REDUCING STAFF WORKLOAD VARIATION THROUGH A FORECAST-DRIVEN TACTICAL STAFF PLANNING

A case study at the obstetrics department of Diakonessenhuis Utrecht

Master thesis

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MANAGEMENT SUMMARY

Current situation

This research aims to improve the tactical staff planning at the obstetrics department of Diakonessenhuis Utrecht. The obstetrics department consists of the obstetrics and triage department where pregnant inpatients and outpatients are treated. Within the obstetrics department patients are provided medical assistance during and after the delivery. The triage department provides care for pregnant patients that experience complications before the delivery. The aim of the department is to provide the total medical care before, during, and after a pregnancy.

Currently, the obstetrics department is experiencing capacity problems, specifically a shortage of staff. This leads to an unsafe environment where patients that require medical care either need to be refused or transferred in situations of peak demand. We identified that the shortage of staff could be caused by the current tactical staff planning, which is a guideline for the number of required nurses per day. The current tactical staff planning is not tailored to patient demand, which means that the number of available nurses is not distributed efficiently throughout the week. This leads to a lot of variation in the staff workload with an average of 44%, which means that the planned nurses are underutilized. Therefore, this research aims to develop a model that generates an improved tactical staff planning, which serves as a guideline for the required number of nurses for every day of the week. The improved tactical staff planning aims to increase the staff workload while maintaining the patient demand coverage percentage.

Methodology

We developed a solution approach to generate an improved tactical staff planning which is tailored to the current patient demand at the obstetrics department. The two phase model that we use to estimate the total number of patients consists of a forecasting model and an adapted version of the convolution model. Through the use of patient demand forecasting, we predicted the number of arriving patients at the obstetrics and triage department. We used the forecasted patient arrivals as an input for an adapted version of the convolution model, which is able to calculate the total number of patients based on probability distributions of the number of patient arrivals and the patient length of stay. The output of the convolution model is the number of expected patients based on a specific percentile of the total patient demand. As the management of the obstetrics department aims to provide medical care for 100% of all patients, we examine the convolution model output that provides at least 100% patient demand coverage. Using nurse-to-patient ratios established with expert opinion, we converted the total patient demand to a tactical staff planning, which consists of the total number of required nurses for every day of the week. Figure 1 shows a flowchart of the solution approach we used.

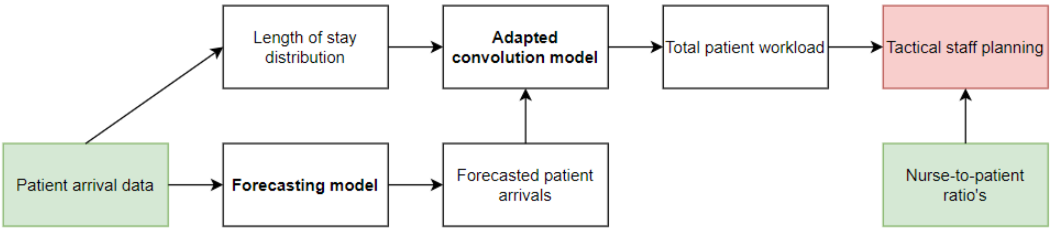

Figure 1: Flowchart of the solution approach we developed. Within the solution approach we use patient arrival data and nurse-to-patient ratio's as inputs (green) and transform this data to a tactical staff planning through a forecasting model and an adapted version of the convolution model, which serve as a two-phase model

Results

We used the two phase model to generate an improved tactical staff planning, which is tailored to current patient demand. We compared the improved tactical staff planning to the current tactical staff planning based on the staff workload percentage and the patient demand coverage percentage. The improved tactical staff planning increases the average staff workload by 15%, thus utilizing the planned staff more efficiently, while still providing care for almost 100% of all patients. Using the improved tactical staff planning, the obstetrics department can reduce the average number of obstetrics nurses by 1 or 2, and the average number of recovery nurses by 3 or 4. The results of our research provide both scientific and practical contributions. Concerning the scientific contributions, we provided a proof of concept of a forecast-driven convolution model that generates a tactical staff planning in an obstetrics environment. To the best of our knowledge, this is a novelty within literature and also adds to the scientific landscape covering the obstetrics department in hospitals. Furthermore, we contributed to the field of patient demand forecasting for an obstetrics department, as it is not widely covered.

Our research also provides several practical contributions for the obstetrics department. The two phase model we developed can be used in two ways. First, the output of the convolution model indicates the total number of patients at the obstetrics and triage department, which provides insight into periods of high and low patient demand. Secondly, using the nurse-to-patient ratios, the impact of the total number of patients on the required number of nurses can be analyzed. Using the proposed tactical staff planning increases the staff workload and reduces the number of required nurses. The freed capacity can be redistributed to deal with days of peak demand, which reduces the number of patients that have to be either rejected or transferred.

Before the solution can be implemented, the obstetrics department needs to investigate why a shortage of staff is experienced, while our research suggests that the number of planned nurses can be reduced. The tactical staff planning we develop only prescribes the required number of nurses and is based on nurse-to-patient ratios. The department should investigate whether the number of nurses actually planned matches the required number of nurses and if the nurse-to-patient ratios are accurate. Verifying both leads to a more accurate interpretation of the results and validates the use of the proposed solution. We suggest that the department uses this research as an incentive to redesign the current tactical staff planning. The proposed tactical staff planning provides an objective basis that can serve as a starting point to distribute the available staff capacity more efficiently by increasing the staff workload and maintaining the patient demand coverage percentage.

ACKNOWLEDGEMENTS

My research at the Diakonessenhuis Utrecht marks the last hurdle I had to overcome before graduating and finishing my degree in Industrial Engineering and Management.

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I am also thankful for my family, friends, loved ones, and everyone that let me ramble on about my thesis. Especially, I want to thank my girlfriend, Isabel, who I had endless conversations with about my thesis. I am glad to have a good support system which allowed me successfully complete this project.

I hope you enjoy reading my thesis,

Koen Zoetekouw

CONTENTS

1 INTRODUCTION

This thesis focuses on developing a tactical staff planning at the obstetrics department of the Diakonessenhuis Utrecht to reduce variation in workload. In this chapter we collect, define, and identify the core problems. Based on these core problems, we introduce the structure of this thesis. Section 1.1 gives some background information and in Section 1.2 we conduct a problem analysis to identify the core problems at the obstetrics department. Lastly, Section 1.3 contains the main research question and sub-questions which form the main structure of this thesis.

1.1 Background information

This research takes place in the Diakonessenhuis Utrecht. It is a hospital located in the city of Utrecht, the Netherlands, and has branch locations in Zeist and Doorn. The Diakonessenhuis has 500 beds and treats both inpatients and outpatients [1]. The hospital is organized in departments, one of which is the gynecology and obstetrics department. Within this department around 3000 births per year take place, and the department is designed such that a pregnant woman can be provided with medical care during all phases of pregnancy. The department consists of the gynecology outpatient clinic, the obstetrics ward, and the triage department. The gynecology outpatient clinic treats outpatients with gynecological health-related issues. The gynecologists provide specific medical interventions, such as a c-section. The obstetrics ward consists of 18 maternity suites which are used to give birth and provide continuous, specialized, care for pregnant women during labor. Lastly, the triage department provides acute care to patients by assessing the severity of health complaints and determining the best follow-up treatment. The triage department consists of one examination room, four consultation beds and four beds for inpatients [2].

1.2 Problem identification

The goal of this section is to identify the core problem and give structure to the research. In Section 1.2.1 we discuss the problem context, which gives more background information about the problem we studied. Section 1.2.2 elaborates on the problem analysis using a problem cluster and identifying the core problems. Furthermore, we select the core problems of interest for this research to narrow down the scope.

1.2.1 Problem context

In 2021 there was a high number of births in comparison to previous years [3], partially due to the COVID-19 pandemic. in 2021 the number of births increased with 10.000 with respect to 2020, which is in crease of around 7%. This led to high pressure on the obstetrics department and resulted in an unsafe environment for pregnant woman, because of patient refusals and patient transfers [4].
Although the number of births have dropped to an average level in 2022 the capacity problems at the obstetrics department still persist. The main problem is a lack of available staff, in particular obstetric nurses, which cause patient refusals or transfers. The hospital wants to provide care for every patient that needs it, and the lack of capacity has an influence on the performance. The lack of capacity, in this case the shortage of staff, leads to patient refusals and patient transfers which have a negative

impact on patient well-being. However, when a shortage of staff is experienced, just hiring more staff is often not the optimal solution. Allocating the available staff more efficiently is therefore a better start of tackling the problem. Thus, it is of utmost importance to identify the core problems within the department. This thesis focuses on resolving some of these problems and consequently relieve the working pressure that is currently being experienced at the obstetrics department. In the next section, we collect the relevant problems that contribute to the capacity problems at the obstetrics department and identify the core problems that we use to structure this research.

1.2.2 Core problems

To identify the causes of capacity problems, we made an inventory of the problems that occur at the gynecology and obstetrics department at the Diakonessenhuis Utrecht. Following the Managerial Problem-Solving Method from Heerkens and van Winden [5], we collected the relevant problems, and visualized them using a problem cluster where we identify the cause and effect relationships between the problems. Core problems are easily identified in this problem cluster, as they do not have a cause and thus affect all the consequential problems in the cluster. Solving the core problems leads to solving all the subsequent problems, which is the main focus of this thesis. The problem cluster can be found in Appendix A, where we highlighted the core problems that follow from the cluster. In the next part, we elaborate on the core problems that we identified.

1. **There is no forecast available of future patient demand**

There is no forecast of future patient demand available at the obstetrics department. Without insight into future demand, it is difficult to plan personnel, especially because the workload at the department varies a lot within a week and within a day. Balancing the workload to make sure that supply, number of personnel planned, and demand, patients that need medical assistance, are matched is therefore a challenge.

2. **The current tactical staff planning does not incorporate uncertainty**

Currently, the planner of the obstetrics department makes a staff planning based on a blueprint planning. This blueprint planning, which was made over 20 years ago, consists of a fixed number of personnel that needs to be planned every day to make sure that demand is met. We assume that demand has changed since then, and therefore the blueprint planning may not be suitable anymore to cope with current demand. Furthermore, the number of patients arriving at the obstetrics department is stochastic, which means that there is a lot of uncertainty around the total number of patients arriving every day. the current blueprint planning does not incorporate this stochasticity and is therefore is not able to deal with moments of peak demand. The blueprint planning exists on a tactical level, which means that the planning horizon varies from 4 weeks to 6 months. In this case, the planning is made two months in advance. We explain the tactical level in detail in the next chapter.

3. **The change in a patient's condition is uncertain**

The obstetrics department offers different types of medical care, therefore, when patients enter the system, their care pathway depends on their medical condition. This means that patients require different medical attention and a broad variation of resources during their stay in the department. Changes in the medical condition can happen at any time, which means that here is a lot of uncertainty in the need for different personnel throughout the day. As an effect, the degree of workload varies, and it becomes more difficult to have an accurate insight into the actual available capacity at the department.

4. **Only four hospitalization rooms available at the triage department for pregnant patients (>16 weeks)**

Another core problem is the shortage of space at the triage department. The triage department can only utilize four rooms for the hospitalization of pregnant patients (>16 weeks) which could result in problems during high-workload situations.

The number of rooms available at the triage department is a strategic decision, hence falls outside the scope of this research. To narrow down the scope, this research is focused on the first three core problems that are mentioned earlier. The problem that patients can not give birth at the hospitals' obstetrics department at peak levels of workload is selected as the action problem for this research. The action problem is derived from the problem cluster, as it is the problem that does not have any consequential problem. The variation of workload at the obstetrics department will serve as the main KPI for this research. Solving the core problems results in solving the action problem. In the next section, we will elaborate on the methodology that we used to solve the core problems.

1.3 Problem statement

In Section 1.2 we identified the core problems that contribute to the capacity issues at the obstetrics department. In this section, we discuss the methodology that we used to solve these core problems. The main problem is that the current tactical staff planning does not incorporate the uncertainty that comes with patient arrivals and patient length of stay. The current tactical staff planning consists of a blueprint that prescribes the same number of nurses every day, while the patient demand at the obstetrics department is dynamic. We illustrate this effect in Figure 1.1, where the figure on the left represents the current tactical staff planning and the figure on the right the proposed tactical staff planning. We can see that the current tactical staff planning provides a lot of variation in staff workload as it plans a static number of nurses every day, even though the number of required nurses is much lower during the weekend. By developing an improved tactical staff planning that is tailored to the dynamic patient demand, we can level the workload and reduce workload variation by planning the available number of nurses more efficiently.

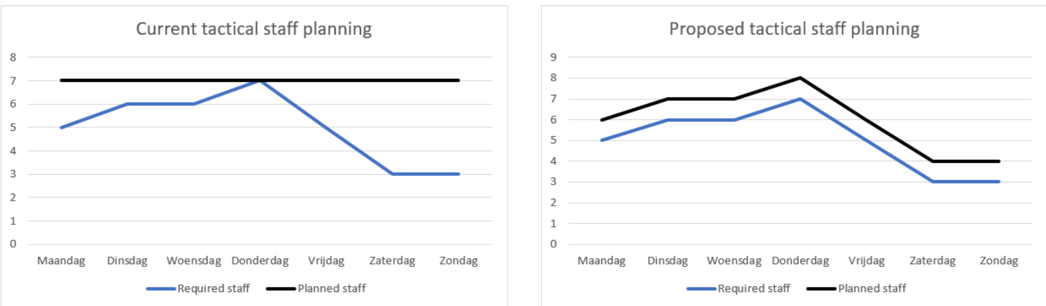


Figure 1.1: Illustration of the benefit of using a tactical staff planning that is tailored to the dynamic patient demand.

However, to develop a tactical staff planning that is tailored to the dynamic patient demand, we need insight into future patient demand. By using patient demand forecasting, we can provide this insight and use this as an input for our tactical staff planning. In this research, we develop a forecast-driven tactical staff planning model to generate an improved tactical staff planning for the obstetrics department to reduce the variation in staff workload. We structure this research using the main research question, and the subsequent sub-questions.

Therefore, the main research question for this research is:

"To what extent can the variation in staff workload at the hospitals' obstetrics department be minimized by developing an improved tactical planning of staff at the obstetrics department using forecasted patient demand?"

We developed several sub-questions, which will serve as a structure for this research and to solve the main research question.

1. **Which techniques are used to ...**

1a. ... forecast patient demand in the obstetrics department

Chapter 2 discusses relevant methods from the literature. Within this literature review, several forecasting methods that are used in a healthcare context are discussed together with their benefits and drawbacks. We will choose a suitable forecasting method and develop a forecasting model for the patient demand at the obstetrics department in Chapter 4.

1b. ... generate a tactical staff blueprint planning based on forecasted patient demand?

Furthermore, in Chapter 2, we will review the methods that are able to generate a tactical staff blueprint planning based on forecasted demand and select the most suitable technique. We develop a method that uses the appropriate forecasting model output as an input in Chapter 4.

2. **How is the obstetrics department currently organized, and what are the characteristics of the patient arrival data?**

In Chapter 3, we provide an overview of the patient flows, nurse types, and the current staff planning method of the obstetrics department in the Diakonessenhuis. We visualize and quantify the patient flows to analyze the patient arrival patterns and trends. This information is used to shape the parameters of the model developed in Chapter 4.

3. **How can we create a tactical staff planning model which uses forecasted patient demand as an input?**

In Chapter 4 we develop a two phase model to generate a tactical staff planning model. The parameters and inputs of the model are shaped by the conclusions of Chapter 3. The first stage consists of a forecasting model to estimate patient demand. The second stage uses the forecasting model output to generate the total patient workload.

4. **How can we convert the model output to a tactical staff planning and what is the performance of the generated tactical staff planning compared to the current tactical staff planning?**

The output of the model developed in Chapter 4 is used to convert to a tactical staff planning using nurse-patient ratio's in Chapter 5. The current tactical staff planning is used as a baseline and compared to the generated tactical staff planning. We evaluate the tactical staff planning on two defined KPIs, the patient demand coverage percentage and the staff workload percentage.

5. **How can we implement the generated tactical staff planning at the obstetrics department, and what are the obstacles that come with implementation?**

Chapter 6 concludes this research by answering the research question and critically reflecting on the outcomes and research approach. We also elaborate on the best way to implement the findings of this research. Furthermore, we will discuss opportunities for further research.

2 LITERATURE REVIEW

In this chapter, we aim to answer research question 1a and 1b. First, Section 2.1 provides the theoretical framework for this research. In Section 2.2 we will answer the first part of research question 1: *"Which techniques are used to forecast patient demand in the obstetrics department?"*. To answer this question, we conduct a literature review to analyze the available forecasting techniques that have been applied within a healthcare context, and also specifically within an obstetrics environment. Only forecasting patient demand does not solve the problem set in Section 1.3 as the aim of this research is to develop a tactical staff planning. Therefore, in Section 2.3, we evaluate literature on tactical blueprint scheduling in healthcare. Here, we aim to answer part two of research question 1: *"Which techniques are used to generate a tactical staff blueprint planning based on forecast patient demand?"*. In Section 2.4 we discuss the findings of the literature review and choose the most suitable models to develop our tactical staff planning model.

2.1 Theoretical framework

We follow the theoretical framework on healthcare planning and control, as proposed by Hans et al. [6] Within this framework, four hierarchical levels of planning and control are defined in which different decisions have to be made. The hierarchical decision levels are strategic, tactical, and operational, which are characterized by the time horizon that the level operates on. Strategic planning and control is concerned with long-term decisions with a time horizon of more than a year. Tactical planning and control has a shorter time horizon, which varies between a couple of weeks to a year. Operational planning and control is focused on short-term decisions, which have to be made either weekly or daily.

The strategic level focuses on structural decision-making. An example of strategic planning is capacity dimensioning. Tactical planning operates on a shorter time horizon (months) than strategic planning. Within tactical planning, the organization of the operations is a given, and there is flexibility to allocate and move resources where needed. Examples of tactical decisions are planning blueprints, capacity allocation, temporary capacity expansions, and nurse staffing [7]. Operational planning is divided between offline and online operational planning. Operational planning is focused on the execution of the planning decisions made on the top levels. Both types of operational planning deal with short-term decision-making. Offline operational planning is concerned with, for example, appointment scheduling and rostering, which mostly focuses on planning in advance (weeks). Online operational planning decisions are reactive decisions, such as scheduling of emergencies or triaging, which concerns decisions on an even shorter-term (days) than offline operational scheduling.

At the Diakonessenhuis Utrecht, strategic planning decisions have already been made and therefore cannot be influenced on the short term. This consequently means that strategic planning is out of scope for this thesis. However, changes to the tactical and operational planning decisions are more flexible as they can be influenced on a short-term basis. Tactical planning decisions have a direct impact on operational planning decisions, and for that reason, the decisions made on a tactical level need to be improved first. The scope of this research will therefore be narrowed down to the tactical level of planning decisions.

2.2 Forecasting patient demand

In this section, we answer part one of research question 1, which is: *"Which techniques are used to forecast patient demand in the obstetrics department"?*. We perform a literature review on forecasting techniques that are applied within healthcare, and specifically within an obstetrics setting. In Section 2.2.1 we introduce time series forecasting in healthcare and its applications. Section 2.2.2 briefly touches on the subject of forecasting accuracy, to define how we evaluate the performance of a forecasting model. Section 2.2.3 elaborates on linear time series forecasting models, while Section 2.2.4 discusses non-linear time series forecasting models. In Section 2.2.5 we summarize the findings of the literature review and conclude on the most suitable forecasting model for this problem context to develop a forecasting model to estimate patient demand in Chapter 4.

2.2.1 Time series forecasting in healthcare

Forecasting has been applied across many industries and is used to make predictions about certain events in the future based on current and past knowledge. A literature review by Petropoulos et al. [8] provides an overview on the research done in the field of forecasting. The applications of forecasting in healthcare are also discussed. The authors differentiate between applying forecasting for clinical decision-making and non-clinical decision-making. Examples of forecasting for clinical decision-making are patient screening for preventive health care, predicting medical issues, assistance with disease progression and recommending treatments for patients. Non-clinical forecasting in health-care is concerned with patient demand forecasting, epidemic forecasting, and forecasting in health care supply chains. As this research will focus on developing a tactical planning of staff using a demand forecast, the literature review will be narrowed down to non-clinical forecasting with a focus on demand forecasting. Demand forecasting in healthcare is mainly executed through time series forecasting models. We will explain through a literature review what time series forecasting models are, and which models have successfully been used to forecast patient demand in a healthcare context. Furthermore, we will develop a framework which assists with choosing the most suitable time series forecasting model to achieve the best forecasting performance possible.

A time series is an ordered sequence of observations which are gathered at a constant time interval [9]. This can be hourly, daily, weekly, monthly, yearly, etc. Time series models are widely used to forecast future values by analyzing the historical data of the series [10]. Various time series forecasting models exist within literature, and the suitability of each model depends on the characteristics of the time series data. These characteristics are patterns within the data like volatility, trend, seasonality, and noise. We identified two main categories of time series forecasting models: linear forecasting models and non-linear forecasting models.

Linear forecasting techniques are easy to implement and interpret while being able to pick up linear patterns like trend and seasonality. Non-linear forecasting techniques are more difficult to implement and interpret, however these techniques have the ability to identify non-linear patterns within data. Most papers that we studied examine patient arrivals forecasting for emergency departments, as it is an environment with high uncertainty. Furthermore, the studies we included use several time series forecasting models instead of focusing on one technique. This is partly because using multiple models is useful for comparison, but also because the performance of a specific forecasting model is dependent on the characteristics of the data.

2.2.2 Forecasting accuracy

Before we discuss the relevant forecasting techniques for the estimation of patient demand, we briefly touch on the subject of forecasting accuracy. The papers that we study in this review compare the results of the used forecasting models based on performance indicators that measure the forecasting accuracy. Forecasting accuracy is defined as the degree of how close the predicted value is to the actual value, which is also called the forecasting error [11]. By, for example, averaging all forecasting errors, we can acquire the forecasting accuracy. We use this definition to indicate whether specific forecasting techniques perform better in comparison to other forecasting techniques in this review. Forecasting accuracy metrics can measure the absolute deviation from the actual value, the percentage deviation, or give an indication of the forecasting model over- or underpredicting the actual value. Figure 2.1 contains a visual representation of the forecasting error, which is used to calculate the overall forecasting accuracy. Most often, researchers use multiple forecasting accuracy metrics to evaluate forecasting performance, as there is no one best forecasting accuracy metric. With this in mind, we discuss linear forecasting techniques in the following section.

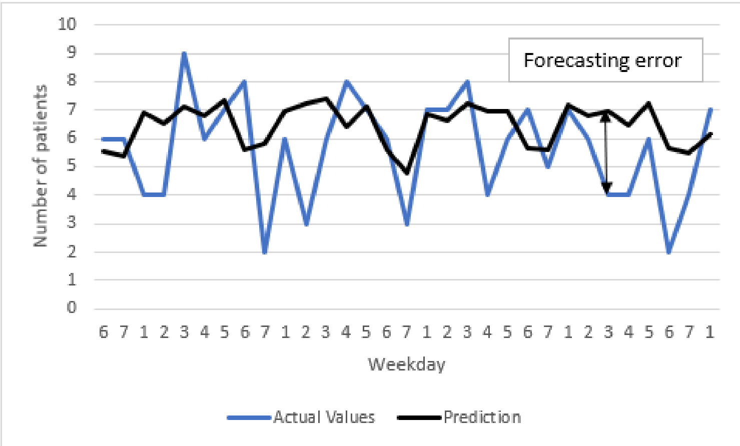


Figure 2.1: Visual representation of the forecasting error, indicated by the black arrow.

2.2.3 Linear forecasting

Linear forecasting techniques are relatively easy to implement and do not require a vast amount of data to produce accurate results. Therefore, these techniques are very popular for forecasting patient demand. The main classes of linear forecasting techniques that are used within literature are exponential smoothing, regression and autoregressive models.

Exponential smoothing models use exponentially decreasing weights over time to create a forecast for time series data. The most recent observation will be assigned the highest weight while the earlier observations will have exponentially lower weights. The forecast is calculated based on the average weighted value of the historical observations, where the most recent observations has the greatest impact on the estimation [12]. Simple exponential smoothing, the basic form of exponential smoothing, has been used by Assad et al., in combination with autoregressive and deep learning forecasting models to forecast emergency department arrivals [13]. Holt-Winters or triple exponential smoothing incorporates a trend and seasonality equations in the exponential smoothing model [14]. Holt-Winters forecasting has been used to forecast patient arrivals at emergency departments [15] and also for an outpatient clinic [16]. In obstetrics, the exponential weighted moving average forecasting model and Holt-Winters model have been used to forecast the arrivals of pregnant patients. [17, 18]. Exponential smoothing provides the least accurate forecasts when compared to other forecasting techniques. The best forecasting performance of the exponential smoothing forecasting class is achieved by the Holt-Winters model, as this model is able to capture both trend and seasonality [17, 18].

Another common linear forecasting method is *regression*. Regression forecasting models are used to capture important relationships between the forecast variable of interest and the predictor variables. Variables like a specific day of the week, weather, and holidays can be of influence when predicting patient demand. These variables can be incorporated into a regression forecasting model [19]. Various types of regression forecasting models are used within literature to forecast patient demand. Simple regression models like linear regression and poisson regression are common to forecast emergency department patient demand when there is only one predictor variable of interest [20, 21]. More advanced models that incorporate multiple predictor variables, like multiple linear regression and the ridge and lasso regression variants, are mostly used in situations where the researchers wanted to study the impact of multiple variables on the forecast estimation [20, 22, 23]. Regression is also not the first choice when forecasting patient demand in a high uncertainty environment. This is mainly caused by the fact that models of the autoregressive class possess the functions of regression forecasting models and also provide a better forecasting performance. Multiple Linear Regression is the most suitable choice of forecasting model to estimate patient demand.

