BACHELOR THESIS INDUSTRIAL ENGINEERING AND MANAGEMENT

IMPROVING THE CAPACITY PLANNING OF THE HOSPICE TEAM AT TWB

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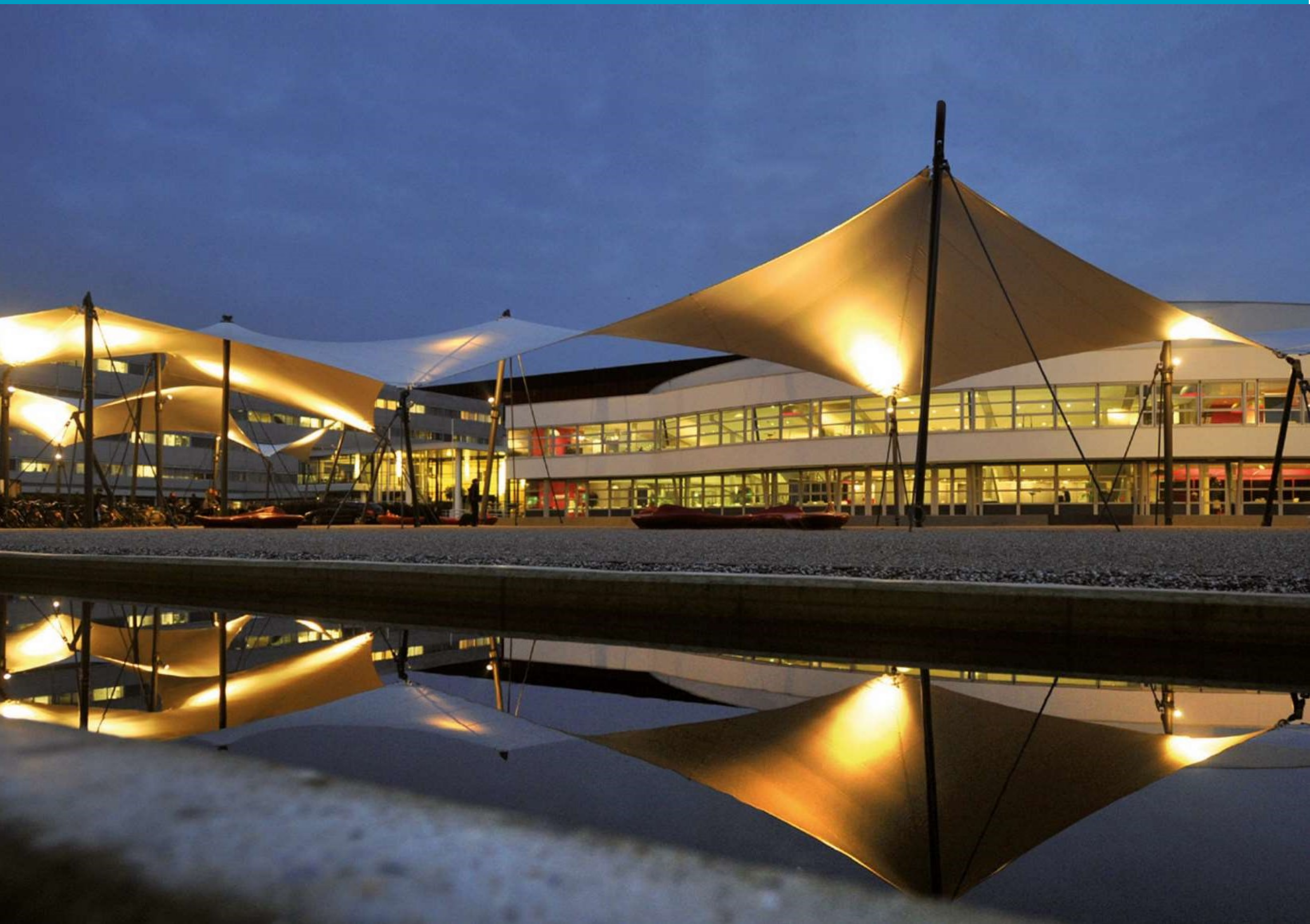

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Management Summary

Context

Thuiszorg West Brabant (TWB) is a home care company from Roosendaal that provides various types of home care to their patients that require different levels of care. The care ranges from simpler tasks like household help or showering to more complex tasks like giving medication or injections. The research has been conducted in cooperation with the hospice team of TWB which is one of several specialized teams.

The focus of the research is on improving the capacity planning of the hospice team. In the past, the hospice team experienced a high capacity-demand mismatch. Often, the number of scheduled nurses exceeded the care demand which leads to overcapacity. Consequently, the planned worktime cannot be sufficiently filled with work for the nurses, so they have to end their shifts earlier and have trouble to reach their weekly worktime according to their contracts. In fewer cases TWB also experienced undercapacity. With improving the capacity planning we aim to align the capacity of nurses with the actual care demand, so that the capacity-demand mismatch is reduced and therefore goals such as higher job satisfaction of the nurses and cost reduction can be reached. Following the steps of the managerial problem-solving method (MPSM) we address our main research question: *How can the capacity planning of the hospice team be improved in order to reduce the capacity-demand mismatch?*

Methods

To answer our research question, we create an integer linear program (ILP) that decides under the objective of salary cost minimization about the optimal number of nurses that is required to satisfy the amount of care demand. Since the amount of care usually varies a lot, we need to analyze the care demand to be able to model the demand uncertainty. In doing so, we analyze the empirical distributions of care for both clusters of the hospice team as well as for all shift types and days. After that, we run a Monte-Carlo simulation to generate different demand scenarios that we can further use as an input for the linear program.

We formulate our linear program using the technique of robust optimization to ensure that the decisions made hold for the worst case under demand uncertainty. In our model, the uncertain parameter that we consider is the number of patients who need to be treated per shift.

Results

We solve the model multiple times for the optimal number of nurses by using the historical care demand as an input as well as six different levels of robustness that are based on the care demand scenarios generated by the Monte-Carlo simulation. Those generated scenarios include different number of patients of each level that need to be treated per shift.

The output that the model produces contains the number of nurses per level that are necessary to cope with the care demand of each scenario for every day in the past 12 months. Possible shift lengths that are used by the model are 8, 6 and 4 hours. We summarized the solutions in terms of total suggested working hours and compared the different levels of robustness with the actually scheduled shifts in the hospice team. Furthermore, we solved our model with the real care demand of each day in the last year. Table 1 contains the deviation of total working hours of the solutions measured in % compared to the actually scheduled shifts. Negative numbers imply that a reduction in working hours is possible while positive numbers would mean an increase compared to working hours scheduled by TWB.

	Real Demand	50th	60th	70th	80th	90th	100th
Noord Morning shift	-42%	-45%	-40%	-31%	-18%	-4%	13%
Noord Evening shift	-17%	-24%	-12%	0%	14%	32%	61%
Zuid Morning shift	-35%	-46%	-35%	-32%	-20%	-5%	21%
Zuid Evening shift	-18%	-37%	-21%	-16%	-5%	22%	56%

Table 1 – Deviation of working hours in % of solutions generated by the model compared to actually scheduled working hours

In Table 1 we can see the deviations of working hours in % compared to the actually scheduled shifts for both clusters of the hospice team. The first column "Real Demand" contains the produced overcapacity in the past year compared to the historical schedule which barely made use of shorter shifts. So, it is the solution of our model where the real demand of the last 365 days was used as an input. The other columns contain the differences in total working hours based on different levels of robustness where the 50th percentile scenario is the lowest level of robustness and the 100th percentile is the highest level of robustness. Dark red colored cells show solutions that are infeasible because their solutions fall below the possible reduction for the real demand scenario of the last year and thus would produce more undercapacity. Light red colored cells show solutions that produce schedules with more working hours than what was actually scheduled by TWB and therefore increase overcapacity even more. Thus, those solutions are not recommendable. Lastly, the green colored cells show feasible solutions that can be considered as recommendations to create new working schedules.

Conclusion

During the execution of this research, we developed an integer linear program that enabled us to calculate the optimal number of nurses of each qualification level to cope with the care demand. Looking at the results we see that in both clusters of the hospice team overcapacity is a problem that needs to be resolved. While the morning shifts tend to produce larger overcapacity, the evening shifts do not show that high values and are more aligned with the real demand. Even though, our model created for both clusters and shifts feasible solutions that potentially reduce the overcapacity by up to 40%. In general, the feasible solutions are located between the 60th and the 90th percentile of scenarios which correspond to a medium till high level of robustness.

Which level of robustness to choose is up to the decision makers at TWB. The higher the level of robustness of the solution, the "safer" it is and the risk of undercapacity is reduced. But on the other hand, choosing a solution with high robustness means that total hours and thus salary costs cannot be as much reduced compared to a solution with lower robustness. Since our research belongs to the home care environment and undercapacity can have serious medical consequences, it is recommendable to not use the lowest level of robustness possible.

Contents

1. Introduction

In this chapter, we introduce the company and define our research assignment. Next, we determine the problem-solving approach that we use for our thesis and select our main research question with the help of a problem cluster. For each step of the problem-solving approach, we formulate sub-research questions that are answered in the following chapters. Lastly, we elaborate on limitations that our research design includes.

1.1 About TWB

Thuiszorg West Brabant (TWB) is a home healthcare company located in Roosendaal. They provide various types of home care in the whole region of West-Brabant. Compared to other home care companies TWB is a large employee. The services by TWB include a large range, from household help to specialized care of complex diseases based on the patient's requirements (Thuiszorg West-Brabant, 2024). Services can be for example simpler tasks like cleaning and help changing, or more complicated tasks like preparing the medication, giving injections, or treating wounds. The majority of patients that are served by TWB belong to the elderly people that wish to stay at home in a familiar environment.

Since the several tasks provided differ significantly from each other, employees from TWB have different qualifications that allow to perform different types of care. TWB distinguishes in total between 6 levels of qualification. The lowest qualification level is called ADL, which covers simple household tasks where no special competencies are needed. The other levels are 2, 3, 3IG, 4 and 5 and grow in competencies that are needed to qualify as an employee that performs more complex types of care. Level 4 and 5 are considered as nursing levels. If an employee has a certain level of qualification, he or she is allowed to perform all care activities that belong to this specific qualification and all qualifications below. For example, while a level 2 employee is only allowed to perform tasks of ADL and level 2 care, a level 5 nurse can perform all kinds of tasks.

Next to the structure of qualification levels, TWB is structured into several regional clusters that describe an area where care is provided. Those clusters are even further divided into specific teams, for example the hospice team, the night care team or the district nursing teams which are all specialized into different types of care that they provide. Usually, in each of the cluster there are several nurses of level 5 which can perform all types of care. All the tasks that are performed by employees are registered in a database system called NEDAP. This data can be used by e.g., the management to keep track of the payment costs.

1.2 Research Assignment

As mentioned in section 1.1, TWB has several teams that are providing various kinds of care to their patients. This assignment is focused on only the hospice team because TWB is interested in an improvement of the capacity planning for this team. The hospice team accompanies patients at home in their final stage of their life to allow that the patients can stay in their familiar environment close to their loved ones. Still, the tasks performed vary from simpler care like the preparation of medication to complex treatment tasks where a higher competency is needed. So, the hospice team includes nurses from levels 3IG to 5. Furthermore, the hospice team is divided into two sub-teams, the hospice team Noord and the hospice team Zuid which are responsible for different geographical areas. Each day of the year is divided into a morning shift from 7:00 until 15:00 and an evening shift from 15:00 until 23:00 for both the Noord and the Zuid team. For every shift there is a break of 30 minutes planned, so the net worktime should ideally be 7:30 hours.

Moreover, there is a differentiation between both planned and unplanned care. The planned care is scheduled in advance of a week, so parts of the work schedule is already known. On top of that there is the unplanned care which includes unforeseen activities that require additional care for a patient. In case a patient needs additional care, they call a hotline, and a nurse is sent to the patient to provide the care. As the name already indicates, the unplanned care is hard to predict and underlies many fluctuations in the care demand. The combination of both the planned as well as the unplanned care demand makes the total care demand which fluctuates over the day (in terms of daytime) and over the year (in terms of months) where the workload is not always the same.

Currently, TWB is experiencing capacity-demand mismatch for the hospice team, meaning that either the capacity of nurses exceeds the total care demand, and we have the problem of overcapacity. Or it happens, that the total care demand exceeds the capacity of nurses, and we have the problem of undercapacity. Based on past experiences it seems that overcapacity seems to be a bigger problem that occurs more frequently. When it comes to overcapacity, it can happen that nurses that are scheduled in a shift are inactive and cannot fill their full worktime, so they must end their shift earlier. This is a problem because most of the nurses have a 40-hours contract and have trouble filling those 40 hours if they cannot fill each 8-hour shift. So, they need to work in more shifts than actually planned. The described difficulties can lead to a lower job satisfaction of the nurses and is not in favor of TWB as they want to become an even better employer with highly satisfied employees. Even though undercapacity seems to be not that big of an issue, it still occurs and leads to a longer waiting time for the patient until a nurse is coming to their home to provide the care. This leads both to unsatisfied patients because of increased waiting times as well as unsatisfied nurses because they are facing a higher stress level. TWB wishes to avoid both scenarios of either over- or undercapacity and would like to plan their capacity in line with the real care demand.

The whole healthcare industry is under pressure because there is both a maldistribution of nurses as well as a scarcity of nurses in general (Both-Nwabuwe et al., 2018) that is facing a growing care demand. As TWB is part of this industry, they also face those challenges. To become a better employer and maybe even gain competitive advantage, they want to increase the satisfaction of their staff and their patients by improving the quality of their capacity planning. Thus, the care demand of the past needs to be analyzed and a method to calculate the required number of nurses per qualification must be developed.

1.3 Problem Solving Approach and Research Question

In the execution of this thesis, we make use of the Managerial Problem-Solving Method (MPSM). The MPSM is an established research approach and was developed by Heerkens & van Winden to solve action problems, which do not go as desired (Heerkens H & van Winden A, 2017). Furthermore, the problem needs to be measured in terms of norms and reality. As the problem that we want to solve identifies as an action problem, the MPSM is a suitable method to address our research question. The 7 different phases of the MPSM are shown in Figure 2.

In Figure 1 we can see the problem cluster and the selected core problem as well as the action problem of our research. As the action problem we can identify the fact that the capacity of nurses per shift mismatches the actual care demand and results in either over- or undercapacity, as described in section 1.2.

