption and reality, multiple conclusions could be drawn. If the process mining shows that the actual process is not how it is documented, it could mean that the process needs a system change. Another possibility is that the assumption of the process was wrong, and that the real process is how it should work. In this case, the assumption of the process can change, either in one's head or in the documentation.

5.2 Process Mining tools

This paper used two different process mining tools, namely PAFnow and Celonis. The two tools are compared to eachother, and their main advantages and disadvantages will be discussed.

The first tool is PAFnow. Power BI was already integrated in the system of Arkin. For the first tool, this paper looked within Power BI to explore the options. Here, PAFnow gave the opportunity to use process mining with various options of visualization. A screenshot of the process mining tool is shown in Figure 9. This tool shows the most common patient flows in the system. The number of patient flows is up to the user, and can be modified by the slider below. In this case, it is set to 10, which means this screenshot shows the 10 most frequently used patient flows of Arkins process. The arrows represent the flows, with the boxes that are put on the arrows containing information about the average length of stay and the volume of patient that walked this specific path.

The second tool this paper used is Celonis [5]. Celonis is the global leader in execution management. This paper used the free plan of Celonis, which means that not all of the available tools were utilized. A screenshot of the process mining can be seen in Figure 10. Similarly to PAF now, Celonis shows the most used routes of the patients in Arkin. The numbers on the line represent the number of patients that flowed from one department to the other. The numbers mentioned in the department boxes show the total amount of patient that went via the department to the exit. Similarly to PAF now, the number of paths displayed can be changed. In the bottom left corner, there are two options to increase the complexity of the process mining. The left option, with the blue hexagon icon, offers the option of adding a department to the process mining. The right option, with the arrow icon, reveals the next most walked path within the displayed model (i.e. only the departments that are currently shown). Next to showing the patient flow of the system, Celonis also offers the option of playing the patient flow dynamically, showing how patients moved from one department to the other over time.

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Both models are very useful for showing the flow of patients within a healthcare system. The preference of visualization depends on the user, but only Celonis offers the option to dynamically display the flow of patients.

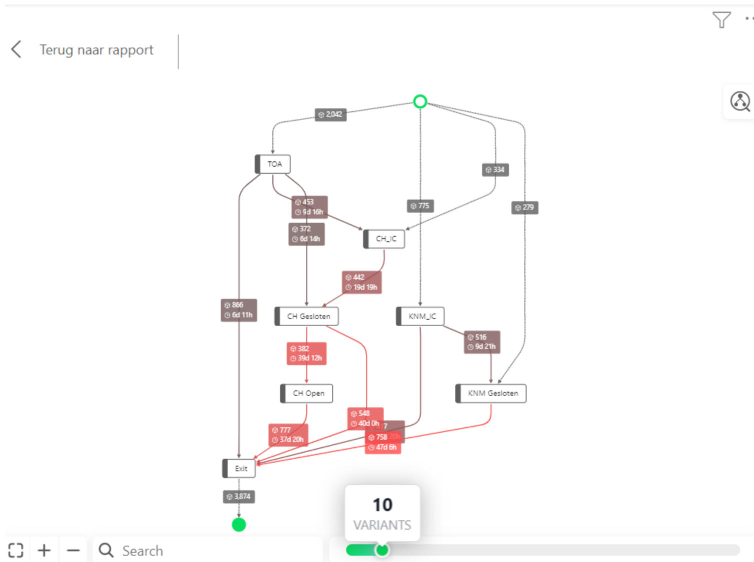

Figure 9: The PAFnow Process Mining Tool

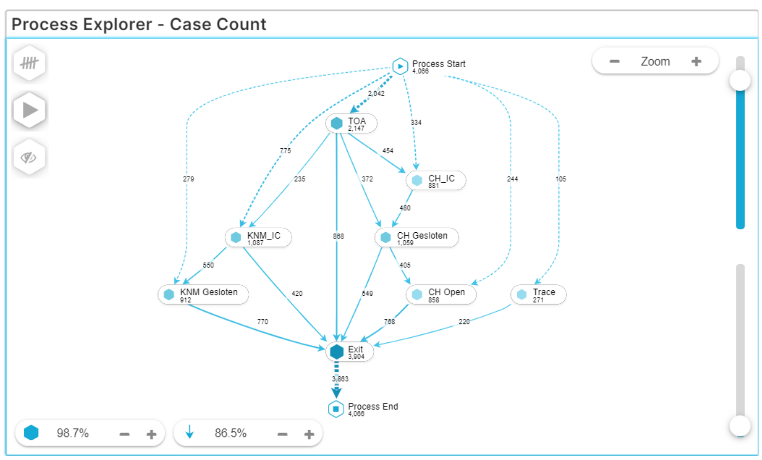

Figure 10: The Celonis Process Mining Tool

5.3 Process Mining insights

The process mining gave various insights into the system of Arkin. One of the most interesting insights is the TOA. After analyzing the processes of both tools, it appears that most patient flows include the use of the TOA (Temporal Admission Department). As mentioned in Chapter 7, the TOA is meant to be a temporary buffer for acute patients that require immediate treatment. Although the heavy use of the TOA was familiar at Arkin, the amount of patients that went via the TOA was still surprising. Out of around 3500 patients, more than 2000 followed a route via the TOA.

The most important insight retrieved from process mining is the model description. As both tools gave information about which paths were followed and how many times that path has been used, the process mining can be used as main inspiration for the model design that is used for simulation. As said before, it is usual that there is a discrepancy between a model assumption and the actual model. Visualizing the actual model is very important, as it gives a clear view of how the process of Arkin looks like in reality. This process are the building blocks of the simulation tool. connecting one department to another.

An example of a good insight from the process mining is the path of acute patients. Acute patients are believed to follow the route from an IC department, to a closed department, and exit via an open department. Process mining however showed that this is not always the case. In fact, from the around 800 patients that leave the CH IC, around 20% skip the closed department and are directly admitted to the open department and around 26% leave the system from the IC department after treatment. It appears that it happens often that patients leave the system from their initial department instead of going through i.e. the closed and open departments.

Arkin mentioned that the HIBZ and TRACE department (An explanation of these departments are found in Chapter 6) can get patients that are already in the system. From the process mining however, it shows that the probability of a patient moving from one of the departments to the HIBZ or TRACE department is very little. Most patient enter these departments from the start of the process, and leave the system after their treatment.

Looking at the outgoing paths from one department, together with its volume of patients that walked these paths, a transition probability can be made. This can be done for every department, and a transition matrix can be created. This transition matrix is shown in Chapter 6, and is used in the simulation tool. The transition matrix is a crucial part of the process, as it describes which paths are the most used, and makes it that the simulation tool comes closer to reality.