Autoregressive forecasting models are models that use a linear combination of the past values of the variable to create a forecast for the same variable, which is therefore a regression of the variable against itself [24]. Autoregressive models are restricted to stationary data, which means that the mean and variance of the data throughout the time series does not change over time. The most used autoregressive model is the ARIMA model, developed by Box and Jenkins [25]. The ARIMA model combines an autoregressive model (AR) with a moving average model (MA). Furthermore, by differencing the data (I) a non-stationary time series can be made stationary and therefore usable in an autoregressive forecasting model. ARIMA models are commonly used to forecast patient demand in emergency departments, outpatient clinics, and also hospital-wide [26, 27, 28]. SARIMA models incorporate seasonality in an ARIMA model and are mostly used to forecast patient demand in emergency departments, but also for forecasting specific types of patients, like COVID-19 patients [29, 30]. Within obstetrics, the ARIMA and SARIMA model is also used to forecast the arrivals of pregnant patients [18, 31]. Lastly, ARIMAX and SARIMAX models introduce exogenous variables which may affect patient demand and therefore influence the forecast. These models are also used to forecast patient demand in emergency departments, using variables like public holidays and weather [32, 23]. Autoregressive forecasting models are the most common forecasting models in patient demand forecasting. This is mainly due to the ease of implementation and high accuracy results.

2.2.4 Non-linear forecasting

We identify three main categories of non-linear forecasting methods that have been researched within patient demand forecasting literature. These are machine learning models, deep learning models, and hybrid models [33].

Machine learning forecasting models can learn from data over time without the assistance of the user. This means that the model can identify patterns within the time series data and also adapt to changes within these patterns. Through this, these models can produce an accurate forecast, especially for data that does not consist of stable and recurring patterns [34]. Gradient boosting is the most commonly used machine learning forecasting model used to forecast patient demand. Gradient boosting utilizes a collection of weak prediction models, like decision trees, and combines this information to make more accurate predictions. Gradient boosting, and its variant XGBoost, is used in literature to forecast emergency department patient arrivals [35, 36]. Another commonly used machine learning forecasting technique is support vector regression. Support vector regression is also mostly used to forecast emergency department patient arrivals [37, 20].

Deep learning forecasting models are a subset of machine learning forecasting models that use neural networks to identify patterns through various layers of algorithms. Deep learning forecasting models require a lot of data and require significant setup time, but they produce more accurate results than machine learning and basic forecasting models. The most prominently used deep learning forecasting models are artificial neural networks (ANN) and long short-term memory models (LSTM). Both types of models have been used within literature to forecast emergency department patient arrivals [38, 39].

Lastly, *hybrid models* combine classes of forecasting models to overcome disadvantages of specific models or because the context requires a unique method. Hybrid models are complex because of the combination of two or more models, but can provide accurate results when applied in the right context. Because of the complexity, hybrid forecasting models require extensive testing and are therefore not likely to be suitable for implementation in our problem context. However, hybrid models have been successfully applied in forecasting emergency department patient arrivals and provide very accurate results in comparison to only using one method [40, 22].

2.2.5 Summary and performance comparison

Most of the authors use multiple forecasting models within their research. Through comparison, they can also find out the performance of each forecasting model used and thus the best performing forecasting model. Table 2.1 summarizes the research we included in this literature review and the model classes used. It also displays which forecasting model performed the best in forecasting patient demand for that specific setting. It should be noted that researchers often include simple forecasting models, like naïve forecasting, which consists of copying the last known demand value, and exponential smoothing to compare to more advanced methods which often provide more accurate results.

To conclude this literature review, we use Table 2.1 to identify the most suitable forecasting model to estimate patient demand. Autoregressive models are used by most authors and provide the most accurate estimations when used in comparison to exponential smoothing and regression models. Among the autoregressive models used, the SARIMAX and ARIMAX models provided the best performance. For exponential smoothing this was the Holt-Winters model, and for regression the multiple linear regression model. When machine learning and deep learning models are used in research they provide the most accurate estimations, with deep learning outperforming every other forecasting model class when used in comparison. The best machine learning and deep learning forecasting models were the support vector regression model and the random forest regression model. We conclude that using models from model the autoregressive, machine learning and deep learning classes will provide the most accurate estimations to predict patient demand. However, the performance of a time series forecasting model depends on the characteristics of the data like trend and seasonality. For this reason, it is wise to analyze the patient arrival data to make a more informed decision on choosing the forecasting model that provides the most accurate results depending on the ability of the model to make prediction based on specific data characteristics. Therefore, we perform a data analysis in Chapter 3.

Author(s)	**Setting**	**NA**	**ES**	**RG**	**AR**	**ML**	**DL**	**HB**
Assad et al. (2020)	ED	x	x	x	x			
Xu et al. (2011)	ED		x	x	x			
Claudio et al. (2014)	OD	x	x	x	x			
Bigelow et al. (2019)	OD				x	x	x	
Fan et al. (2022)	ED				x	x	x	
Whitt & Zhang (2019)	ED				x			
Carvalho-Silva et al. (2018)	ED				x			
Lin & Chia (2017)	ED				x			
Darbey & Kane (2022)	OD				x			
Aroua & Abdul-Nour (2015)	ED			x	x			
Tavakoli et al. (2022)	SPD				x			
Mizan & Taghipour (2022)	RA					x		
Zhang et al. (2022)	ED			x	x	x	x	
Cusidó et al. (2022)	ED					x		
Hu et al. (2023)	ED			x	x	x		
Khaldi et al. (2019)	ED				x		x	
Harrou et al. (2020)	ED						x	
Yusecan et al. (2020)	ED		x	x	x		x	x
Jian et al. (2019)	ED							x
Zhang et al. (2019)	ED				x	x		x
McCarthy et al. (2008)	ED			x				
Essuman et al. (2017)	OD		x		x			
Count	-	0	1	2	12	4	5	0

Table 2.1: Reviewed literature on forecasting patient demand. the symbol "x" indicates whether a model from that model class is used by the authors. The yellow colored squares indicates that the model had the best performance. NA = Naïve, ES = Exponential Smoothing, RG = Regression, AG = Autoregressive, ML = Machine Learning, DL = Deep learning. The Table also indicates the problem setting, where ED = Emergency Department, OD = Obstetrics Department, SPD = Single Patient Demand, and RA = Radiology.

Providing an accurate estimation of the number of patient arrivals partly solves the problem of the uncertainty around patient workload at the obstetrics department. The total patient workload at the obstetrics department consists of the total number of arriving patients and the total number of recovering patients, as the department treats both inpatients and outpatients. This adds another layer of uncertainty to the problem, which is the uncertainty around the length of stay of a patient. Furthermore, providing a forecast for the number of patients only gives an estimation on the average number of patient arrivals, while it does not indicate the range of the number of patient arrivals. Lastly, we want to know how this patient workload can be converted to a tactical staff planning, which serves as a blueprint planning for the departments' staff planner. In the next section, we perform a literature review on the techniques that can achieve the goal we described.

2.3 Tactical blueprint scheduling in healthcare

Tactical blueprint scheduling has been applied in a healthcare setting by many researchers. According to Hulshof et al., [7] tactical blueprints are used as an input for operational planning. Developing tactical blueprints consist of defining patient groups according to diagnosis and determining their resource requirements. The blueprints then determine the allocation of the available resources to the patient demand, settled at the strategic level. Patient demand forecasting is often used to estimate patient arrivals, which are used as an input for tactical blueprint scheduling models [7]. In this case, the allocation of the available resources is the efficient distribution of the available workforce through determining the number of required nurses. In this section, we determine the most appropriate tactical blueprint scheduling technique to develop a tactical staff planning using forecasted patient demand as an input. The suitability of a tactical blueprint scheduling technique for our problem context depends on a few key characteristics which are mentioned in Section 2.3.2. Section 2.3.1 provides a literature review of tactical blueprint scheduling techniques that are applied in a healthcare context. In Section 2.3.2 we summarize our findings and select the most suitable model for this problem context.

2.3.1 Applications of tactical blueprint scheduling in healthcare

Most literature on tactical blueprint scheduling in healthcare is focused on patient appointment scheduling problems in outpatient clinics. Ahmadi-Javid et al., provide an overview of tactical decisions within appointment scheduling systems for outpatient clinics [41]. The researchers consider the allocation of capacity to different patient groups, the appointment intervals, appointment scheduling window, number of appointments per consultation session, and panel size as key characteristics for tactical blueprints used for outpatient clinics [41]. Considering these decisions, a tactical blueprint can be developed for an outpatient clinic such that patients can be scheduled according to these guidelines at the operational level. Furthermore, Ali and Feng provide a comprehensive review on the applications and solution approaches of appointment scheduling systems in healthcare. The researchers found that mathematical programming, simulation, and queuing theory are the main solution approaches for appointment scheduling systems in healthcare [42].

Nguyen et al., developed a deterministic model which minimizes the maximum required capacity through mathematical programming while still achieving the service targets for patients [43]. Aslani et al., extended this model through incorporating uncertainty in this model [44]. Anvaryazdi et al., also adopt a stochastic programming approach to solve an appointment scheduling at an OBYGN outpatient clinic. They develop a blueprint schedule which determines the number of patients per patient type that can be scheduled within an appointment slot on a specific day. This is achieved by a two-stage stochastic programming model, which is evaluated by a discrete event simulation model [45]. Moreover, Leeftink et al., developed a stochastic integer programming model for a multidisciplinary outpatient clinic which jointly optimizes all appointment schedules [46]. These techniques are also applied to generate blueprint schedules for primary care clinics [47, 48].

Tactical blueprint scheduling is also often used to develop operating room schedules or Master Surgical Schedules (MSS). An MSS is a cyclic schedule dictating the specialty-to-OR assignment. Khairulamirin et al., provide an overview of the literature that is available on modelling and solving MSS models. They conclude that mathematical programming is most frequently used to model these problems and heuristics to solve these mathematical models [49]. Furthermore, simulation is also often used to evaluate the MSS. Xiankai et al., developed a deterministic multi-objective mathematical model to generate a MSS which is solved by meta heuristics [50]. These models can also be formulated to incorporate uncertainty by adding probabilistic constraints. Multiple researchers have applied this technique to their models, which brings their model closer to reality [51, 52, 53, 54]. Furthermore, Moustafa et al., combined tactical blueprints scheduling for OR's with operational surgery scheduling [55]. Lastly, Vanberkel et al., developed a model, which is called the convolution model, that calculates the total patient workload on every day of a MSS based on probability distributions, which is used to calculate the required number of staffed beds for a specific demand percentile [56].

Within the area of personnel planning, tactical blueprint scheduling also has applications. Through tactical blueprint scheduling, the number of required employees, the number of shifts, and the distribution of available working time can be calculated. Isken and Aydas developed a tactical implicit tour scheduling model which uses a mixed integer mathematical programming model to develop a blueprint which prescribes the number of shifts and the number of employees that are required per shift to meet patient demand [57]. Al-Mudahka and Alhamad also used mathematical programming to solve a personnel planning model. They used a binary satisfaction integer programming model to develop timetables for radiologists [58].

2.3.2 Summary and model selection

In this thesis, we focus on tactical blueprint scheduling techniques that generate a blueprint planning for the number of required employees. The solution approach that is the most suitable for the problem context of this thesis depends on a few characteristics. First, the solution approach has to include both inpatients and outpatients to acquire the total patient workload. Therefore, the tactical blueprint scheduling techniques that only consider outpatients are not suitable. Furthermore, the solution approach needs to include stochasticity to incorporate patient demand and patient length of stay uncertainty. In Table 2.2 we summarized the findings of the literature review and identified whether the sources possess the characteristics needed for our solution. The five highlighted sources in Table 2.2 possess all the characteristics and therefore are suitable to use as a solution approach. Of these sources, we decided to use the convolution model developed by Vanberkel [56] for the following reasons. The first reason is that the convolution model is easy to implement, as it does not require time intensive techniques like simulation or complicated heuristics. Furthermore, the output of the convolution model gives the required number of staffed beds for a chosen demand percentile, which can be converted through minimum nurse-to-patient ratios [59, 60] to a tactical staff planning.

Source	**Inpatients**	**Outpatients**	**DM or ST**	**Solution Method**
Nguyen et al. (2015)		x	DM	MP
Aslani et al. (2021)		x	ST	MP
Anvaryazdi et al. (2020)		x	ST	MP & SIM
Leeftink et al. (2021)		x	ST	MP
Faridimehr et al. (2021)		x	ST	MP & SIM
Zaerpour et al. (2017)		x	DM	MP & HR
Xiankai et al. (2022)	x	x	ST	HR
van Oostrum et al. (2008)	x	x	ST	MP
Rachuba et al. (2022)	x	x	ST	MP & SIM
Zhang et al. (2020)		x	ST	MP
Moustafa et al. (2019)	x	x	ST	MP
*Vanberkel et al. (2011)**	x	x	ST	MP
Isken & Aydas (2022)	x	x	ST	MP
Al-Mudahka et al. (2022)	x	x	ST	MP

Table 2.2: Summary of the findings from the literature on tactical blueprint scheduling. The Table indicates if the solution is aimed at inpatient, outpatients, or at both. It also shows whether the solution includes stochasticity or not. Lastly, the solution method is mentioned where MP = Mathematical Programming, SIM = Simulation, and HR = Heuristics. The papers containing suitable solution approaches for our problem context are highlighted.

2.4 Conclusion

The aim of this chapter was to answer research question one, which consisted of two parts. Part one of research question one was: *"Which techniques are used to forecast patient demand in the obstetrics department?"*. Time series forecasting models are widely considered the best option within literature to provide accurate estimations of patient demand within a healthcare context. Autoregressive models like the SARIMAX model are preferred in an obstetrics context. However, the accuracy performance of a forecasting model mainly depends on selecting the most suitable model based on the characteristics of the patient data. Therefore, we perform a data analysis in Chapter 3 which serves as a basis for selecting the most appropriate forecasting model in Chapter 4.

Providing an estimation of the number of patient arrivals is not enough to develop a tactical staff planning. To achieve this goal, we require a tactical blueprint planning technique which is able to transform the number of patient arrivals into the total estimated patient workload, by incorporating the uncertainty around patient arrivals and patient length of stay. The total estimated patient workload can then be converted into a tactical staff planning, which consists of a blueprint containing the required number of nurses needed every day at the obstetrics department. Finding a suitable method to achieve this answers part two of research question one, which was: *"Which techniques are used to generate a tactical staff blueprint planning based on forecasted patient demand?"*. We choose to use the convolution model developed by Vanberkel to acquire this total estimated patient workload. The convolution model of Vanberkel achieves the same goal as we want, namely calculating the estimated patient workload during a specific period of time while accounting for stochasticity. Furthermore, we do not require optimization and simulation is very time intensive, which makes the convolution model the best fit for our research. The output of the convolution model can be converted to a tactical staff planning using nurse-patient ratio's.

To summarize, we will develop a two-stage model which is able to develop a tactical staff planning. The first stage consists of a time series forecasting model, which is selected based on the characteristics of the patient arrival data. The most accurate forecasting result will then be used as an input for the convolution model, developed by Vanberkel, to acquire the total estimated patient workload [56]. Using nurse-patient ratio's we generate a tactical staff planning, which consists of the required number of nurses for every day of the week.

The novelty of this research is two-fold. First, although patient demand forecasting has been mentioned in the context of an obstetrics department, both tactical blueprint scheduling and nurse staffing are not covered within literature to the best of our knowledge in this specific context. Furthermore, most tactical blueprint scheduling techniques use either only historic or distributions as patient data input. Therefore, using forecasted patient demand as an input for a tactical blueprint scheduling model and converting this to a tactical staff planning complements existing literature and can serve as a proof of concept for, at least, the obstetrics department and even cross departmental.

3 CURRENT SITUATION AND DATA ANALYSIS

In Chapter 2 we concluded that a tactical staff planning model using forecasted patient input is the best method to generate a tactical staff planning. The model that we will use requires historic patient arrival data as input. Data characteristics like seasonality, trend and volatility have a significant impact on the accuracy of the forecasting model, therefore it is important to analyze whether these characteristics can be observed within the patient arrival data. Furthermore, we need to analyze the nurse types and nurse-to-patient ratio's, which is needed to convert the patient workload to a tactical staff planning.

For this reason, we analyze the patient arrival data at the obstetrics department in this chapter. In Section 3.1 we identify the patient types at the obstetrics department and their care pathways. The care pathways are visualized using process maps, which display the processes and decisions for each patient type that take place within the hospital. Section 3.2 contains a data analysis based on the identified patient types. In this section we analyze patient frequency, patient arrival patterns, and patient length of stay, using patient arrival data acquired from the database of the Diakonessenhuis Utrecht. In Section 3.3 we discuss the nurse types, nurse-to-patient ratios and the current tactical staff planning.

3.1 Patient types

In this section, we will discuss the patient types that require medical care at the obstetrics department. Within these patient types, we differ between outpatients and inpatients. Outpatients are patients who do not need to be hospitalized after treatment or consultation and therefore do not require a hospital bed. Inpatients are patients that need to stay at least one night in the hospital to recover or because of a high risk factor which requires observation.

Within the obstetrics department, we identify two main patient types, namely delivery patients and patients with complications. These patients are handled by the obstetrics and triage department respectively and both have different care pathways. Delivery patients are patients that go into labor, are in labor, or are recovering from delivery. Complications patients are patients that are pregnant for at least 16 weeks and experience pregnancy-related complications. Within these patient types, we also differ between inpatients and outpatients. Inpatients require at least one overnight stay at the hospital, while outpatients can leave the hospital the same day after treatment. Section 3.1.1 discusses the data set used, and Section 3.1.2 gives the patient case mix. Section 3.1.3 will discuss the patient type "delivery" while Section 3.1.4 covers the patient type "complications".

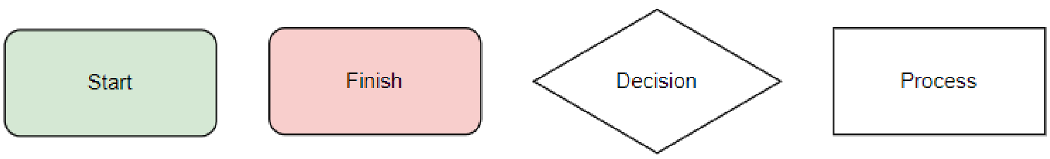


Figure 3.1: meaning of symbols used in care pathway flowcharts.

3.1.1 Dataset

We acquired data from the obstetrics department at the Diakonessenhuis Utrecht. The data ranges from the first of January 2018 until the 31st of December 2022. The data consists of all patients that visited the obstetrics department through entering the triage department or directly at the obstetrics department. We cleaned the dataset first to prepare for the time series analysis. The data cleaning strategy is displayed in the flowchart in appendix C.

3.1.2 Patient case mix

Using the cleaned dataset, which contains the patient arrivals at the obstetrics and triage department for the period 2018-2022, we can determine the patient case mix. The dataset contains 27.122 data entries, where one data entry represents one patient arrival. Table 3.1 provides a summary of the patient case mix.

Patient type	Frequency	Percentage (total)
Delivery	11799	43,5%
Outpatient	2541	9,4%
Inpatient	9258	34,1%
Complications	15323	56,5%
Outpatient	13317	49,1%
Inpatient	2006	7,4%

Table 3.1: Patient case mix for the obstetrics and triage department.

3.1.3 Delivery

The obstetrics department mostly deals with patients of the patient type "delivery". This includes patients that have to go into labor, are in labor, or are recovering after giving birth. We distinguish three different types of delivery patients: outpatient delivery, inpatient delivery, and instrumental delivery. Outpatient delivery patients are patients who can return home after giving birth and therefore do not have to stay overnight in the hospital. Inpatient delivery patients are patients who need to recover after giving birth and require at least one night of stay in the hospital. Instrumental delivery patients are patients who need to give birth through instrumental delivery, like a c-section. These patients always require at least one night of stay in the hospital to recover, and therefore are also inpatients. Figure 3.2 describes the basic care pathway for a delivery patient. In Appendix C we visualized the detailed care pathways of the different types of delivery patients. For modelling purposes, we only focus on the difference between delivery inpatients and delivery outpatients.

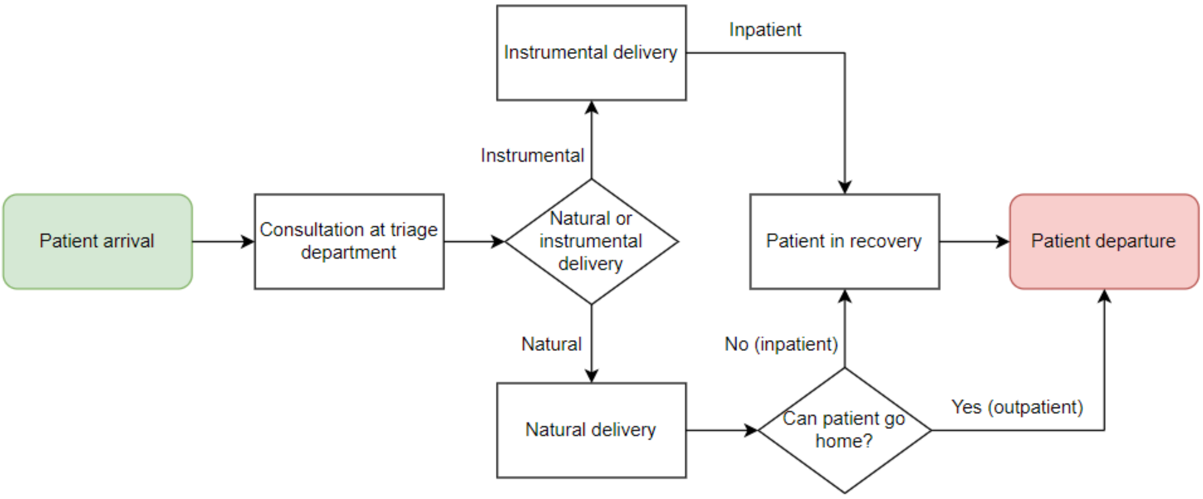


Figure 3.2: Basic care pathway for a delivery patient.

3.1.4 Complications

The other main patient type that requires medical assistance at the obstetrics department is ”complications” patients. These patients are mainly cared for by the triage department, which serves as an obstetrics emergency department. The triage department provides acute medical care for pregnant patients who are pregnant for more than sixteen weeks. Most of the patients that require the help of the triage department are emergency patients. When the patient arrives, the patient is first examined at the triage department. Depending on the severity of the situation, the patient may be hospitalized or sent home. During hospitalization, patients will be monitored, receive surgery if needed, or go into labor. We consider both inpatients and outpatients of the patient type ”complications”.

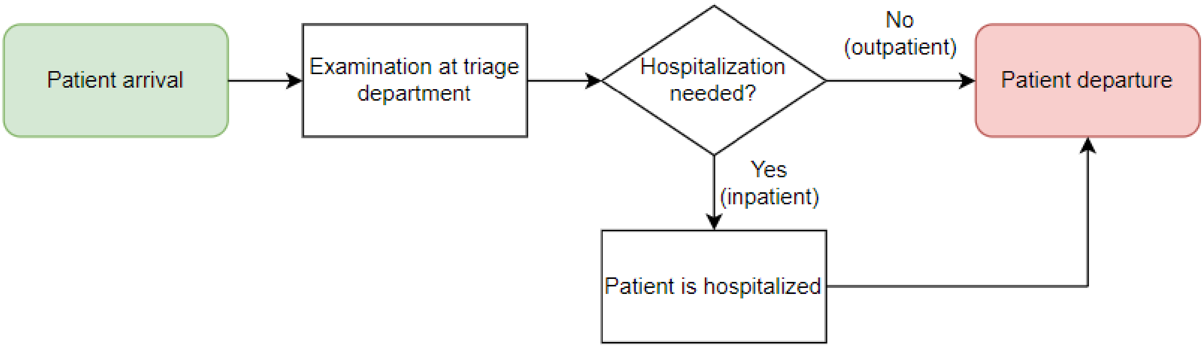


Figure 3.3: Basic care pathway for a patient with complications.

3.2 Data analysis

In this section, we analyze the patient arrival data based on the two patient types we identified in section 3.1. In section 3.2.1 We analyze the arrival data for patient type "delivery" on a yearly, monthly and daily level to identify if there is a trend and seasonal effect. Both trend and seasonality have a big impact in choosing the most suitable forecasting model, therefore the result of this analysis assists in making that decision. Furthermore, we analyze the spread and volatility of the arrival data. Lastly, we study the length of stay of the arriving patients. In Section 3.2.2 we conduct the same analysis for the patient type "complications". Section 3.2.3 gives an overview of the findings of this section.

3.2.1 Patient type "delivery"

In this section, we analyze the arrival data for patient type "delivery". We use the patient arrival data from the cleaned dataset for the period 2018 until 2022. The total number of data entries for patient type "delivery" is 11.799. The figures in this section are all based on the same dataset, meaning that we use the same number of data points for every figure. We study the impact that the year, month, and weekday has on the number of daily patient arrivals and the variation of the patient arrivals. We use this information in the development of the forecasting model. Furthermore, we examine the distribution of the patient length of stay.