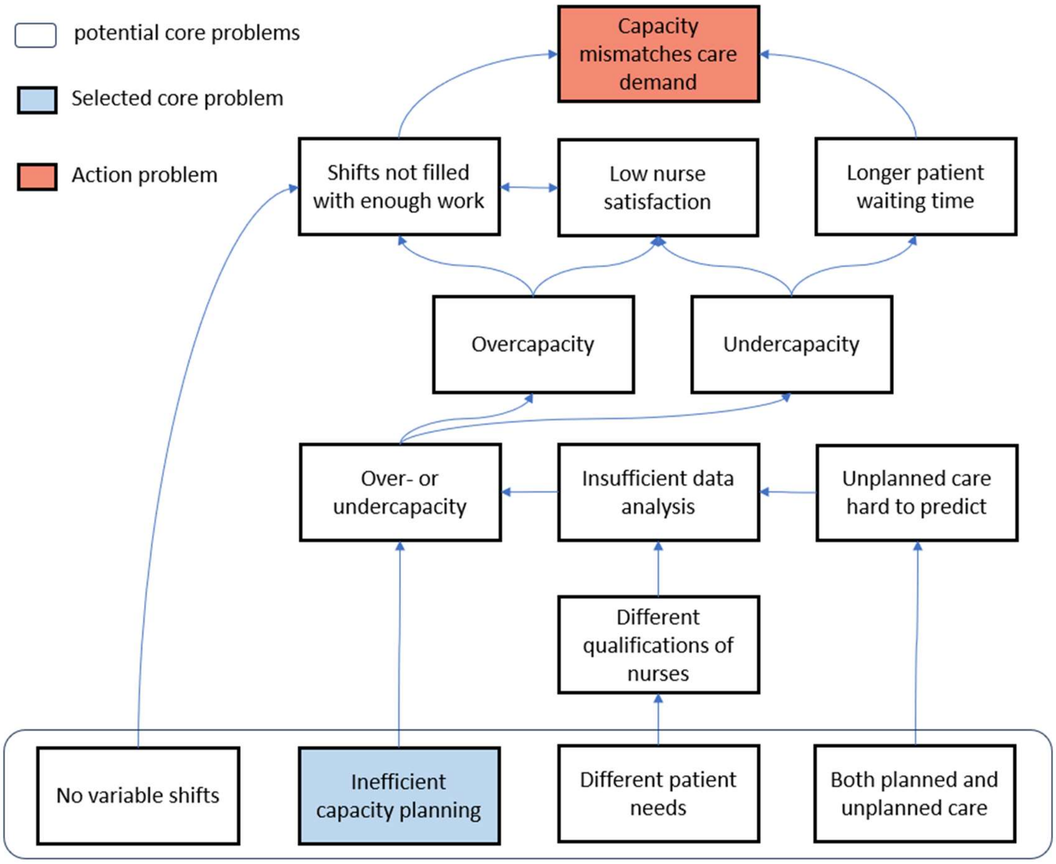

Figure 1 - Problem cluster

To identify the core problem, we can go back in the causal chain of this problem cluster. TWB suffers from a capacity-demand mismatch because there is in many cases either over- or undercapacity. In the case of overcapacity nurses cannot fill their shifts fully because there is not enough care demand. Also, the standard shift length is 8 hours and there is no high variability in the shift lengths. In case of undercapacity there are not enough nurses working at the same time to cope with the care demand and patients must wait longer. Both scenarios lead to a lower satisfaction of the nurses. The over- or undercapacity has more potential reasons. There is no sufficient data analysis about the care demand because of the differentiation of planned and unplanned care. While the planned care is to some extent known in advance, the unplanned care occurs more infrequently and underlies many fluctuations. Furthermore, the hospice team employs nurses of different qualification levels since their patients require different care. Another reason for both over- and undercapacity is the inefficient capacity planning. We analyze the four potential core problems in the Table 2:

Problem	Influenceable ?	If yes, is it feasible?	Reason for influenceability and feasibility
No variable shifts	Yes	To some extent	It is possible to change the shifts, but that requires data analysis and a different capacity planning as a first step.
Inefficient capacity planning	Yes	Yes	Currently there is no consistent method for the capacity planning. There are models that allow better capacity planning.
Different patient needs	No	/	The fact that patients require different treatments and therefore nurses have different competencies cannot be influenced.
Both planned and unplanned care	No	/	The unplanned care cannot be avoided, but it can be analyzed.

Table 2 - Core problem identification

Following the reasoning in Table 2 we select the inefficient capacity planning as the core problem.

The selected core problem can also be measured in a gap between norm and reality, as Heerkens proposes (Heerkens, 2017). The reality is that there is a mismatch between capacity and care demand which leads to either over- or undercapacity which is caused because the current capacity planning of the hospice team produces inefficiencies. The norm is that the capacity perfectly matches the care demand and there is neither inactivity nor overload for the nurses due to an improved capacity planning. The aim of this research is to reduce this gap between norm and reality.

Since we identified the action problem and the core problem, we can define our main research question that we are going to answer in this thesis. The **main research question** is:

"How can the capacity planning of the hospice team be improved to reduce the capacity-demand mismatch?"

1.4 Sub-Research Questions

To find an answer to the above-mentioned research question, we go through each step of the MPSM (Figure 2) and define knowledge questions that need to be answered within the execution of this thesis.

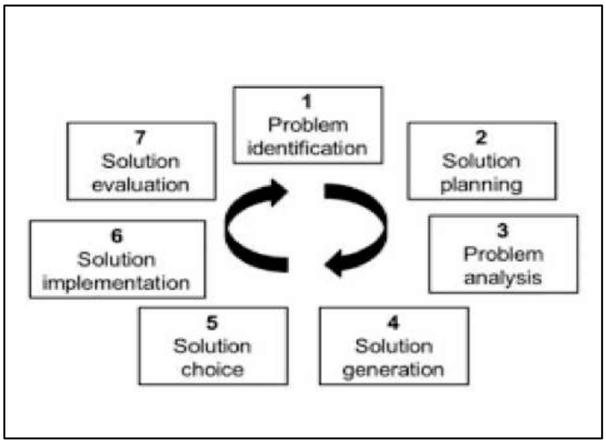

Figure 2 - Managerial Problem-Solving Method by Heerkens

Furthermore, the **scope** of the research we are conducting is clearly limited. As described in section 1.1, TWB is a large company for home care which serves a whole region and includes multiple different teams. Since analyzing each team and each cluster in the region would exceed the scope of feasibility of our research project in a limited time period, we are focusing only on the hospice team and their sub-teams Noord and Zuid.

The goal of our research is to answer the main research question. To do so, we need to elaborate on smaller sub-research questions and formulate knowledge problems that can be assigned to the several phases of the MPSM.

1. *How does the capacity planning of the hospice team currently work?*

To find an answer to this question, we will organize meetings and less formal conversations with employees from TWB, especially from the care logistics department and the hospice team itself. During those conversations we will gain knowledge about how the capacity planning of the hospice team is organized. This first question belongs to phase 3 of the MPSM.

2. *How can the existing data be analyzed and assessed to answer the following questions?*

TWB provides a data file that contains all registrations that have been made in NEDAP in the time from 01.05.2023 until 30.04.2024. This file needs to be systematically analyzed since it contains more than 88,000 entries. As the question before, also this question and the related sub-questions 2.1, 2.2 and 2.3 belong to the third phase of the MPSM.

   2.1. *How high is the care demand per team and per qualification level?*

   For the research it is interesting to analyze the care demand for the Noord and Zuid team and for each qualification level. As TWB is interested in the optimal number of nurses that should work in each shift to cope with the care demand of planned and unplanned care, we must determine the exact care demand first and analyze if there are any patterns recognizable.

   2.2. *How is the division of total care demand into the planned care and unplanned care?*

   The planned care can be scheduled in advance and the amount is to some extent known. But the unplanned care is more difficult to predict and should be analyzed as well.

   2.3. *What is the productivity per nurse?*

   The productivity per nurse that can be delivered is another variable that is essential to determine an optimal number of nurses per shift. Based on the productivity we can calculate how many patients of each level can be treated per hour or per shift.

3. *What methods or models are used to improve the capacity planning in a home care environment?*

The aim of this question is to find out what methods or models were used in other research articles to improve the capacity planning. Finding an answer to this question will help in finding a suitable method/model for this specific bachelor assignment. To answer this question, we perform a systematic literature review (SLR) which is summarized in Appendix A. This question belongs to phase 4 of the MPSM, as we find through the SLR current methods/models that help us in generating a suitable solution.

4. *How can the capacity planning be formulated in a mathematical model?*

Based on the existing literature about similar research we need to decide what kind of mathematical model we want to choose for our research and how the capacity planning of the hospice team can be translated into such a model. Further, the mathematical model needs to be solved. This question covers phase 4 because we are actively generating a model that should produce a solution to the problem.

5. *What are the results of the mathematical model?*

In this section we are displaying and describing the outputs that the mathematical model is producing. Next to that, we discuss the different outputs compared to our expectations as well as the real-life data. This question belongs to phase 5 (solution choice) of the MPSM.

6. *How can the results be used to improve the capacity planning?*

This question is connected to conclusions and recommendations that result from the research conducted and need to be discussed together with TWB to see if proposed changes are feasible and realistic. We also discuss limitations and validity of the outcomes. It relates both to phase 6 (solution implementation) as well as to phase 7 (solution evaluation) of the MPSM.

An overview of our research design can be found in Appendix B, as well as an elaboration on the used data gathering methods as well as considerations in terms of reliability and validity.

1.5 Limitations

Our research design also underlies certain limitations. For example, the dataset that we are using only contains data about the past and we will base our data analysis on the empirical distribution of care. So, all the used input data consists of historical data and there is no guarantee that the future development of the demand will be somewhat similar to the past. Furthermore, we cannot use older data than from the 01.05.2023 because before that date the hospice team was structured differently and therefor any recorded data would not be applicable to the current situation. A larger dataset would increase the reliability even more and could indicate if e.g., seasonal effects occurred in different years. Besides that, our research is located in the health care industry and the total care demand is dependent on the health conditions of the patients. If for example another pandemic like Covid-19 occurs, which significantly increased care demand and stressed health systems worldwide (McCabe et al., 2020), we cannot say with certainty that our findings still can be applied. Even though we will create different scenarios that cover different demand for care.

2. Current situation in the hospice team

In this chapter we describe how the current capacity planning in the hospice team works and assess available data to determine the nurse productivity as well as the care demand. To answer those questions and describe the current situation we conducted meetings and less formal conversations with employees from the hospice team, both with a basis planner of work schedules as well as the manager of the team. Further, we analyze data that TWB provides to us.

2.1 Current capacity planning

In each cluster either 2 or 3 nurses work in the morning shift and 2 nurses work in the evening shift. This number of nurses is usually scheduled every day and is based on a manual estimation about how many nurses are needed. Since most of the care delivered by the hospice team belongs to qualification level 3IG and 4, mainly nurses of those qualifications are scheduled and in fewer cases also level 5 nurses are working. A requirement of TWB is that at least one of the nurses always working (in both the morning as well as the evening shift) belongs to level 4 because they can treat the majority of patients, both planned and unplanned. The number of nurses is usually not varied, so most of the time the same number of nurses are active. Only if during a longer period a significantly large over- or undercapacity is perceived, the number of nurses is adjusted.

Furthermore, TWB tries to plan full shifts of 8 hours because this is desired by most of the nurses. They have a preference for 8-hour-shifts because 8-hour shifts enable them to fill their weekly hours quicker. So, nurses with a 40-hour contract would have to work 5 days a week and nurses with a 20-hour contract would have to work only 2.5 days a week. If shifts become shorter their amount of working days increases. On the other hand, empty shifts due to too little care demand are also a problem and lead to a lower job satisfaction, because nurses have to end their shift earlier and their day does not go according to their planning. Even though, sometimes shifts of shorter length than 8 hours are scheduled and TWB is interested in investigating whether shorter shifts can be a solution to decrease the capacity-demand mismatch.

2.2 Data Analysis

The data that we are mainly using is stored in the so-called registrations file. It contains all registrations made by nurses from the hospice team, including delivered care, travel time, breaks, trainings etc. The registrations made in the file are not directly assigned to a certain qualification level but rather to a category of care which is registered with a certain registration type. So, for the analysis we have to allocate each registration type to a qualification level. The relevant qualification levels of nurses in the hospice team are 3IG, 4 and 5. An overview of which registration type belongs to each of the levels can be found in Appendix C.

We are analyzing the time period from 01.05.2023 until 30.04.2024. Data before May 2023 cannot be used because the structure of the hospice team was different to the current structure and would yield inconsistent results.

The structure of the hospice team got changed because the covered region is large, and much time was spent on travelling from one point of the region to another one. So, TWB decided to divide the region into cluster “Noord” and cluster “Zuid”. Before the split, the region was considered as a whole. But to reduce the travelling times of nurses and therefore increase their productivity the area was divided. In the following we will elaborate on the current nurse productivity.

2.2.1 Nurse productivity

Determining the nurse productivity plays a key role in calculating how many patients can be treated in a certain time by one nurse. To determine the productivity per nurse we can use the registrations file. For each registration made in that file there is the starting and end time stored, from which the duration of the treatment is calculated. So, for the analysis we separately filter for all registration types that belong to level 3IG, 4 or 5 respectively. Per level, we consider all the durations that are stored and take the average of those to gather a deterministic value for the care duration per level, as Restrepo et al. (2020) proposes.

Taking a full hour of 60 minutes as a basis, we can deduct the friction that belongs to travel time because this time cannot be used effectively to deliver care. According to the registrations file and the management report of TWB (TWB, 2024), we can see that 18.16% of the time gets spent on traveling. On top of that, several smaller factors that can be found in the management report reduce the net working time.

Further, the average treatment time per patient for each level is included in Table 3. Dividing the average treatment time per patient by the productive time, we get the productivity for each level (measured in patients that can be treated per hour). The results can be seen in the Table 3 below.

Time factors / Levels	**Level 3IG**	**Level 4**	**Level 5**
Travel time	18.16 %	18.16 %	18.16 %
Illness	10.15 %	6.62 %	5.00 %
Training	3.66 %	7.04 %	6.46 %
Planning time	2.00 %	1.21 %	0.78 %
Consultation time	1.00 %	1.83 %	4.38 %
Other	0.53 %	6.65 %	6.13 %
Productive time	**64.50 % (38.7 min)**	**58.49 % (35.1 min)**	**59.09 % (35.5 min)**
Avg. treatment time per patient	**33.4 min**	**38.3 min**	**28.1 min**
Productivity (Patients per hour)	**1.2**	**0.9**	**1.3**

Table 3 - Productivity of nurses per qualification level

To determine the nurse productivity per shift, we can simply multiply the productivity per hour with the shift length, respectively 8, 6 or 4 hours.

2.2.2 Care demand

As described in section 1.2, the care of the hospice team is split into planned and unplanned care. Both types of care are affected by large fluctuations and vary drastically over time. Even the realization of the planned care has significant differences to the preplanned schedule for the week because often patients suddenly require more care than actually assumed or they pass away and do not require care anymore. This proportion of unforeseen care activities is called unplanned care.

In this section we analyze the total care demand in detail and measure the care demand in number of patients that require care. If the same patient requires care twice a day, it is considered as two patients. We differentiate between the following criteria:

- Date
- Cluster (Noord and Zuid)
- Qualification level (3IG / 4 / 5)
- Shift (Morning and Evening)
- Planned or unplanned care

To assess the provided registrations file systematically, we are considering the different registration types and allocate them to the corresponding levels of care. As mentioned above, a detailed allocation of which registration types belong to which level of care can be found in the Appendix C.

For having an overview, we created an Excel sheet that summarizes the care demand according to the criteria that are defined above. It contains the number of registrations, so the number of patients that have been treated per criteria in the time from 01.05.2023 until 30.04.2024. A small example of the Excel sheet can be found in Appendix D.

The total care demand per month, measured in the number of patients is shown below in Figure 3 for cluster Noord and Figure 4 for cluster Zuid.