6 MODEL DESIGN

In order to make the simulation as realistic as possible, it is important to know how the system and different departments are connected to each other. The process mining comes in very handy, as it shows the most walked paths in the system. Using the process mining, the outgoing probabilities of a department can be computed. This means that, given that a patient is in a specific department, the process mining gives insight into what the probability is of that patient moving to another specific department, or leaving the system as a whole. This chapter will start with an overview of the different department types within Arkin, explaining what each department is used for, with also mentioning the capacity of the department. Next, the model design together with a probability matrix will be given, where the matrix represents the transfer probability of one department to another.

6.1 Departments of Arkin

Arkin has many different departments spread over two clinics, the 1ste Constantijn Huygensstraat (CH) and the Kliniek Nieuwe meer (KNM). In total, CH consists of 8 departments belonging to Mentrum, while KNM contains 4. Some of these departments can be considered the same, as they treat patients with similar severity and diagnosis. For this reason, the departments are put into categories. The model treats departments within the same category as one department with a capacity that is equal to the sum of the departments included. The different categories and the departments belonging to each category are shown below, with the capacities of each type of department given in Figure 11.

- **CH IC**: 1A, 1B
- **CH Closed**: 2B, 3A, 3B
- **CH Open**: 4A, 4B
- **KNM IC**: HIC+, HIC
- **KNM Closed**: MC
- **TOA**: TOA
- **TRACE**: TRACE
- **HIBZ**: HIBZ

As can be seen, the CH clinic (which includes TOA) consists of 8 departments, and KNM (which includes TRACE) consists of 4. The IC departments (CH IC & KNM IC) are meant for patients with the most acute severity. A bed in one of the IC departments can be locked and closed off from other beds. This means that the patient is alone, with the purpose of him/her not being a danger to the other patients. Next to the IC departments, there are closed departments (CH Closed, KNM Closed). Closed departments are meant for treating less severe patients, the semi-acute patients. These departments are closed off, but within the departments the patients are allowed to walk freely. These patients are often in need of strong medical attention, but are not considered to be dangerous towards other people. The departments are closed off because patients are not allowed to leave the clinic. Arkin is worried that a lot of these patients would walk away if the department was open. These patients are forced to be admitted by judicial authorization, and often do not think themselves that they are sick. The third type of department is the Open department (CH Open). Only the CH has an open department, but sometimes the staff of the KNM Closed department can treat a patient as if he/she was in an open department. Open departments are meant for the least

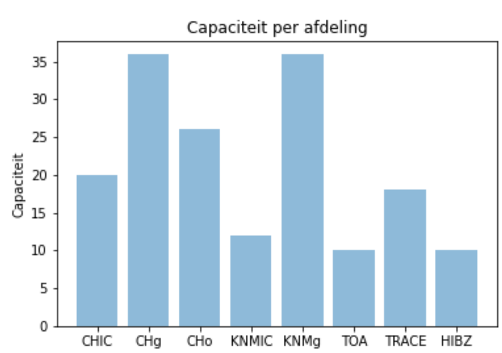

Figure 11: Capacity of each department

severe patients within Mentrum, the regular patients. These patients often admitted themselves into the department, wanting to be treated themselves. They are not considered a danger towards other people and are allowed to leave the department at will.

The TOA is an IC department, but works differently than CH IC and KNM IC. The TOA department is a Temporal Admission Unit, meaning that patients who need an IC bed, but cannot get one due to capacity limits, can be admitted here. The TOA is located in the clinic 1ste Constantijns Huygensstraat, but works for the whole of Amsterdam. Different mental healthcare providers, such as inGeest, or AMC, can make use of the TOA. Whenever a bed within one of the IC departments frees up, a patient lying in the TOA will be transferred as soon as possible to that specific bed.

The TRACE and HIBZ departments are also different from the others. TRACE is specialized in dealing patients that are mild mental disabled (i.e. patients with low IQ). These patients need different type of treatment than others. Often, it is not known beforehand whether a patient is handicapped or not. Whenever it is found out that a patient is indeed mentally handicapped, he or she will be transferred into the TRACE department to be treated properly, and leave the system once finished.

The HIBZ department is similar to the TRACE department, as it also receives patients from within the system. The difference here is the type of patients. While TRACE deals with mentally handicapped patients, HIBZ are specialized in treating aggresive patients. When patients are not willing to cooperate with their treatment, they can get violent towards the staff of the department. If this is the case, the patient will be transferred to the HIBZ department, which has staff more capable of treating aggressive patients, and will finish his or hers treatment there.

6.2 Waiting lists

What happens when all the departments are full, but there are still incoming patients? Not every patient can be admitted immediately into the needed department. As mentioned before, acute patients can make use of the TOA department when needed. However, this department is often completely full as well. Patients that cannot be admitted into one of the departments are put on a waiting list. When a bed needed by a patient on a waiting list becomes available, that patient will be admitted into that department, meaning that the waiting list will decrease by 1. Waiting lists are an important performance measure for the simulation, as it aims to find solutions for the long waiting lists.

There are three kinds of waiting lists implemented for the simulation: the acute waiting list, semi-acute waiting list, and the regular waiting list. The distinction between the different types of urgency is made so that the influence of a specific scenario on the different kinds of urgency can be tested. For example, a scenario that favors helping acute patients might have a positive influence on the waiting list for acute patients, while having a negative influence on the waiting lists of the semi-acute and regular patients.

6.3 Model

An simplified illustration of the model used for simulation can be seen in Figure 12. The model is based on the illustrations provided by both Process Mining tools in Chapter 5.

When a new patient is admitted to the system, the first thing done by the model is determine its urgency. When the patient is considered an acute patient, he or she needs a bed in one of the IC Departments. To check whether there is room, the occupancy rate of the departments are calculated. This is done by dividing the amount of patients in that department by the capacity. If the occupancy rate is not equal to 1 (i.e. there is room in the department), the patient is admitted into one of the IC units. When there is no room in either of the IC Departments, the occupancy rate of the TOA is checked in the same way. If not full, the patient will be admitted in the TOA. If the TOA is also full, the patient will be placed on the acute waiting list.

For semi-acute patients, the system will try to place the patient in one of the Closed Departments. When the closed departments are full, the semi-acute patient will be placed on the semi-acute waiting list. Regular patients will, if beds are available, be placed in the Open Department. For the regular patients it also holds that, if the capacity is full, he or she will be placed on the regular waiting list.