Yearly

The impact of the year on the number of daily arrivals for patient type "delivery" indicates whether there is a trend component present in the arrival data. Significant differences between the average number of daily arrivals throughout the years means that the forecasting model we will develop needs to be able to incorporate the trend to prevent over- and underpredicting the estimated values. Figure 3.4 visualizes the daily number of patient arrivals, while Table 3.2 indicates the spread and mean throughout the years. It should be noted that the end of the whiskers of the box plots in Figure 3.4 do not indicate the minimum and maximum value of the dataset, as the dataset contains outliers. In our case, the end of the whiskers represent 1.5 times the interquartile range. This is the case for every subsequent figure

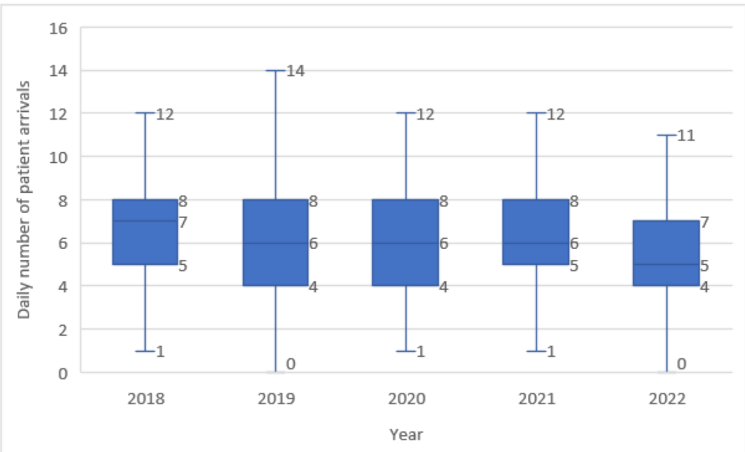


Figure 3.4: Daily arrivals for patient type "delivery" in a specific year.

Year	Mean	IQR
2018	6,5	3
2019	6,2	4
2020	6,0	4
2021	6,2	3
2022	5,3	3

Table 3.2: Descriptive statistics for the spread of the daily arrivals for patient type "delivery" in a specific year.

There is a minimal effect that the year has on the average number of patient arrivals. Only in 2022 there are is on average about one patient less that arrives at the obstetrics department every day. It should be noted that this could increase the chance, of the forecasting model that we develop, to overshoot the actual number of delivery patients. Furthermore, the increase in the number of births in The Netherlands did not have a big impact on the number of delivery patients for the obstetrics department. This could be caused by the fact that the department did not have the capacity to deal with the increased number of patients and therefore does not reflect the whole patient population. The variation in the number of patient arrivals is relatively identical for every year, however the minimum and maximum observed values for every year indicates that there is a lot of variation in the number of patient that arrive at the department.

Monthly

We also studied the effect of the months of the year on the daily number of patient arrivals for patient type "delivery". Studying the effect of the months has the purpose of identifying trends throughout the year based on different periods of the year, this is called seasonality. Forecasting models can incorporate seasonality based on specific time intervals, which can be months or days. Therefore, it is important to identify these patterns in the patient arrival data. Figure 3.5 shows the average number of daily arrivals for patient type "delivery" for every month of the year, and Table 3.3 provides descriptive statistics on the mean and spread of the arrival data.

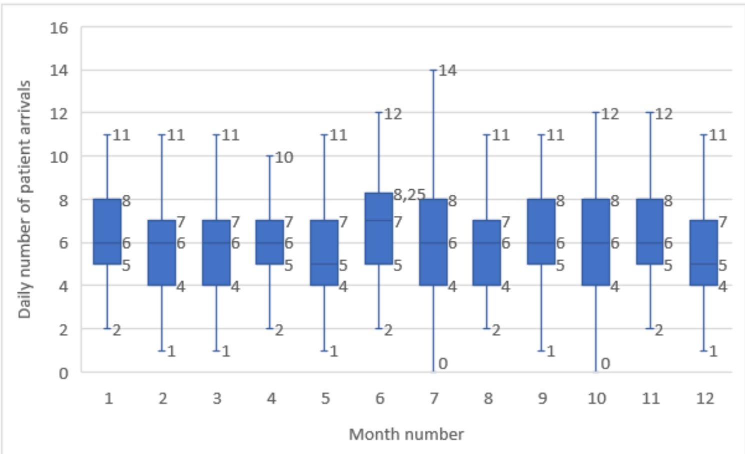


Figure 3.5: Daily arrivals for patient type "delivery" in a specific month.

Month	Mean	IQR
January	6,3	3
February	5,8	3
March	5,8	3
April	6,1	2
May	5,6	3
June	6,6	3,25
July	6,4	4
August	6,0	3
September	6,3	3
October	6,1	4
November	6,2	3
December	5,6	3

Table 3.3: Descriptive statistics for the spread of the daily arrivals for patient type "delivery" in a specific month.

We do not observe a seasonal effect of the months on the average number of daily delivery patients at the obstetrics department. There are small differences between the months, but no clear pattern is observed. Therefore, we can conclude that there is no monthly seasonal effect on the arrival data for patient type "delivery". Furthermore, the variation of the data within the months is comparable across all months, as can be concluded from the interquartile ranges in Table 3.3. The minimum and maximum observed values indicate that there the spread of the data within the months is very high, which means that there is a lot of variation in the data, with the month of July having the most variation.

Daily

To complete the patient arrival data analysis for patient type "delivery" we analyze the impact of the weekdays on the average daily number of patient arrivals. Seasonality patterns throughout the week have a big influence on the forecasting model performance. Often, these patterns are recurrent throughout every week of the year, and forecasting models are able to replicate these patterns to make accurate estimations. Figure 3.6 shows the average daily arrivals for patient type "delivery" on every day of the week, and Table 3.4 indicates the spread and mean of the arrival data.

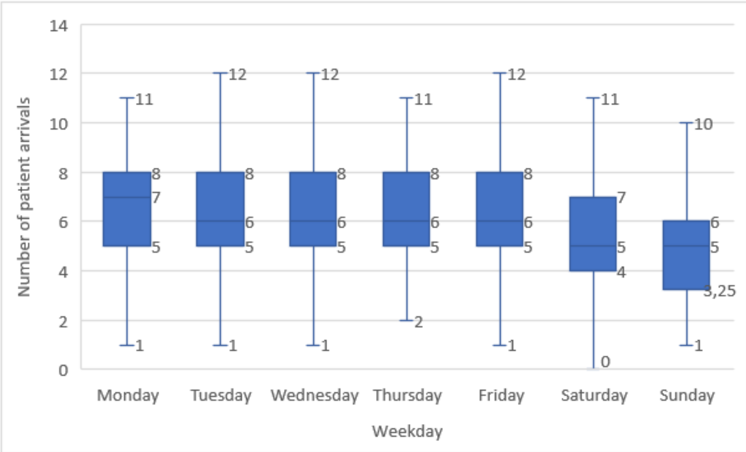


Figure 3.6: Daily arrivals for patient type "delivery" on a specific weekday.

Day	Mean	IQR
Monday	6,5	3
Tuesday	6,4	3
Wednesday	6,5	3
Thursday	6,5	3
Friday	6,4	3
Saturday	5,2	3
Sunday	4,9	3

Table 3.4: Descriptive statistics for the spread of the daily arrivals for patient type "delivery" on a specific weekday.

Figure 3.6 shows box plots for the daily arrivals for patient type "delivery" based on the days of the week. Within this figure, we observe a clear pattern where the number of daily arrivals from Monday to Friday is relatively the same, while the numbers in the weekend are about 20 percent lower. This is mainly due to the fact that part of the care for delivery patients is plannable, like c-sections, and mostly planned throughout Monday to Friday. Furthermore, Table 3.4 shows that the variation between the number of arrivals are relatively the same across the different days of the week, but the degree of variation is very high. We conclude that there is a daily seasonal effect of the weekdays that impacts the arrival data for patient type "delivery". We can confirm this by looking at the plotted time series of the patient arrival data in Figure 3.7. In the next section, we discuss the spread and volatility of the patient arrival data to get a more detailed insight into the variation of the arrival data.

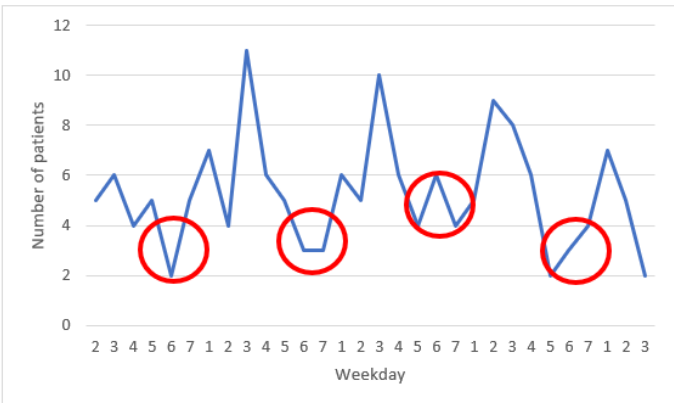


Figure 3.7: Time series of delivery patient arrivals for four weeks. The red circles indicate the lower number of patient arrivals during the weekend.

Spread and volatility

Choosing the most suitable forecasting model partly depends on the volatility of the data, as volatile data often consists of complex patterns which cannot be replicated by simple forecasting models. In Figure 3.8 we plotted the data in a histogram to analyze the spread, combined with Table 3.5 which contains descriptive statistics that are concerned with data spread and variation. Furthermore, we used a control chart to analyze the data volatility. The control chart contains several straight lines representing standard deviations from the mean. Assessing the number of observations that fall beyond these lines indicate whether the data is very volatile or if the data is under control. The control chart for the number of patient arrivals for patient type "delivery" can be found in Figure 3.8.

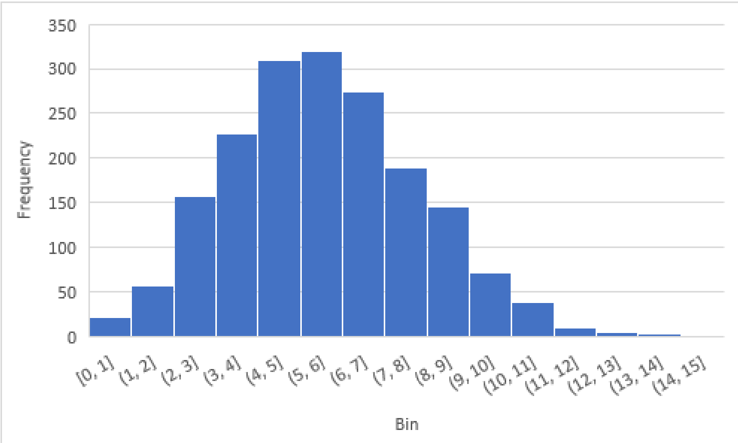


Figure 3.8: Histogram of the daily arrivals for patient type "delivery".

Statistic	**Value**
Mean	6,06
Min	0
Max	15
Standard deviation	2,26
Kurtosis	0,29
Skewness	-0,01

Table 3.5: Descriptive statistics for the spread of the daily arrivals for patient type "delivery".

Figure 3.8 shows that the number of daily arrivals for delivery patients is slightly positive skewed, which means that there are higher than lower values within the data. The kurtosis value is near zero, which means that the data approaches a normal distribution. Furthermore, the standard deviation is relatively high, which indicates a lot of variation within the arrival data. Figure 3.9 confirms this hypothesis, as there are a lot of data points that lie outside the yellow line, indicating one standard deviation from the mean. Within two standard deviations of the mean, the data is relatively stable.

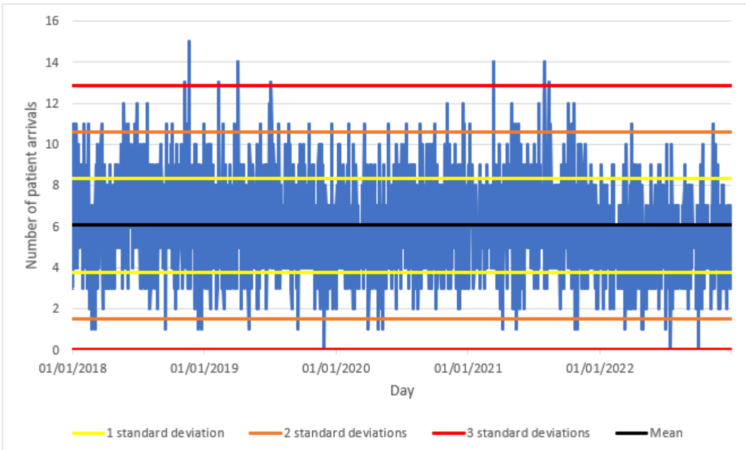


Figure 3.9: Control chart for the variation in the number of patient arrivals for patient type "delivery".

Length of stay

Lastly, analyzing the distribution of patient length of stay for patient type "delivery" is important as it is used as an input for the convolution model we developed in Chapter 4. The distribution of the length of stay of delivery patients is visualized in figure 3.10. For modelling purposes the length of stay is rounded to days, with a value lower than 0.5 rounded down and a value ≥ 0.5 rounded up to the nearest integer. It should be noted that a patient with a length of stay lower than one day is considered an outpatient, and a patient with a length of stay of at least one day is an inpatient. Table 3.6 provides descriptive statistics for the spread of length of stay. The figures show that delivery patients mostly consist of inpatients, with the average length of stay being around 1.4 days.

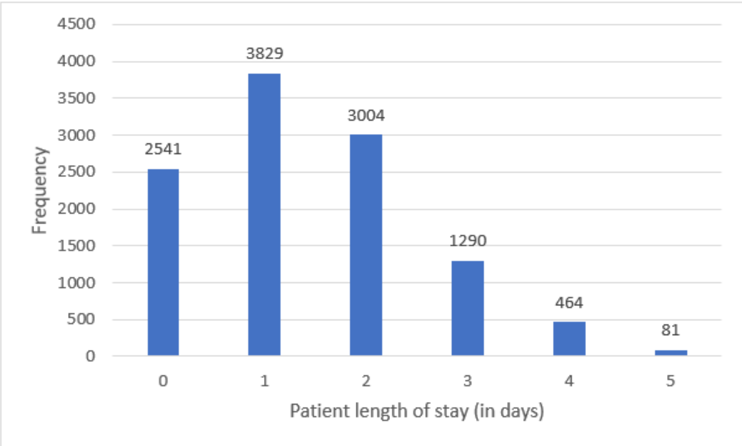


Figure 3.10: Distribution of length of stay for patient type "delivery".

Statistic	Value (in days)
Mean	1,4
Standard deviation	1,1
Minimum	0
Maximum	5

Table 3.6: Descriptive statistics for the spread of the length of stay for patient type "delivery".

3.2.2 Patient type "complications"

In Section 3.1.2 we analyzed the patient case mix, which included the frequencies for the main patient types. Within the dataset with patient arrivals we used there were 15.323 data entries, during the period 2018-2022, for patient type "complications" where one data entry represents one complication patient arrival. In this section, all the figures we use for analysis use the same number of data entries. In this section, we perform the same data analysis for patient type "complications". First, the impact of the year, month, and weekday on the daily number of patient arrivals is analyzed, together with a brief analysis of the arrival data spread. Then a detailed analysis of the data spread and volatility is given to indicate the amount of variation within the arrival data. Lastly, the distribution of patient length of stay is analyzed.

Yearly

Figure 3.11 shows the average number of daily arrivals throughout the years from 2018 to 2022. Table 3.7 provides descriptive statistics concerning the mean and spread of the arrival data. Using the graph, we can identify whether there is a trend present in the number of daily arrivals throughout the years.

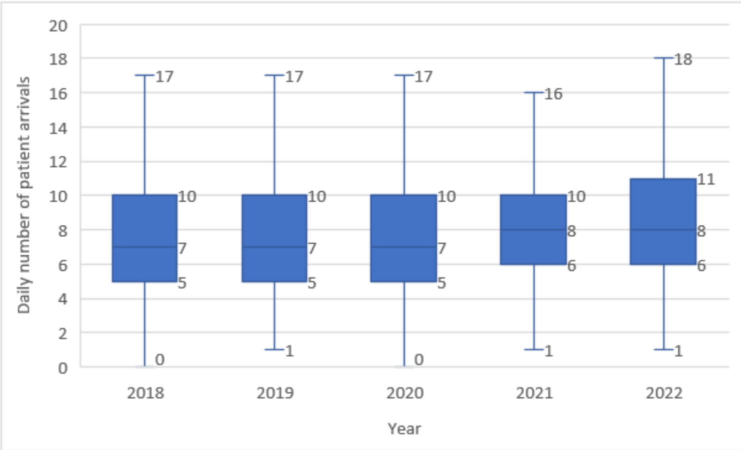


Figure 3.11: Daily arrivals for patient type "complications" in a specific year.

Year	Mean	IQR
2018	7,8	5
2019	7,5	5
2020	7,6	5
2021	7,9	4
2022	8,4	5

Table 3.7: Descriptive statistics for the spread of the daily arrivals in a specific year for patient type "complications".

There is no significant difference visible effect of the year on the daily number of arrivals for patients with complications. Only 2022 shows an increase in the daily number of arrivals, which could impact the forecasting model. Moreover, the variation in the arrival data between the years is relatively stable, although the degree of variation is very high.

Monthly

The effect of the months of the year on the average daily number of patient arrivals for patient type "complications" is visualized in Figure 3.1'2. Supplementary descriptive statistics covering the mean and the spread of the arrival data is given in Table 3.8.

Month	Mean	IQR
January	7,6	5
February	7,0	4
March	7,4	6
April	7,6	4
May	7,6	3
June	7,8	5
July	7,9	4
August	8,3	4
September	8,4	5,25
October	8,1	5
November	8,4	5
December	7,9	4

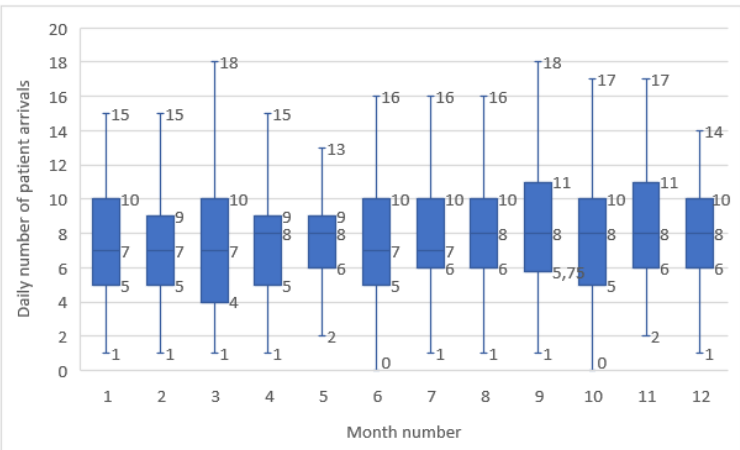


Figure 3.12: Daily arrivals for patient type "complications" in a specific month.

Table 3.8: Descriptive statistics for the spread of the daily arrivals in a specific month for patient type "complications".

We observe no significant seasonal effect of the months on the daily number of arrivals, although it can be argued that the average number of patient arrivals is slightly higher in the second half of the year. This should be noted when evaluating the forecasting model. The degree of variation is high throughout the different months, while the amount of variation is comparable.

Daily

In Figure 3.13 we show the impact of the different days of the week on the average daily number of patient arrivals for patient type "complications". The descriptive statistics on the mean and spread of the arrival data are given in Table 3.9.

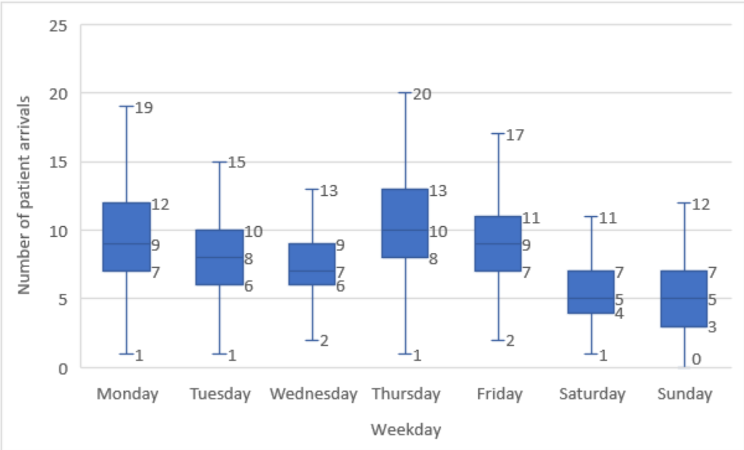


Figure 3.13: Daily arrivals for patient type "complications" on a specific weekday.

Day	Mean	IQR
Monday	9,6	5
Tuesday	8,1	4
Wednesday	7,6	3
Thursday	10,4	5
Friday	8,9	4
Saturday	5,2	3
Sunday	5,1	4

Table 3.9: Descriptive statistics for the spread of the daily arrivals on a specific weekday for patient type "complications".

We observe a very strong seasonal effect of the weekday on the number of patient arrivals for patient type "complications". Figure 3.13 shows that there is a clear pattern visible throughout the week, with peak demand on Monday, Thursday and Friday and significant lower patient arrivals during the weekend. This pattern is also observed when plotting the data as a time series in Figure 3.14. The degree of variation is also higher on the peak demand days in comparison to the lower demand days.

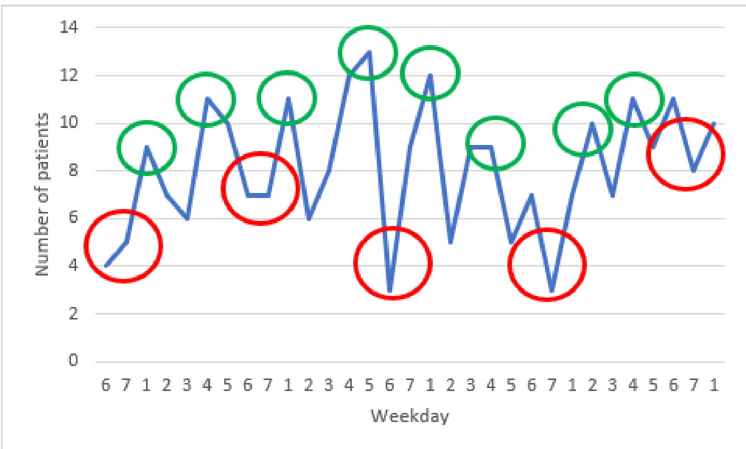


Figure 3.14: Time series of complications, patients arrivals for four weeks. The red circles indicate the number of patients arrivals during the weekend, while the green circles indicate the peak demand days, which are Monday and Thursday.

Spread and volatility

In this section, we discuss the spread and volatility of the patient arrival data for patient type "complications" in more detail. Figure 3.15 shows a histogram of the arrival data, while Table 3.10 provides additional descriptive statistics on the data spread. Figure 3.16 assesses the volatility of the data using a control chart.

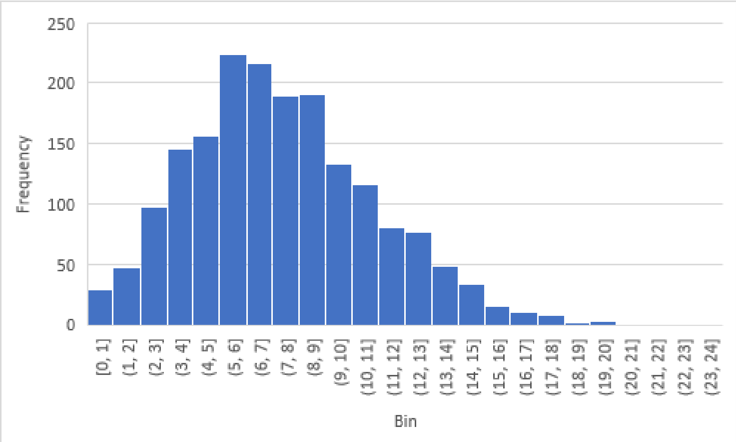


Figure 3.15: Histogram of the daily number of arrivals for patient type "complications".

Statistic	Value
Mean	7,85
Min	0
Max	24
Standard deviation	3,50
Kurtosis	0,49
Skewness	0,15

Table 3.10: Descriptive statistics for the spread of the daily arrivals for patient type "complications".

The histogram shows that the data is positively skewed, which is confirmed by the statistics in Table 3.10, which means that there are more values higher than the mean than lower. Furthermore, the kurtosis value indicates that the data approximates a normal distribution, but it is not as convincing as for the patient delivery data. Lastly, the standard deviation is relatively high, which indicates high data volatility. Figure 3.16 confirms this hypothesis, as there are a lot of points which lie outside one standard deviation from the mean. However, the data is less volatile in comparison to the delivery patient arrival data. This could be the case as most of the complications patients consists of outpatients which can be planned in forward. The consequence of this is that there is less unexplained variation which can be observed as high and low peaks.

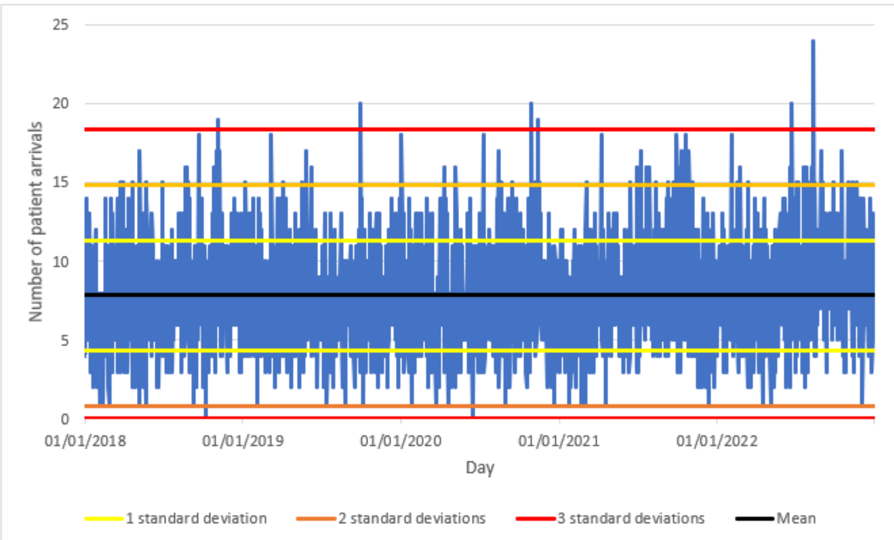


Figure 3.16: Control chart for the variation in the number of patient arrivals for patient type "complications".