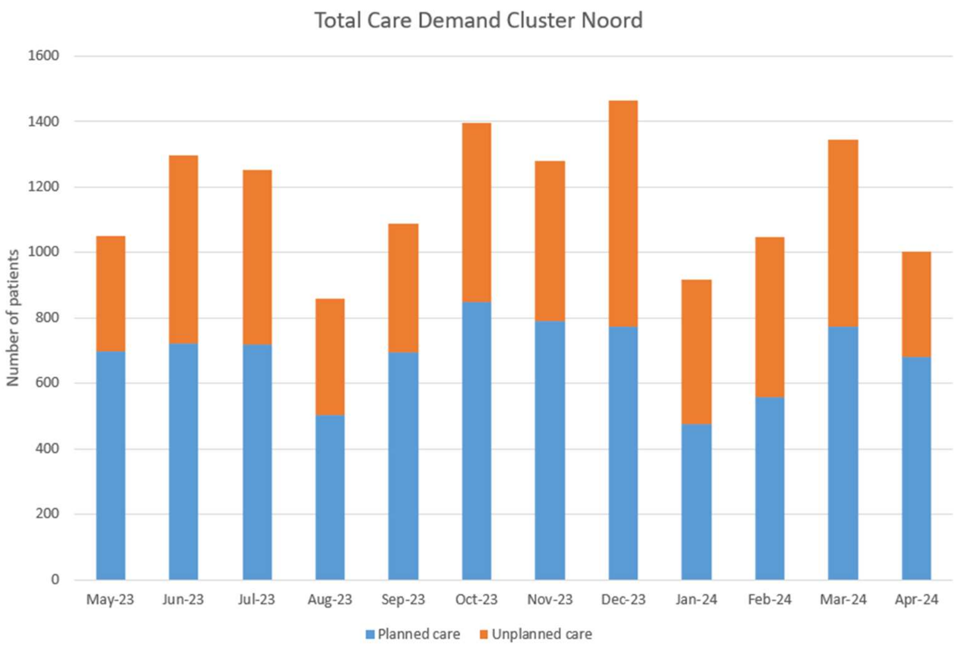

Figure 3 - Total care demand in cluster Noord

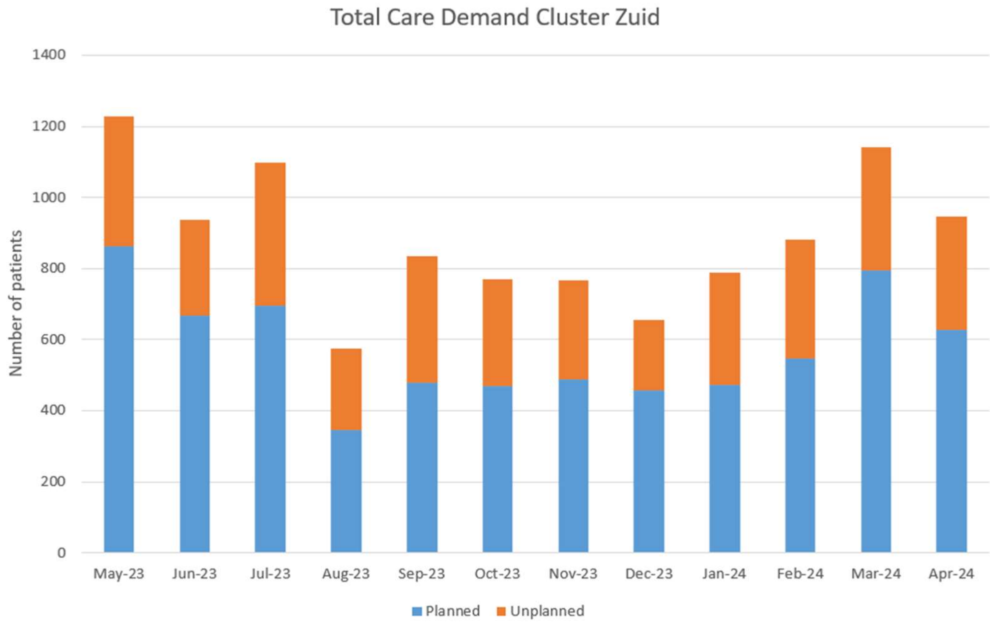

Figure 4 - Total care demand in cluster Zuid

In cluster Noord the share of planned care from the total care demand amounts to 59% on average. Therefore, the share of unplanned care is at 41%. On the other hand, in cluster Zuid the share of planned care is on average slightly higher with 65% and logically, the share of unplanned care is lower with 35%.

2.3 Conclusion

To conclude, we can say that currently the capacity planning in the hospice team is done manually and does not follow certain rules and regulations in terms of decision-making. Cluster Noord and Zuid are usually treated equally. Even though, the demand for care in cluster Zuid is on average lower than the demand for care in cluster Noord. For both clusters the unplanned care equals a smaller share of the total care, while unplanned care in cluster Zuid is slightly lower than in cluster Noord.

About the nurse productivities we can say that is on a similar level for all qualification levels. While type 4 care consumes on average most of the time (0.9 patients / hour possible), type 5 care is the shortest (1.3 patients / hour possible), according to the data. For all levels, the largest friction of time gets lost because of travelling (18%).

The only strict requirement regarding nurse scheduling that the hospice team has, is that at least one level 4 nurse is working all the time in each cluster. Decision making is so far barely based on data, but rather on intuition and an estimation of how high the demand is.

3. Literature Review

In this chapter, we will first locate our research problem in an existing theoretical framework. Further, we analyze the problem theoretically and summarize findings about related works and answering the knowledge question of “what methods or models are used to improve the capacity planning in a home care environment?” by having performed a systematic literature review. To some extent we will also address the question of how the existing data at TWB can be analyzed and assessed.

3.1 Framework for Healthcare Planning and Control

To categorize our research of improving the capacity planning of the hospice team, we can locate it within an existing framework for healthcare planning and control by Hall (2012). Even though this framework is meant for a general hospital and not home care specifically, it still has significant overlaps with a home care setting, so we can use it for our purpose.

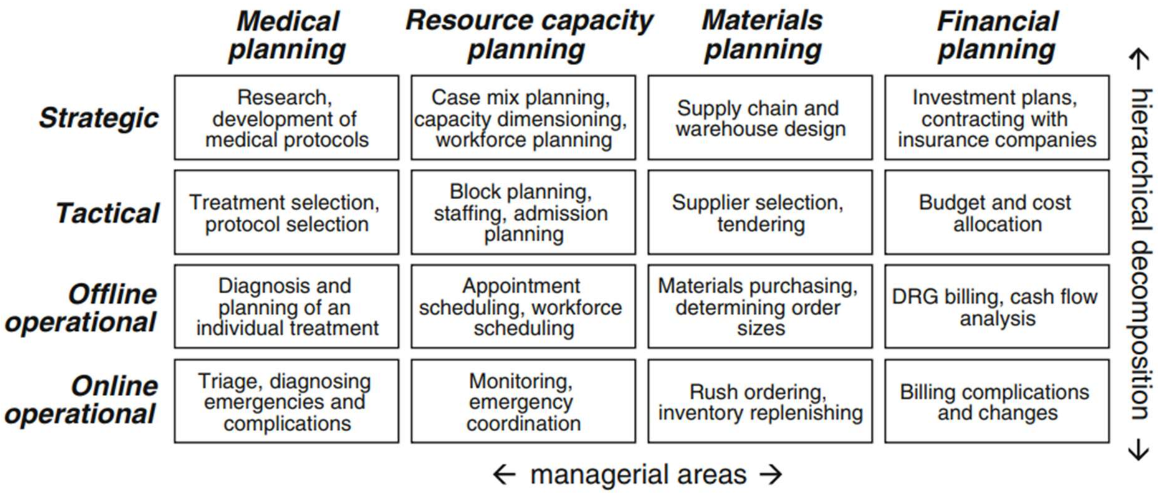

Figure 5 - theoretical framework for health care planning and control (Hall, 2012)

The framework is divided into four managerial areas and four hierarchical decompositions, which creates a four-by-four matrix. By looking at the different managerial areas, we can already know by the name that our research belongs to the area of resource capacity planning. According to Hall, the resource capacity planning is about the “dimensioning, planning, scheduling, monitoring, and control of renewable resources” (Hall, 2012), where also staff belongs to.

To identify the cluster that our research belongs to, we first summarize each hierarchical decomposition according to the definitions of Hall and check where we can locate our research best.

The strategic level is about decision making with a long timely horizon, e.g. long-term contracts, investments, and expansions.

To shorten the time horizon drastically, we come to the operational level which involves short-term decision making and can be split into two categories. While the offline operational level is considered as planning in advance, e.g., by creating weekly rosters, the online operational level deals with monitoring and reacting to real time events such as triaging.

In between the operational levels and the strategic level, there is the tactical level. It has a large overlap with the operational level, but for a longer planning horizon, so e.g. the demand uncertainty becomes higher.

By looking at the different hierarchical decompositions, we can see that our research does not belong to the strategic level, because possible decision making based on our results does not have a long-time horizon. The decisions regarding scheduling are done with a maximum of a couple of weeks in advance, but not longer and can be regularly changed based on the current care demand.

Furthermore, our research shows characteristics of each of the other three levels. Since we try to find the optimal number of nurses in a shift, we deal to some extent with workforce scheduling, even though it is not the aim to plan appointments but to scale the workforce capacity. According to that and looking at the time horizon, our research is located somewhere between the tactical and the (offline) operational level.

Next to that we also discover some characteristics of the online operational level because our data includes both planned and unplanned care. The unplanned care can be seen as emergency coordination because patients who were not planned before call a hotline and request promptly care. This is happening on a daily basis at the hospice team.

To conclude, our research is located somewhere between the operational and the tactical level because the recommendations that we will give cover a maximum period of one month and can be changed regularly based on the current care demand, if needed.

3.2 Related literature

The research problem that we are considering belongs to the field of home health care and therefore identifies as a home health care problem (HHCP). According to Grieco et al. (2021), there are several studies that apply operations research methods to HHCPs. Even though, the majority of those studies are about staff-to-patient allocation, visit scheduling or routing of visits and less concerned with strategical or tactical decisions such as team size or team composition. Problems that are concerned with e.g. the routing of visits and treated by Cheng & Rich (1998) and several more, are certainly of high importance in HHC but less relevant to our research problem, as we are interested in the required team size and composition at different times.

Another well-known problem in healthcare, namely the nurse scheduling problem (NSP) is also to some extent related to our research and discussed by Abdalkareem et al. and Muniyan et al., among others. In comparison to the HHCP, the NSP is located in the environment of a hospital and not in a home care setting. Often, a NSP deals with scheduling specific nurses to predetermined shifts while considering several hard and soft constraints (Muniyan et al., 2022). Satisfying a hard constraint such as allocating shifts to a restricted number of nurses is necessary to create a feasible solution. Soft constraints such as balancing the workload do not need to be fulfilled but violating them leads to penalty costs and therefore to a worse solution.

From the conducted systematic literature review (SLR) about the question of what models or methods exist to improve the capacity planning in a home care environment, we created a conceptual matrix that can be found in the Appendix A. Concepts that have been covered frequently are data analysis, modelling care demand under uncertainty and common solution methods to solve the problems. We will elaborate on each of them in the following.

Data analysis:

For analyzing existing data there are several different key numbers that are worth it to be investigated. The first and most significant one is the total number of care cases that appear in a certain time, e.g., per week (Clapper et al., 2023). While Clapper et al. (2023) is making use of historical data and uses them for a planning on a tactical or operational level, Hare et al. (2009) focusses on the strategic level and predicts the growing future demand as a consequence of an aging population.

Further, the average length of stay, so the average treatment time per patient is of high importance as well. Additionally, the travel time from one patient to another plays a key role in determining the capacity of a caregiver per shift. Restrepo et al. (2020) assumes those two parameters to be deterministic and includes them to determine the caregiver's capacity (the number of patients visited per shift). This capacity varies e.g., with the type of shift. Lastly, the level of care that a patient requires should also be known in order to allocate a suitable care giver to the patient.

Modelling demand uncertainty:

Since modelling the care demand under uncertainty is mentioned in the majority of the found literature, we can conclude that is a substantial aspect of an optimal capacity planning in a home care setting.

A frequently used approach to model demand uncertainty is to use a Monte-Carlo simulation that determines the amount of care demand by generating different scenarios. Rodriguez et al. (2018) creates those different scenarios based on the assumption that the care demand underlies different distributions, e.g., a uniform distribution. A similar approach is used by Aslani et al. (2021) who suggests creating different demand scenarios with a Monte-Carlo simulation from a predefined set of uncertainties.

Another approach of modeling the demand uncertainty is to use Malahanobis distance, as Xie et al. (2023) proposes. The Malahanobis distance is a statistical measure between the distance of a data point and a distribution using the mean and covariance matrix to take the correlation of a data set into account (McLachlan, 2005).

Creating different scenarios to cope with the uncertainty makes a generated solution more robust compared to a solution that is only based on a deterministic demand. Thus, it is recommendable to solve the assignment problem with several scenarios for the future care demand at the same time to retrieve a robust plan (Lanzarone et al., 2012).

Common solution methods:

To solve the problem of coming up with an optimal capacity planning, the majority of the analyzed literature is making use of variations of linear programs. A frequently used approach is for example to divide the problem into two subproblems and solve each of them separately. This so-called two-stage approach based on integer linear stochastic programming is used e.g., by Rodriguez et al. (2018). The first model (Slave problem) is solved to calculate the minimum number of resources needed for possible demand scenarios and the second model (Master problem) is solved to calculate the number of caregivers to reach a certain target coverage ratio.

A similar two-stage approach is developed by Xie et al. (2023), where service type and capacity are the first stage decision, and the homecare resource allocation is the second stage decision.

Usually, the developed models are of large complexity because they are aiming to solve multiple decisions such as districting, staff dimensioning, resource assignment and scheduling and routing simultaneously (Nikzad et al., 2021). Therefore, most of the models are not solved for an exact solution, but rather a heuristic is applied to reduce the computational time significantly.

Frequently selected objectives, which are defined in the objective function of the linear programs are minimizing the total staff costs while matching capacity offer and demand (Rodriguez et al., 2018) or to maximize total profit (Xie et al., 2023).

The discussed solution methods are used to solve the HHCPs, but also to solve the NSP (Santos et al., 2014).

3.3 Selected solution approach

As analyzed above, there are several different approaches to improve the capacity planning in a home care environment and solve a HHCP or NSP. In the following we describe which approaches fit best to our research problem and will be pursued in the execution of this bachelor thesis.

Since TWB provides a large amount of historical data about the care demand, we analyzed that data to determine the care demand in the past 12 months. In doing so, we counted the amount of care that was required per level and per shift on each day. Further, we analyzed the caregiver's capacity to determine their productivities per shift, such as Restrepo et al. (2020) proposes. A detailed execution can be found in subsection 2.2.1.

In a next step we want to model the demand uncertainty. For that, we will analyze the empirical distribution of the care demand of each level and run a Monte-Carlo simulation that creates different care demand scenarios, based on the empirical distribution. By that we are following the procedure that Rodriguez et al. (2018) and Aslani et al. (2021) suggest.

To reduce the capacity-demand mismatch as an overall goal we will follow the example of e.g. Restrepo et al. (2020) and create a linear program that aims to satisfy the care demand under the objective of minimizing the total salary costs. As a decision variable we will use the number of nurses that are needed per qualification level. The linear program will be an integer linear program. Since we do not consider other decisions, such as routing the complexity of the program is rather small and can be solved by finding an exact solution without making use of a heuristic.

3.4 Conclusion

Our research problem belongs to the field of home health care problems (HHCPs) and also shows some characteristics of nurse scheduling problems (NSPs), even though NSPs are usually located in a hospital setting instead of the home care environment. About both the HHCP and NSP, there are several articles that apply common operations research methods such as linear programming. Before solving the linear programs, the considered articles emphasize to perform a detailed data analysis on given historical data to get deterministic values for e.g. nurse productivity according to Restrepo et al. (2020), and model uncertain parameters like the care demand with e.g. a Monte-Carlo simulation (Aslani et al., 2021).

Since the models from e.g. Rodriguez et al. (2018), Xie et al. (2023) or Nikzad et al. (2021) are of large complexity, they are solved with an algorithm to reduce the computational time drastically.

4. Modelling demand uncertainty

In this chapter we will discuss how to analyze the total care demand in order to create different demand scenarios that represent the demand uncertainty.

4.1 Evaluating care demand systematically

To get an estimation how busy certain months from May 2023 until April 2024 were, we present an overview of the total care demand of both cluster Noord and the Zuid in Figure 6.