Acute patients can follow many paths towards the exit. The most common route of an acute patient is via the closed and open department. It is normal for an acute patient to get better slowly, meaning that after being treated in one of the IC departments, he or she can move to one of the closed departments. When a patient get sufficiently better after being treated in

Figure 12: Simplified Illustration of the Model Design used for Simulation

the closed department, the patient can be transferred to an open department.
Sometimes, acute patients can leave the system prior to this path. For example. a patient can leave the system after being treated in only the IC unit. This is also possible in the closed department, meaning the patient can leave the system without being admitted into one of the open departments.

Semi acute patients follow the same logic. The most common route here goes from the closed department through the open department to the exit. However, some semi-acute patients leave the system after treatment in the closed department. Regular patients go via the open department to the exit.

As mentioned before in Chapter 6.1, the HIBZ and TRACE departments can admit patients from the departments within the system of Arkin, as sometimes it is not known beforehand whether a patient is aggressive or mentally handicapped. The patients that are known to be mentally handicapped, or have a history of aggression, will be admitted immediately into respectively the TRACE or the HIBZ department.

6.4 Model parameters

Recall that the length of stay of all departments follow approximately an exponential distribution. The location and scale parameters are shown in Table 1 (rounded to one decimal). The inter-arrival times also follow an exponential distribution with $Location = 0.0$ and $Scale = 0.45$.

Department	Location	Scale
TOA	0.0	3.40
CH IC	0.0	23.20
CH C	0.0	35.70
CH O	0.0	33.30
KNM IC	0.0	18.80
KNM C	0.0	50.60
TRACE	0.0	56.40
HIBZ	1.0	26.75

Table 1: Parameters of the exponential distribution for length of stay for each department

6.5 Transition matrix

Recall that there are many routes that a patient can take towards the exit. For the simulation, the route that the patient takes depends on probabilities. These probabilities are computed with the help of the process mining visuals. Looking at the paths shown by the process mining tools, together with the quantity of each path, the probabilities for each transition can be calculated, and a transition matrix can be constructed. This matrix is seen in Table 2. The values are rounded to two decimals.

	TOA	CH IC	CH C	CH O	KNM IC	KNM C	TRACE	HIBZ	Exit
Start	0.50	0.08	0.05	0.06	0.19	0.07	0.03	0.02	0
TOA	0	0.24	0.19	0	0.12	0	0	0	0.45
CH IC	0	0	0.55	0.20	0	0	0	0	0.26
CH C	0	0	0	0.41	0	0	0	0	0.59
CH O	0	0	0	0	0	0	0	0	1.00
KNM IC	0	0	0	0	0	0.55	0	0	0.45
KNM C	0	0	0	0	0	0	0	0	1.00
TRACE	0	0	0	0	0	0	0	0	1.00
HIBZ	0	0	0	0	0	0	0	0	1.00

Table 2: Transition matrix of the model. The values are based on the Process Mining visuals

7 SIMULATION: WHAT-IF SCENARIO'S

The simulation can compute performance results of different inputs. Computing the outputs of different inputs and comparing them with each other can give insights to the user in what would be useful to implement in the system. It also increases the predictability of certain events. This chapter will first discuss the performance measures that the simulation can compute. After, different what-if scenarios are given and the performance measures of each scenario are computed and given, and compared to the situation as of now.

7.1 Performance measures

It is usually subjective whether one scenario gives better results than others. If the acute waiting list decreases, but the semi-acute and regular waiting lists increase, then is that a good outcome or a bad one? It all depends on the goal of the mental health institute. The goal could for example be that as many patients as possible are helped, no matter what urgency the patient has. It might also be that the mental health institute strives to have acute patients a waiting time of no longer than one day before getting admitted. To be able to compare the outcomes of different scenarios the best, and be able to find the best scenario for many different goals, the simulation will compute the following outputs:

- **Length waiting lists**: The length of the three different waiting lists (acute, semi-acute, and regular) over time.
- **Average waiting time**: The average waiting time of the three types of patients before getting admitted.
- **Occupancy rate**: The occupancy rate of each of the departments.

With these performance measures, it offers the possibility to prioritize the measurement that is most important for the health care institute. For example, if the occupancy rate of one of the departments cannot go lower than 0.8, then the simulation allows to try different inputs in order to see which scenario gives this result.

7.2 Input of the simulation

For the simulation to work, the user has to give the necessary input. This input represents a what-if scenario, where the simulation can give the results of. The input consist of the following elements:

- **Capacity**: The capacity of each department type
- **Length of stay**: The average length of stay of each department
- **Arrival rate**: The amount of arrivals per day into the system
- **Ratio urgency**: The ratio between acute, semi-acute and regular. Shows how much percent of the arrivals belong to each urgency

With this input, a lot of different scenarios can be computed. For example, a department can get an extra bed, while another department loses one. This input makes it possible to prepare the mental health institute to prepare itself against future scenario's, in order to provide the best care it can for its patients.

7.3 The What-if scenario's

In discussion with the mental health institute, several what-if questions were formulated that were interesting to investigate. These questions are as follows:

- **Scenario 1**: What if the length of stay can be shortened?
- **Scenario 2**: What if the amount of arrivals increase?
- **Scenario 3**: What if the capacities of the departments can increase?
- **Scenario 4**: What if the TOA will not be available anymore?
- **Scenario 5**: What if semi-acute and acute patients can be considered the same?

Comparing the performance measures of these scenarios with the performance measures of how the situation is now, it can give insights into how to better the system in order to get closer to the mental health institutes goal.

7.4 The system now

First, the simulation is run with the input representing the system as it is now. This means that the capacity is as shown in Figure 11, the length of stay is assumed to be exponentially distributed as shown in Figure 4. Figure 13 gives the plots of the waiting lists for acute, semi-acute, and regular patients.

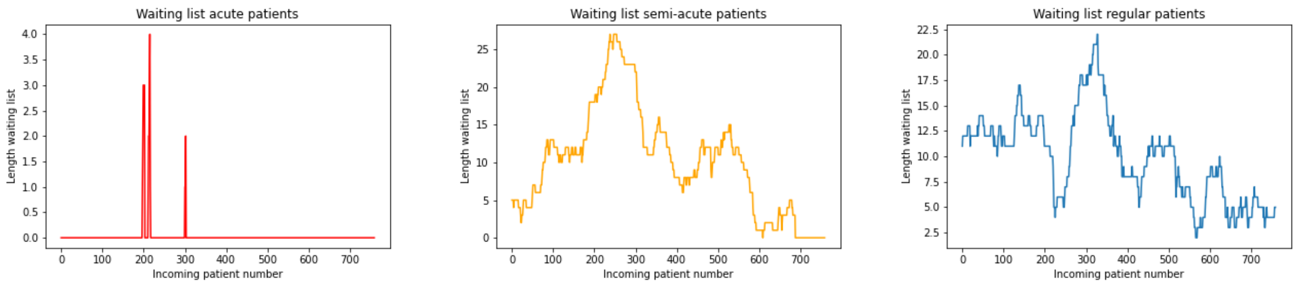

Figure 13: Waiting lists of the three different types of urgencies as of now

Figure 14: Total waiting list (left), TOA occupation rates (middle), and the waiting times for acute patients