Length of stay

Lastly, we analyze the patient length of stay of complications patients, which is used as an input for the convolution model we developed in Chapter 4. Figure 3.17 displays the distribution of the length of stay for patients of patient type ”complications” while Table 3.11 contains additional descriptive statistics. It should be noted that the descriptive statistics for Table 3.11 are not rounded to give an indication of the true length of stay of patients. For modelling purposes, the length of stay is rounded to days, with a value lower than $0,5$ rounded down and a value $\geq 0,5$ rounded up to the nearest integer. It should be noted that a patient with a length of stay lower than one day is considered an outpatient, and a patient with a length of stay of at least one day is an inpatient.

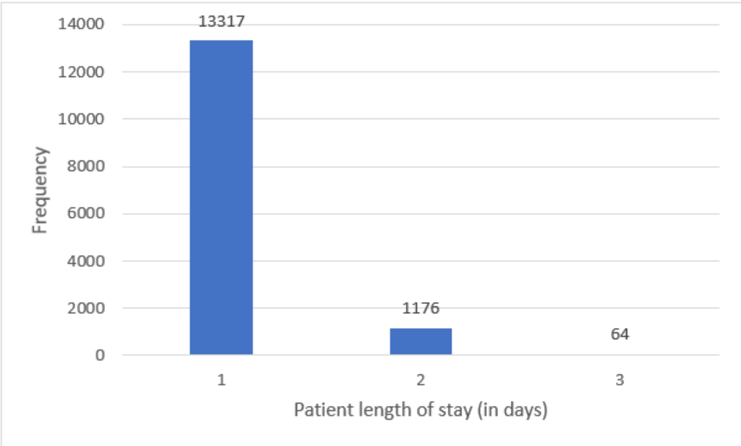


Figure 3.17: Distribution of the length of stay for patient type ”complications”.

Statistic	**Value (in days)**
Mean	0,1
Standard deviation	0,3
Minimum	0
Maximum	3

Table 3.11: Descriptive statistics for the spread of the length of stay for patient type ”complications”.

Figure 3.17 displays the distribution of the length of stay for patients of patient type ”complications”. Together with Table 3.11 we conclude that most patients with complications are outpatients with the mean length of stay being 0.1 day. Furthermore, the maximum length of stay observed in the dataset is three days.

3.2.3 Summary

To conclude this section, we summarize the findings of our data analysis. We analyzed the patient arrival data from the period 2018-2022 to identify seasonal patterns and trend. Furthermore, we examined the spread and volatility of the arrival data. Lastly, we studied the patient length of stay to provide a complete overview of the patient data.

Patient type "delivery"

Within our data analysis, we identified a daily seasonal effect that can be observed within the patient arrival data for patient type "delivery". The number of patients arriving from Monday to Friday are relatively equal, while the number of patients arriving throughout the patients is lower than average. This is partly due to the fact that there are less instrumental deliveries planned during the weekend. There is a negligible monthly seasonal effect present throughout the year. Lastly, in comparison to 2021, there are fewer delivery patients in 2022. This could lead to the forecasting model we develop to overshoot the actual number of delivery patients.

Although the average number of delivery patient arrivals are relatively stable throughout the week, the data has a relatively high standard deviation and volatility. This is due to the fact that most of the delivery patients that arrive at the obstetrics department can not be planned in forward. This causes unexpected peaks in demand, which contribute to the difficulty in forecasting the actual number of patients. Lastly, the average length of stay of delivery patients is 1.4 days, which is expected as most delivery patients are inpatients. Figure 3.18 gives an overview of delivery patients plotted in a time series for two months. Note that the number of patients during the weekend, day six and seven, are lower than the other days of the week. Furthermore, a lot of volatility can be observed.

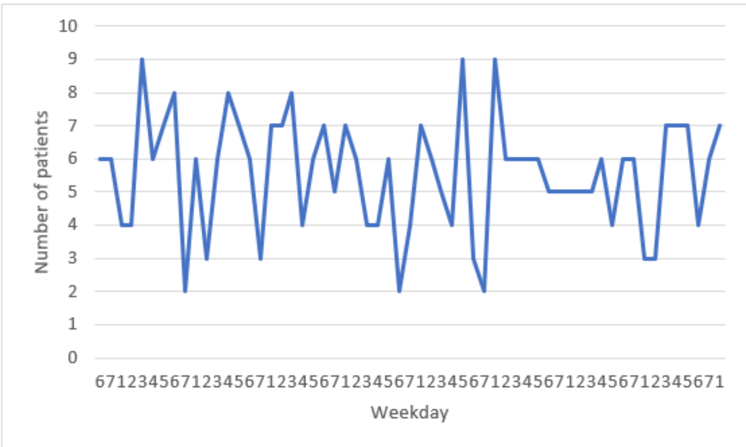


Figure 3.18: Time series of delivery patient arrivals for a period of 2 months. Note the low points during the weekend (day 6 and 7). There is also no clear trend observable between the 2 months.

Patient type ”complications”

The data analysis for the patient arrivals of patient type ”complications” also yielded interesting results. We identified a daily seasonal effect within the patient arrival data with Monday and Thursday coming forward as peak demand days and the weekend consisting of a lower number of patient arrivals. The lower number of patient arrivals during the weekend may also be due to the fact that fewer patients are planned during the weekend. Furthermore, there is no monthly or yearly trend visible within the data.

Concerning the spread and volatility of the arrival data for patient type ”complications” the data is relatively stable with a moderate standard deviation and moderate volatility. The data still has some unexpected peaks in demand, however less in comparison to the arrival data for patient type ”delivery”. This could be due to the fact that most complications patients are plannable outpatients, and thus the number of patients arriving at the hospital can be influenced. Lastly, the average length of stay of complications patients is 0.1 day, which confirms the fact that most complications patients arriving at the triage department are outpatients. Figure 3.19 gives a time series of two months for the number of complications patients. Note the relatively high number of patients on Monday and Thursday, day one and four, and the relatively low number of patients during the weekend, day six and seven. There is also less volatility when compared to the delivery patients time series.

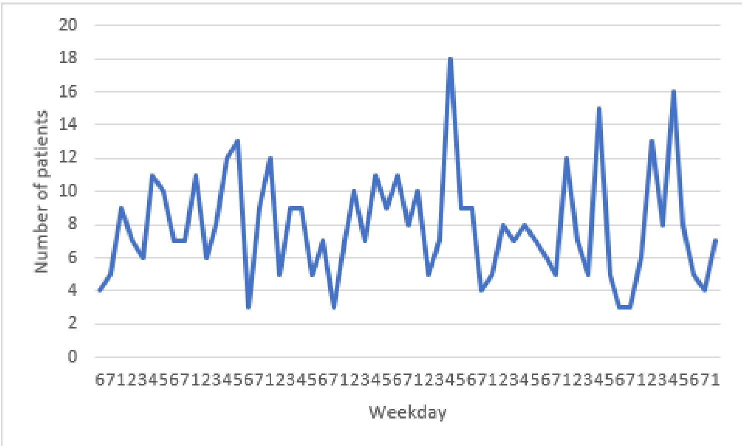


Figure 3.19: Time series of complications patient arrivals for a period of 2 months. Note the low points during the weekend (day 6 and 7) and the high points on Monday and Thursday (day 1 and 4). There is also no clear trend observable between the 2 months.

This concludes this section, where we analyzed the patient arrival data for both patient types to make a more informed decision when choosing a suitable forecasting model. In the next section we analyze the staff at the obstetrics department which we use to convert the total patient workload to a tactical staff planning.

3.3 Employees

In this section, we define the different types of employees that provide medical assistance at the obstetrics and triage department, and we discuss the current tactical staff planning. Section 3.3.1 covers the different employee types and their responsibilities based on the patient types we identified. In Section 3.3.2 we provide nurse-to-patient ratios for the patient types we identified, which we use as a conversion tool for the model output. Lastly, in Section 3.3.3, we present the current tactical staff planning which will be used as a baseline comparison.

3.3.1 Employee types

This section covers the types of nurses that are needed to provide medical assistance to the patient types we identified in Section 3.1. We discuss both patient types separately based on the nurse type requirements and how these requirements change throughout the care pathway.

Patient type "delivery"

Patients of patient type "delivery" can be viewed as having two phases of their treatment. Phase one is the delivery of the baby, and phase two is recovering from labor. Within the obstetrics department there are specialized nurses, named obstetrics nurses, who need to assist the doctor during delivery. Therefore, it is of utmost importance to have enough obstetrics nurses to cover the total number of delivery patients, which is why the obstetrics nurses are the bottleneck resource at the obstetrics department. After labor there are patients that need to recover at the hospital for one or more night. The obstetrics department plans midwives and regular nurses to provide medical assistance to these recovering delivery patients. For modelling purposes, we call these nurses, "recovery nurses".

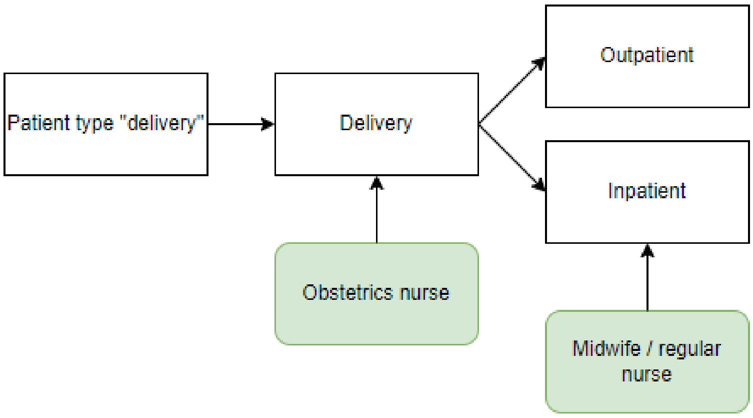


Figure 3.20: Responsibilities of the different types of nurses for patient type "delivery".

Patient type "complications"

Patients of patient type "complications" also require different nurse types depending on their care pathway. We already mentioned that the triage department treats both outpatients and inpatients. Treatment for outpatients consists of an examination or consultation, which is done by a doctor or clinical obstetrician. There is a fixed number of slots available for these patients, and therefore the number of staff planned is not dependent on patient demand. For this reason, we do not consider complications outpatients when we develop a new tactical staff planning. The other part of the complications patients are inpatients, which are cared for by regular nurses and obstetrics nurses. The triage department requires at least one obstetrics nurse and one regular nurse.

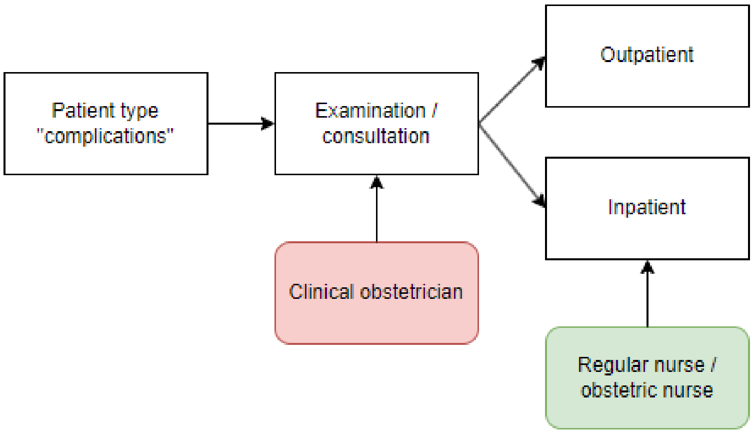


Figure 3.21: Responsibilities of the different types of nurses for patient type ”complications”.

3.3.2 Nurse-to-patient ratios

To convert the total patients workload to a tactical staff planning, we use nurse-to-patient ratios. We identified the nurse-to-patient ratios based on the patient types set in Section 3.1 and according to the different states of the patients. These ratios are based on expert opinion and set by using average estimations. In reality there are a lot of factors, like severity of complications, treatment duration, and length of stay that can influence the number of patients that a single employee can help during a day.

Nurse type	**Delivery patient**	**Recovering delivery patient**	**Complications inpatient**
Obstetrics nurse	1 to 2	–	1 to 3
Regular nurse	–	1 to 3	1 to 3
Midwife	–	1 to 3	–

Table 3.12: Nurse-to-patient ratios.

3.3.3 Current tactical planning

Table 3.13 shows the current tactical staff planning that the obstetrics department uses. The planning does not differ per day, month, or season and therefore is static. There are three different shifts during a working day, namely the day, evening and night shift. We will use the current planning to compare to the planning that we develop using the model. For modelling purposes, we only focus on the total number of required nurses instead of separating these numbers per shift. It should be noted that we do not consider clinical obstetricians in our model, but they are included in the planning as they are planned by the obstetrics and triage department.

Nurse type	**Day**	**Evening**	**Night**	**Total**
Obstetric nurse	5	4	4	**13**
Regular nurse	2	2	2	**6**
Midwife	1	1	1	**3**
Clinical obstetrician	2	2	1	5

Table 3.13: Current tactical staff schedule used by the obstetrics department.

3.4 Conclusion

In this chapter, we answered research question two, which was: *"How is the obstetrics department currently organized and what are the characteristics of the patient arrival data?"*. We did this by defining the patient types that require medical assistance at the obstetrics and triage department and analyzing the patient arrival data over the period 2018-2022 based on these patient types. Through this data analysis we discovered seasonal patterns in the patient arrival data which we will use as an input for the forecasting model. Furthermore, we analyzed the spread and volatility of the arrival data, which assists in narrowing down the number of suitable options for a forecasting model.

In Section 3.3 we identified the different employee types that are needed at the obstetrics department and which employees are needed to treat both patient types. Moreover, we used an expert opinion to get the nurse-to-patient ratios, which we need to convert the total patient workload into a staff planning. Lastly, we acquired the current tactical staff planning, which functions as a baseline comparison to the final solution. In the next chapter we use the information gathered during the data analysis to develop the tactical staff planning model which uses a patient arrival forecasting model as an input.

4 MODEL

In this chapter, we develop a model to estimate the total number of patients that require medical assistance at the obstetrics department. We will use this information to develop a tactical staff planning which is better tailored to the total patient workload. Section 4.1 discusses the solution approach, where we explain which steps we take to develop the model. In Section 4.2 we develop the forecasting model to predict patient arrivals. Lastly, in Section 4.3, we use the input of the forecasting model together with the patient length of stay to acquire the total workload at the obstetrics department using an adapted version of the convolution model of Vanberkel [56].

4.1 Solution approach

We propose a two-step solution approach to solve the problem we identified in Chapter 1. Step one consists of developing a time series forecasting model to predict the number of patient arrivals for the patient types we identified in Chapter 3. In Section 4.2 we choose several time series forecasting models based on the data characteristics studied in Chapter 3. Through evaluation, we decide on the most accurate forecasting model to make predictions of the number of patient arrivals for both patient types. The number of patient arrivals is a part of the total workload at the obstetrics department, as the department also treats inpatients. Figure 4.1 shows the difference between only considering patient arrivals and adjusting the patient arrivals for length of stay, giving the total number of patients at the obstetrics department.

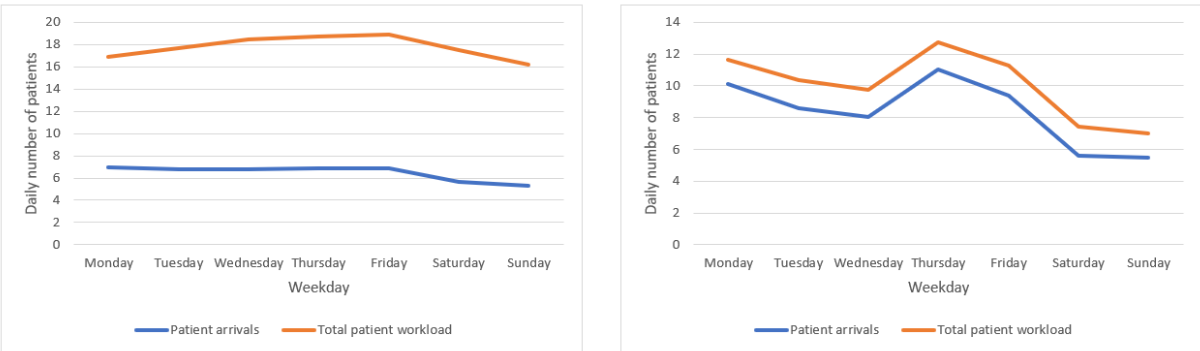


Figure 4.1: Total patient workload compared to the number of patient arrivals for patient type ”delivery” (left) and ”complications” (right).

To calculate the total number of patients requiring medical assistance at the obstetrics department, we develop a model which is an adaption of the convolution model from Vanberkel [56] in Section 4.3. The model uses the patient arrival forecast, from Section 4.2 and length of stay, from Chapter 3, to estimate the total number of patients present at the obstetrics and triage department based on a specific percentile of demand. The model is able to incorporate stochasticity into the model to deal with the variation in patient arrivals and patient length of stay. In Chapter 5 we use the output of the model to convert the total workload at the obstetrics department to a tactical staff planning using the nurse-to-patient ratios established in Chapter 3.

4.2 Forecasting model

In this section, we develop a time series forecasting model to predict the number of patient arrivals for both patient types separately for a set time period. This time period will be two months, as the staff planning for the obstetrics and triage department is produced two months beforehand by the departments' planner. Section 4.2.1 discusses the forecasting model selection and gives an overview and short description of the models used. In Section 4.2.2 we explain how we implemented and evaluated the selected forecasting models. Section 4.2.3 contains the model validation process and concludes which model is the most suitable for this problem context and therefore is used as an input for the second modelling step.

4.2.1 Model selection

We use the data analysis from Section 3.2 to make an informed decision on selecting the most suitable forecasting model for this problem context. Choosing the most suitable forecasting model depends on the data characteristics. As we recall, the arrival data for both patient types showed a clear recurring daily seasonal pattern. Furthermore, the arrival data did not show a clear trend, but we observed some small changes in the average number of arrivals throughout the year on a monthly level. The data analysis on the spread and volatility of the arrival data show that there is a lot of variation in the range of the daily number of patient arrivals. Although the seasonality patterns are stable, there is also a lot of volatility in the data, causing irregularities through periods of high and low demand. From the literature we reviewed in Section 2.2 we concluded that autoregressive models, like the SARIMAX model and machine and deep learning models, like random forest regression, have the best performance when it comes to the prediction of future patient arrivals. Moreover, we concluded that using a combination of linear and non-linear forecasting models and comparing them is best practice when deciding on the most suitable forecasting model.

Taking all this information into account, we choose five time series forecasting models that we implement and evaluate to generate accurate predictions for the number of patient arrivals for both patient types at the obstetrics department. We included three linear forecasting models that incorporate seasonality and trend in the calculations to make predictions. We decided to use one model from each class to compare the performance of each forecasting model class. The models we chose are the Holt-Winters Additive Damped model, the multiple linear regression model, and the SARIMAX model. Furthermore, to account for complex patterns within the data that are caused by volatility we included a machine learning model, which is the random forest regression model. Lastly, we added a simple exponential smoothing model as a baseline comparison performance indicator.

Forecasting model	**Description**
Simple Exponential Smoothing [61]	Exponential smoothing model implemented as baseline comparison
Holt-Winters Additive Damped [62]	Exponential smoothing model with integrated trend and seasonality factor
Multiple Linear Regression [19]	Simple linear regression model which uses multiple exogenous variables (seasonality factors) to make an estimation
SARIMAX [63]	Autoregressive model which is able to recognize seasonal patterns and uses exogenous variables (seasonality factors) to make an estimation
Random Forest [64]	Ensemble learning model which creates lag variables and seasonal component variables manually

Table 4.1: A short description of the selected forecasting methods. Extensive information on these models can be found within the mentioned sources.

The forecasting models we use are summarized in Table 4.1. We will not explain the inner workings of the forecasting models in this thesis. Further information on the formula's and calculations of the models can be found within the sources in the Table. In the next part, we elaborate on the implementation and evaluation of the selected forecasting models.

4.2.2 Model implementation and evaluation

In this section, we explain how we implemented the forecasting models and how we evaluated the predictions. In the first part of this section, we elaborate on the method we used to implement the forecasting models and the relevant settings for the input of the forecasting models. The second part of this section explains how we evaluated the accuracy of the selected forecasting model predictions using performance metrics.

Implementation

The selected forecasting models use the historic patient arrival data from the cleaned dataset we used in Chapter 3. We separated the data for both patient types and converted the data to a time series format where the number of patient arrivals per day is given for every day of the period 2018-2022, which spans from January 1st 2018 to December 31st 2022. The linear forecasting models that incorporate seasonality are programmed to use daily seasonality. The MLR and SARIMAX model use exogenous variables in the form of seasonality factors for both the day of the week and the month of the year. The input parameters we used for the forecasting models can be found in table 4.2.

We developed a model in Python which automatically fits, executes, and evaluates the selected forecasting models. The flowchart in Appendix E explains the workflow of the model. We used several Python packages that contain pre-programmed forecasting models. The package statsmodels was used to develop the simple exponential smoothing [65] and Holt-Winters additive damped forecasting model [66]. The pmdarima package provided code for the SARIMAX forecasting model [67] and we used the sklearn package to program the multiple linear regression [66] and random forest regression forecasting models [68]. The output of the model consists of a point forecast and several prediction intervals for the number of patient arrivals for both patient types. In Section 4.2.3 we go into more detail on point forecasts and prediction intervals. These outputs are evaluated based on the performance metrics set in the following subsection, and the forecasting models are sorted based on forecasting performance.

Forecasting model	**Seasonality**	**Exogenous variables**
Simple Exponential Smoothing	-	-
Holt-Winters Additive Damped	Daily	-
Multiple Linear Regression	-	Daily and monthly seasonal index
SARIMAX	Daily	Daily and monthly seasonal index
Random Forest	-	-

Table 4.2: Input settings for the selected forecasting models.

In the following subsection, we discuss the evaluation process of the forecasting model outputs, as this decides which forecast provides the most accurate results.

Evaluation

We evaluate the selected forecasting models by using several error metrics and specific forecasting accuracy metrics. The mean absolute error, Equation 4.1, and root mean squared error, Equation 4.2, are widely used in describing the magnitude of forecasting errors. The remaining three accuracy metrics are more intuitive and therefore can be used to better interpret the evaluation results. The mean absolute deviation, Equation 4.3, describes the average error in terms of number of patients or percentage respectively. The Bias metric, Equation 4.4 describes the direction of the average error which tells if the forecast either underpredicts or overpredicts. x_i is the forecasted value for the number of patient arrivals on day i, while y_i is the actual value. n is the number of data points that are being compared.

$$MAE = \frac{\sum_{i=1}^{n} |x_i - y_i|}{n} \tag{4.1}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (x_i - y_i)^2}{n}} \tag{4.2}$$

$$MAD = \frac{\sum_{i=1}^{n} |x_i - \bar{y}|}{n} \tag{4.3}$$

$$BIAS = \frac{\sum_{i=1}^{n} x_i - y_i}{n} \tag{4.4}$$

Before fitting a forecasting model to the time series data, we need to split the data into a training data set and a test data set. The forecasting model will be fitted to the training data set and the parameters will be adjusted accordingly. The test data will be used to evaluate the model, which will give an indication of how accurate the model is and how well the model fits the data. Deciding where to split the data depends on the preferred forecasting time horizon or specific patterns or cycles within the time series. We use a time horizon of two months to forecast demand. To test the forecasting models extensively, the first four years of the dataset, 2018 to 2021, is used for training purposes while the last year, 2022, is used as a test dataset. We use one year of testing data to examine whether the forecasting models are able to provide accurate estimations for every month of the year, as small trends between the months can impact the accuracy. By applying k-fold cross validation, multiple, indicated by k, training and test data splits can be generated to determine the accuracy of the forecasting model throughout different points in time. We opt to choose for a rolling evaluation, which means that the train-test splits move up by two months when testing for a new fold. This method is visually represented in figure 4.2. The forecasting method that provides the lowest average MAE value over all the folds is determined as the most suitable forecasting method and used as an input for the planning model.

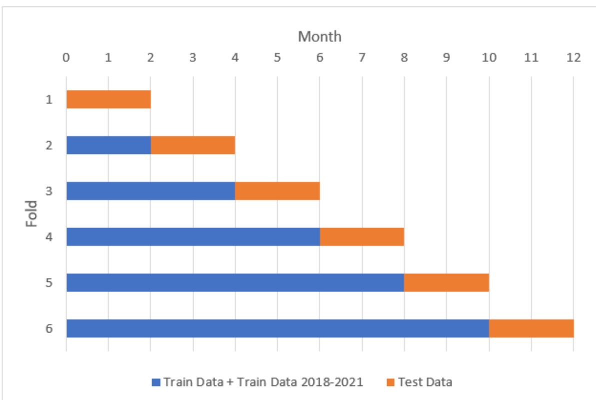


Figure 4.2: K-fold cross validation. We use 6 folds, each forecasting 2 months of data and using 2 months more train data. The training data includes the patient arrival data from 2018-2021.

4.2.3 Model results

This section discusses the predictions of the forecasting model by using the performance metrics mentioned in Section 4.2.2. We analyze the performance of the forecasting models for both patient types separately and conclude which model is the most suitable to use as an input for the tactical planning model. Furthermore, we developed prediction intervals to incorporate uncertainty into the forecasting model. First we elaborate on the results for patient type "delivery" and then we discuss the results for patient type "complications".

Prediction accuracy for patient type "delivery".

Table 4.3 displays the results for the selected forecasting methods for patient type "delivery". The results are based on the cleaned data set we used in Chapter 3, which means that the forecast is based on 11.799 data entries. The SARIMAX model proved to be the most accurate, based on all the performance metrics. The model has a mean absolute error value of about 1.5 patients. Furthermore, based on the BIAS statistics, the model underpredicts the number of patient arrivals compared to the actual true value. We took this in consideration while analyzing the output of the planning model. We took a sample of the total forecast output, the months January and February 2022, to give a more detailed view of the forecasting performance. Figure 4.3 shows that the SARIMAX model replicates the daily seasonal pattern within the data, however the actual data still has some irregular high and low values which the model can not predict.