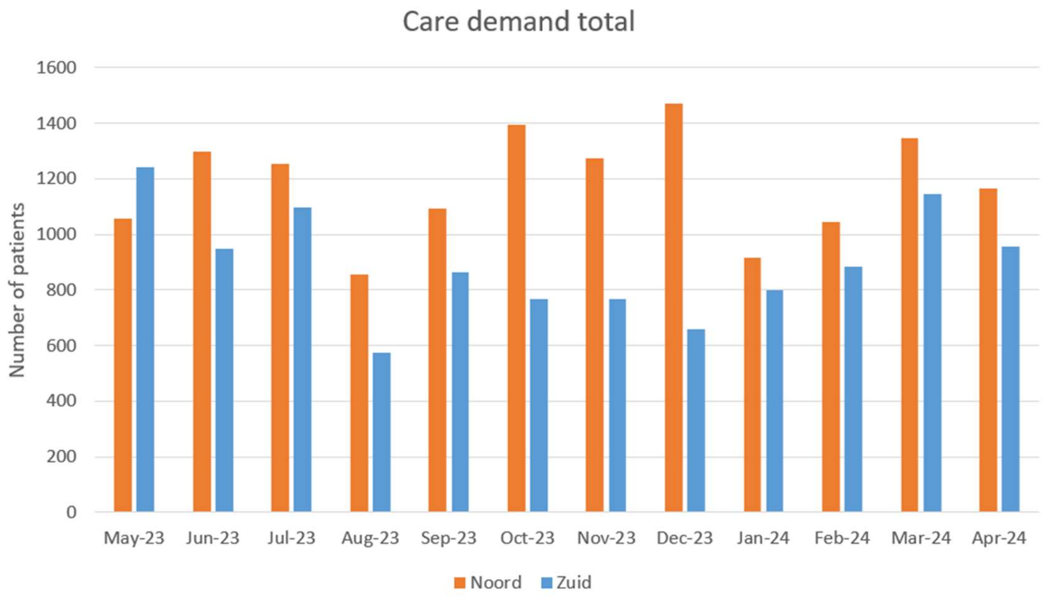

Figure 6 - Overview total care demand per month

TWB is interested in an analysis that enables us to improve the capacity planning and recommend the right number of nurses of each qualification level per shift. Since the hospice team works all week from Monday until Sunday and we want to find out if there are specific month or weekdays that are busier than others, we summarize all different weekdays and analyze each of them separately.

To avoid that we are analyzing each month separately and only have a sample size between 4 and 5 (number of each weekdays per month), we combine months with a similar level of care demand together to increase the sample size. Further, grouping months with similar care demand together increases the accuracy of our analysis. The groupings can be seen in the Table 4 below.

Demand classification	**Months**	
	Cluster Noord	**Cluster Zuid**
Low	January, August	August, December
Middle	February, April, May, September	January, February, April, June, September, October, November
High	March, June, July, October, November, December	March, May, July

Table 4 - Groups of months with similar total care demand

To check if we can identify a theoretical distribution we analyze as an example the high care demand group of cluster Noord. In doing so, we plot the total care demand of all days (in total 184) in the regarding months. Further, we compare the created histogram of the analyzed sample with common theoretical distributions, such as normal distribution, exponential distribution, and Poisson distribution using the descriptive statistics of our sample. The results can be seen in Figure 7.

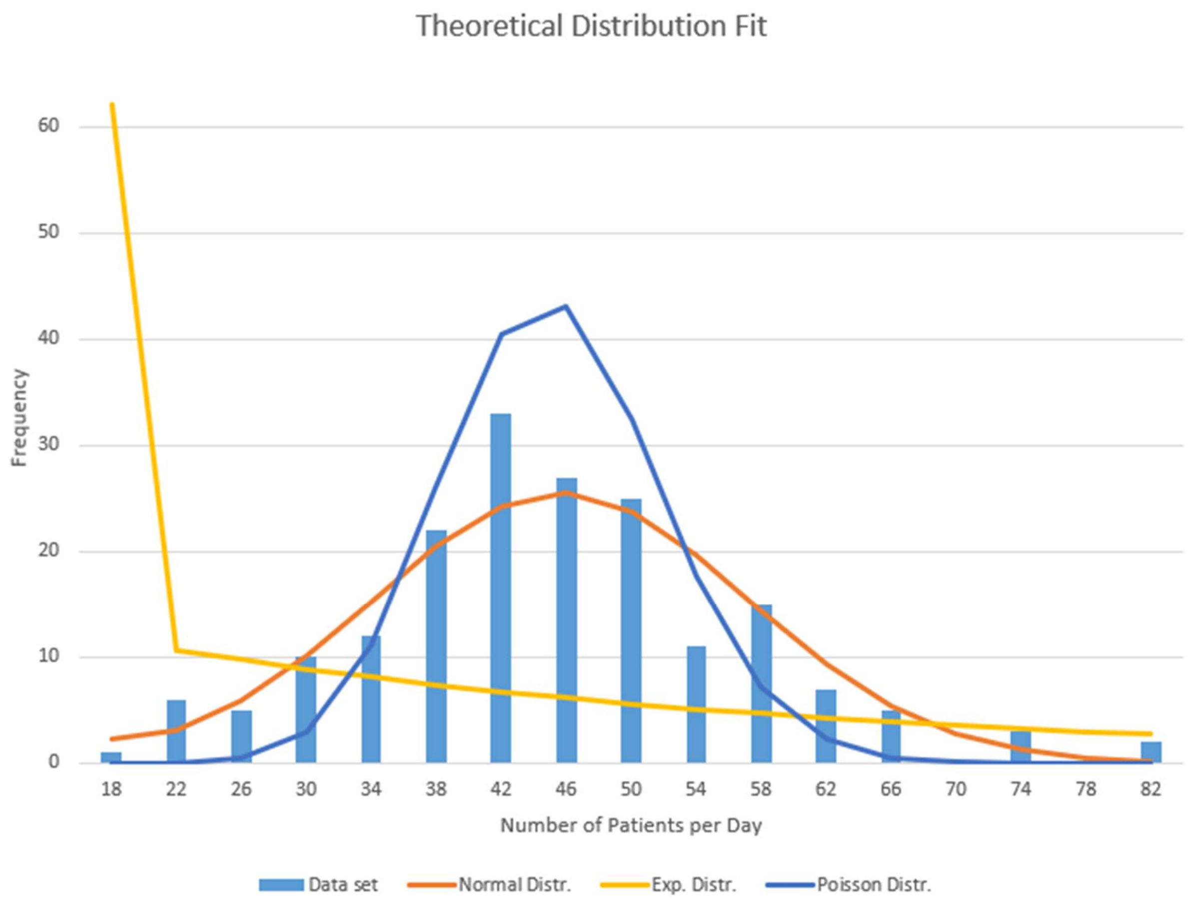

Figure 7 - Theoretical Distribution Fit for Care Demand in High Demand Group - Cluster Noord

As we can see, none of the theoretical distributions fit the observed data perfectly. Visually evaluating we can say that the bell curved shape of the normal distribution comes closest to the shape of the observed sample. Even though, a statistical goodness of fit test which can be found in Appendix E led us to reject the hypothesis that our sample is normally distributed. Other tests that we applied on different samples which included care of only one qualification level for the last 12 months also failed in finding a suitable theoretical distribution. Since we could not identify a theoretical distribution, we focus on the empirical distributions of the care demand.

In the following, we analyze the empirical distributions of care demand per weekday, qualification level and shift and differentiate between planned and unplanned care. We do that because the true statistical distribution is unknown to us, and we can use the empirical distribution function (EDF) as an estimator for the cumulative distribution function (CDF) (Ramachandran & Tsokos, 2021).

To analyze the empirical distribution, we count the number of times a certain care demand (measured in number of patients) occurred and divide that by the total number of events. We take the cumulative probabilities as a result. As an example, the analysis for cluster Noord for high demand months on a Sunday can be seen in the appendix F.

4.2 Monte Carlo Simulation

So far, we have collected the data to see how high the care demand on every single day was. To generalize our findings, we summarized similar months together to low, middle, and high demand periods, as described in Table 4. According to our findings of the literature review we will proceed with setting up a Monte Carlo simulation that creates different demand scenarios that we can further use as an input in the linear program to calculate the optimal number of nurses required to cover the care demand (Rodriguez et al., 2018).

The principle of a Monte Carlo simulation is to assess the behavior of a statistic in random samples by the empirical process of simply drawing many random samples and observe their behavior (Mooney, 1997). In our case we draw a random number. A function that we created retrieves the corresponding number of patients per level based on the empirical distributions. Hereby, the probabilities are taken from the tables that can be found in Appendix F. Since we are using the method of a Monte Carlo simulation, we repeat this process a thousand times. We selected this number because it is a typical number of runs that gives sufficient results to properly further use them (Heijungs, 2020). A higher number of runs would possibly decrease the variations of results but running the simulation with 10,000 runs instead of 1,000 runs did not show any difference in the generated number of patients in our case. So, we decided that increasing the number of runs is not necessary since it would also increase the computational time significantly.

Next, the number of patients per level and per shift are stored. The data stored contains the number of patients for level 3IG, 4 and 5 for each the morning and the evening shift. All the used code can be found in Appendix G.

Further, we determine different scenarios based on the 0^{th} until the 100^{th} percentiles of the population in steps of 10 to represent that the care demand is not deterministic and underlies a lot of fluctuations.

In the following we show boxplots of the care demand (measured in number of patients) for cluster Noord for each of the groups of months. The figures for cluster Zuid are shown in Appendix H.

4.2.1 Care Demand in Cluster Noord

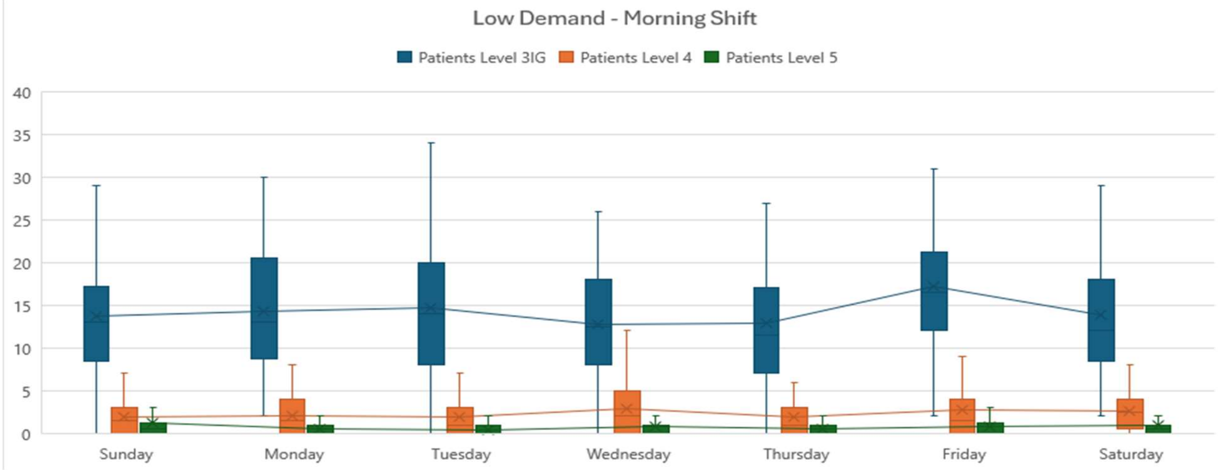

Figure 8 - Demand pattern for months January, August – Morning Shift

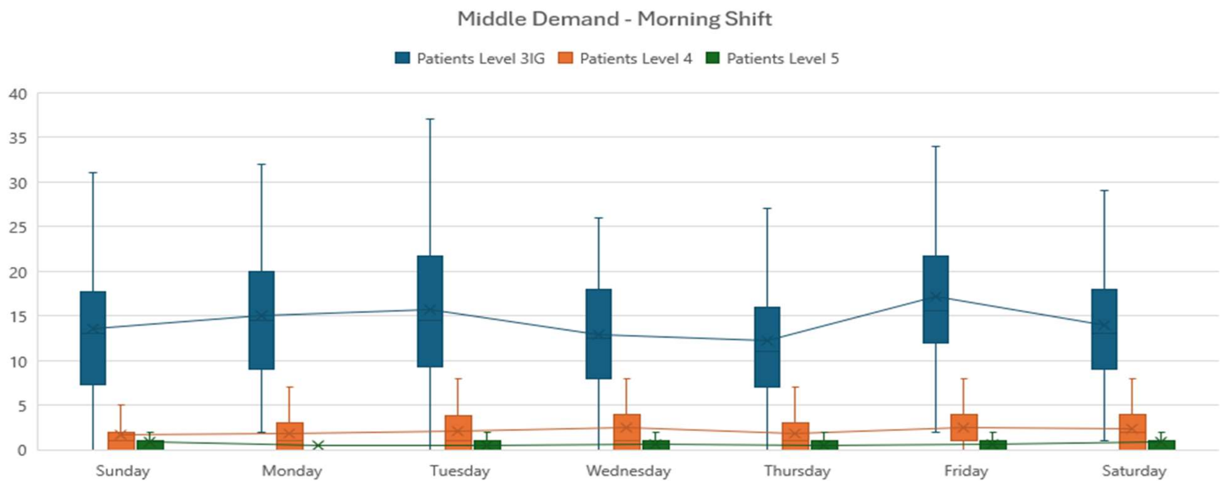

Figure 9 - Demand pattern for months February, April, May, September – Morning Shift

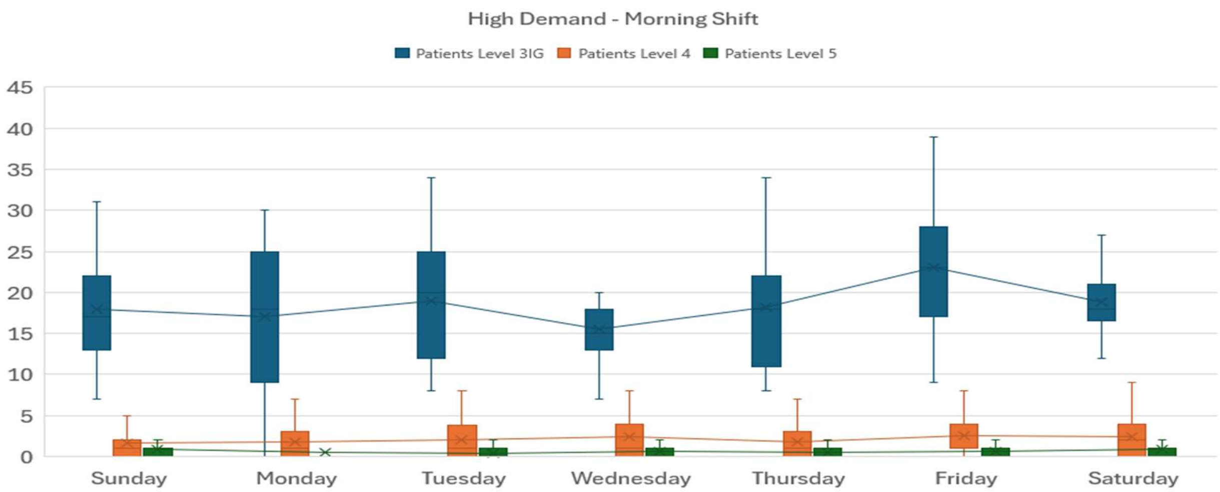

Figure 10 - Demand pattern for months March, June, July, October, November, December - Morning Shift