The x-axis show the incoming patients, i.e. an x-axis value of 100 represents the waiting list at the time where the 100th patient tries to enter the system. The plot shows that the acute waiting list is mostly 0. This differs from the waiting list seen in Figure 6. The difference can be explained by the definitions of the waiting list. The waiting list retrieved from the data (Figure 6) likely considers patients in the TOA as patients on the waiting list, as they are waiting for a bed of one of the IC departments. The simulation tool however puts an acute patient on the waiting list if he or she does not have a bed at all (i.e. the patient cannot be admitted to the TOA as it is full). The semi-acute waiting list shows a mean of around 14. The mean of the regular waiting lists seems to be around 11.
Summing the values up, a plot of the total waiting list can be made. This plot is shown in Figure 14. Comparing the total waiting list to the waiting list plot in Figure 6, and having the different definitions of acute waiting list in mind, the plots look very similar.

Another interesting statistic to look at is the occupation rate, specifically of the TOA. It is already known that the TOA is used more than it is actually intended to in the Process Mining (Chapter 5). The simulation will give insight into how full the TOA is, given the input representing the situation now. The occupation rate is given in Figure 14, and has a mean of 0.19.

This figure omits the first 250 patients that are admitted to the system. The reason for this is that the simulation assumes that the system is empty at the start, while in reality, this is not the case. Starting from patient 250 therefore gives a more realistic image of the occupation rate in the TOA. This figure shows that the TOA has a low occupation rate, which was surprising. A possible explanation could be that the TOA is not only used for Arkin patients, but also other mental health institutes such as inGeest [10] or AMC [2].

The waiting times are also an interesting statistic to look at. As of now, almost all the acute patients follow a route via the TOA. Therefore, the acute waiting times for acute patients could be represented by the waiting time for acute patients before being admitted to the TOA. The waiting times are plotted in Figure 14. For this plot, the first 200 patients are omitted. The reason for this is the same as for the occupation rate plot, as the first patients are admitted to an empty system. The average waiting time of an acute patient is 0.09 days. It seems to have a similar shape as the waiting times in Figure 7.

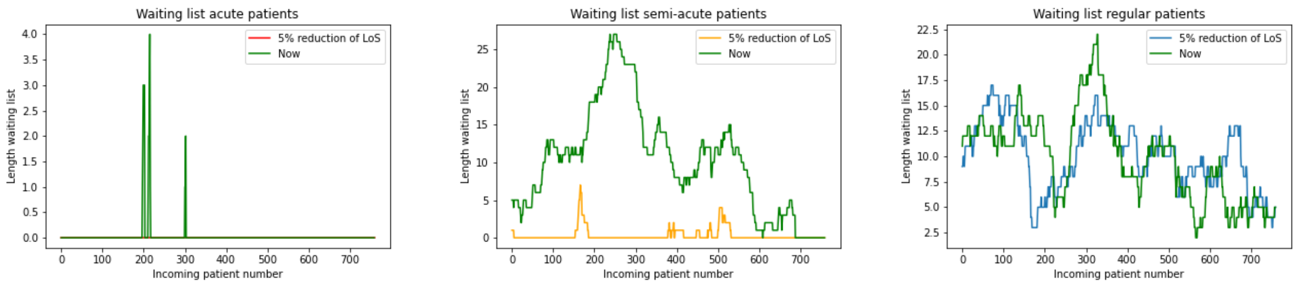

Figure 15: Waiting lists after a 5% reduction in length of stay for each department

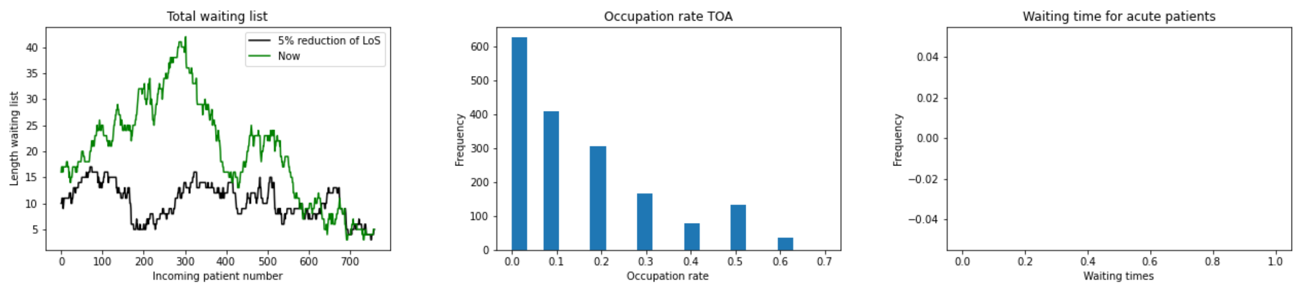

Figure 16: Total waiting list (left), TOA occupation rates (middle), and the waiting times for acute patients after a 5% reduction in length of stay for each department

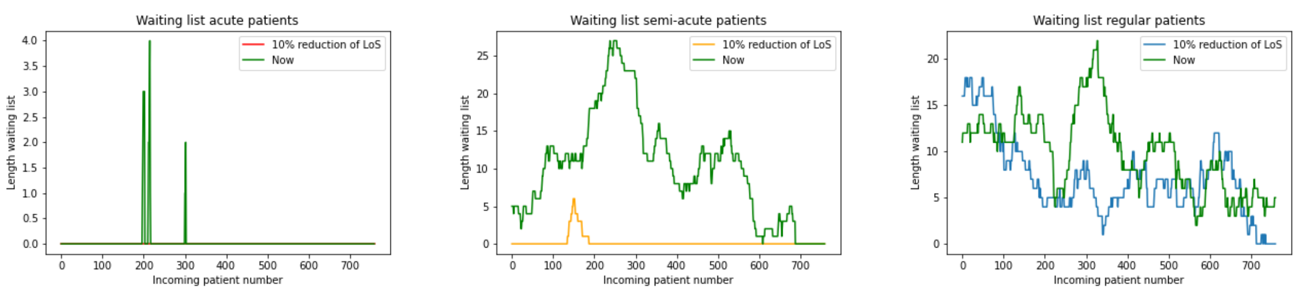

Figure 17: Waiting lists after a 10% reduction in length of stay for each department

7.5 Scenario 1: What if the length of stay can be shortened?

The first scenario discusses the effect of a reduced length of stay in the departments. Arkin has informed that a shortened length of stay could be possible, as patients often stay longer than needed in the departments. To investigate the effect of a shortened length of stay, the results of the simulation will be provided where the length of stay in each department is shortened by 5% and 10%.