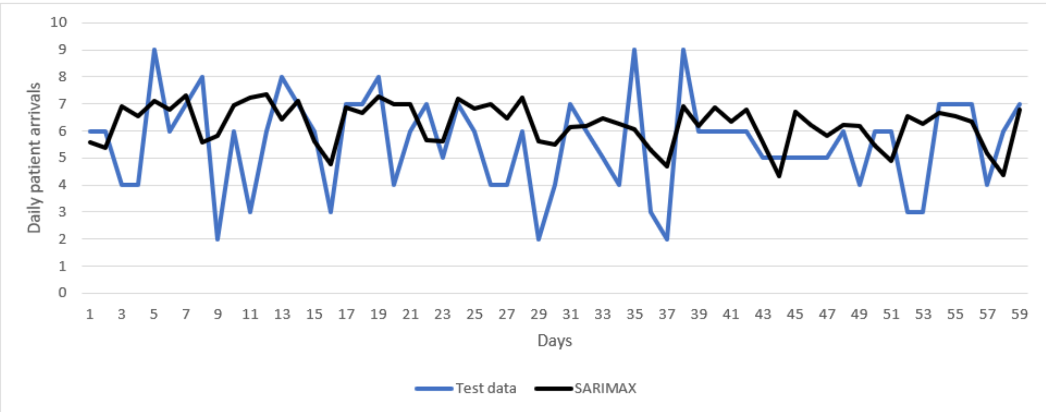


Figure 4.3: The most accurate forecasting model, the SARIMAX model, plotted against the test data for January and February 2022 for patient type "delivery".

Forecasting model	MAE	RMSE	MAD	BIAS
SARIMAX*	1,5	1,9	1,2	-0,3
MLR	1,7	2,1	1,4	-0,9
HW Additive Damped	1,6	2,0	1,4	-0,4
RF	1,6	2,0	1,4	-0,8
SES	1,6	2,0	1,4	-0,4

Table 4.3: Performance metrics for the implemented forecasts for patient type "delivery".

Prediction accuracy for patient type "complications"

Table 4.4 shows the results of the selected forecasting methods used for patient type "complications". The results are based on the cleaned dataset used in Chapter 3, and for patient type "complications" this consists of 15.323 data entries. Based on the mean absolute error, the SARIMAX model provides the most accurate forecasting results, which means that the model estimates the number of daily arrivals wrong with about 2.3 patient. Furthermore, the BIAS statistic shows that the forecast most of the time overpredicts the actual true value. Lastly, the results clearly show that the linear forecasting methods outperform the non-linear forecasting methods. Figure 4.4 shows the most accurate forecasting model plotted against a fraction of the true test data.

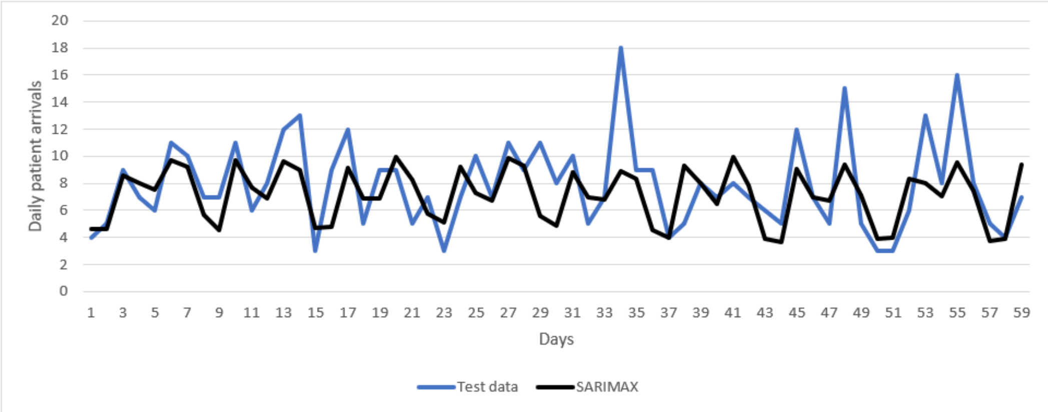


Figure 4.4: The most accurate forecasting model, the SARIMAX model, plotted against the test data for January and February 2022 for patient type ”complications”.

Forecasting model	MAE	RMSE	MAD	BIAS
SARIMAX*	2,3	2,9	1,8	0,6
MLR	2,3	3,0	1,8	0,6
HW Additive Damped	2,4	3,0	2,0	0,1
RF	2,8	3,4	2,0	1,1
SES	2,8	3,6	2,3	0,1

Table 4.4: Performance metrics for the implemented forecasts for patient type ”complications”.

Prediction intervals

The output of the best performing forecast models for the two main patient types are so-called ”point forecasts”, which means that it contains an estimation for the average number of patient arrivals on that specific day. However, as the number of daily patient arrivals is very uncertain, it is more interesting to look at the range of estimated values. To achieve this, we develop prediction intervals of the point forecasts using Equation 4.5 [11]. A prediction interval gives an interval within which we expect the estimated point forecast value to lie with a specified probability. in Equation 4.5 we use x_i to indicate the point forecast value on day i, σ is calculated by taking the standard error of the forecast compared to the actual data. This is calculated by using Equation 4.6. y_i is the actual value in this case and n is the number of observations. the symbol c indicates the coverage probability. for example, setting $c = 0,8$ gives a prediction interval where we expect the value of the point forecast x_i to lie within with a probability of 80%.

$$x_i \pm c\sigma \tag{4.5}$$

$$\sigma = \sqrt{\frac{\sum_{i=1}^{n}(y_i - x_i)^2}{n}} \tag{4.6}$$

The specified coverage probability has a impact on the width of the prediction interval. As the probability increases, the width of the interval also increases. Therefore, the main trade-off in developing prediction intervals is the amount of uncertainty that you are willing to accept within your demand forecast. We conducted an experiment for the best forecasting models for both patient types and generated prediction intervals for a set of confidence levels ranging from 0.05 to 1 with steps of 0.05. The percentage of observations of the test data covered by the prediction interval is given, and the average range of the prediction interval is given. To visualize this effect, Figure 4.5 and 4.6 show the prediction intervals for January and February 2022 with confidence levels 0.25, 0.50 and 0.75. The full results of the experiment are displayed in the Table in Appendix F.

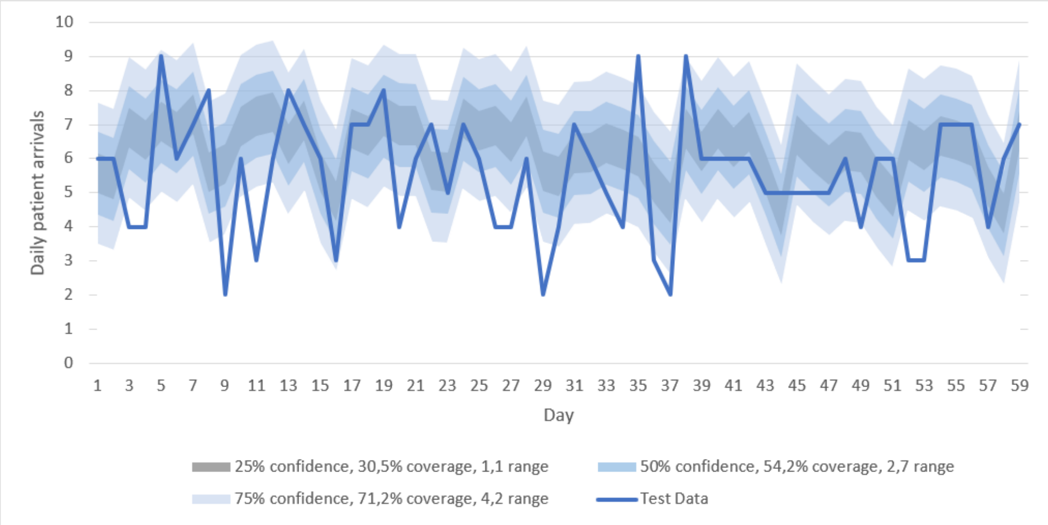


Figure 4.5: Three different prediction intervals based on the point forecast of the SARIMAX forecasting model for patient type "deliveries" using increasing confidence levels plotted against the actual data.

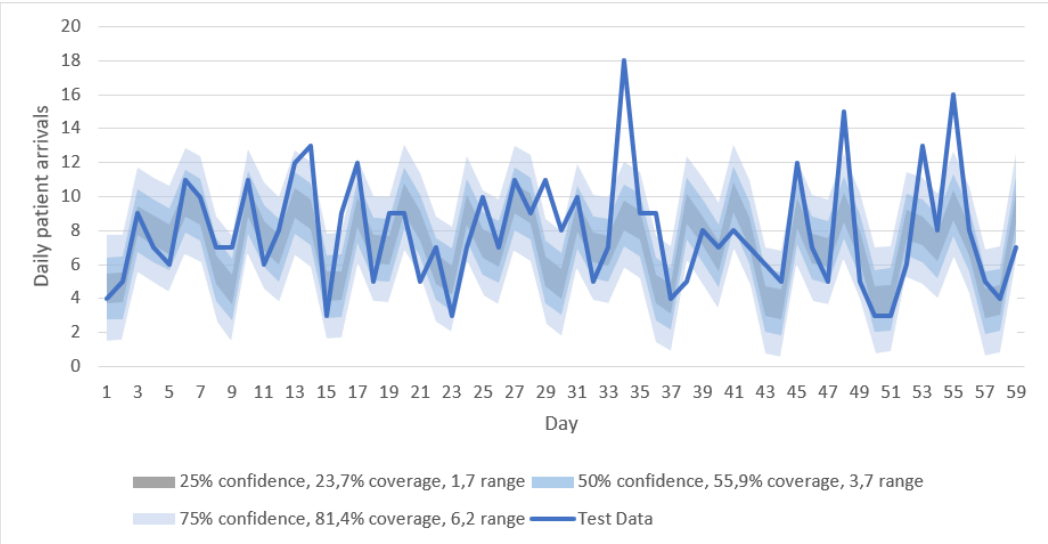


Figure 4.6: Three different prediction intervals based on the point forecast of the SARIMAX forecasting model for patient type "complications" using increasing confidence levels plotted against the actual data.

The point forecasts and prediction intervals generated using the SARIMAX models for both patient types will be used as an input for the convolution model, which we will discuss in the next Section. The implemented forecasting model can be used in two ways, namely analyzing the most suitable forecasting model and executing the most accurate forecasting model. Both applications are included in the final Python model.

4.3 Convolution model

The second modelling step is to use the output of the SARIMAX forecasting model from section 4.2 and calculate the total number of patients requiring medical assistance at the obstetrics and triage department using patient length of stay. Furthermore, we want to incorporate the uncertainty in the number of patients arriving at a specific weekday and how long their length of stay will be. In this section, we use an adaption of the convolution model of Vanberkel [56] to acquire the steady-state distributions of the total number of patients at the obstetrics department for every day of the week using the forecasted patient arrivals.

To calculate the total number of patients requiring medical assistance at the obstetrics department, we use the convolution model of Vanberkel [56]. The convolution model can be seen as a queuing model, which consists of blocks of patients within a master surgical schedule. these blocks of patients are described by patient arrival patterns, and the impact of these blocks on subsequent blocks depends on the length of stay of these patients. The arrival patterns and length of stay of patients consist of discrete probability distributions, which incorporates stochasticity into the model. The model output gives an indication of the total number of patients requiring medical assistance on a specific day of the week based on a chosen percentile. In this way, management can decide for which percentage of coverage they want to create a tactical staff planning. We implemented the adapted convolution model of Vanberkel et al. [56] in Python. Section 4.3.1 discusses the model inputs, which are based on the data analysis from Chapter 3 and the forecasted demand from Section 4.2. In Section 4.3.2 we elaborate on the model calculations and how we adapted the convolution model to our problem context. Section 4.3.3 shows the model output, and Section 4.3.4 discusses an extension to the model to separate the total number of arriving and recovering patients, which we will use to make a more accurate estimation of the required number of nurses.

4.3.1 Model input

The convolution model relies on patient data, which we acquired from the dataset analyzed in Chapter 3. The predictions generated by the forecasting model we developed in Section 4.2 is used as an input for the number of patient arrivals for both patient types. The inputs are used to create the needed probability distributions for patient arrivals and patient length of stay. The dimensions of the model, the length of the master surgical schedule and the number of patient types, were determined during the data analysis. In this section, we elaborate on the inputs for the adapted convolution model.

Master surgical schedule

The convolution model requires an empty MSS as a starting point. An MSS is a cyclic schedule dictating the specialty-to-OR assignment. The dimensions of the MSS are set by the parameters Q and I. The parameter Q indicates the number of days that the MSS cycle consists of with $q \in \{1, 2, ..., Q\}$. The parameter I indicates the number of available operating rooms according to the model of Vanberkel. However, to adapt the model to the obstetrics department, the parameter I will indicate the number of different patient types arriving at the department with $i \in \{1, 2, ..., I\}$. Using these parameters, the MSS can be filled with blocks, indicated by variable $b_{i,q}$. Within these blocks, patients arrive to the department and these arrival patterns depend on the day q and patient type i

Using the information gathered in chapter 3 we set Q to 7, as we concluded that there is a strong daily seasonal effect observed within the data which depends on the day of the week. Furthermore, we identified two patient types at the obstetrics department, which means that we will set I to 2 Figure 4.7 gives a visual representation of the empty MSS for this problem context.

Specialties			Days in MSS						
			Monday	*Tuesday*	*Wednesday*	*Thursday*	*Friday*	*Saturday*	*Sunday*
			$q = 1$	$q = 2$	$q = 3$	$q = 4$	$q = 5$	$q = 6$	$q = 7$
	Specialty 1	$i = 1$	$b_{1,1}$	$b_{1,2}$	$b_{1,3}$	$b_{1,4}$	$b_{1,5}$	$b_{1,6}$	$b_{1,7}$
	Specialty 2	$i = 2$	$b_{2,1}$	$b_{2,2}$	$b_{2,3}$	$b_{2,4}$	$b_{2,5}$	$b_{2,6}$	$b_{2,7}$

Figure 4.7: Empty Master surgical schedule, containing several blocks $b_{i,q}$.

Specialties

The master surgical schedule indicates whether a certain specialty is assigned to a block within the schedule. We assume, in the problem context we study, that patients from all the patient types can arrive at every given day. However, we concluded in chapter 3 that the number of patients arriving at the obstetrics department depends on the day of the week. To include this effect in our model, we split the patient types into seven different specialties each, corresponding to the days of the week. Using this method, the seasonal effects of the different weekdays can be incorporated into the model by assigning the specialties corresponding to a specific weekday and patient type to the right block in the MSS. We indicate the specialties using index j, with $j \epsilon \{1, 2, ..., Q * I\}$. Figure 4.8 contains the master surgical schedule with assigned specialties.

Specialties			Days in MSS						
			Monday	*Tuesday*	*Wednesday*	*Thursday*	*Friday*	*Saturday*	*Sunday*
			$q = 1$	$q = 2$	$q = 3$	$q = 4$	$q = 5$	$q = 6$	$q = 7$
	Specialty 1	$i = 1$	$j = 1$	$j = 2$	$j = 3$	$j = 4$	$j = 5$	$j = 6$	$j = 7$
	Specialty 2	$i = 2$	$j = 8$	$j = 9$	$j = 10$	$j = 11$	$j = 12$	$j = 13$	$j = 14$

Figure 4.8: Master surgical schedule with assigned specialties.

Discrete probability distributions for patient arrivals

The blocks occupied by specialty j are described by two parameters, c^j and d_n^j. First, we explain the parameter c^j, which is a discrete distribution for the number of patients arriving in one block. A discrete distribution is a probability distribution where the random variable, in this case c^j, can only take on a finite or countable number of values. $c^j(x)$ is the probability of x number of patients arriving with $x \epsilon \{0, 1, ..., C^j\}$, where C^j is the maximum number of patients that can arrive in one block. Therefore, the number of patients arriving in one block is finite and thus c^j is a discrete distribution.

The patient arrival distributions are created by counting the number of observations of x patients on a specific weekday and dividing this by the total number of observations of that weekday. This process is repeated for every day of the week and both patient types, to get c^j, with $j \epsilon \{1, 2, ..., Q * I\}$.

Discrete probability distributions for patient length of stay

The other parameter describing the operating room blocks is d_n^j, which is the probability that a patient, who is still in the ward on day n, is to be discharged that day. We assume that patient length of stay is not dependent on the day of the week, and therefore the probabilities calculated for a specific patient type are the same regardless of the day of the week. To calculate d_n^j we first calculate the probabilities, which we call $P_j(n)$, that a patient's total length of stay is exactly n days with $n \epsilon \{0, 1, ..., L^j\}$ where L^j is the maximum length of stay for specialty j. The historic input data is used to calculate the probabilities. These probabilities are calculated by counting the number of observations of a specific patient type having a length of stay of exactly n days and dividing this by the total number of observations. This process is repeated for every patient type.

d_n^j is then calculated by dividing the probability that a patient's total length of stay is exactly n days by the probability that a patient was not yet discharged before day n. This follows equation 4.7. This process is repeated for every specialty j to get d_n^j, with $j \in \{1, 2, ..., Q * I\}$.

$$d_n^j = \frac{P^j(n)}{\sum_{k=n}^{L^j} P^j(k)} \tag{4.7}$$

4.3.2 Model calculations

Using the model inputs calculated in section 4.3.1 we can use the equations provided by Vanberkel [56] to calculate the steady-state distribution of the total number of recovering patients on each day of the MSS. The research identifies three separate steps to get to the steady-state distributions. These steps will be given below with additional explanation. It must be noted that step 2 and 3 are adapted to fit the problem context.

Step 1: distribution of recovering patients from specialty j following from a single operating room block

The first step of the model is to calculate the distribution of recovering patient from specialty j which follows from a single operating room block. To calculate these distributions, we use parameters c^j and d_n^j. We want to find out what the probabilities are that x patients of a single operating room block of specialty j are still in recovery after n days. This is a discrete probability distribution, which we indicate by $h_n^j(x)$, with $n \in \{0, 1, ..., L^j\}$ and $x \in \{0, 1, ..., C^j\}$. The number of patients in recovery from specialty j on day $n = 0$ is equal to the number of patients arriving that day for specialty j. Using this as a starting point, we can iteratively calculate the needed probabilities. The probabilities for the number of patients in recovery from specialty j for $n > 0$ is calculated by using a binomial distribution. Equation 4.8 shows the binomial distribution.

$$\binom{k}{x}(d_n^j)^{k-x}(1 - d_n^j)^x \tag{4.8}$$

d_n^j is the probability that a patient is discharged on day n, while $1 - d_n^j$ is the probability that the patient stays that day. Furthermore, k indicates the number of patients in recovery on day n, while s is the number of patients in recovery on day $n + 1$. Putting this all together, using equation 4.9 we can calculate the discrete distribution $h_n^j(x)$ iteratively for all days n and repeat this process to get the distribution for all specialties j.

$$h_n^j(x) = \begin{cases} c^j(x) & when\, n = 0, \\ \sum_{k=x}^{C^j} \binom{k}{x}(d_n^j)^{k-x}(1 - d_n^j)^x & otherwise \end{cases} \tag{4.9}$$

Step 2: aggregate distributions of recovering patients following from a single MSS cycle

Using the distributions calculated in step 1 and the MSS, we calculate the aggregate distributions of recovering patients following from a single MSS cycle. To do this, we "execute" every single block in the MSS using the $h_n^j(x)$ distributions matched with the right specialty and incorporate the impact on the subsequent days of the MSS. The length of stay of patients causes some recovering patients to flow over into the next cycle of the MSS. However, as we study a single MSS cycle, we add these days to the cycle. We calculate the discrete distribution for the total number of recovering patients on day m resulting from a single MSS cycle, which we call H_m.

Because the workload differs between the two patient types we defined, we want to calculate the total number of patients at the obstetrics department separately for every patient type. Therefore, we adapt the equations used in the paper of Vanberkel [56] to fit the problem context. We do this by giving an extra index i to H_m, giving $H_{m,i}$, to create separate distributions for the two patient types. We use equations 4.10 and 4.11 to calculate the discrete distribution for the total number of recovering patients on day m resulting from a single MSS cycle

$$H_{m,i}(x) = h_m^{i,1} * h_m^{i,2} * ... * h_m^{i,Q} \, \forall i, with \, i \, \epsilon \, \{1, 2, ..., I\} \tag{4.10}$$

$$h_m^{i,q}(x) = \begin{cases} h_{m-q}^j & if \, q \leq m < L^j + q, \\ 0 & otherwise \end{cases} \tag{4.11}$$

Equation 4.10 adds the blocks of subsequent days in the MSS together for the two patient types separately. Equation 4.11 makes sure that the right blocks are included in equation 4.10 based on the day m and the specialty m. This is done by setting the probability $h_m^{i,q}(0)$ of the distribution corresponding to a block $h_m^{i,q}$ to 1, which means that there is a one hundred percent probability that there are zero patients recovering from that block on day m. This has to be paired by setting all other probabilities $h_m^{i,q}(x)$ for $x > 0$ to zero.

We add the distributions together by means of discrete convolutions because we add two independent discrete distributions together. The discrete convolutions are indicated by $*$. Equation 4.12 explains how two independent discrete distributions can be added together.

$$C(x) = \sum_{k=0}^{\tau} A(x)B(x-k) \tag{4.12}$$

With $C(x)$ being the new distribution and $A(x)$ and $B(x)$ being the two discrete distributions which we want to add together. The symbol τ indicates that the summation goes until the largest x value with a positive probability that can result from $A(x) * B(x)$. This is equal to the sum of the largest x value of A and the largest x value of B. The range of m is decided by taking the last day of the MSS and adding the highest value for the length of stay of a patient across all patient types.So $M = max_j \left\{L^j + q\right\}$, which consequently means that $m \, \epsilon \, \{1, 2, ..., M\}$.

Step 3: steady-state distribution of recovering patients

To achieve the steady-state distribution of recovering patients, we go through one final step. Because of the length of stay of patients, some recovering patients flow into the next MSS cycle. Therefore, we need to consider consecutive MSS cycles to make sure that we incorporate these patients, such that the probabilities of various states remain constant overtime, which is the steady-state result. The number of consecutive MSS cycles needed depends on the parameter m which is calculated in step 2. In our case, the largest LOS across the two patient types is 6, which means that $max_j \left\{L^j + q\right\} = 13$ Figure 4.9 gives a schematic overview of the overlapping MSS cycles for this specific problem context.

As we did in step 2, we adapt the following equations to fit the problem context by separating the distributions for every patient type. We calculate the steady-state distribution, named $H_{q,i}^{SS}$, of the number of recovering patients on every day of the MSS cycle with $q \, \epsilon \, \{1, 2, ..., Q\}$. Adding the extra index i guarantees that we separate the distributions of the two patient types. We use equation 5.7 to calculate the steady-state distribution for every patient type.

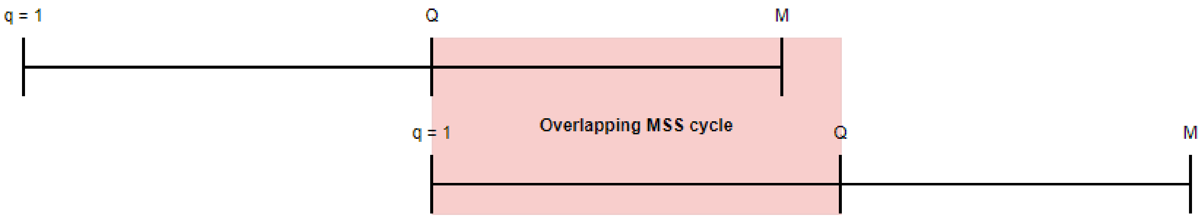


Figure 4.9: Overlapping MSS cycle.

$$H_{q,i}^{SS} = H_{q,i} * H_{q+Q,i} * H_{q+2Q,i} * ... * H_{q+[M+Q]Q,i} \, \forall i, with \, i \, \epsilon \, \{1, 2, ..., I\} \tag{4.13}$$

4.3.3 Model output

The steady-state distribution for the total number of recovering patients on every day of the MSS cycle serves as the model output. To interpret the output, we use the cumulative distribution function of $H_{q,i}^{SS}(x)$. The management of the obstetrics department decides on how much coverage for patient demand they want to provide. If, for example, management decides that the department has to provide sufficient coverage for at least 80 percent of the days of the MSS, then we need to find the 80th percentile of demand using the steady-state distribution for each day. In this case, the 80th percentile of the total number of patients recovering on a specific day is given by the minimum x such that $H_{q,i}^{SS}(x) \geq 0.8$. Calculating the value for x for a range of percentiles gives a good overview of the total number of recovering patients on every day of the MSS cycle, and thus an insight into the dynamics of the workload at the department. Figure 4.10 gives a visual representation of the output of the adapted convolution model using the point forecasts of the number of daily patient arrivals. In the figure, the value for x is given for every day of the week for the 25th, 50th and 75th percentile of patient demand.

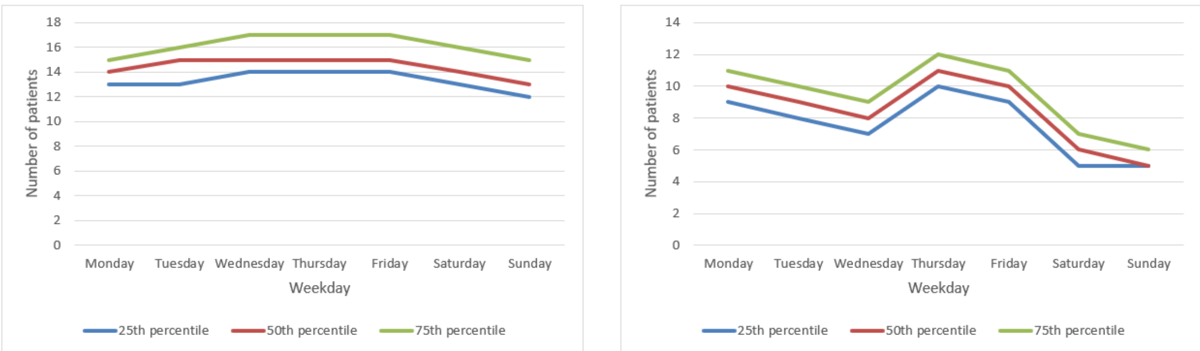


Figure 4.10: Total number of patients for different percentiles of demand for patient type "delivery" (left) and patient type "complications" (right).