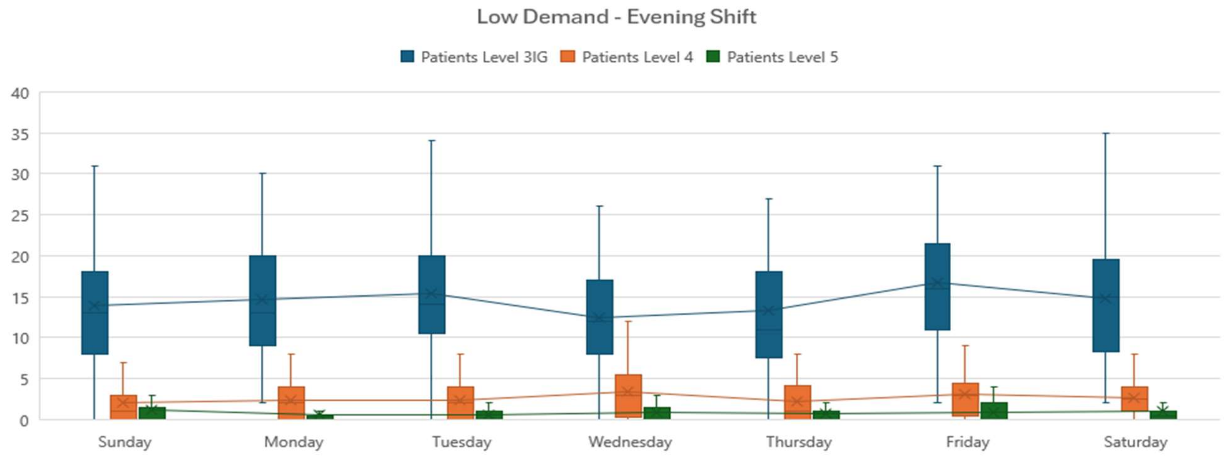

Figure 11 - Demand pattern for months January, August – Evening Shift

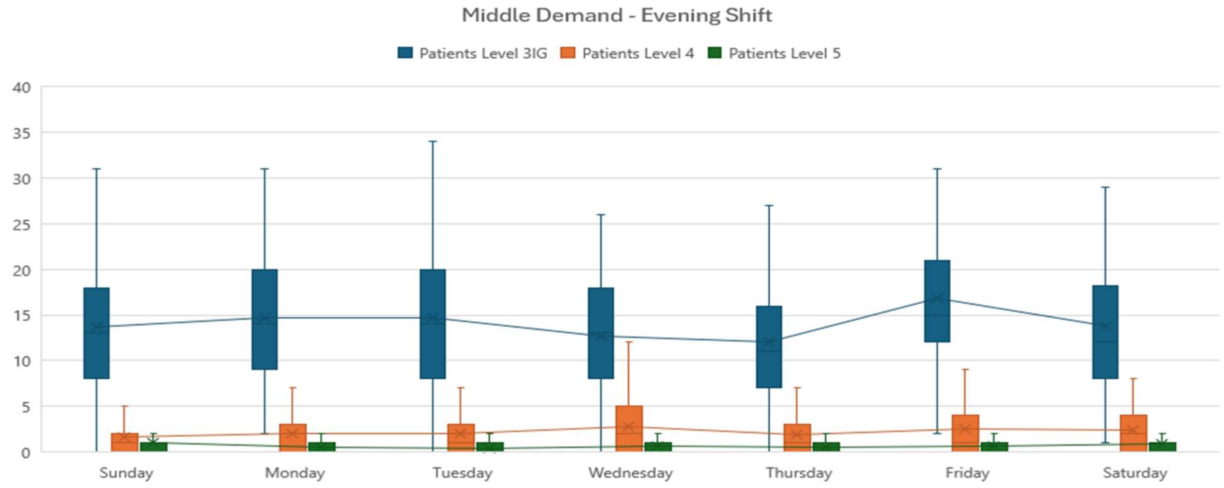

Figure 12 - Demand pattern for months February, April, May, September – Evening Shift

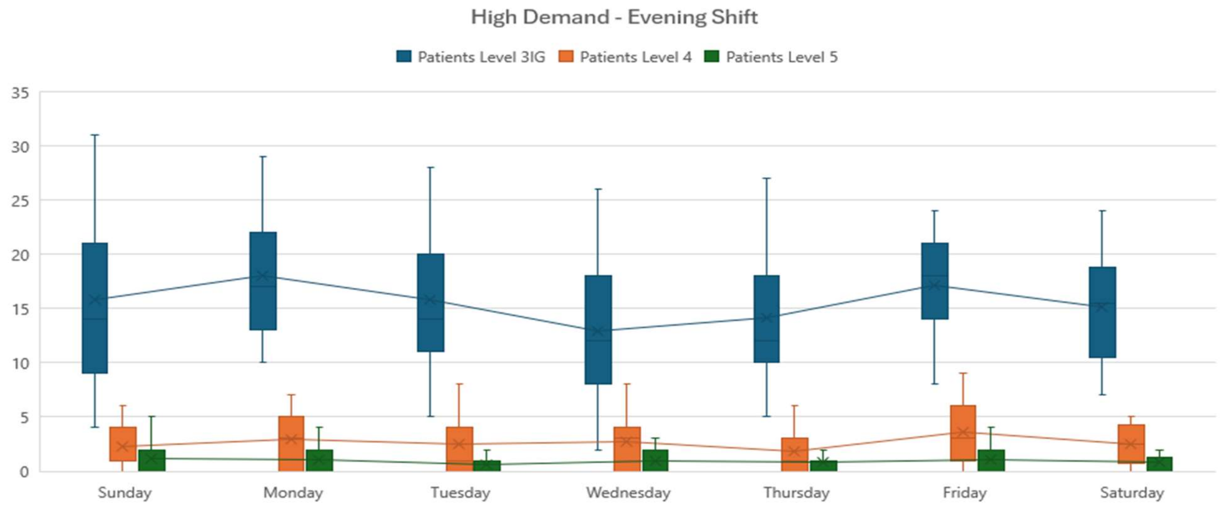

Figure 13 - Demand pattern for months March, June, July, October, November, December - Evening Shift

4.3 Conclusion

We have analyzed the care demand systematically for both Cluster Noord and Zuid and differentiated between the three levels of care. As described above, the past 12 months were divided into three different demand groups to enlarge the used sample size for finding out the empirical distributions which is the basis for the Monte-Carlo simulation.

The generated care demand underlies high fluctuations and no significant differences between the weekdays can be determined but we can see that the amount of level 3IG care clearly is the highest. At a later stage of this thesis, we will further use the generated care demand as an input for our mathematical model that is described in the following chapter.

5. Mathematical Model

In this chapter we answer the question of how the problem of the capacity planning at the hospice team can be translated and defined in a mathematical way.

We decided to develop an integer linear program, such as Rodriguez et al. (2018) and Xie et al. (2023) suggest. A linear programming problem is defined as the problem of either minimizing or maximizing a linear function, also called the objective function while considering certain constraints (Sakarovitch, 2013). It is a type of well-known operations research (OR) models. While a classical linear program allows the decision variables to be continuous, an integer linear program (ILP) requires some or all decision variables to be integers.

Additionally, we follow the approach of Xie et al. (2023) and use a robust optimization technique where we construct a budget of uncertainty set that consists of values from our Monte-Carlo simulation. We use robust optimization instead of following a deterministic approach in order to create solutions that can still be used under the influence of demand uncertainty (Aslani et al., 2021). For the formulation of our robust optimization within the ILP we have consulted the work of Gorissen et al. (2015). The creation of the LP belongs to phase 4 of the MPSM, the solution generation.

The overall goal for us is it to come up with a model and thus an improved capacity planning that allows TWB to reduce the capacity-demand mismatch in the hospice team.

In the following our ILP, including the used sets, parameters, decision variables, objective function, box uncertainty set, and constraints will be defined and explained.

5.1 Sets

Shift length

Notation: $L = \{8, 6, 4\}$

Definition: Set of shift lengths where shifts can be either 8, 6 or 4 hours long.

Qualification

Notation: $Q = \{3, 4, 5\}$

Definition: Set of qualifications. The care work is divided into 3 different levels of care.

5.2 Parameters

Productivity

Notation: $\alpha_{l,q} \in \{9.6, 7.2, 4.8, 7.2, 5.4, 3.6, 10.4, 7.8, 5.2\}$

Definition: Nr. of patients of level $q \in Q$ that can be treated in a shift of length $l \in L$.

To calculate the values for $\alpha_{l,q}$ we multiplied the productivity of nurses per level determined in section 2.1 with the possible shift lengths of 8, 6 and 4 hours.

Patients

Notation: $\widetilde{P_q} \in \mathbb{Q}$

Definition: Nr. of patients that require care of level $q \in Q$, which is uncertain and based on uncertainty sets which we have modelled using the Monte-Carlo sampling

Costs

Notation: $c_{l,q} \in \{252.64, 190.48, 127.32, 281.2, 211.90, 141.60, 322.40, 242.80, 162.20\}$
Definition: Salary costs in € that a nurse of level $q \in Q$ is paid for a shift of length $l \in L$

More details about the used values for costs can be found in section 6.1.

5.3 Decision variables

The decision variable that we use in this model is the number of nurses with a certain qualification level that work in a shift of either 8, 6 or 4 hours in the morning or evening.

Nurses

Notation: $N_{l,q} \epsilon \mathbb{N}$
Definition: Nr of nurses that work with a shift length $l \in L$ and of qualification $q \in Q$

5.4 Objective function

$$\min z = \sum_{l \epsilon L} \sum_{q \epsilon Q} c_{l,q} * N_{l,q} \quad (1)$$

Our objective function minimizes the total salary costs. To do so, we sum all possible salary costs for different shifts together. In total, we have 9 different costs for shifts because there are three different shift lengths and three different qualification levels that require different payments.

5.5 Constraints

Qualification constraints and demand coverage

The following constraint ensures that the demand for patients that require care of level q is satisfied. The coefficient $\alpha_{l,q'}$ determines how many patients can be treated by a nurse that works in a shift of length $l \in L$ and of qualification $q \in Q$. The nurse productivities that we have calculated in section 2.2.1 determine the coefficients which are defined above. Furthermore, all patients that require care of a certain level can also be treated by nurses of higher levels.

$$\sum_{l \in L} \sum_{q' \geq q} \alpha_{l,q'} * N_{l,q'} \geq \widetilde{P_q} \quad \forall\, q \quad (2)$$

The constraint below ensures that at least one level 4 nurse is working an 8-hour shift in both the morning and the evening shift. This is a strict requirement that TWB has.

$$N_{8,4} \geq 1 \quad (3)$$

This constraint ensures that all the decision variables have a non-negative value.

$$N_{l,q} \geq 0 \quad \forall\, l, q \quad (4)$$

The last constraint defines that all decisions about $N_{l,q}$ belong to the natural numbers including 0.

$$N_{l,q} \epsilon \mathbb{N}_0 \text{ (5)}$$

5.6 Box Uncertainty Set

So far, our model includes an uncertain parameter in constraint (2) which contains the number of patients for each level that need to be treated. To correctly create our model, we need to reformulate it and include robust optimization according to Gorissen et al. (2015). In the following, the updated model will be explained including the box uncertainty set for the patient demand.

Patient Demand

Notation: $\tilde{P}_q \in \{\bar{P}_q + \delta * X_q\}$ $\forall q$ with $|\delta| \leq 1$ where $\bar{P}_q$ is the mean patient demand of qualification q and δ is the uncertainty parameter. X_q describes the value of the maximum deviation from the mean, based on percentiles. The deviation based on percentiles will go in steps of 10, so including percentile [50], [40-60], [30-70], [20-80], [10-90] and [0-100]. So, $\bar{P}_q + X_q$ represents the worst case that is possible in terms of care demand for each box uncertainty set. Thus, the worst case is the upper bound.

Definition: Nr. of patients that require care of level $q \in Q$

5.6.1 Reformulated Constraint

Qualification constraints and demand coverage

In a first step we copy the constraint (2) from the first version of the model.

$$\sum_{l \in L} \sum_{q' \geq q} \alpha_{l,q'} * N_{l,q'} \geq \widetilde{P_q} \quad \forall q \quad (6)$$

Next, we replace the uncertain parameter $\widetilde{P_q}$ for the patient demand with the uncertainty set.

$$\sum_{l \in L} \sum_{q' \geq q} \alpha_{l,q'} * N_{l,q'} \geq \bar{P}_q + \delta * X_q \quad \forall q \; with \; |\delta| \leq 1 \quad (7)$$

With the formulation above we would have an infinite number of constraints, which cannot be solved by a linear solver. Since we are making use of robust optimization, we are only interested in the worst-case realization of the uncertainty. Thus, we can reformulate our constraint:

$$\sum_{l \in L} \sum_{q' \geq q} \alpha_{l,q'} * N_{l,q'} \geq \max_{-1 \leq \delta \leq 1} \{\bar{P}_q + \delta * X_q\} \; \forall q \quad (8)$$

Further, we can replace the worst case with absolute values.

$$\sum_{l \in L} \sum_{q' \geq q} \alpha_{l,q'} * N_{l,q'} \geq |\bar{P}_q + X_q| \; \forall q \quad (9)$$

Since $\bar{P}_q$ and X_q are always positive values, we do not need the formulation with absolute values in this case. Finally, the constraint holds for the worst case which is the upper percentile of the box uncertainty set.

$$\sum_{l \in L} \sum_{q' \geq q} \alpha_{l,q'} * N_{l,q'} \geq \bar{P}_q + X_q \quad \forall\, q \quad (10)$$

5.7 Reformulated Model

To provide an overview, we state the complete model as defined above again.

5.7.1 Decision Variables

Nurses

Notation: $N_{l,q} \in \mathbb{N}$

Definition: Nr of nurses that work with a shift length $l \in L$ and of qualification $q \in Q$

5.7.2 Objective function

$$\min z = \sum_{l \in L} \sum_{q \in Q} c_{l,q} * N_{l,q} \quad (11)$$

5.7.3 Constraints

$$\sum_{l \in L} \sum_{q' \geq q} \alpha_{l,q'} * N_{l,q'} \geq \bar{P}_q + X_q \quad \forall\, q \quad (12)$$

$$N_{8,4} \geq 1 \quad (13)$$

$$N_{l,q} \geq 0 \quad \forall\, l, q \quad (14)$$

$$N_{l,q} \in \mathbb{N}_0 \quad (15)$$

The developed mathematical model also needs to be solved. For that, we will implement the ILP using Python (PyCharm Community Edition 2023.3.3) and solve it with the Gurobi Opimization Solver (version 11). The solver will give us an exact solution for each scenario that will be analyzed in the following chapter.

5.8 Conclusion

To formulate our problem of improving the capacity planning in the hospice team in a mathematical model, we have created an ILP. Further, we are following the technique of robust optimization for that we have constructed a set of uncertainties with our Monte-Carlo simulation to ensure that we are considering the worst-case scenario (Gorissen et al., 2015). We do that to take the high demand uncertainty and its fluctuations into account.

Our program decides about the optimal number of nurses of level 3IG, 4 and 5 that can all work with a shift length of 8, 6 and 4 hours. So, in total there are 9 decisions made by the program under the objective of minimizing salary costs while fulfilling the total care. The program is solved multiple times with different scenarios that imply different levels of robustness.

6. Results

In this chapter we present and discuss the results of the linear program and compare a possible schedule with the actual schedule that was used in the hospice team in the past. This chapter is meant to answer the fifth question of our research design, namely "What are the results of the mathematical model?". Furthermore, the results will build the basis for conclusions and recommendation that we elaborate on in the next chapter.

6.1 Input and Output Data

Input

In our model we use two main inputs that we elaborate on in the following.

First, one of the inputs is the salary costs $c_{l,q}$ that nurses are paid for the different kind of shifts. The salaries per hour build the basis for the shift costs and can be seen in Table 5 below.

Qualification level	Hourly payment
3IG	€ 31.58
4	€ 35.15
5	€ 40.30

Table 5 - Hourly salary costs per qualification level

Multiplied with the different shift lengths we get the following costs per shift in Table 6.

Qualification level	8-Hour-Shift	6-Hour-Shift	4-Hour-Shift
3IG	€ 252.64	€ 190.48	€ 127.32
4	€ 281.20	€ 211.90	€ 141.60
5	€ 322.40	€242.80	€ 162.20

Table 6 - Shift costs for each length and qualification

As explained in section 2.1, TWB and thus the nurses prefer shifts of 8 hours. To take this preference into account and to avoid that our model would decide e.g., for two 4-hour shifts instead of one 8-hour shift (assuming that the care demand requires this amount of work), we added the value of 1€ to all the shifts with the length of 4 or 6 hours. Consequently, 2 shifts of 4 hours are slightly more expensive than one 8-hour shift and the model would decide for the longer shift rather than two short ones because it is following the objective of salary cost minimization. In the case that one shift of 4 or 6 hours is sufficient to cover the demand $\bar{P}_q + X_q$, the model would still decide for one of those because they are cheaper than an 8-hour shift.