A decrease of 5% in the length of stay for each department shows a significant decrease in the waiting lists and waiting times. The waiting lists for acute, semi-acute, and regular patients are shown in Figure 15, with the total waiting list, the occupation rate of the TOA, and the waiting times for acute patients being illustrated in Figure 16. The average occupation rate of the TOA is 0.14, and the average waiting time for acute patients is 0.00.

The influence of a decrease of 10% in the length of stay on the three waiting lists can be seen in Figure 17, with the plots for the total waiting list, the occupation rate of the TOA, and the waiting times for acute patients in Figure 18. The average occupation rate of the TOA will be reduced to 0.02, and the average waiting time of acute patients is 0.00.

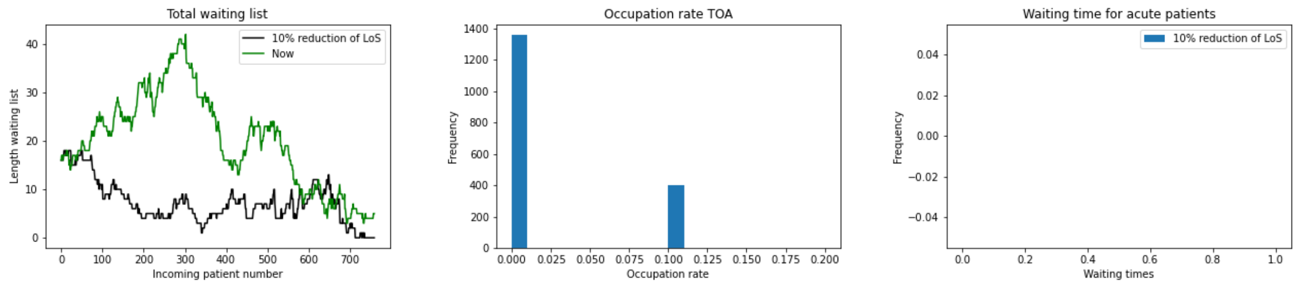

Figure 18: Total waiting list (left), TOA occupation rates (middle), and the waiting times for acute patients after a 10% reduction in length of stay for each department

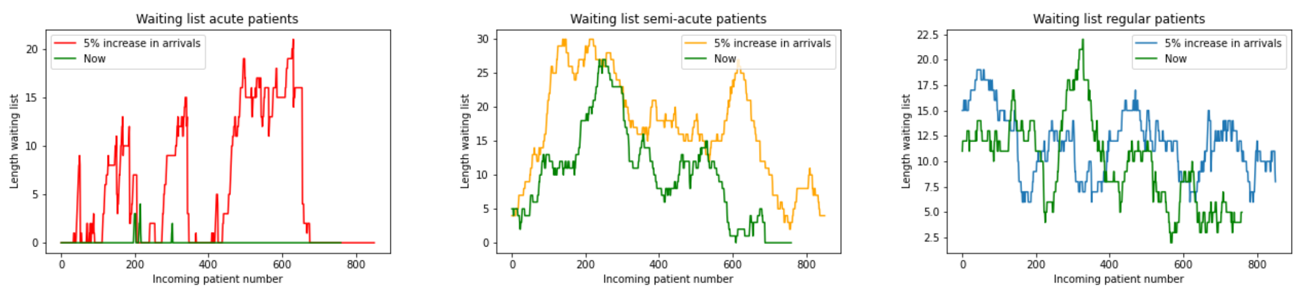

Figure 19: Waiting lists after a 5% increase in the arrivals per day

Figure 20: Total waiting list (left), TOA occupation rates (middle), and the waiting times for acute patients after a 5% increase in the arrivals per day

7.6 Scenario 2: What if the amount of arrivals increase?

The second scenario investigates the influence of an increase in arrivals. This scenario is very important, as an increase in arrivals can be a realistic expectation. The second scenario deals with increases of 5%, and 10% in the amount of arrivals per day. All the other factors are the same, i.e. the length of stay is back to how it is now.

For an increase of 5% in arrivals per day, the waiting lists are as shown in Figure 19. This figure shows that the waiting lists significantly increase for acute and semi-acute patients.

The total waiting list, occupation rate of the TOA and the waiting times for acute patients are shown in Figure 20. The waiting times for acute patients seem to have increased. The occupation rate of the TOA is on average 0.38. The average waiting time for acute patients is 1.28 days.