4.3.4 Model extension

As we identified in Section 3.3 that specific nurses types are needed for either the total number of patients or only the recovering patients, we are also interested in the total number of recovering patients. A small change to the model input can be made to acquire the total number of arriving patients. By manipulating the input for the length of stay data, we can set the probability for a patient being an outpatient ($n = 0$) to 100%, which means that the model only considers arriving patients in the model output. Simply subtracting the number of arriving patients from the total number of patients leaves the total number of recovering patients.

4.4 Conclusion

In this chapter we answered research question 3 which is: *"How can we create a tactical staff planning model which uses forecasted patient demand as an input?"*. We achieved this by developing a two-stage model that consists of a time series forecasting model and an adaption of the convolution model of Vanberkel [56].

We developed a Python model which is able to implement, execute, and evaluate several forecasting models. The most accurate forecasting model can be easily identified by using the model, and prediction intervals are automatically generated based on a chosen coverage level. The autoregressive SARIMAX forecasting model proved to be the most accurate forecasting model in this problem context, and therefore we will use the forecast of this model as an input for the convolution model to generate results.

We extended the model by using an adaptation of the convolution model of Vanberkel [56] to acquire the total patient workload at the obstetrics department for every day of the week. In the next chapter, we use the output of the model together with the nurse-patient ratio's established in Chapter 3 to convert the total patient workload to a tactical staff planning. Furthermore, we compare the output of the model to the actual data to validate the model. Figure 4.11 contains a schematic overview of the modelling steps.

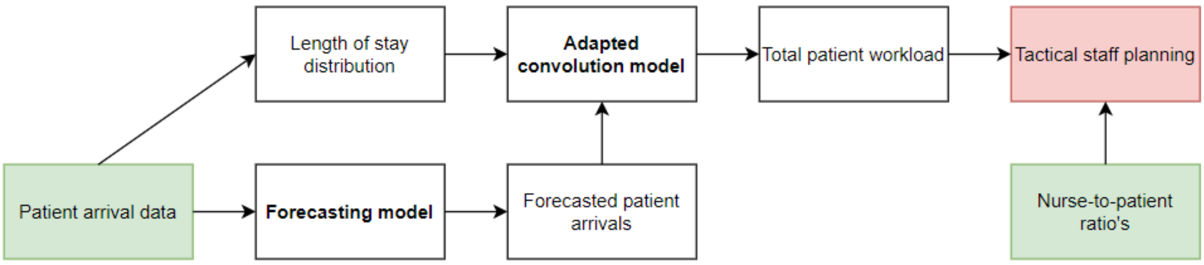


Figure 4.11: Flowchart of the model we developed. The model uses patient arrival data and nurse-to-patient ratio's as inputs (green) and transforms this data to a tactical staff planning through a forecasting model and an adapted version of the convolution model.

5 MODEL VALIDATION AND RESULTS

In this chapter, we use the model that we developed in Chapter 4 to generate a tactical staff planning. In Section 5.1 we define the key performance indicators we use to evaluate the tactical staff planning. In Section 5.2 we validate the convolution model output using the actual patient data and verify whether using the forecasted patient arrivals provide a better model performance than using empirical patient arrivals as an input. Section 5.3 discusses the conversion of the model output to a tactical staff planning. In this section, we also compare the current tactical staff planning with the planning that we generated. Furthermore, we use sensitivity analysis to study the relationship between staff workload and the patient demand coverage percentage and the implications on the required number of nurses. In Section 5.4 we summarize the findings of this chapter and perform a sensitivity analysis and interpret the results. Lastly, Section 5.5 concludes this chapter.

5.1 Key performance indicators

Before we validate and evaluate the output of the convolution model, we define the key performance indicators. We use two KPIs to analyze the convolution model output, which evaluate the staff workload and the patient coverage.

- **Patient demand coverage percentage (PDCP):** with this KPI, we measure the percentage of the total patient demand we can cover using the proposed planning method. The KPI is evaluated using actual historical patient data and can be used retrospectively to validate the planning method.
- **Staff workload percentage (SWP):** we define the staff workload percentage as a percentage that indicates the proportion of the planned patient capacity that is used in comparison to the actual number of patients. It is calculated by dividing the actual number of patients by the planned patient capacity. The KPI can be used to analyze the utilization of the planned staff and conclude whether over- or under planning issues arise from the planning method.

5.2 Model validation

In this section, we validate the convolution model output using the actual patient arrival data adjusted for the patient length of stay. We use the k-fold cross validation method, which we also used to evaluate the forecasting models in Chapter 4.2. To validate the convolution model, we use the actual patient data of 2022. We validate the convolution model output for two different inputs:

- **Forecasted patient arrivals:** this input is based on the forecasted patient arrivals for a planning period of two months. This is our proposed method.
- **Empirical patient arrivals:** this input is based on the empirical patient arrivals and thus uses the actual patient data directly until two months before the end of the planning period. This is also the method that Vanberkel et al. [56] use in the paper.

In Section 4.2.3 we developed prediction intervals for the forecasting model output which are based on specific confidence levels. We conducted an experiment where we used the upper limit of a prediction interval for a set of confidence levels as an input for the convolution model. For every model output, we observed the percentage of patient coverage. To ensure a fair comparison, we chose the upper limit of the prediction intervals that provide close to 100 percent patient coverage, as management aims to provide medical assistance for all patients.

Patient type "delivery"

Figure 5.1 shows two graphs representing the total number of delivery patients corresponding to the 95th percentile of demand from the model output together with the actual total number of delivery patients for a planning period of two months, January and February 2022. The graph on the left used the empirical patient arrivals as an input, while the graph on the right used the output of the forecasting model as an input for the convolution model. We can conclude that both model outputs follow the daily seasonal pattern.

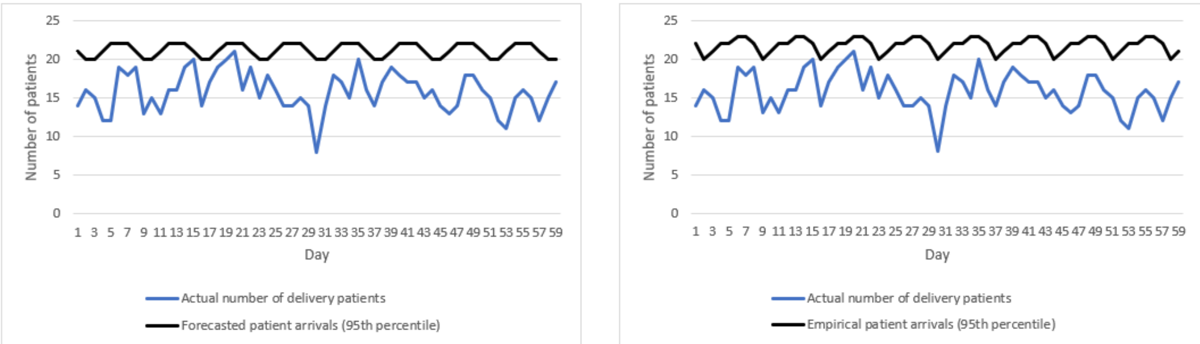
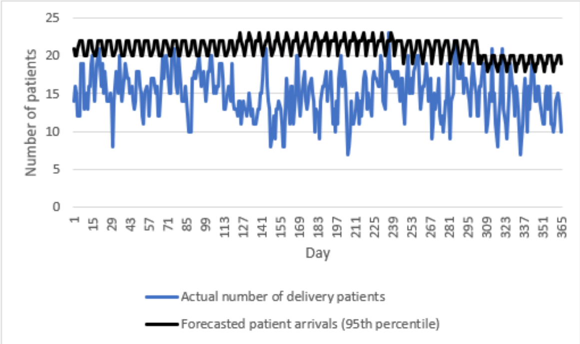


Figure 5.1: Total number of delivery patients compared to the model output using forecasted patient arrivals (left) and empirical patient arrivals (right) for January and February 2022.

KPI	Forecast	Empirical
PDCP	100%	100%
SWP	76%	73,5%

Table 5.1: KPIs for the output of the convolution model for two months (January and February 2022) using the two defined inputs for patient arrivals.

If we evaluate the convolution model outputs using the defined KPIs, we can make some objective conclusions. Using the forecasted input, we achieve a staff workload percentage of 76%. Comparing this to the empirical patient arrival data, the total workload percentage is 73.5%. Both inputs achieve a patient demand coverage percentage of 100%. We need to broaden the time horizon and examine and evaluate the data over the whole year to give conclusive evidence.



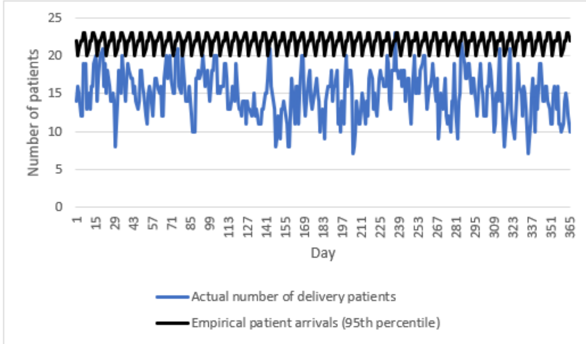


Figure 5.2: Total number of delivery patients compared to the model output using forecasted patient arrivals (left) and empirical patient arrivals (right) for the year 2022.

KPI	**Forecast**	**Empirical**
PDCP	99,2%	99,7%
SWP	71,7%	68,8%

Table 5.2: KPIs for the output of the convolution model for 2022 using the two defined inputs for patient arrivals.

If we examine Figure 5.2 only visually, we can see that the convolution model output using the forecasted patient arrivals adjusts its level according to small trends that occur between the different months, and therefore fits the actual patient data better. In Table 5.2 we display the results of the KPIs when comparing the two data inputs for the convolution model. With an average staff workload percentage of 71.7% using the forecast patient arrivals as an input for the convolution model is objectively the best method to use. The increased workload percentage has an impact on the total number of required nurses, and therefore a high percentage yields better results in the end. Although the empirical patient arrivals input provides slightly more patient demand coverage, this does not outweigh the increase in the staff workload percentage. The forecasted patient arrivals input has an advantage in terms of recognizing trends, while the empirical patient arrival data only provides a static estimation of the total number of patients. Therefore, we use the forecasted patient arrivals as an input for patient type "delivery" to compare to the current planning method.

Patient type "complications"

Figure 5.3 shows two graphs representing the total number of complications patients corresponding to the 95th percentile of demand from the model output together with the actual total number of complications patients for a two-month planning period, January and February 2022. Both model outputs follow the daily seasonal pattern clearly. Table 5.3 gives the evaluation of the outputs based on the KPIs, which favor the forecasted patient arrival input because the staff workload percentage is about the same while the patient demand coverage percentage is higher.

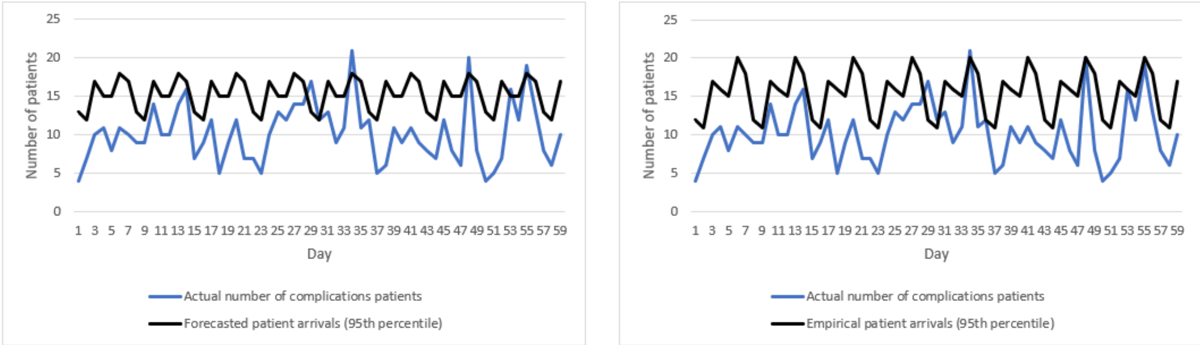


Figure 5.3: Total number of complications patients compared to the model output using forecasted patient arrivals (left) and empirical patient arrivals (right) for January and February 2022.

KPI	**Forecast**	**Empirical**
PDCP	99,2%	99,7%
SWP	63,4%	63,7%

Table 5.3: KPI's for the output of the convolution model for two months (January and February 2022 using the two defined inputs for patient arrivals.

However, when we broaden the time horizon to the full test year, we can clearly see that forecast driven model output fits the data better than the historic data driven model output. This effect can be seen in Figure 5.4. This is because the forecasting model incorporates trend throughout the year and therefore adapts the level of the forecast to this trend. Table 5.4 confirms this phenomenon, as the convolution model output that uses the forecasted patient arrivals as an input provides almost 4% more patient demand coverage. Although this does bring a difference in staff workload percentage with it, the increase in patient demand coverage is more important in this case, as 93.4% is too low when we aim for almost 100%. For this reason, we also choose to use the forecasted patient arrivals as an input for the convolution model to estimate the total patient workload for complications patients. In the next section, we will use the convolution model outputs using the forecasted patient arrivals as an input to generate a tactical staff planning using nurse-to-patient ratios.

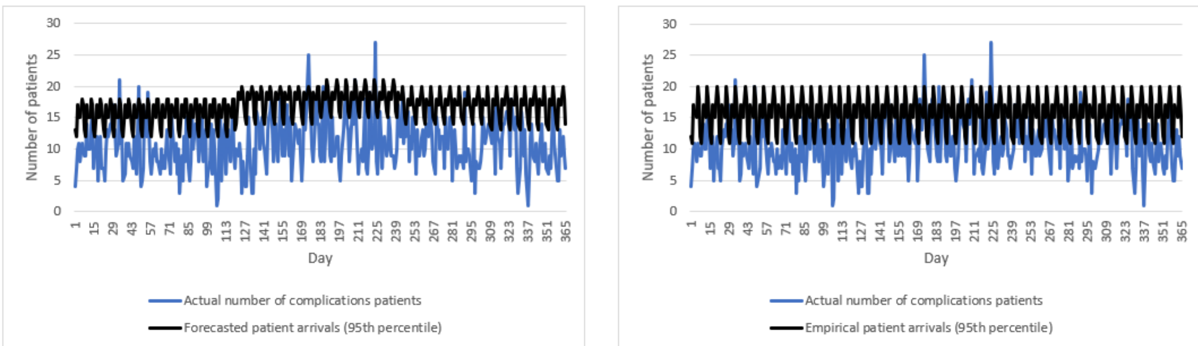


Figure 5.4: Total number of complications patients compared to the model output using forecasted patient arrivals (left) and empirical patient arrivals (right) for the year 2022.

KPI	Forecast	Empirical
PDCP	97,3%	93,4%
SWP	63,7%	69,2%

Table 5.4: KPI's for the output of the convolution model for 2022 using the two defined inputs for patient arrivals.

5.3 Conversion to staff planning

Having validated the model in Section 5.1, we convert the total patient workload from the model output to a tactical staff planning in this section. We use the validated model output which covers the total patient workload for both patient types and the nurse-patient ratio's we established in Section 3.2. We discuss the patient types separately as they both require different personnel and therefore also have different ratio's. In Section 5.3.1 we discuss the conversion of total patient workload to required number of staff for patient type "delivery" and in Section 5.3.2 we do the same for patient type "complications". For each patient type, we compare the proposed tactical staff planning to the current tactical staff planning. We use a time horizon equal to the planning period, which is two months, to compare the current and proposed planning. We use the month January and February as an example. Furthermore, we use sensitivity analysis to investigate the impact of using different percentiles of demand on the tactical staff planning.

5.3.1 Patient type "Delivery"

As mentioned in Section 3.3.1, all three nurse types of interest are considered for patients of patient type "delivery". Depending on the state of the patient, there are different types of nurses required to provide medical assistance. Obstetrics nurses assist during labor, therefore we consider the total number of delivery patients when calculating the required number of obstetric nurses. One obstetric nurse can provide medical assistance to two delivery patients during a day. Regular nurses and midwives are required to provide care for recovering inpatients after delivery. For modelling purposes, we take these two types together and call these "recovery nurses". One recovery nurse can provide medical assistance to three recovering delivery inpatients. The number of recovering patients is calculated by using the model extension explained in Section 4.3.4.

Current planning method

Obstetric nurses assist with the delivering of a baby and are therefore a critical resource for the obstetrics department. As stated in Section 3.3.2 one obstetrics nurse can provide medical care for two patients on a working day. Therefore, the total number of delivery patients at the obstetrics department cannot exceed 24, as the obstetrics department plans 12 obstetrics nurses every day. Furthermore, we assume that 3 midwives and 5 regular nurses available to provide medical care for recovering patients after labor. For modelling purposes, we generalize both employee types to "recovery nurses". This means that the total number of recovering delivery patients cannot exceed 24, as this would cause capacity problems. Figure 5.5 shows the patient capacity for obstetrics nurses (left) and recovery nurses (right) plotted against the actual number of total delivery patients (left) and delivery inpatients (right). Lastly, for modelling purposes, we assume that a patient is in recovery when the length of stay of a patient is at least 1 day or higher. We make the assumption that an obstetrics nurse needs to provide medical assistance to the total patient workload, which consists of both patient arrivals and recovering patients, and a recovery nurse only provides care for patients that are on day 1 or higher of their recovery.

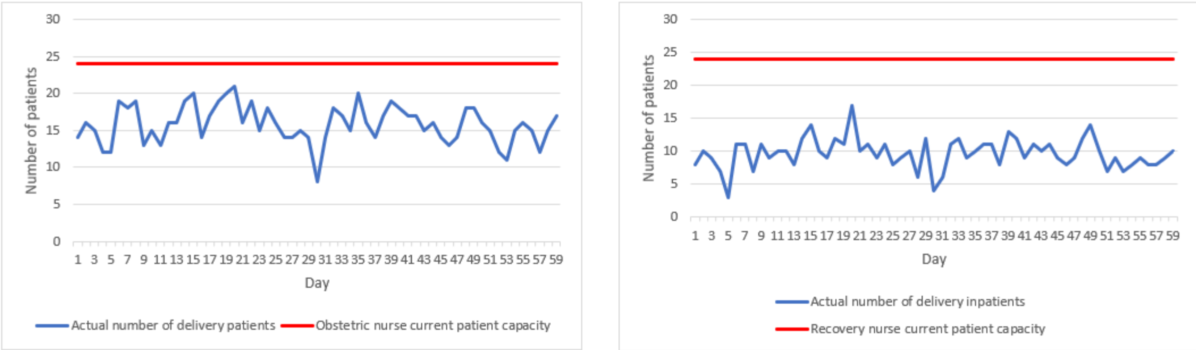


Figure 5.5: Obstetrics nurses (left) and recovery nurses (right) patient capacity based on the current tactical staff planning plotted against the actual patient data.

We conclude from figure 5.5 that the current tactical staff planning causes over-planning issues for every day of the planning period, especially considering the recovery nurses. This means that valuable resources, in this case nurses, are underutilized. This can also be concluded from the low staff workload, which is 66.9% for obstetric nurses, and 41.6% for recovery nurses. The KPIs in Table 5.3 provide a baseline comparison for the proposed planning method. In the following part, we investigate whether our proposed tactical staff planning solves this problem.

KPI	ON patient capacity	RN patient capacity
PDCP	100%	100%
SWP	66,9%	41,6%

Table 5.5: KPI's for the patient capacity based on the current tactical staff planning. ON = obstetric nurse, RN = recovery nurse.

Proposed planning method

Figure 5.6 shows the proposed capacity for obstetrics nurses from the convolution model output plotted against the actual data and the current capacity. We plotted two convolution model outputs, one for the obstetric nurses capacity and one for the recovery nurses capacity. We used the convolution model output that corresponds with the 95th percentile of demand.

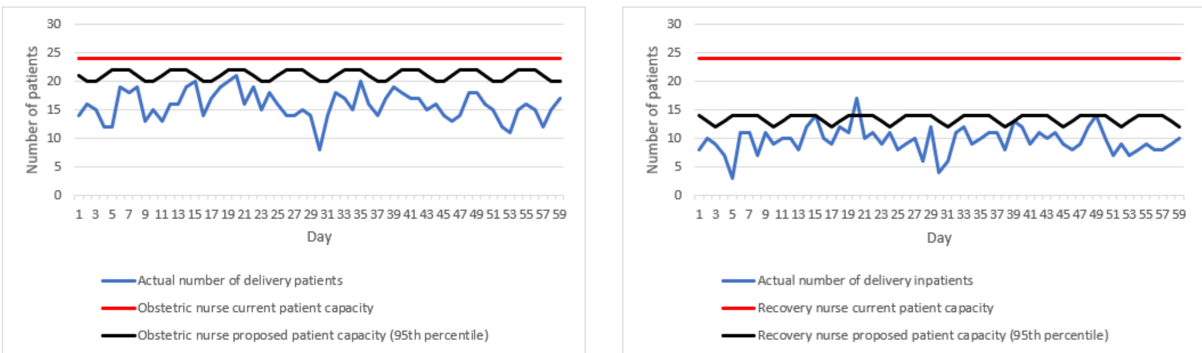


Figure 5.6: Obstetrics nurses (left) and recovery nurses (right) patient capacity based on the proposed tactical staff planning plotted against the actual patient data and current patient capacity.

KPI	ON patient capacity	RN patient capacity
PDCP	100%	97%
SWP	76%	74%

Table 5.6: KPIs for the patient capacity based on the proposed tactical staff planning. ON = obstetric nurse, RN = recovery nurse.

Visually, we can see that the proposed patient capacity fits the data better and therefore eliminates a part of the over-planning issues. Table 5.6 confirms this, with the staff workload increasing with around 10% for the obstetric nurses and with around 25% for the recovery nurses. This can be achieved while still attaining around 100% patient coverage, which is the goal of the obstetrics department. Table 5.7 shows the impact of using the proposed patient capacity on the required number of nurses. The proposed tactical planning prescribes a lower number of required nurses than the current tactical for both obstetrics nurses and recovery nurses. Furthermore, the number of required nurses throughout the week is not the same every day, as the proposed planning method incorporates the seasonality of patient demand throughout the week. On average, the department can plan 1 or 2 obstetric nurses less and 3 or 4 recovery nurses less. In Section 5.4 we will elaborate on this difference.

Nurse type	Obstetrics nurses		Recovery nurses	
Day	**Current**	**Proposed**	**Current**	**Proposed**
Monday	12	10	8	4
Tuesday	12	11	8	4
Wednesday	12	11	8	4
Thursday	12	11	8	4
Friday	12	11	8	5
Saturday	12	11	8	5
Sunday	12	10	8	4

Table 5.7: Current tactical staff planning compared to the proposed tactical staff planning for obstetrics nurses and recovery nurses (January and February 2022)

Sensitivity analysis

As the convolution model can be used to calculate the required number of nurses based on a specific percentage of demand, we also investigate the impact of using different percentiles of demand on the total staff workload, patient demand coverage, and the required number of nurses. We perform a sensitivity analysis to examine the relationship between these factors. To get a complete overview, we use the data of the full year of 2022 to compare the different proposed tactical staff plannings. We set a minimum patient demand coverage percentage of 90% as everything below that percentage is unacceptable for a hospital department. Table 5.8 gives the results of the sensitivity analysis for the planning of obstetric nurses.

Day	70th	75th	80th	85th	90th	95th	Current
Average required	10	10	10	10	11	11	12
Total required	77	78	79	80	84	86	96
PDCP	91,2%	94,0%	95,6%	97,3%	98,4%	99,2%	100%
SWP	81,3%	79,8%	78,2%	76,4%	74,2%	71,6%	62,6%

Table 5.8: Sensitivity analysis on the impact of planning for a specific percentile of the total patient demand on the average and total number of required obstetric nurses throughout a week, patient demand coverage percentage (PDCP) and staff workload percentage (SWP).

Table 5.8 gives an indication of the total reduction in the number of required obstetric nurses that can be achieved through using a new proposed tactical staff planning. It indicates that the department could plan on average two obstetric nurses less than they do with the current tactical staff planning and still provide medical care for 91.2% of all patients. Furthermore, the staff workload percentage increases with the reduction in required staff, as it will be closer to the actual number of patients when the number of over planned nurses decreases. Figure 5.7 shows this phenomenon for the output of the convolution model for the 70th percentile of demand. The full weekly tactical staff plannings for the different percentiles can be found in Appendix G.

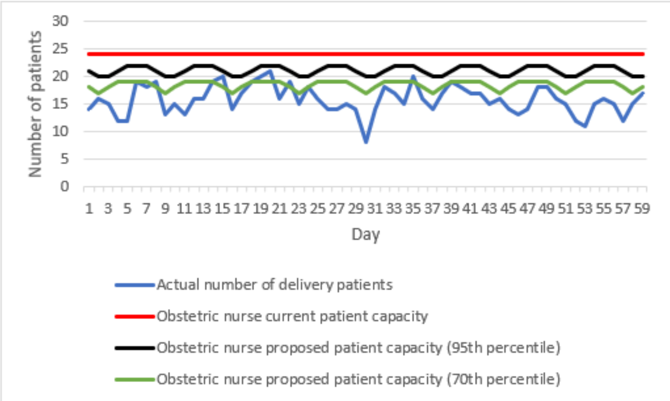


Figure 5.7: Obstetric nurses patient capacity based on the current tactical staff planning, the proposed tactical staff planning for the 95th percentile of demand, and the tactical staff planning for the 70th percentile of demand.