Secondly, the other input data that we used for our model is based on the historical data that we have received from the database of TWB in form of the registrations file. From that data we have analyzed the total care demand per month and created three different groups for cluster Noord and Zuid that include months with similar care demand. An overview of those groups is presented in Table 5, section 4.1.

For those groups, we analyzed the empirical distribution of the care demand for each level, cluster and shift and applied a Monte Carlo Simulation to create thousand scenarios which we presented in the section 4.2.1. Dividing those scenarios into percentiles from 50 until 100 (in steps of 10) categorizes demand scenarios and excludes very low care demand scenarios that are unlikely to occur. Further, percentiles lower than 50 would not be considered anyways by our model because we are using robust optimization and always choose the worst-case scenario from the possible set. Finally, we used those percentiles of the care demand (measured in number of patients) and used them as input data for our ILP. An example of the input data for one day can be seen in Figure 14. This example contains values for the upper bound of the box uncertainty set $\bar{P}_q + X_q$ as defined in section 5.6.

	Morning			Evening		
Percentiles	L3IG	L4	L5	L3IG	L4	L5
50	17	1	0	14	1	0
60	18	2	1	17	3	1
70	22	3	1	21	4	2
80	29	4	3	26	5	3
90	31	7	3	31	6	5
100	38	9	8	42	15	10

Figure 14 - Demand scenarios for Cluster Noord (High demand group) on Sunday

In total, our LP is solved for a number of 504 different care demand cases that consist of:

- 2 Clusters * 3 Demand groups of different months * 7 Weekdays * 2 Shifts (morning and evening) * 6 different percentiles

Output

The output of the model contains the optimal number of nurses that are necessary to provide care to the required number of patients (input). The decision variables of the ILP are the number of nurses per qualification level (3IG, 4, 5) with possible shift lengths of 8, 6, or 4 hours. So, per scenario 9 decisions can be made. Since the objective function of the LP minimizes the total salary costs, the decisions are made in such a way that there are sufficient nurses to satisfy the care demand but there is hardly any overcapacity because no more nurses are hired than needed.

Of course, the results of the ILP are very different for the percentiles. The percentiles can be interpreted as the robustness of the solution. For example, the 80^{th} percentile chooses a demand for each level where 80% of the generated scenarios are lower and only 20% are higher. So, selecting the 80^{th} percentile ensures that at least 80% of the patients can be taken care of immediately without producing any undercapacity assuming that the real cases follow the analyzed empirical distributions. On the other hand, the solution for the 50^{th} percentile ensures a certain demand coverage for at least half of the cases. Because of that we do not consider percentiles lower than 50. Providing a recommendation that ensures that less than 50% of the demand can be covered for sure can be seen as irresponsible in our case. So, the higher the percentile that we select as a scenario, the more certain it is that all the possible care demand can be treated directly.

As an example, we present the solution of the ILP for the 70^{th} percentile of cluster Noord in Figure 15, using the middle care demand group which includes the months February, April, May and September. In total, solving the model with 504 care demand cases took 1.39 seconds using the Gurobi Solver in PyCharm.

			8 - hour shift			6 - hour shift			4 - hour shift		
Demand Group	Weekday	Percentile	Nurse L3IG	Nurse L4	Nurse L5	Nurse L3IG2	Nurse L43	Nurse L54	Nurse L3IG2	Nurse L43	Nurse L54
Middle Morning	Sunday	70	0	1	0	1	0	0	0	0	0
Middle Morning	Monday	70	1	1	0	0	0	0	0	0	0
Middle Morning	Tuesday	70	1	1	0	1	0	0	0	0	0
Middle Morning	Wednesday	70	1	1	0	0	0	0	0	0	0
Middle Morning	Thursday	70	0	1	0	1	0	0	0	0	0
Middle Morning	Friday	70	1	1	0	0	0	0	1	0	1
Middle Morning	Saturday	70	1	1	0	0	0	0	0	0	0
Middle Evening	Sunday	70	0	1	0	1	0	0	0	0	1
Middle Evening	Monday	70	1	1	0	0	0	0	0	0	0
Middle Evening	Tuesday	70	1	1	0	0	0	0	0	0	1
Middle Evening	Wednesday	70	0	1	0	1	0	0	0	0	0
Middle Evening	Thursday	70	0	1	0	0	0	0	1	0	0
Middle Evening	Friday	70	1	1	0	0	0	0	0	0	0
Middle Evening	Saturday	70	0	1	0	1	0	0	0	0	1

Figure 15 - Solution for 70th percentile - Cluster Noord Middle Care Demand

6.2 Solution Analysis

The results of our model enable us to create schedules for the upcoming 12 months and evaluate the schedules since the beginning of the data recording, so the 01.05.2023.

TWB provided another file that contains data about the shifts that have been scheduled in the hospice team since May 2023. The file also includes the future planning until the end of 2024.

In the following, we compare the actually scheduled shifts (measured in total hours) taken from that file and compare it with the total hours that our model would suggest scheduling for the different levels of robustness or the percentiles. Furthermore, we show the total hours that our model would schedule to cover at least the real care demand from last year which we analyzed in section 2.2.2. The data that we used for this starts at May 2023 and stops in April 2024, thus the line “Real Demand” does not go further. Since we solved the model also with the real demand, we can say that we solved the model with “perfect information”.

The Figures 16-19 below show a comparison of suggestions of the model based on scenarios, the actually scheduled amount of hours by TWB and the solution of the model with perfect information (real demand). We show that for the morning and evening shift as well as for both clusters.

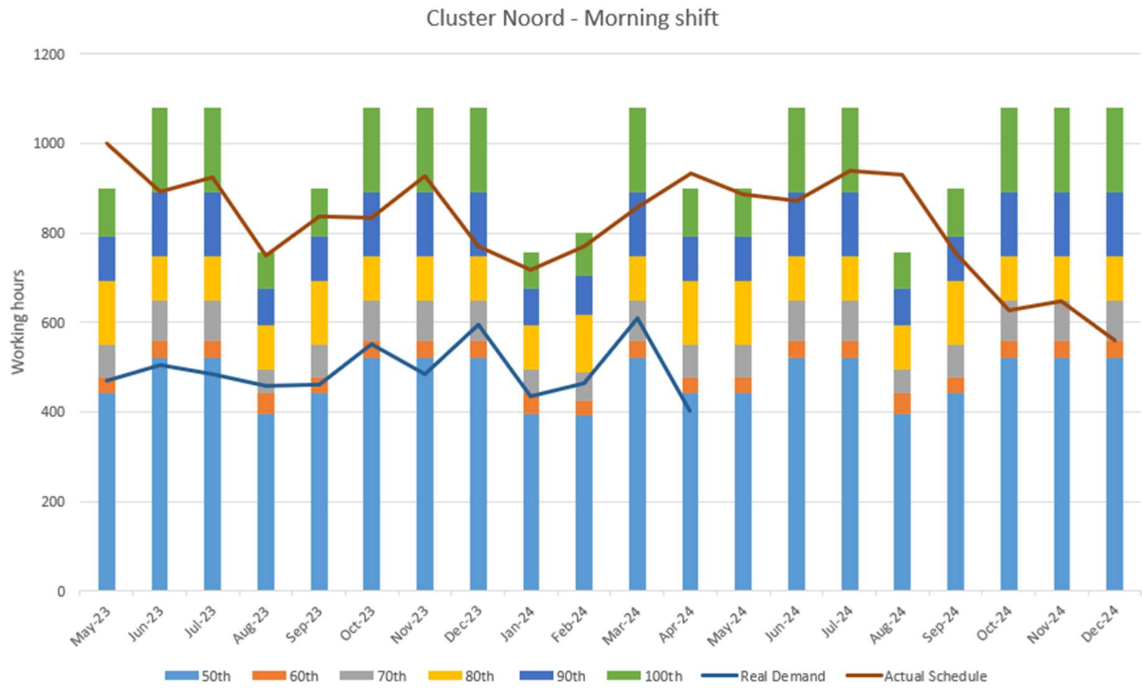

Figure 16 - Comparison of model solutions with actually scheduled shifts - Cluster Noord - Morning shift

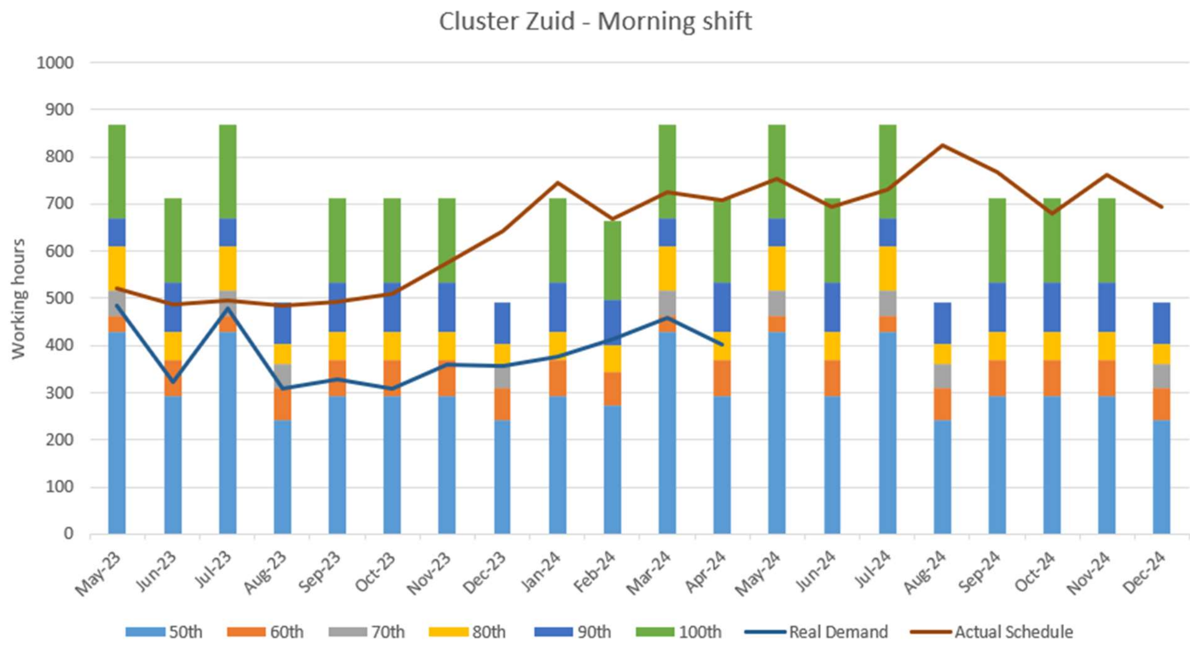

Figure 17- Comparison of model solutions with actually scheduled shifts - Cluster Zuid - Morning shift

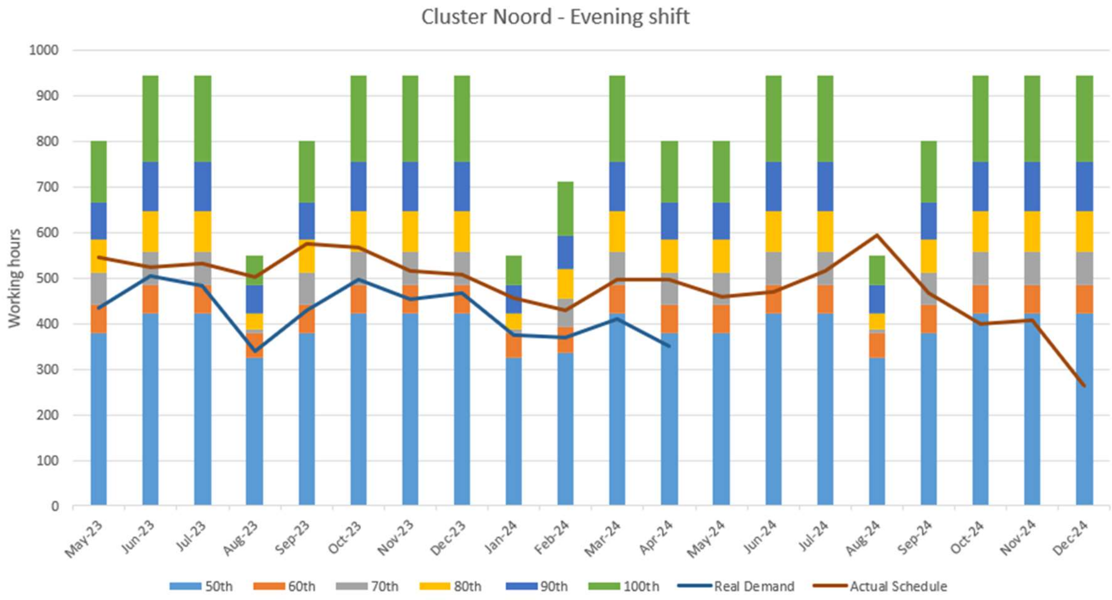

Figure 18 - Comparison of model solutions with actually scheduled shifts - Cluster Noord - Evening shift

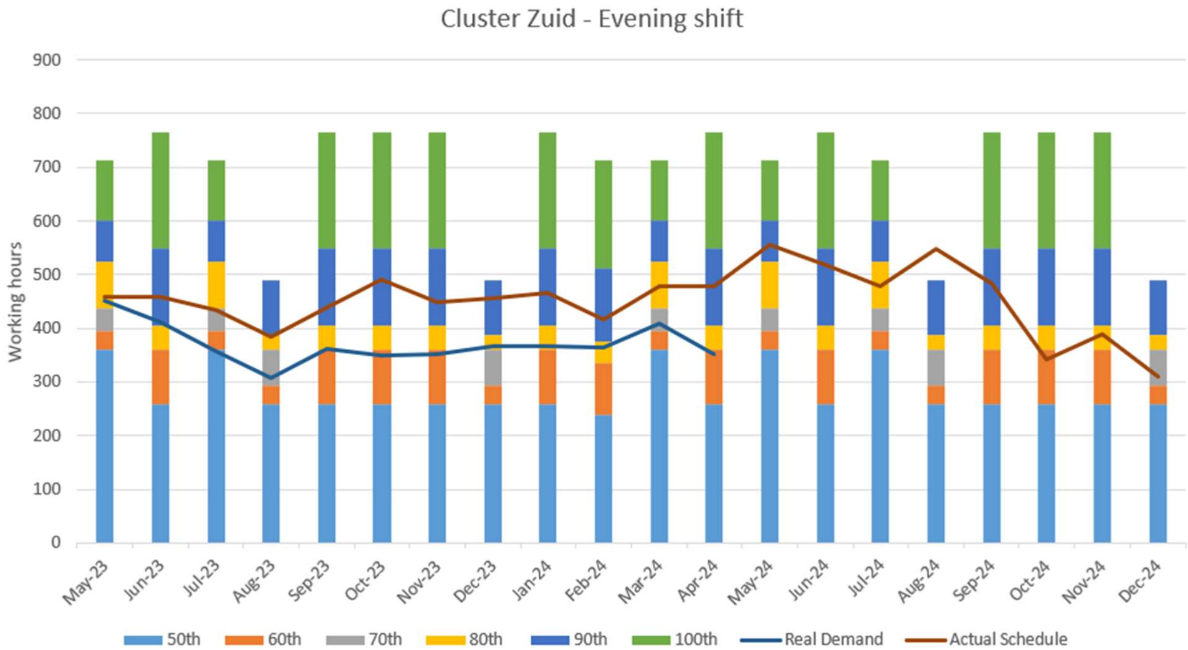

Figure 19 - Comparison of model solutions with actually scheduled shifts - Cluster Zuid - Evening shift

In the comparison we can see that especially in the morning shifts the actual schedule contains more work time and thus more nurses than what was actually needed based on the real demand. In the evening shifts the difference between actual schedule and real demand is smaller. For the last 12 months, we show the difference between the actual schedule and real demand in working hours in the Tables 7 and 8 below.