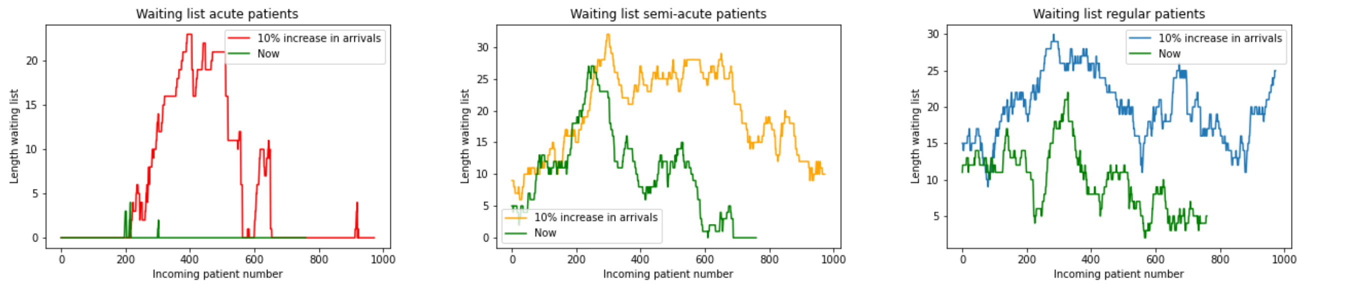

Figure 21: Waiting lists after a 10% increase in the arrivals per day

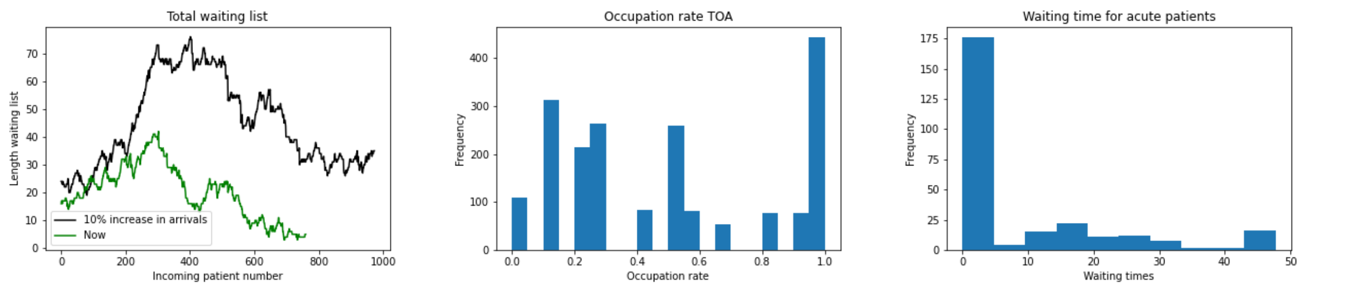

Figure 22: Total waiting list (left), TOA occupation rates (middle), and the waiting times for acute patients after a 10% increase in the arrivals per day

The results of an increase of 10% in arrivals on the different waiting lists, occupation rate of the TOA, and the waiting time of acute patients are shown in Figures 21 and 22. The average occupation rate of the TOA increases to 0.52, and the average waiting time for acute patients goes up to 9.29 days.

7.7 Scenario 3: What if the capacities of the departments can increase?

Sometimes, there is room for an increase in capacity in the departments, in order to try to help more patients. It is however not without consequences. Extra beds means extra patients in a department, resulting in more staff needed to deal with this increase of care. Therefore, it is up to the mental health institute whether the increase of care for the patients is worth the extra costs. This scenario will investigate the influence of one, and two extra beds in each department on the performance measures.

The waiting lists for all types of urgencies with 1 extra bed in each department are shown in Figure 23. The total waiting list, together with the occupation rate of the TOA and the waiting times of acute patients, are shown in Figure 24. The average occupation rate is 0.16, and the average waiting time for acute patients drops down to 0.00.

When adding 2 extra beds to each departments, the waiting lists, and other performance measurements are as shown in Figures 25 and 26. The average occupation rate of the TOA is 0.23, while the average waiting time for acute patients is 0.00.

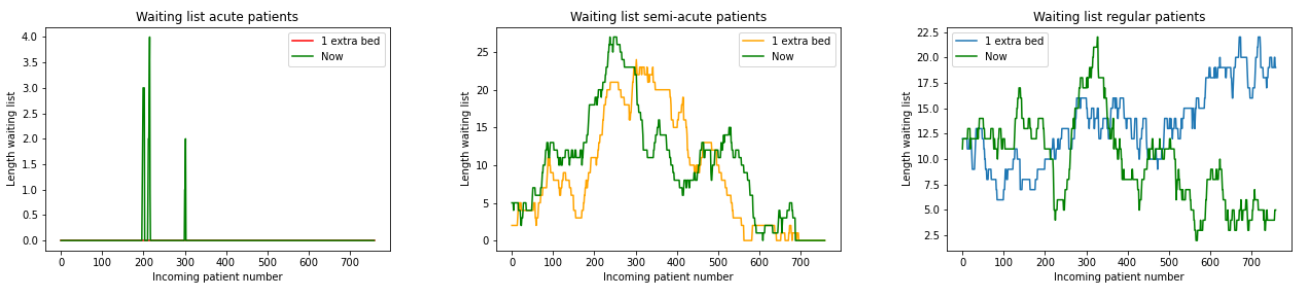

Figure 23: Waiting lists after an increase in capacity of 1 for each department

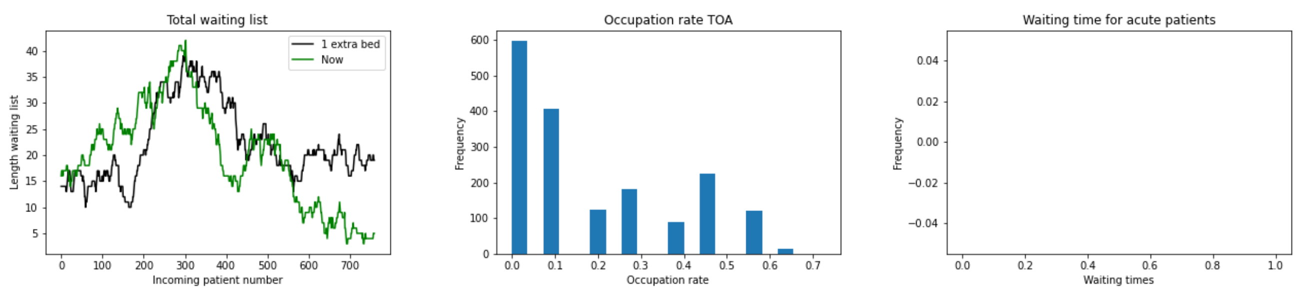

Figure 24: Total waiting list (left), TOA occupation rates (middle), and the waiting times for acute patients after an increase of 1 in capacity for each department