We did the same experiment for the recovery nurses. Table 5.9 shows the results of the sensitivity analysis on the different percentiles of demand for the required number of recovery nurses, the patient demand coverage percentage and the staff workload percentage. We can conclude from the table that the initial gain from the proposed planning method using the 95th percentile of demand has the biggest margin of improvement, as the department requires on average 3 recovery nurses less than using the current tactical staff planning. Furthermore, a further reduction of 4 recovery nurses throughout the week in total can be acquired while still attaining a patient demand coverage percentage of 91.5%. The full weekly tactical staff planning for the different demand percentiles can be found in Appendix G. Figure 5.8 shows the proposed patient capacity for the 85th percentile of demand, which has the lowest possible patient demand coverage percentage above the safe percentage of 90% and the highest staff workload percentage.

Day	**85th**	**90th**	**95th**	**Current**
Average required	5	5	5	8
Total required	35	37	39	64
PDCP	91,5%	93,4%	97,8%	100%
SWP	77,4%	74,6%	70,5%	39,1%

Table 5.9: Sensitivity analysis on the impact of planning for a specific percentile of the total patient demand on the average and total number of required recovery nurses throughout a week, patient demand coverage percentage (PDCP) and staff workload percentage (SWP).

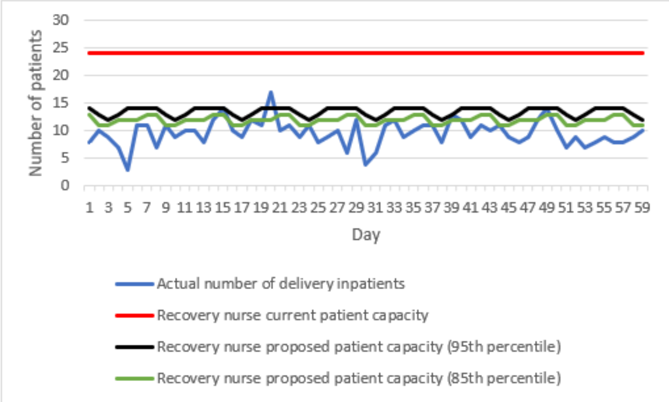


Figure 5.8: Recovery nurses patient capacity based on the current tactical staff planning, the proposed tactical staff planning for the 95th percentile of demand, and the tactical staff planning for the 85th percentile of demand.

5.3.2 Patient type "Complications"

For the patient type "complications" we only study the recovering inpatients who require medical assistance at the triage department. The triage department uses one obstetric nurse and one regular nurse every day. Following the nurse-patient ratio's in Section 3.3.2 a single regular nurse and obstetric nurse can provide medical assistance to three complications inpatients during one day. For modelling purposes, we call these nurses "complications nurses" from now on. The number of recovering patients is calculated by using the model extension explained in Section 4.3.4.

Current planning method

Looking at figure 5.9 we can conclude that the triage department over-plans the number of complications nurses needed, as demand does not exceed 6 patients. The current patient capacity for complications nurses exceeds the actual number of complications inpatients 100% of the time, thus attaining a patient demand coverage percentage of 100%. However, the staff workload KPI shows that it is very low, with 26% of the capacity being used on average every day. Therefore, we want to investigate whether the output of the convolution model can provide a more tailored tactical staff planning.

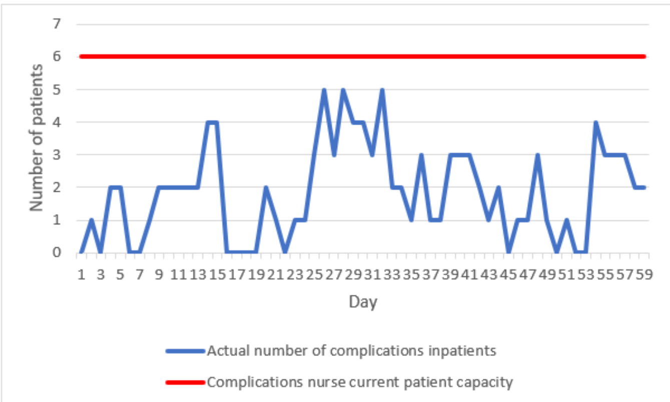


Figure 5.9: Complications nurses patient capacity based on the current tactical staff planning plotted against the actual patient data.

KPI	CN capacity
PDCP	100%
SWP	26%

Table 5.10: KPIs for the current tactical staff planning for the complications nurses. CN = complications nurse.

Proposed planning method

Figure 5.10 shows the proposed capacity for complications nurses caring for inpatients with complications. With the proposed tactical staff planning, we still attain 96% patient demand coverage while increasing the total staff workload to 39%, which is still low regardless of the improvement. We go in detail on why this could be the case.

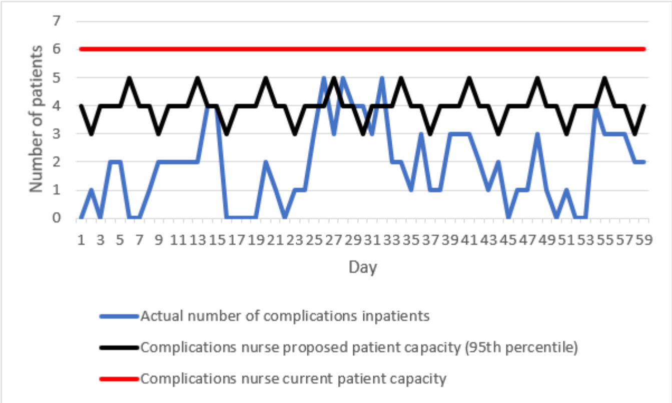


Figure 5.10: Complications nurses patient capacity based on the proposed tactical staff planning plotted against the actual patient data and the current patient capacity.

KPI	CN capacity
PDCP	96%
SWP	39%

Table 5.11: KPIs for the proposed tactical staff planning for the complications nurses. CN = complications nurse.

Table 5.12 shows the current tactical staff planning compared to the proposed tactical staff planning based on the proposed capacity for complications nurses. We can see that the proposed tactical staff planning does not have much of an impact on the number of required complications nurses, which means that the current tactical staff planning for complications nurses was not that bad to begin with. However, as the capacity of the triage department is only four beds for inpatients, and the nurse-to-patient ratio is 1 to 3, it is difficult to precisely tailor the tactical staff planning to the patient demand. However, the output of the convolution model does indicate whether a specific day of the week is less busy than other days and translates this to the tactical staff planning accordingly, as can be seen in the difference between the current and proposed staff planning on Sunday.

Day	Current	Proposed
Monday	2	2
Tuesday	2	2
Wednesday	2	2
Thursday	2	2
Friday	2	2
Saturday	2	2
Sunday	2	1

Table 5.12: Current tactical staff planning compared to the proposed tactical staff planning for complications nurses (January and February 2022).

Sensitivity analysis

We executed the same sensitivity analysis for the number of required complications nurses by using different percentiles of demand. The results of this sensitivity analysis can be found in Table 5.13. We again assume a minimum safe patient demand coverage percentage of 90%.

Day	85th	90th	95th	Current
Average required	1	2	2	2
Total Required	7	14	13	14
PDCP	91,5%	94,5%	96,7%	99,5%
SWP	54,0%	45,9%	40,7%	30,6%

Table 5.13: Sensitivity analysis on the impact of planning for a specific percentile of the total patient demand on the average and total number of required complications nurses throughout a week, patient demand coverage percentage (PDCP) and staff workload percentage (SWP).

From Table 5.13 we can conclude that the department can hypothetically reduce the number of required complications nurses to only one and still attain 91.5% patient demand coverage. Furthermore, this would increase the total staff workload to 54% which is not that high, but a significant increase from the total staff workload that is achieved through using the current tactical staff planning. The full tactical staff planning from Monday to Sunday of the sensitivity analysis experiments can be found in Appendix G. Figure 5.11 shows the lowest achievable complications nurse patient capacity compared to the proposed patient capacity for the 95th percentile of demand and the current complications nurse patient capacity.

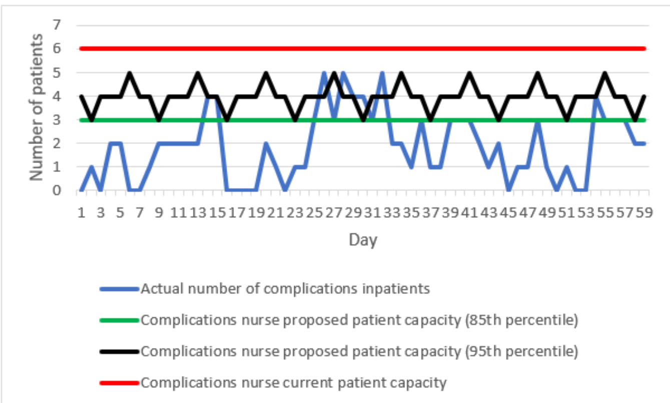


Figure 5.11: Complications nurses patient capacity based on the current tactical staff planning, the proposed tactical staff planning for the 95th percentile of demand, and the tactical staff planning for the 85th percentile of demand.

5.4 Summary and findings

Section 5.2 shows that the convolution model can generate a tactical staff planning that is tailored to the total patient demand for a planning period of two months. Using the forecasted patient arrivals as an input can provide a tactical staff planning that is also adjusted to the patient demand level of a specific 2-month period. The tactical staff panning consists of a required number of obstetric, recovery and complications nurses. Translating this back to the current tactical staff planning, this gives an indication of the number of obstetric nurses, regular nurses and midwives are needed in total to cover patient demand. We developed an improved tactical staff planning that increased the total staff workload, while maintaining the patient demand coverage percentage of around 100%. The difference between the current and proposed tactical staff planning can be viewed in Table 5.14. The full results can be found in Appendix H. Furthermore, we did a sensitivity analysis to study the effect of developing a tactical staff planning based on different percentiles of demand on the total staff workload, the patient demand coverage percentage, and the required number of nurses.

Nurse type	Obstetrics nurses		Recovery nurses		Complications nurses	
Day	**Current**	**Proposed**	**Current**	**Proposed**	**Current**	**Proposed**
Monday	12	10	8	4	2	2
Tuesday	12	11	8	4	2	2
Wednesday	12	11	8	4	2	2
Thursday	12	11	8	4	2	2
Friday	12	11	8	5	2	2
Saturday	12	11	8	5	2	2
Sunday	12	10	8	4	2	1
PDCP	**100%**	**99,2%**	**100%**	**97,8%**	**100%**	**99,5%**
SWP	**62,6%**	**71,6%**	**39,1%**	**70,5%**	**30,6%**	**40,7%**

Table 5.14: Current tactical staff planning compared to the average improved tactical staff planning for the 95th percentile of demand.

This means that on average, the department can plan on average 1-2 fewer obstetrics nurses and 3-4 fewer regular nurses, while still attaining almost 100% patient demand coverage and increasing the staff workload percentage with an average of around 15% by using the tactical staff planning we propose. If the department chooses to take more risk and sacrifice patient demand coverage percentage for increased staff workload, this further reduces the number of required nurses. When a minimum of 90% patient demand coverage is set, the department can plan on average 2-3 fewer obstetrics nurses and 4-5 fewer regular nurses. Although these results are very promising, it does not correspond with the current situation, where a shortage of staff is experienced. We discuss this in the following paragraphs.

In Chapter 1, we discussed the problems that were encountered at the obstetrics department. The staff at the obstetrics department experienced a shortage of staff, especially for obstetrics nurses. However, the results and findings of our model show that the department requires fewer nurses compared to the current number of required nurses, as the department over plans the number of nurses every day. The proposed method can assist in solving this problem, as the improved tactical staff planning indicates that there is some capacity in the form of staff that can be redistributed over the different weekdays based on peak demand. Using this extra freed capacity on days with peak demand can make sure that the experienced shortage of personnel is diminished by leveling the workload.

However, we should note that there are other factors that could have an influence on the differences between the results and current practice. We provide a solution that can be used on the tactical level of planning, while literature suggests that staff planning consists of two steps. These steps are:

calculating the required number of nurses per day or shift, and assigning specific nurses to these shifts. The second part of staff planning is operational and is out of scope for this research, but this might explain the difference between the results and current practice. It could be the case that the number of required nurses according to the current tactical staff planning cannot be reached due to vacations, illness, or other reasons of absence. The model we developed could also provide assistance in this case, as the sensitivity analysis sheds a light onto the impact of planning fewer nurses on the patient demand coverage percentage and therefore make a more informed decision on which day nurses should be planned.

Another factor that could have an influence on the differences between the results and current practice is the accuracy of the nurse-to-patient ratios. We used fixed nurse-to-patient ratios to convert the total patient workload to a tactical staff planning, which are based on expert opinion. However, it could be the case that these ratios are not accurate anymore, or that these ratios are more dynamic than we think. Within literature, there are a lot of solutions discussed that cover dynamic nurse-to-patient ratios which could be applied to our situation.

5.5 Conclusion

In this chapter, we answered research question 4, which is: *"How can we convert the model output to a tactical staff planning and what is the performance of the generated tactical staff planning compared to the current tactical staff planning"*. We verified that using the forecasted demand output as an input for the tactical staff planning model provides better performance than only using historic data as the forecasted output is able to predict trends within the data.

In Section 5.3 we converted the model output, the total patient workload, to a tactical staff planning using the nurse-patient ratios identified in Chapter 3. Through comparison, we found that the proposed tactical staff planning increases the staff workload percentage by 15% which results in needing fewer obstetrics nurses and regular nurses. The number of obstetrics nurses can be reduced by 1 or 2 while the number of regular nurses can be reduced by 3 or 4. This result can be achieved while maintaining a patient demand coverage percentage of around 100%, which is the goal of the obstetrics departments' management. This result can be interpreted in two ways. First, the obstetrics department structurally over-plans nurses throughout the week, as the current staff planning is not tailored to the patient demand. The patient demand changed over time and the patient demand varies between the different weeks of the day and even slightly between months. This means that valuable resources, in this case nurses, are being underutilized, which is not efficient. Second, by reducing the number of planned nurses, the obstetrics department frees a lot of capacity. This capacity can be redistributed according to the forecasted patient workload to make sure that the department is able to deal with peak demand.

In conclusion, the model that we developed can be used to provide insight into future patient workload and as a guideline for developing a staff planning. Redistributing the total available capacity, in this case nurses, can make sure that the department can deal with peak demand and therefore provide medical assistance to as many patients as possible.

6 CONCLUSION

In this chapter, we finalize this research by answering research question 5. In Section 6.1 we summarize the findings of this research by using the sub questions defined in Chapter 1, and in Section 6.2 we provide a discussion on this research. Section 6.3 contains recommendations for practice, which contains the steps for implementation and obstacles that come with it. Finally, Section 6.4 contains opportunities for further research.

6.1 Conclusion

This goal of this research is to develop a tactical staff planning for the obstetrics department of the Diakonessenhuis to reduce the variation in workload. This was achieved through developing a two phase model which forecasts the patient demand and uses this as an input to calculate the total workload by incorporating variation through an adapted convolution model. We found that, on average, the number of obstetrics nurses can be reduced by 1 or 2 and the number of regular nurses by 3 or 4, while still providing medical assistance for almost 100% of all patients requiring medical assistance. By using the sub questions we defined in Chapter 1 we summarize the findings of our research that led to this result.

The first research question we defined was: *"which techniques are used to forecast patient demand in the obstetrics department and generate a tactical staff blueprint planning based on forecasted patient demand"?*. Through a literature review, we found that time series forecasting provides the most accurate results to estimate patient demand. However, the time series forecasting model only estimates the patient arrivals and does not incorporate length of stay, which gives a more complete overview of the total patient workload. We found that using the convolution model from Vanberkel et al. [56] solves this problem by incorporating the variation in patient arrival data and adjusting the data for patient length of stay. The convolution model proved to be the most suitable option for our problem context as it incorporates inpatients and outpatients and also can deal with stochasticity. The output of the model, the total patient workload, can be converted to a tactical staff planning using nurse-patient ratios. This answered the first research question and defined our solution approach.

The second research question we defined was: *"How is the obstetrics department currently organized, and what are the characteristics of the patient arrival data"?*. Our solution approach required historic patient arrival data to develop a tactical staff planning, which we analyzed through a data analysis. We analyzed the patient data on patient types, arrival patterns and variation, and length of stay. Furthermore, we analyzed the different types of nurses required to provide care for the defined patients together with the nurse-to-patient ratios. We used the results of the data analysis to shape the parameters of the forecasting model and the convolution model.

Using the results of the data analysis, we developed a model that calculates the total patient workload. This step answers research question three: *"How can we create a tactical staff planning model which uses forecasted patient demand as an input?"*. Using the solution approach developed in Chapter 2 and the results of the data analysis, we programmed two separate models using the programming language Python. The first model consists of a forecasting model that is able to predict future patient arrivals based on historical arrival data. The forecasting model also evaluates several forecasting models and is able to pick the model that provides the most accurate results. The output of the forecasting model is used as an input for our adapted version of the convolution model developed by Vanberkel et al.[56]. The output of the convolution model consists of the total patient workload, which is the sum of the patient arrivals and the number of recovering patients.

We required one last step to answer research question four. Research question four was: *"How can we convert the model output to a tactical staff planning and what is the performance of the generated tactical staff planning compared to the current tactical staff planning?"*. Using the nurse-to-patient ratios, we were able to convert the total patient workload to a tactical staff planning. in Chapter 5 we validated the output of the convolution model using actual patient data, and we converted the output of the convolution model to a tactical staff planning. The improved tactical staff planning uses fewer nurses while still attaining the required patient demand coverage percentage management has in mind, which is 100%.

We can make several conclusions based on the results. The first conclusion is that the tactical staff planning model is able to generate a tailored tactical staff planning which reduces the amount of over-planning of nurses and therefore reduces the amount of variation in workload. The tailored tactical staff planning includes the variation throughout the days of the week and accounts for trends throughout different periods of the year. Secondly, the model output provides insight into the variation in workload throughout the week and therefore indicates periods of low and high demand, which can be used as an advisory tool to plan more or less nurses. Moreover, through the reduction of the number of nurses needed, the amount of assignable capacity increases. Using this extra freed capacity together with the analysis of the workload throughout the week provides consultation on assigning extra nurses during periods of peak demand. Lastly, through sensitivity analysis, we studied the impact of staffing for different percentiles of demand. Through this we could study the relationship between staff workload and patient demand coverage and the subsequent effect on the required number of nurses. This could assist the departments' planner in efficiently distributing the number of available nurses when an actual shortage of nurses is experienced, and the effect of planning one less nurse on the amount of patients that could be provided with medical care.

Although we proved that the solution approach we propose provides good results, the interpretation of these results led to an observable difference between current practice and theory. Therefore, it is very important to identify the potential causes of this difference and develop an implementation plan which includes these obstacles and how to overcome them. Section 6.4 will cover this by answering research question five, which was: *"How can we implement the generated tactical staff planning at the obstetrics department, and what are the obstacles that come with this implementation?"*.

6.2 Discussion

The aim of our research was to develop an improved tactical staff planning that was more tailored to the current patient demand to reduce the amount of staff workload variation. The tactical staff planning should consist of a required number of nurses per nurse type and per day. In this section, we discuss our research on a scientific and practical level. We analyze whether we reached the goals we set, reflect on the methods used and limitations that we encountered, and identify opportunities for further research.

We developed our solution approach using techniques derived from literature, selecting the most suitable techniques for our problem context for patient demand forecasting and tactical blueprint planning. First, there is a lot of research already done on patient demand forecasting across various hospital departments. However, patient demand forecasting for an obstetrics department is not specifically covered that much, which means that our research contributes here. We developed a forecasting model that implements and evaluates several forecasting models from different classes to study which forecasting model provides the most accurate results. the autoregressive SARIMAX model proved to be the best model, which is also a popular patient demand forecasting method in literature. Therefore, this research provides evidence on the effectiveness of the SARIMAX model in forecasting patient demand for an obstetrics department, but also on the ineffectiveness of forecasting models of other classes. The only limitation of our research is that non-linear complex forecasting models like machine learning and deep learning forecasting models are not covered as intensively, which could be an interesting direction for further research as patient arrival data in the obstetrics department is very volatile.

Concerning the calculation of the total staff workload, we used an adapted version of the convolution model by Vanberkel et al. [56]. Our research builds on existing literature by using the forecasted patient arrivals as an input for the convolution model to generate the total number of patients more accurately than only using empirical arrival data. To the best of our knowledge, we are the first to combine a forecasting model and the convolution model in a two phase model which is able to estimate the total number of patients. The novelty of this model is the fact that it uses forecasted patient arrivals instead of patient distributions. The two phase model is also applicable to other settings, as it is easy to adapt and only requires minor modifications with respect to patient types.

Although we did achieve our goal in analyzing and solving the problem on a tactical level, there are staff planning and scheduling models that function on both the tactical and operational level. Currently, the two phase model provides the total number of patients which can be converted to a tactical staff planning using nurse-to-patient ratios, which are based on expert opinion. This part is not included in our model and is mainly done through our own calculations using the output. Therefore, an interesting direction for further research would be to include this conversion into the model and also look at the operational level of staff planning. Assigning the available number of nurses to the tactical staff planning using optimization is a popular method in literature and can provide a useful extension to our model. We will further elaborate on these recommendations for research in Section 6.4.

With respect to the practical implications of this research, we focus mainly on the interpretation of the results. We showed that the two phase model we developed is able to estimate the total number of patients based on a specific percentile of the total demand. Using nurse-to-patient ratios, we generated results which translates to a tactical staff planning, which consists of the number of required nurses. First, we should note that the patient data we were provided with was not structured and accurate. The data cleaning strategy we used was very time intensive as the patient arrival data lacked a clear indication for the patient type, which is integral to generate an accurate model output. Furthermore, the length of stay of every patient is not always correctly registered, which further influences the model output accuracy. For this reason, the model lacks repeatability, as part of the data cleaning had to be done by hand instead of through automation.

Secondly, we also touched in this subject in Chapter 5, there is a difference between the problem we encountered in current practice and the results we generated. Although there is a shortage of staff experienced at the obstetrics department, our results prove otherwise. We identified three possible causes that could explain this difference. The first cause is the quality of data, as we mentioned that the quality of data is not up to standard we cannot say with 100% certainty that our results are accurate. However, we do not think that this would influence the results to such an extent that it would change the conclusion. The second cause is the difference between the tactical staff planning and the operational staff planning. Even though the current tactical staff planning prescribes a certain number of nurses, it could be the case that this number cannot be reached often because of staff absence. The third cause is that the nurse-to-patient ratios might not be accurate anymore, as nurses could have a higher workload per patient than we estimate. All three potential causes could influence the interpretation of our results and therefore should be carefully considered. Although the model functions on a tactical level, the realization of the tactical level into an operational planning is just as important to achieve good results. Therefore, we develop an implementation plan in the next section, which contains recommendations for practice based on our solution.

6.3 Recommendations for practice

In Section 6.2 we mentioned the difference between the results of the model and current practice. We also discussed several potential causes for this difference, and how our solution can assist in that. In this section, we formulate three steps that the obstetrics department can take to improve on current practice by using the proposed solution and findings.

The first step the obstetrics department should take is to find out why a shortage of staff is experienced. In Section 6.2 we provide two potential causes for this problem. The first cause is the gap between the tactical and operational planning. The obstetrics department should confer with the departments' planner to investigate whether the required number of nurses that have to be planned can be achieved. Furthermore, if the required number of nurses cannot be achieved, they should find out what the number of nurses is that can be reached and what days provide the most issues. Secondly, the obstetrics department should critically evaluate the nurse-to-patient ratios by gathering information and experiences from the nurses themselves. If the nurse-to-patient ratios are not accurate, the results of our model can be interpreted in a very different way, even leading to the current tactical staff planning leading to consequently planning fewer nurses than required. Using the updated information, the department can find out whether the proposed tactical staff planning matches the number of nurses that can be planned on an operational level.

The second step the obstetrics department should take is to use the results from our research as a starting point in developing a new and improved tactical staff planning. The results from our research can provide some insights on the number of patients to be expected and the impact that this has on the number of required nurses. The output of the convolution model gives the total number of patients for a specific percentile of demand. Therefore, the model output provides objective evidence of the periods of high and low demand, which can be used to distribute resources accordingly. Furthermore, sensitivity analysis investigating the impact of planning for specific percentiles of demand can assist on the operational planning level. The sensitivity analysis examines the impact of the number of planned nurses on the patient demand coverage percentage. This could help with making a decision on assigning the available number of nurses to days while maximizing the patient demand coverage percentage. The improved tactical staff planning could then be seen as a range of required nurses per day.

The last step that needs to be taken to implement the solution is to adapt our model to the updated assumptions that come from step one and two. Currently, the solution we propose is not directly implementable for the obstetrics department as a product that can be used to generate a tactical staff planning for a planning period of two months. By validating the model with new assumptions and gathering new quality data for the patient arrivals, the model can be used in practice as an advisory tool. Using our solution as an advisory tool can help with planning on a tactical level to distribute the available nurses more efficiently based on objective data that estimates the total patient demand.

6.4 Further research

The results of this thesis can be used in new research opportunities for patient demand forecasting and tactical staffing. We discuss several topics that could be interesting to explore based on this research, which are also mentioned in Section 6.2.

The current forecasting model we use as an input for the convolution model is the SARIMAX model, which is a relatively simple autoregressive forecasting model. Although the model provides good results, it is not able to detect unexpected periods of high and low demand. Therefore, it could be interesting to investigate whether more non-linear forecasting models, like machine learning and deep learning models, are able to detect hidden patterns within the data and therefore provide a more accurate estimation of the number of patient arrivals. Improving forecasting accuracy also improves the ability of the two phase model to estimate the total patient workload and thus tailor the tactical staff planning to patient demand.