	Morning	Evening
Actually scheduled	10205 hours	6147 hours
Real demand	5920 hours	5122 hours
Difference	-42 %	-17 %

Table 7 - Cluster Noord – Scheduled hours vs. required hours in past 12 months

	Morning	Evening
Actually scheduled	7058 hours	5410 hours
Real demand	4600 hours	4454 hours
Difference	-35 %	-18 %

Table 8 - Cluster Zuid - Scheduled hours vs. required hours in past 12 months

Actual schedule

As we can see in Figures 16 and 17, in the morning shifts the actually scheduled shifts fluctuate between the recommendations of the 80th until the 100th percentile and in some cases, they even go beyond the recommended shifts. Only in the future period from October until December 2024 the planned shifts are significantly less compared to the other months.

In Figures 18 and 19, we see for the evening shifts that the actually scheduled shifts are on average lower than in the morning shifts and closer to what our model recommends. Comparing this with the recommended shifts for the different levels of robustness, they are mostly located between the 70th and 100th percentile.

We observe a similar behavior for both cluster Noord and Zuid but can determine an even larger mismatch between actual schedule and real demand for the morning shifts of cluster Noord. The evening shifts were scheduled more accurately and are more in line with the real demand. Still, they do have a mismatch of 17-18 %.

Real demand

For both the clusters as well as the shifts we see that the real demand fluctuates between the 50th and the 80th percentile for the several months. As also expressed in Tables 7 and 8, the working hours or shifts that are necessary to cover the real demand are significantly lower than what was actually scheduled.

Overview of possible time reductions

The following overview (Table 9) contains deviations of working hours in % compared to the actually scheduled shifts for both clusters of the hospice team. The first column "Real Demand" contains the produced overcapacity in the past year compared to the historical schedule that barely made use of shorter shifts. So, it is the solution of our model where the real demand of the last 365 days was used as an input. The other columns contain the differences in total working hours based on different levels of robustness where the 50th percentile scenario is the lowest level of robustness and the 100th percentile is the highest level of robustness. Dark red colored cells show solutions that are infeasible because their solutions fall below the possible reduction for the real demand scenario of the last year and thus would produce more undercapacity. Light red colored cells show solutions that produce schedules with more working hours than what was actually scheduled by TWB and therefore increase overcapacity even more. Thus, those solutions are not recommendable. Lastly, the green colored cells show feasible solutions that can be considered as recommendations to create new working schedules. For each cluster and for each shift we can decide which level of robustness suits best and reduces the working hours while still having a low risk that understaffing could occur.

	Real Demand	50th	60th	70th	80th	90th	100th
Noord Morning shift	-42%	-45%	-40%	-31%	-18%	-4%	13%
Noord Evening shift	-17%	-24%	-12%	0%	14%	32%	61%
Zuid Morning shift	-35%	-46%	-35%	-32%	-20%	-5%	21%
Zuid Evening shift	-18%	-37%	-21%	-16%	-5%	22%	56%

Table 9 – Deviation of working hours in % of solutions generated by the model compared to actually scheduled working hours

6.3 Possible Schedules Evaluation

From the results of the ILP we can create possible work schedules accordingly to the number of nurses that the model outputs per shift.

Since our objective is to reduce the capacity-demand mismatch we are looking for a percentile scenario that is close to the real historical demand and produces neither high overcapacity nor undercapacity. Still, we want to suggest a solution that has a rather high level of robustness to avoid understaffing because this could have serious medical consequences for the patients. Therefore, we decide to create and evaluate schedules that cover the following percentiles of care demand scenarios, based on our results in section 6.2:

Cluster Noord:

- Morning shift: 70th percentile
- Evening shift: 70th percentile

Cluster Zuid:

- Morning shift: 80th percentile
- Evening shift: 80th percentile

The abovementioned percentiles were chosen, so that we did not select the highest reduction possible but the second highest for each cluster and shift. Thus, a reduction between 0.5% and 31% compared to the actually scheduled shifts are still possible while maintaining a low risk of understaffing. Further, another decision factor for our selection was that the selected percentiles never go below the line of the real demand (Figure 16-19). For those selected levels of robustness or percentiles we compare the scheduled shifts/total working hours with the actual schedule and determine the differences in terms of hours worked and therefore in salary costs as well.

	Morning shift	Evening shift
Actual Schedule	10205 hours	6147 hours
Recommendation	7013 hours	6117 hours
Difference	-31 %	-0.5 %

Table 10 - Cluster Noord – Scheduled hours vs. recommended hours in past 12 months

	Morning shift	Evening shift
Actual Schedule	7058 hours	5410 hours
Recommendation	5620 hours	5149 hours
Difference	-20 %	-5 %

Table 11 - Cluster Zuid – Scheduled hours vs. recommended hours in past 12 months

As we can see in Tables 10 and 11, especially the capacity planning in the morning shifts can be changed, meaning that a reduced number of nurses should work at the same time. The total reduction of work time would be 31% for cluster Noord and 20% for cluster Zuid. On the other hand, the evening shifts are almost in line with the recommendations and only small adjustments could be made (between 0.5 and 5%).

In the following, we create detailed schedules that might be used by the hospice team in the future. Since there are shifts with the length of 8, 6 and 4 hours, not all of them can start and end at the same time. To decide about the scheduling of the shorter shifts of 6 and 4 hours within the morning or evening shift, we can analyze the time when the majority of care demand occurs. Since the proportion of planned care during a shift is known to some extent and can be spread out by the planners of TWB, we are interested in the time spread of the unplanned care. The occurrence of unplanned care cannot be influenced by TWB and still, they have to react according to the demand and provide nurses. Therefore, we analyze the time spread of unplanned care during a day for all levels over the past 12 months. Observations can be seen in Figures 20 and 21.

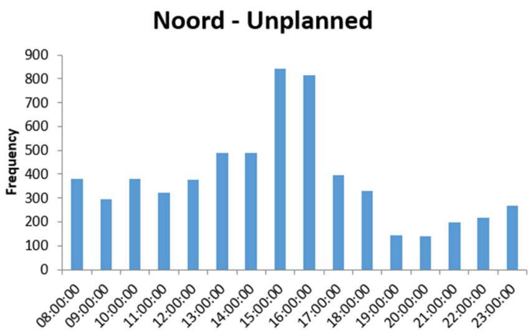

Figure 21 - Distribution unplanned care over time - Cluster Noord

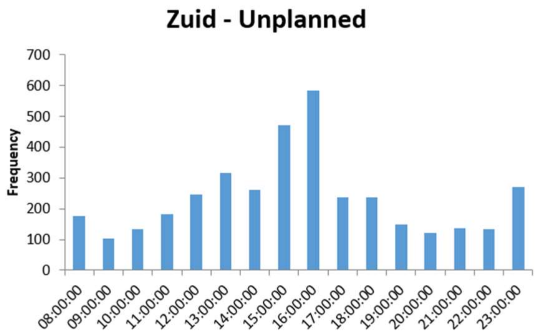

Figure 20 - Distribution unplanned care over time - Cluster Zuid

For both clusters we can observe the trend that the peak amount of unplanned care takes place towards the end of the morning shift and in the beginning of the evening shift (around 15:00). Therefore, we can conclude that shifts of shorter length that cannot cover a full morning or evening shift, should be scheduled towards those peaks. As an example, a possible schedule for cluster Noord and a middle care demand (covering the months February, April, May, September) is shown in Figure 22. Other possible schedules can be found in Appendix I.

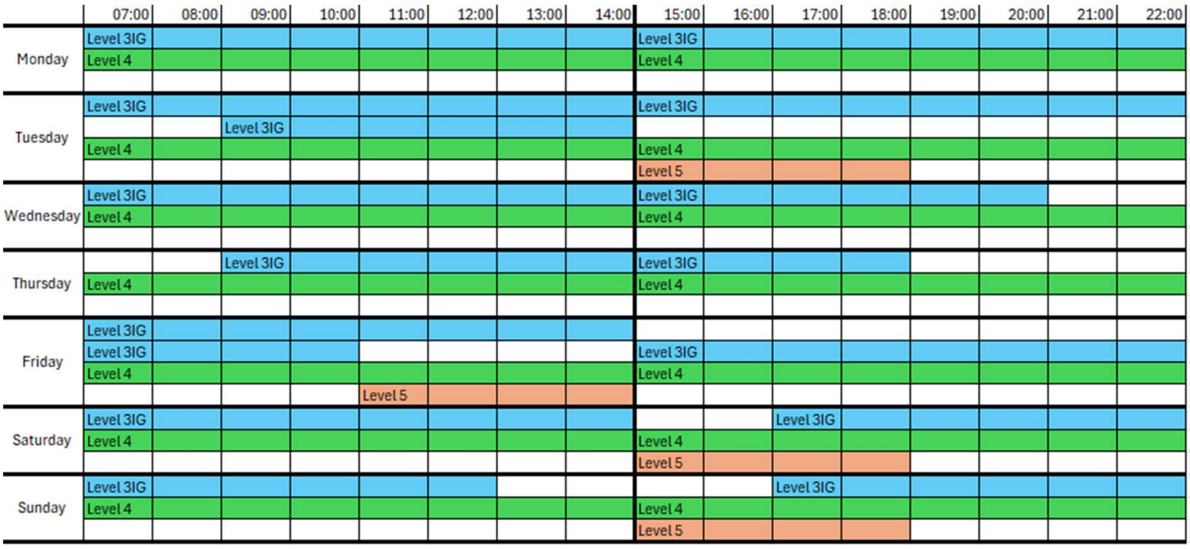

Figure 22 - Possible schedule - Cluster Noord - Middle care demand

6.4 Sensitivity Analysis

In the following, we conduct a sensitivity analysis to test how much the care demand is allowed to increase in the future without the occurrence of understaffing if we use our chosen schedules (Figure 22 and Appendix I) based on the 70th percentile in cluster Noord and the 80th percentile in cluster Zuid. In doing so, we take the real demand, so the “perfect information” as a basis and increase it by 5% to 15%. We use the real demand as a basis instead of another statistical distribution because we could not identify a theoretical distribution of the care demand, as described in section 4.1.

In Figure 23 and 24 we show how the how many working hours would be necessary to cope with the real demand and the increased demands compared to the working hours that are scheduled by using the 70th percentile in cluster Noord. The sensitivity analysis for cluster Zuid can be found in Appendix J.

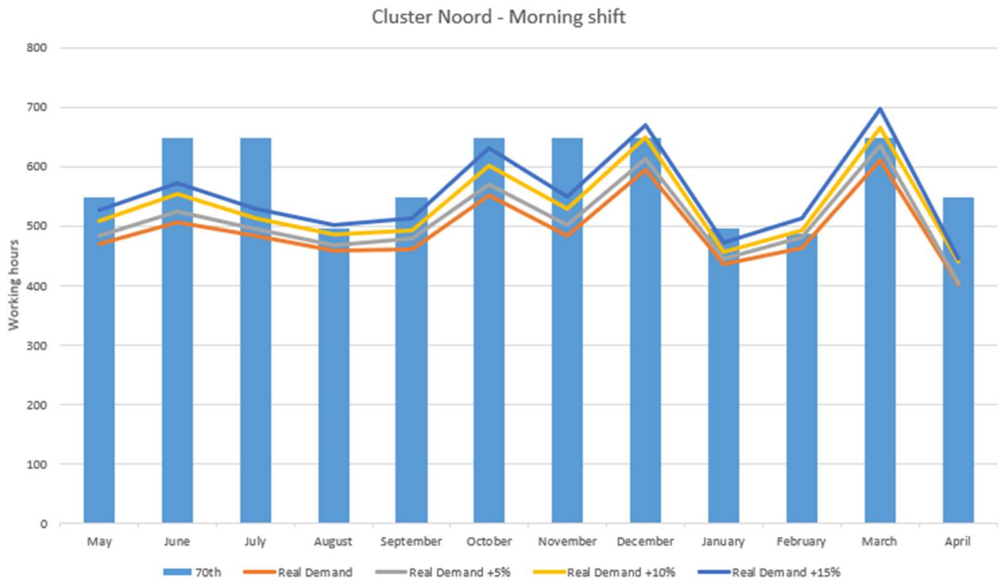

Figure 23 - Robustness of solution for 70th percentile assuming increase in care demand - Cluster Noord - Morning shift

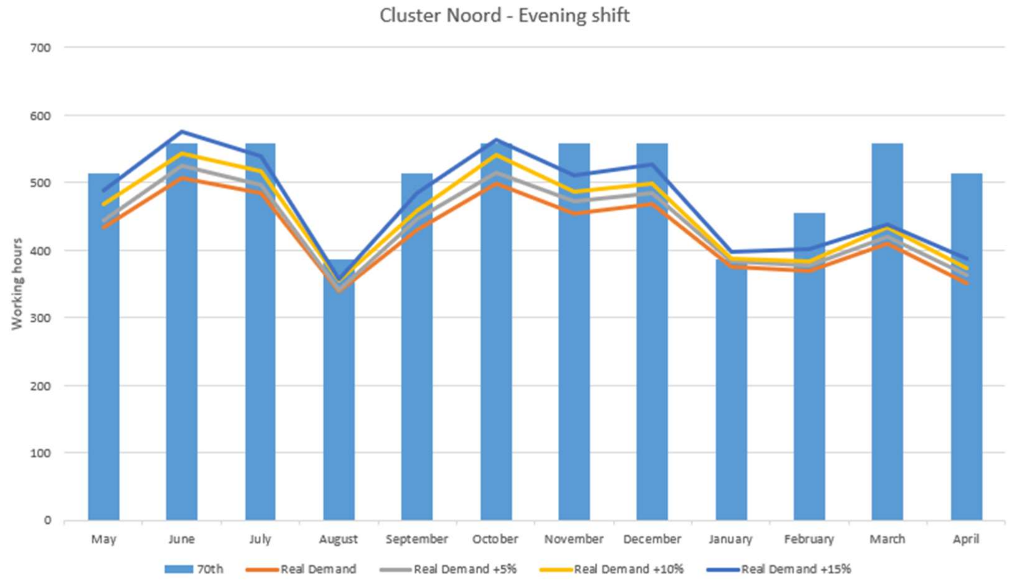

Figure 24 - Robustness of solution for 70th percentile assuming increase in care demand - Cluster Noord - Evening shift

As we see in Figure 23 the use of the schedule based on the 70th percentile in the morning shifts is providing a rather high level of safety. If the total care demand would increase by 10%, only during March the capacity would be exceeded by the care demand and undercapacity could occur. Even if the demand per month would increase by 15%, only 4 months would produce small undercapacity. In the evening shifts (Figure 24) we see a similar, but slightly better picture. Here, only in the months June and January a 15% increase in demand could produce overcapacity.

6.5 Conclusion

We have solved our model for several different scenarios that represent different levels of robustness (ranging from the 50th percentile to the 100th percentile). Next to that, we also solved the model with the real care demand of the last year to be able to compare our solutions with what would have been really needed. Furthermore, we analyzed the number of shifts that have been scheduled in that time period and that are scheduled until the end of 2024.

In the analysis we can see that the actually scheduled shifts were exceeding the real demand significantly which implies an overcapacity of nurses, as already mentioned by the TWB staff. Especially in the morning shifts a large overcapacity of up to 42% in cluster Noord is produced. In cluster Zuid overcapacity of up to 35% occurs. The evening shifts on the other hand were scheduled more in line with the real care demand and our analysis showed that overcapacities of up to 18% occurred.

The solutions that our model recommends depend largely on the selected level of robustness and therefore the percentile of the simulation results. Looking at the solution that we have selected as an example in section 6.3, we would be able to lower the capacity-demand mismatch by decreasing the actually scheduled shifts in the morning by 18% in cluster Noord, 20% in cluster Zuid and by 0.5% in cluster Noord, 5% in cluster Zuid for the evening shifts. Those selected solutions would also still hold in the majority of the months if the care demand would increase between 10% and 15% for the upcoming year, assuming the same distribution of care. To make this reduction possible, our solution suggests using several shorter shifts of either 6 or 4 hours. In total, 36% of the total hours scheduled in cluster Noord and 33% of the total hours scheduled in cluster Zuid would consist of shorter shift lengths than 8 hours.