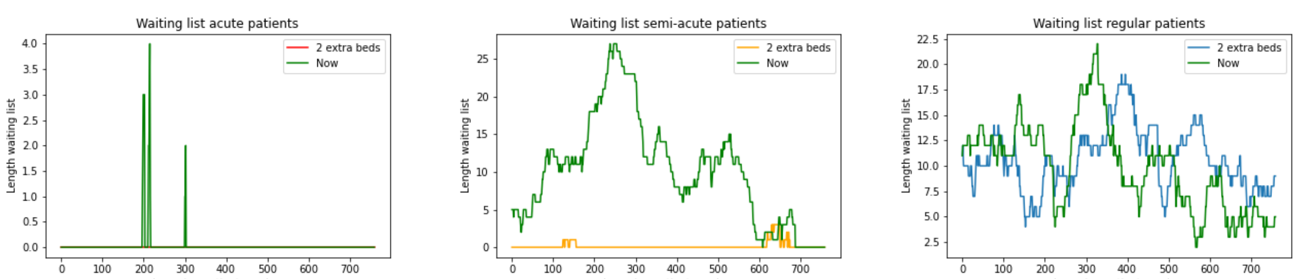

Figure 25: Waiting lists after an increase in capacity of 2 for each department

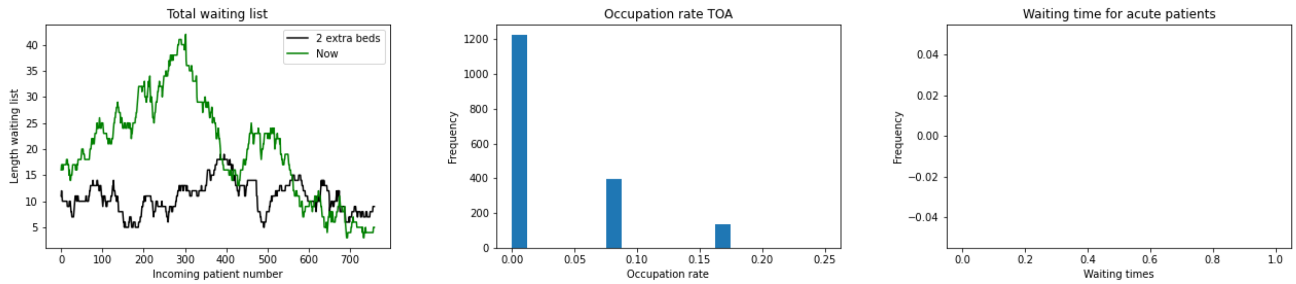

Figure 26: Total waiting list (left), TOA occupation rates (middle), and the waiting times for acute patients after an increase of 2 in capacity for each department

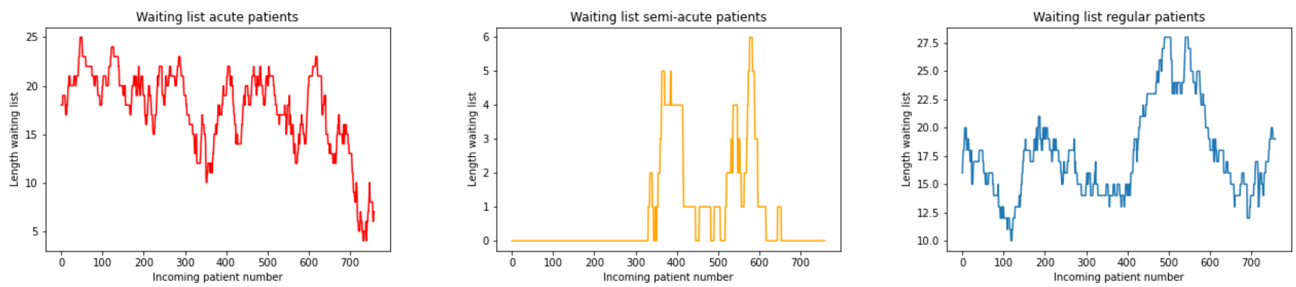

Figure 27: Waiting lists after the TOA is not available anymore

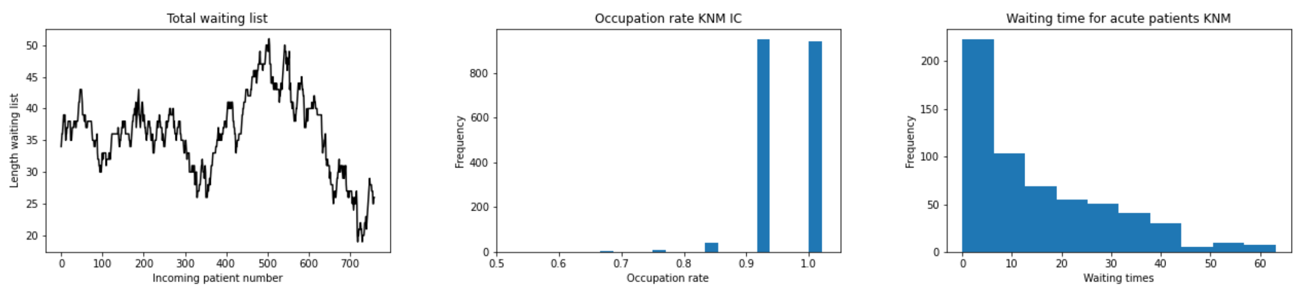

Figure 28: Total waiting list (left), CH IC occupation rates (middle), and KNM IC occupation rates when the TOA is not available anymore

7.8 Scenario 4: What if the TOA will not be available anymore?

It could be a realistic scenario that the TOA cannot be used anymore in the future. Therefore, Arkin is interested in knowing what would happen if the TOA is not available. The way this scenario is modeled is as follows: The TOA is completely omitted. Whenever the IC departments are full, patients have a 50/50 chance of having to wait for either the CH IC department or the KNM IC department.

The plots for the waiting lists are shown in Figure 27. The total waiting list, together with the occupation rate of the KNM IC and the waiting times of acute patients for the KNM IC are shown in Figure 28. The waiting lists increase significantly, which shows the importance of the TOA. The occupation rates of both IC departments are very high. The average occupation rate of both IC departments are around 0.96. The average waiting time to get into the KNM IC is 14.89 days.

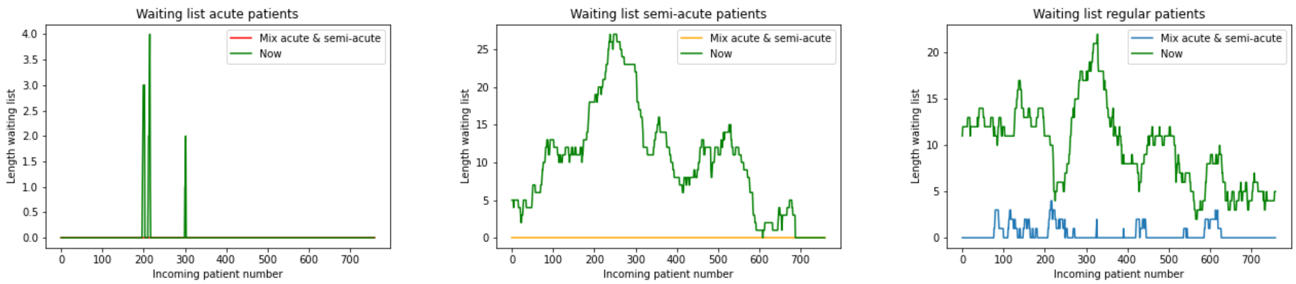

Figure 29: Waiting lists after combing the acute urgency with the semi-acute urgency