We combined a forecasting model with the convolution model to generate the total patient workload and converted this to a tactical staff planning using nurse-patient ratio's. Although this is a two phase model, it would be interesting to combine and formalize this as one model. Furthermore, it could be interesting to include optimization by evaluating the model output through a technique like simulation. This would eliminate the need for a long testing process during the implementation period and provide information on the range of feasible solutions, tactical staff plannings, and the impact this has on the patient demand coverage. This could also assist with staff planning on an operational level. As our solution only prescribes the number of required nurses on a tactical level, it is also interesting to add an optimization model which assigns the available nurses to the days, while optimizing for the patient demand coverage percentage.

Lastly, the model we developed is easily customizable and extendable for patient types, forecasting period, length of the master surgical schedule output and more. This makes it interesting to apply the model to other departments than the obstetrics department as, in essence, the model only requires historic arrival and length of stay data to generate results. Furthermore, to the best of our knowledge a combination of a forecasting driven convolution model has not been mentioned in literature and applied in a real-life context. The model can then be used to provide insight into patient workload for the total number of patients, arriving patients, and recovering patients.

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A PROBLEM CLUSTER

Figure A.1 contains the problem cluster that we used to identify the cause and effect relationships between the collected problems at the obstetrics department. The problems without a cause are indicated by the color green, which are the core problems. The problem marked by the color yellow is a core problem as well, but is out of scope for this research. Lastly, the problem marked by the color red is the action problem. The action problem is a problem that has no consequence and therefore is being influenced by all the problems in the problem cluster. Solving the core problem improves the negative effect of the action problem.

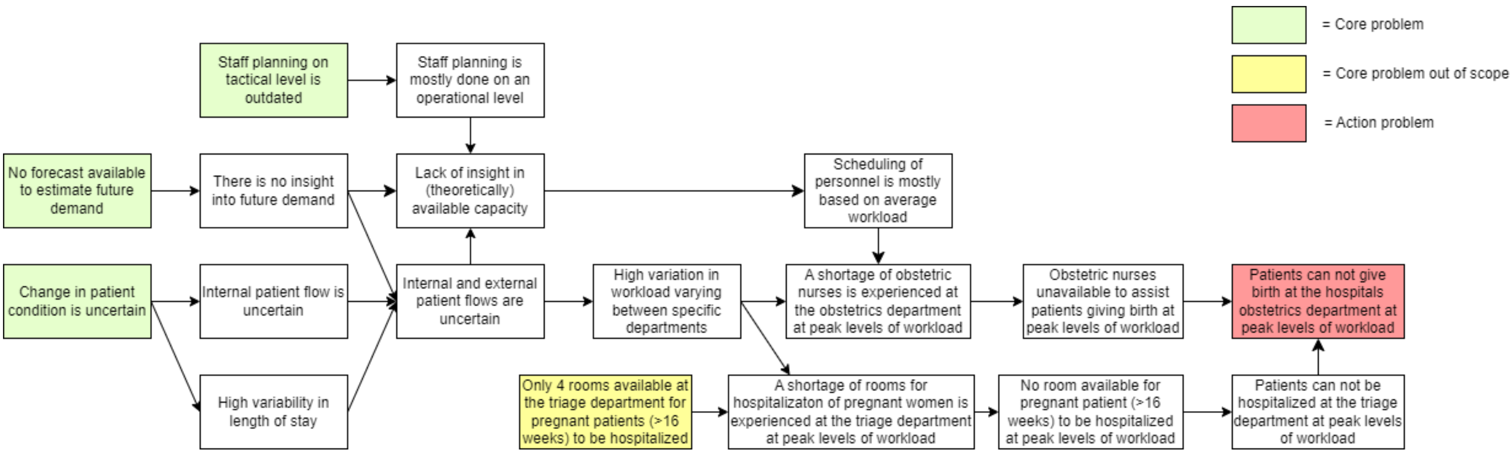

Figure A.1: Problem cluster

B SEARCH STRATEGY

We used the scopus database to search for relevant literature on the subjects studied. We performed three separate literature reviews. The subjects studied are forecasting, tactical blueprint scheduling and nurse staffing. The search strings that we used are:

Forecasting

TITLE-ABS-KEY(”patient demand” AND ”forecasting”) (59 results)
TITLE-ABS-KEY(”arrivals” AND ”forecasting” AND ”healthcare”) (25 results)

Tactical blueprint planning

TITLE-ABS-KEY(“template” AND “scheduling” AND “healthcare”) (24 results)
TITLE-ABS-KEY(“blueprint” AND “scheduling”) (88 results)
TITLE-ABS-KEY(“tactical” AND “scheduling” AND “healthcare”) (27 results)
TITLE-ABS-KEY(“blueprint” AND “scheduling” AND “healthcare”) (6 results)

Nurse staffing

TITLE-ABS-KEY(“nurse” AND “staffing” AND “optimization”) (98 results)

Subject	**Tactical blueprint scheduling**	**Nurse staffing**	**Forecasting**
Total number of sources viewed	145	98	84
Papers chosen	17	19	22
Papers added	3	0	10

Table B.1: Number of sources chosen after review

C DATA CLEANING STRATEGY

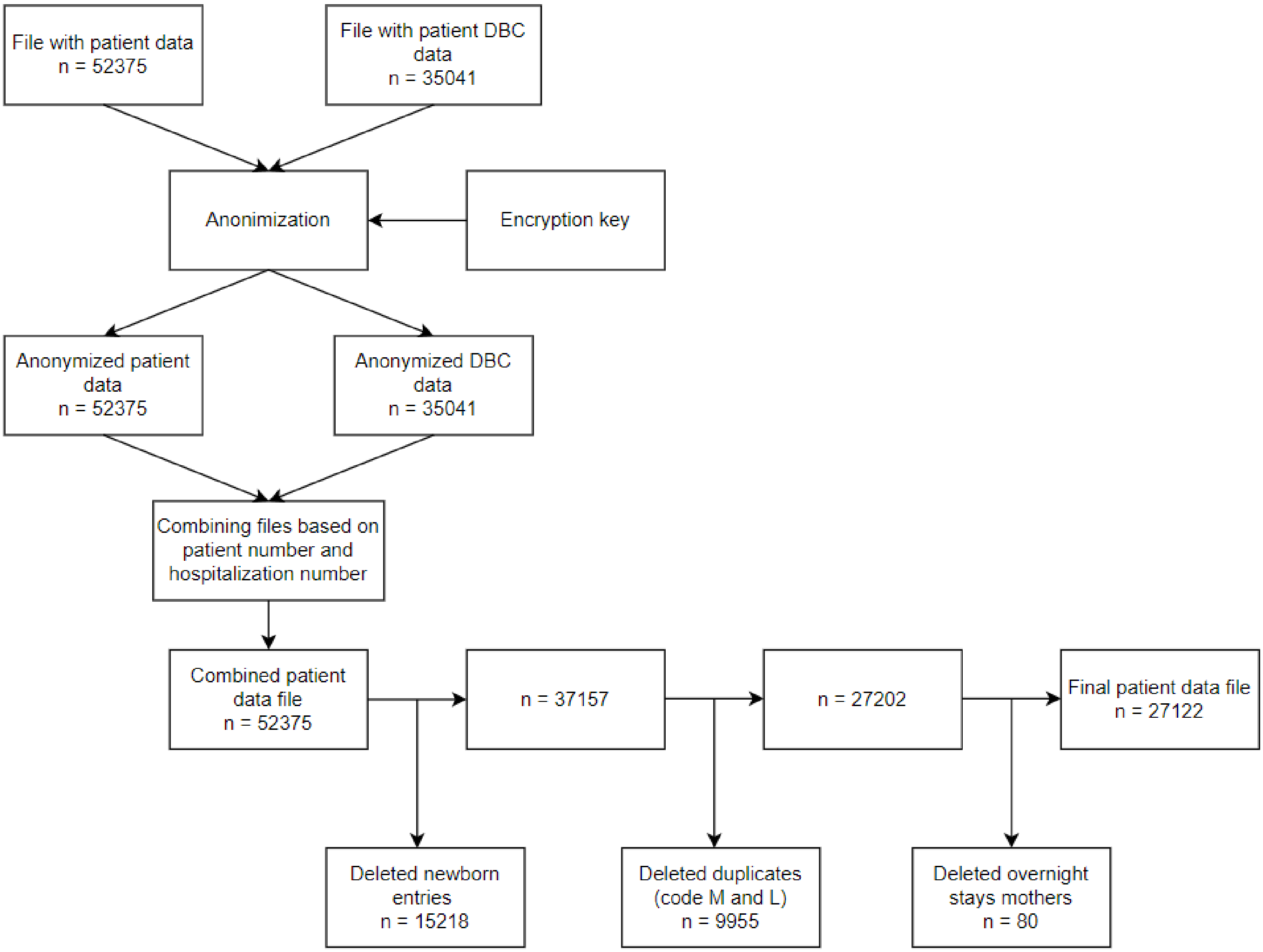

Figure C.1: Data cleaning strategy used to obtain workable patient data

D CARE PATHWAYS

D.1 Natural delivery

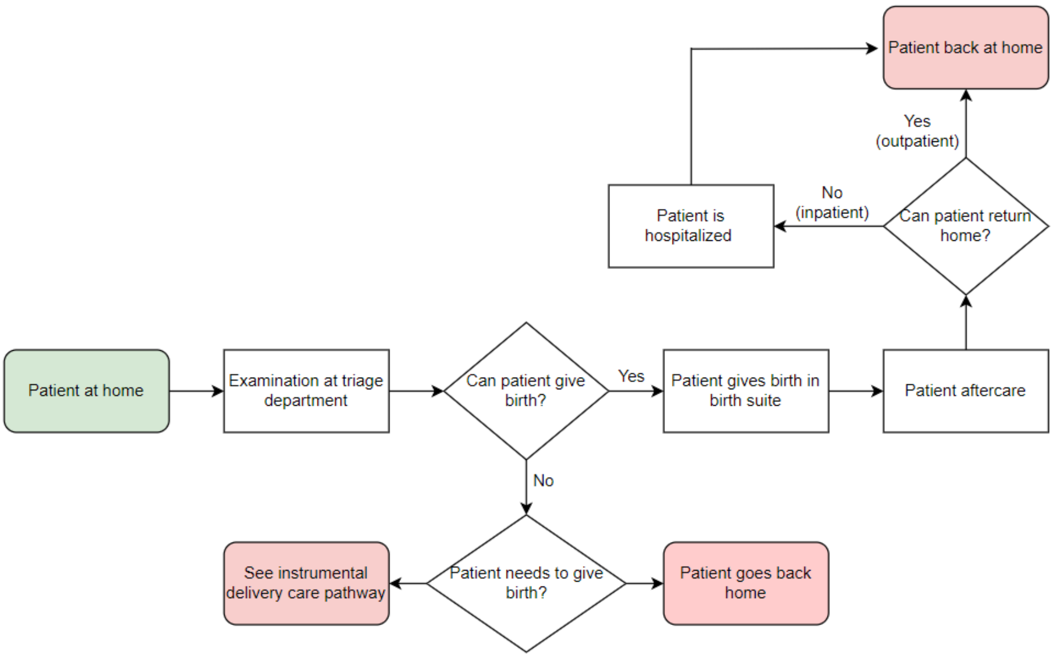

Figure D.1: meaning of symbols used in care pathway flowcharts

D.2 Instrumental delivery

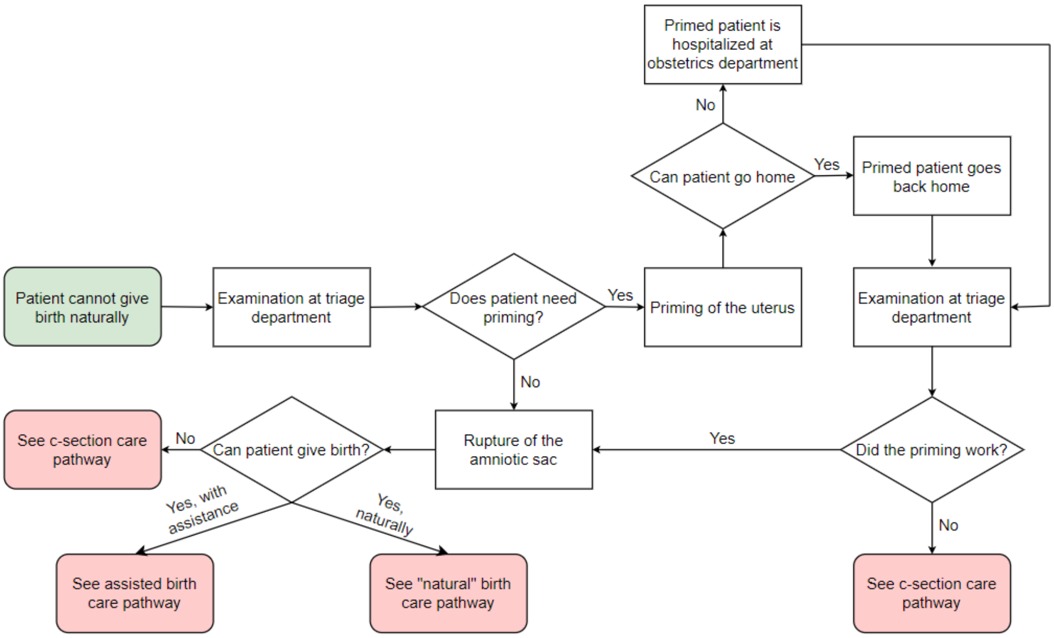

Figure D.2: meaning of symbols used in care pathway flowcharts

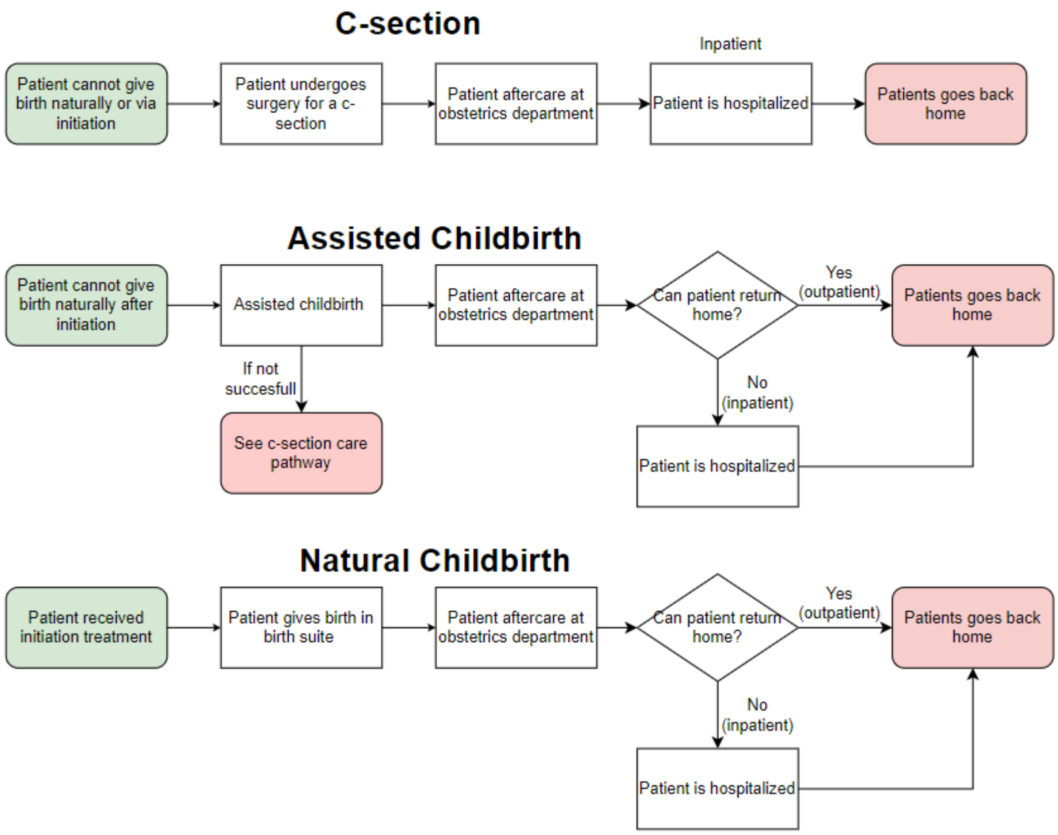

Figure D.3: meaning of symbols used in care pathway flowcharts

E WORKFLOW OF FORECASTING MODEL IN PYTHON

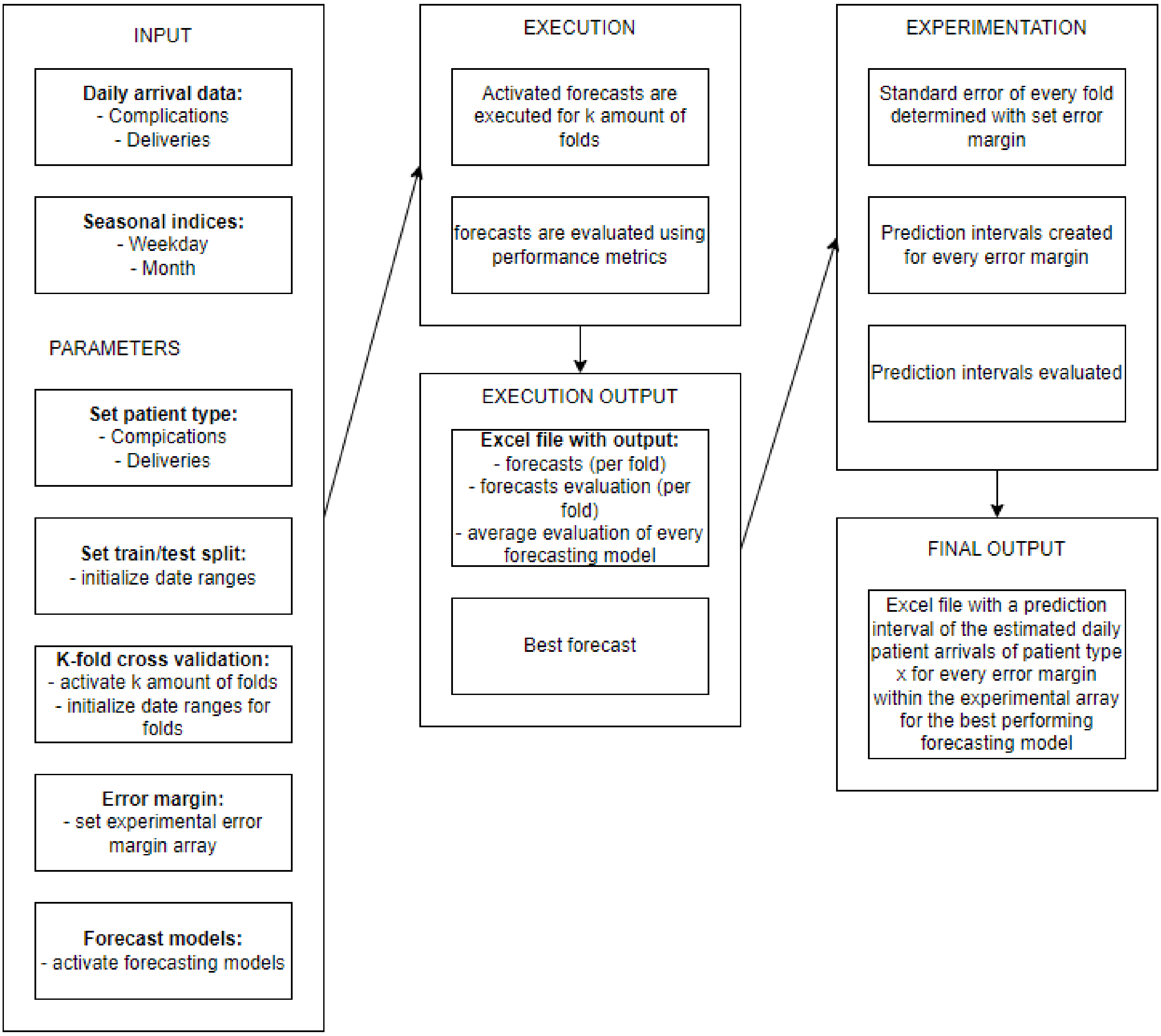

Figure E.1: The workflow of the forecasting model in Python

F RESULTS CONFIDENCE LEVEL EXPERIMENT

Confidence level	**Deliveries**		**Complications**	
	Coverage Percentage	*Range*	*Coverage Percentage*	*Range*
0,05	0,0%	0,2	8,5%	0,3
0,1	10,2%	0,5	11,9%	0,7
0,15	16,9%	0,7	16,9%	1,0
0,2	23,7%	0,9	22,0%	1,4
0,25	27,1%	1,2	23,7%	1,7
0,3	33,9%	1,4	33,9%	2,1
0,35	40,7%	1,6	39,0%	2,5
0,4	45,8%	1,9	49,2%	2,8
0,45	49,2%	2,2	50,8%	3,2
0,5	54,2%	2,4	55,9%	3,7
0,55	57,6%	2,7	61,0%	4,1
0,6	62,7%	3,1	69,5%	4,6
0,65	66,1%	3,4	76,3%	5,1
0,7	69,5%	3,8	78,0%	5,6
0,75	71,2%	4,2	81,4%	6,2
0,8	78,0%	4,6	84,7%	6,9
0,85	83,1%	5,2	84,7%	7,8
0,9	89,8%	6,0	91,5%	8,9
0,95	94,9%	7,1	93,2%	10,6
1	1	inf	1	inf

Table F.1: Results of experiment where we investigated the effect of changing the confidence level on the coverage percentage and range of the prediction interval

G SENSITIVITY ANALYSIS RESULTS

Day	**70th**	**75th**	**80th**	**85th**	**90th**	**95th**	**Current**
Monday	9	9	10	10	10	10	**12**
Tuesday	10	10	10	10	10	11	**12**
Wednesday	10	10	10	10	11	11	**12**
Thursday	10	10	10	10	11	11	**12**
Friday	10	10	10	11	11	11	**12**
Saturday	9	10	10	10	10	11	**12**
Sunday	9	9	9	9	10	10	**12**
Average required	10	10	10	10	11	11	**12**
Total Required	77	78	79	80	84	86	96
PDCP	**91,2%**	**94,0%**	**95,6%**	**97,3%**	**98,4%**	**99,2%**	**100%**
TSW	**81,3%**	**79,8%**	**78,2%**	**76,4%**	**74,2%**	**71,6%**	**62,6%**

Table G.1: Full results for the sensitivity analysis using different percentiles of demand for the number of delivery inpatients. The table shows the required number of obstetric nurses for every tested percentile of demand

Day	**85th**	**90th**	**95th**	**Current**
Monday	1	2	2	2
Tuesday	1	2	2	2
Wednesday	1	2	2	2
Thursday	1	2	2	2
Friday	1	2	2	2
Saturday	1	2	2	2
Sunday	1	2	1	2
Average required	1	2	2	2
Total Required	7	14	13	14
PDCP	**91,5%**	**94,5%**	**96,7%**	**99,5%**
TSW	**54,0%**	**45,9%**	**40,7%**	**30,6%**

Table G.2: Full results for the sensitivity analysis using different percentiles of demand for the number of complications inpatients. The table shows the required number of complications nurses for every tested percentile of demand

Day	**85th**	**90th**	**95th**	**Current**
Monday	4	4	4	8
Tuesday	4	4	5	8
Wednesday	4	5	5	8
Thursday	4	5	5	8
Friday	5	5	5	8
Saturday	5	5	5	8
Sunday	4	4	5	8
Average required	5	5	5	8
Total Required	35	37	39	64
PDCP	**91,5%**	**93,4%**	**97,8%**	**100%**
TSW	**77,4%**	**74,6%**	**70,5%**	**39,1%**

Table G.3: Full results for the sensitivity analysis using different percentiles of demand for the number of delivery inpatients. The table shows the required number of recovery nurses for every tested percentile of demand

H MODEL RESULTS

Day	Fold 1	Fold 2	Fold 3	Fold 4	Fold 5	Fold 6
Monday	10	10	11	11	10	10
Tuesday	11	11	11	11	11	10
Wednesday	11	11	11	11	11	10
Thursday	11	11	12	11	11	10
Friday	11	11	11	12	11	10
Saturday	11	11	11	11	11	10
Sunday	10	10	10	10	10	9
PDCP	**100%**	**100%**	**100%**	**98,4%**	**100%**	**96,7%**
SWP	**74,7%**	**77,2%**	**63,1%**	**69,5%**	**73,7%**	**71,8%**

Table H.1: Proposed tactical staff planning for obstetric nurses (95th percentile)

Day	Fold 1	Fold 2	Fold 3	Fold 4	Fold 5	Fold 6
Monday	4	4	5	5	4	4
Tuesday	5	5	5	5	5	4
Wednesday	5	5	5	5	5	4
Thursday	5	5	5	5	5	5
Friday	5	5	5	5	5	4
Saturday	5	5	5	5	5	5
Sunday	5	5	5	5	4	4
PDCP	**98,3%**	**95,1%**	**96,7%**	**100%**	**100%**	**96,7%**
SWP	**72,1%**	**76,0%**	**60,8%**	**69,3%**	**75,4%**	**69,3%**

Table H.2: Proposed tactical staff planning for recovery nurses (95th percentile)

Day	Fold 1	Fold 2	Fold 3	Fold 4	Fold 5	Fold 6
Monday	2	2	2	2	2	2
Tuesday	2	2	2	2	2	2
Wednesday	2	2	2	2	2	2
Thursday	2	2	2	2	2	2
Friday	2	2	2	2	2	2
Saturday	2	2	2	2	2	2
Sunday	1	1	2	2	2	2
PDCP	**93,2%**	**100%**	**100%**	**100%**	**100%**	**100%**
SWP	**46,6%**	**32,4%**	**54,2%**	**43,7%**	**30,8%**	**36,6%**

Table H.3: Proposed tactical staff planning for complications nurses (95th percentile)