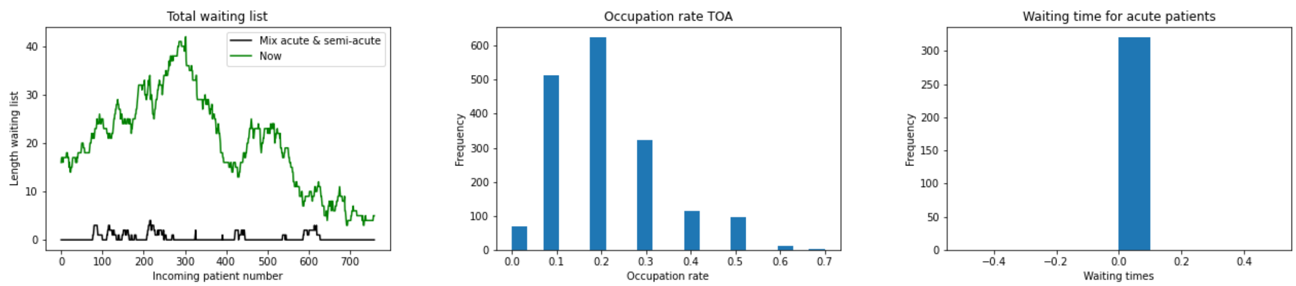

Figure 30: Total waiting list (left), TOA occupation rate (middle), and the acute waiting times after combining the acute urgency with the semi-acute urgency

7.9 Scenario 5: What if semi-acute and acute patients can be considered the same?

Semi-acute patients can be considered very severe. It might be interesting to see what happens when these patients are considered acute. For this scenario, the semi-acute urgency is deleted. Patients that were supposed to be semi-acute, are now treated as acute and will be admitted to an IC department.

The results for the waiting lists are shown in Figure 29. The results of this scenario are very interesting, considering the waiting lists for acute patients being very low. A possible explanation could be that, because there are no semi-acute patients in need of a closed department, the inter waiting times are reduced (i.e. acute patients have to wait less for a bed in a closed department). The total waiting list, occupation rate of the TOA, and the waiting times for acute patients are shown in Figure 30. The TOA occupation rate goes to 0.23, while the acute waiting times go to 0.00.

7.10 Overview of waiting times and TOA occupation rate

Table 3 gives an overview of the different waiting times for acute patients and occupation rates of the TOA, to make comparing the scenarios in regards to these measurements easier.

Scenario	Avg acute waiting time (days)	Avg. TOA occ rate
Now	0.09	0.19
5% decrease LoS	0.0	0.14
10% decrease LoS	0.0	35.70
5% increase arrivals	1.28	0.38
10% increase arrivals	9.29	0.52
1 extra bed	0.0	0.16
2 extra beds	0.0	0.23
No TOA	14.89	-
Mix urgency	0.0	0.23

Table 3: Overview of the different acute waiting times and TOA occupation rates

8 CONCLUSIONS AND RECOMMENDATIONS

After examining all the results of the different scenarios, conclusions can be made about the effects of these scenarios on the performance metrics. This chapter will go over these conclusions, and will give recommendations to Arkin that are based on the simulation tool.

8.1 Scenario 1: Shortened length of stay

A shortened length of stay results in a positive influence on the performance measurements as expected. Between the 5% and 10% decrease in length of stay, there does not seem to be a big reduction of the waiting lists. However, based on the plots of the occupation rate of the TOA and the waiting time for acute patients, a 10% decrease in length of stay has a significant impact into improving the performance, resulting into being able to help more patients.

For Arkin, it can be very beneficial to research the possibilities of reducing the length of stay of patients. This could be done by reducing unnecessary stays in the departments, or offering alternative care, such as home care. Unnecessary stays can be prevented by performing checks more often by the psychiatrists, minimizing the chances of a patient staying longer in a department than needed.

8.2 Scenario 2: Increase in arrivals

The need for mental healthcare keeps increasing. An increase in arrivals therefore is not unrealistic at all. From the plots for an increase of 5% and 10% in arrivals, it looks like it does have a significant impact on the performance measures. For the increase of 10% in arrivals, some waiting times are going up a lot. The waiting lists also increase, and the difference of a 5% increase compared to a 10% increase of the total waiting list is significant.

Because there is a rise in need for mental health care, Arkin should prepare themselves for a rise in arrivals. Arkin can use the simulation tool to see which factors could counter the increase in arrivals. For example, how much should the length of stay be shortened to handle an increase of 10% in arrivals?

8.3 Scenario 3: Increase of capacities

The increase in capacities is not as realistic as other scenarios. An increase in capacities is costly, as it needs staff to treat a patient and take care of the extra bed. However, it is still important to investigate what the influence of an extra bed has on the performance. From the plots, the most interesting result is that the waiting times decrease significantly. Longer waiting times are much rarer and decrease when adding 1 or 2 beds to each department. Adding capacity has a positive influence on all the performance measurements.

Arkin made it clear that an increase in capacity is not realistic. As the influence of extra capacity is relatively small compared to i.e. a reduced length of stay, the advice is to not further investigate this option until it becomes easier to expand the capacity.

8.4 Scenario 4: No TOA available

To research what the influence is of the removal of the TOA, the TOA was omitted in the possible paths for patient, meaning acute patients will wait for a bed on either the CH IC or the KNM IC. From the total waiting list plot, it can be seen that the waiting lists do significantly increase, with a high peak of around 50 patients, with both IC departments being almost always close to full. On top of that, the waiting times for acute patients significantly increase.

When a removal of TOA actually happens, Arkin has to find ways to prepare itself for it. Using the simulation tool with different inputs can help with predicting which factors can help limit the waiting list when the TOA will not be available anymore.

8.5 Scenario 5: Combining acute & semi-acute

This scenario gave very interesting results. By combining these two types of urgency, all the performance measurements drastically improved. The reason for this could be that the removal of semi-acute patients in need of a bed in the closed department, resulting in less waiting time for acute patients that flow from an IC department to a closed department.

Arkin could definitely experiment with this scenario more extensively. As acute patients have to wait less for a bed in the closed department, the length of stay of these patients decrease as well. This could be a simple and cost free method in order to reduce the waiting lists, while also reducing the occupation rate of the TOA and the waiting times.

8.6 Research questions

The research questions of this thesis were as follows:

- What insights can be retrieved from the available data in health care institutes?
- How to develop a performance and capacity model for Arkin?
- How to use a performance and capacity simulation model to answer "What If" questions?

The data brought very valuable information for the model built. Arkin already recorded the data of previous patients that were admitted into the system. Without this data, nothing in this report would have been possible. The data was needed for the process mining, and the model parameters. Insights that were gotten from this data is answers to many what-if questions, as the data made the simulation tool available to use.

With the use of Python and the SimPy library, the simulation tool had been made. The design of this model was based on the visualization made with process mining. The answer to the second research question would be that, with the help of process mining, a model can be developed that can compute the performance of a certain scenario, represented by the input.

The input can be seen as "what-if" question. The simulation tool is used to answer these what-if questions, and gives as output the answer in the form of performance measurements of Arkin. These performance measurements were the length of the waiting lists over time, the waiting times for acute patients, and the occupation rate. The input can be changed at will, allowing the user to form his or her what-if question to the simulation tool.

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