Any further elaboration on the results can be found in section 7.3 where we provide recommendations to TWB.

7. Conclusion and Recommendation

In this chapter, we draw a conclusion and answer our main research question “How can the capacity planning of the hospice team be improved to reduce the capacity-demand mismatch?”. Further, we present a discussion about our research design and elaborate on certain limitations that it has in terms of validity and reliability. Lastly, we provide final recommendations that we can deduct from our research and that can be used by TWB in the future.

7.1 Conclusion

After the execution of our previously defined research steps, we can answer our research question of how the capacity planning can be improved to reduce the capacity-demand mismatch.

First, we had to analyze the care demand systematically to find out the distributions of care demand for patients with different requirements. Based on these distributions we modeled the included uncertainties by using a Monte-Carlo simulation that generated several different robust demand scenarios. Next, creating an integer linear program enabled us to calculate the optimal number of nurses per level and shift length to cope with the care demand scenarios that we just generated. Lastly, solving the model for the generated scenarios and the real care demand of the past showed how accurate the simulation is and which scenarios can be used for possible recommendations. Additionally, we compared those solutions with the shifts that the hospice team actually scheduled in the previous 12 months. The comparison showed that especially in the morning shifts a significant amount of overcapacity occurred in both cluster Noord and Zuid. The schedules for the evening shifts were more in line with the real care demand and showed a smaller capacity-demand mismatch. In section 7.3 a more detailed elaboration can be found.

As mentioned in section 6.5, shifts with a length of 4 or 6 hours are frequently used in our schedules (36% of the total working hours in cluster Noord and 33% of the total working hours in cluster Zuid). If most of these shifts would be replaced by 8-hour shifts as it currently is in the capacity planning of the hospice team, significantly more hours would have been scheduled. Thus, a key assumption and one of the most important recommendations to reduce the capacity-demand mismatch is to use shorter shifts of both 4 and 6 hours.

We can conclude that improving the capacity planning of the hospice team is possible by analyzing and modeling the care demand and use the results to compute the optimal number of nurses. So, moving from a manual capacity planning method that was based on estimations towards a model-based decision-making tool enables TWB to reduce the capacity-demand mismatch.

7.2 Discussion

In the following we present a discussion about limitations in terms of validity and reliability of our research as well as elaborate on things that could have been done differently.

First, we have conducted several interviews or less formal conversations with staff from the hospice team as well as the care logistics department to understand the processes in the company and especially in the hospice team. Next, TWB provided several data files that we used for our data analysis. The most frequently consulted file was the registration file that we used to analyze the nurse productivity and the care demand. As Restrepo et al. (2020) suggests, we followed her approach and took a deterministic value for that. On the other hand, the care demand underlies too large fluctuations and cannot be taken as a deterministic value. To assess its variability, we have analyzed the empirical distributions of care demand for all levels, clusters and shifts. Further, we wanted to avoid analyzing every month separately because this would have limited our sample size drastically and would have made the analysis of the empirical distributions less accurate. Therefore, we combined months with a similar size of care demand together and created groups of low, middle, and high care demand. Consequently, the solutions of this analysis and also the solutions of the ILP at a later stage are similar for all months that are included in the different groups.

Another point that can be seen critically, is that we were only using data about a time period of 12 months. Using data about a longer time period was not possible because the structure of the hospice team changed in April 2023 and comparing data older than that would have been impossible. Because of that, we could not analyze if there are reoccurring seasonal patterns that are recognizable for certain periods in a year. Therefore, there is also no certainty that the demand pattern for the upcoming year will be similar or identical with the one of the past 12 months. But because of the structural change in the team, we cannot influence this fact. So, ideally this research would be conducted again in 12 months from now to compare the care demand of each year and check for seasonal patterns. Also, the sample size would be increased significantly.

Even further, there were some doubts mentioned by the planner of the hospice team whether the dataset is completely accurate. According to her estimation and experience, the proportion of level 4 care is too low compared to the amount of level 3IG care. Since we have analyzed the care demand based on the registrations made in NEDAP, a possible explanation is that nurses do not always register the executed care with the corresponding registration type but sometimes use a different one. Nevertheless, the total amount of work is still correct and there are only doubts if the distribution between level 3IG care and care of level 4 is accurate.

Coming now to the elaboration of the Monte-Carlo simulation, we could have improved our scientific level with using statistical distributions instead of the empirical distribution. Using a statistical distribution, e.g. input parameters can be adjusted easier than it is the case if we want to adjust the probabilities of the empirical distributions. Also, generating new data for future scenarios based on statistical distributions would be easier. Even though, we decided to work with the empirical distributions because we could not find a fitting theoretical distribution for neither one of the demand groups nor for level 3IG care over the whole 12 months. Further, our limited time horizon for writing the thesis did not allow us to test several more samples. Finding the correct distributions for all demand groups, clusters, levels etc. would have been significantly more time consuming because multiple samples would need to be analyzed, and a high number of statistical tests would be necessary. For consecutive future research we can recommend investing even more time in analyzing the theoretical distributions of the samples and further use them to generate new data sets. An alternative would be to use forecast demand functions as well.

As already mentioned above, we reduced the complexity of our data analysis and of our ILP by deciding to take deterministic values when analyzing the treatment time for patients from which we calculated the nurse productivity. In a real world, those values also underlie fluctuations, even though smaller ones than the care demand.

Furthermore, we followed the wish of the TWB employees and included the possibility for shorter shift lengths of 6 and 4 hours in our model. This decision can be seen from different perspectives in order to evaluate whether it is a desired solution. The preferred shift length of nurses are 8 hours because they can fill their weekly contract hours in less working days than they would need in the case of working several times for only 6 or 4 hours. But on the other hand, 8-hour shifts led to overcapacity in the past and nurses where inactive, so they had to end their shift earlier and where unsatisfied because their day did not go as planned. So, knowing in advance that they are scheduled for a shorter shift only, can also be beneficial for them.

Next to this, it is also a question for TWB how the contracts of the nurses are designed and if TWB can schedule the shifts of the nurses still that way that their weekly contract hours are filled. Since introducing regularly shifts of shorter length means a large amount of changes for the planners of the hospice team, the feasibility still needs to be investigated and tried in the future.

7.3 Final Recommendations

Looking at the results in section 6.2, we saw that there is a large deviation between actually scheduled shifts and the real care demand. So, the use of our linear program showed that a reduction of the capacity-demand mismatch is possible. As mentioned above the larger deviation is to find in the morning shifts (35% up to 42% per cluster) and a smaller but also significant deviation is to find in the evening shifts as well (17% up to 18%). So, we need to find a scenario that reduces the capacity-demand mismatch while still having a high level of robustness to avoid undercapacity and satisfy the care demand with certainty. In doing so, the regarding recommendation of the scenario must never be below the real care demand and should ideally be below the actually scheduled shifts in the past to reduce the capacity-demand mismatch. To pursue this overall goal, it is of high importance to constantly keep the patient in mind. Since we are researching in the field of home care optimization and the considered team provides palliative medicine, wrong or too drastic recommendations can lead to undercapacity and therefore to medical consequences for the patient.

Thus, and as already suggested in section 6.3, we should select the following scenarios:

Cluster Noord:

- Morning shifts: 70th percentile
- Evening shifts: 70th percentile

Cluster Zuid:

- Morning shifts: 80th percentile
- Evening shifts: 80th percentile

The recommended schedules based on those scenarios can be found in Appendix I. Using those schedules would have reduced the capacity-demand mismatch in comparison with the historical data by 20% up to 31% in the morning shifts and by 0.5% up to 5% in the evening shifts and possible does this as well in the future. This reduction in working hours implies a similar reduction in salary costs as well.

Reducing the percentile and thus the number of shifts even further would increase the risk of undercapacity and is a trade-off that we cannot recommend. Using a higher percentile decreases the risk of undercapacity even more but also means that we barely reduce the capacity-demand mismatch or even increase it in some cases.

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Appendices

Appendix A: Conceptual Matrix from SLR

In Appendix A, an overview of the most frequently observed concepts is presented that have been found in the execution of the systematic literature review.

Articles / Concept	Data analysis	Modelling demand uncertainty	Linear program	Monte-Carlo simulation	Qualification analysis	Robust optimization	Markov model
(Clapper et al., 2023)	X	x			X		
(Xie et al., 2023)	X	X	X	X		X	
(Rodriguez et al., 2018)		X	X	X	X	X	
(Aslani et al., 2021)	X	X	X	X		X	
(Hare et al., 2009)	X	X			X		X
(Lanzarone et al., 2012)	X	X	X	X		X	X

Appendix B: Research Design

Appendix B shows each step of the research design, allocates them to the regarding phase of the MPSM and shows detailed characteristics of the research. Further, the used data gathering methods are explained and an elaboration about reliability and validity of the research can be found.

Research question	**MPSM phase**	**Research population**	**Research type**	**Data gathering method**	**Research strategy**	**Presentation of outcome**
How does the capacity planning of the hospice team currently work?	3	Hospice team employees	Descriptive	Meetings, less formal conversations	Qualitative	Summary of current situation
How can the existing data be analyzed and assessed?	3	TWB database, registrations file	Descriptive	TWB database	Quantitative	Tables with relevant findings about care demand

What methods or models are used to improve the capacity planning in a home care environment?	4	Literature, databases	Descriptive	Systematic literature review	Qualitative	Summary about common methods or models
How can the capacity planning be formulated in a mathematical model?	4	Literature, Experts at TWB or university, TWB database	Descriptive	Meetings, less formal conversations , literature search	Quantitative	Formulation of a mathematical model
What are the results of the mathematical model?	5	Mathematical model	Explanatory	Modelling	Qualitative and quantitative	Tables about outputs of the model, Evaluation
How can the results be used to improve the capacity planning?	6 & 7	TWB employees	Descriptive	Meetings, observations	Qualitative	Conclusions and recommendat ions

Data Gathering Methods

In this section we motivate why the selected data gathering method is appropriate to answer each knowledge question.

To find out how the current situation is and how the capacity planning is organized, the only way to properly find that out is to talk to responsible employees in meetings/unstructured interviews. There are no files, presentations or similar from which that information could be taken from.

The data analysis is performed on data coming from NEDAP, the database that TWB uses. The used files are prepared by the data engineer from TWB, so they are in a format (CSV) that we can use immediately. How we will use the data exactly is described in the following chapters, based on our findings from the SLR.

The SLR yields access to a variety of scientific articles that are related to our research topic and give us an idea of methods that we can use. Literature reviews will also help us with the creation of a mathematical model. Additionally, regular meetings with experts such as the university supervisor also supports us.

Lastly, we use the results that we can gather from our model to formulate conclusions and recommendations.

Reliability and Validity

Regarding to reliability and validity of the research we can analyze the following two aspects: First, the data that we are using which creates the basis for our data analysis and secondly the conversations and meetings that we have with different employees of TWB.

The dataset contains all registrations of the hospice team in the time from 01.05.2023 until 31.03.2024 and includes in total more than 88,000 entries. The registrations belong to several categories such as appointments, traveling time, breaks and many more. Because of the large size of the dataset, it ensures a high reliability and levels out deviations. Because all the recorded data is real-life data, we can expect it to have a high validity as well.

Coming to the meetings and conversations that we will have with different employees from TWB to answer some of the knowledge questions and understand processes at TWB, we only meet people that are involved in the research. By only including employees from the hospice team as well as the care logistics department that can talk about the real-life situation, we increase the validity.

On top of that, we plan to have regular meetings with both the university supervisor as well as the company supervisor to monitor if we are on track with the research and check if things are going according to the plan.

Appendix C: Allocation of registration types to regarding qualification levels of care

In Appendix C, the various registration types that can be found in the registration file are allocated to their regarding qualification levels of care.

Qualification level	Registration type
3IG	Persoonlijke versorging niveau 3IG, Beeldzorg V&V, Persoonlijke verzorging oproep alarm, Verpleging niveau 3IG
4	Verpleging niveau 4, Persoonlijke verzorging niveau 4/5, Persoonlijke verzorging speciaal, Verpelging oproep alarm
5	Verpleging niveau 5, Coordinatietijd

Appendix D: Total Care Demand

Appendix D contains data that shows how the total care demand has been counted and prepared for further analysis. The included screenshot includes data from 01.05.2023 until 21.05.2023.

Date	Month	Weekday	Morning	Planned	L3IG P	L4 P	L5 P	Unplanned	L3IG UNP	L4 UNP	L5 UNP	Evening	Planned	L3IG P	L4 P	L5 P	Unplanned	L3IG UNP	L4 UNP	L5 UNP	Total
5/1/2023	5	2	20	14	13	1	0	6	5	1	0	21	14	13	1	0	7	5	2	0	41
5/2/2023	5	3	28	23	21	2	0	5	3	2	0	21	16	15	1	0	5	3	2	0	49
5/3/2023	5	4	20	14	12	2	0	6	6	0	0	22	16	16	0	0	6	1	5	0	42
5/4/2023	5	5	10	10	8	2	0	0	0	0	0	20	16	13	3	0	4	4	0	0	30
5/5/2023	5	6	24	18	15	3	0	6	6	0	0	7	7	6	1	0	0	0	0	0	31
5/6/2023	5	7	14	12	12	0	0	2	2	0	0	9	5	5	0	0	4	3	1	0	23
5/7/2023	5	1	17	16	15	1	0	1	1	0	0	7	6	6	0	0	1	1	0	0	24
5/8/2023	5	2	19	15	13	2	0	4	3	1	0	31	12	12	0	0	19	18	1	0	50
5/9/2023	5	3	44	30	27	3	0	14	12	2	0	18	14	14	1	0	4	3	1	0	63
5/10/2023	5	4	6	6	5	1	0	0	0	0	0	14	11	11	0	0	3	3	0	0	20
5/11/2023	5	5	21	15	14	1	0	6	5	1	0	7	6	6	0	0	1	1	0	0	28
5/12/2023	5	6	21	16	14	2	0	5	3	2	0	18	11	11	0	0	7	5	2	0	39
5/13/2023	5	7	26	18	17	1	0	8	8	0	0	1	0	0	0	0	1	1	0	0	27
5/14/2023	5	1	26	18	17	1	0	8	8	0	0	0	0	0	0	0	0	0	0	0	26
5/15/2023	5	2	19	16	15	1	0	3	3	0	0	21	12	12	1	0	9	8	1	0	41
5/16/2023	5	3	18	16	15	1	0	2	2	0	0	18	13	12	3	0	5	3	2	0	38
5/17/2023	5	4	14	14	13	1	0	0	0	0	0	5	4	4	0	0	1	1	0	0	19
5/18/2023	5	5	9	7	7	0	0	2	2	0	0	18	9	9	0	0	9	8	1	0	27
5/19/2023	5	6	9	8	7	1	0	1	1	0	0	19	16	16	0	0	3	1	2	0	28
5/20/2023	5	7	20	12	11	1	0	8	4	4	0	28	16	14	2	0	12	9	3	0	48
5/21/2023	5	1	10	7	7	0	0	3	3	0	0	35	19	19	1	0	16	12	4	0	46

Appendix E: Statistical Goodness of Fit-Test on Normal Distribution

In this Appendix, the results of the statistical goodness of Fit-Test on a normal distribution are presented. Since the value of the total error exceeds the value of the test statistic, the null hypothesis can be rejected.

Bin	*Frequency*	CDF	ExpFrequency	Error
18	1	0.012493	2.298680076	0.733712
22	6	0.02923	3.079658278	2.769267
26	5	0.061435	5.925716754	0.144616
30	10	0.116348	10.10392347	0.001069
34	12	0.19932	15.26699046	0.699105
38	22	0.310421	20.44248656	0.118667
42	33	0.442251	24.25676122	3.15146
46	27	0.580874	25.50655654	0.087443
50	25	0.710047	23.76791613	0.063869
54	11	0.816715	19.62683059	3.791861
58	15	0.894771	14.36242521	0.028303
62	7	0.945389	9.313692401	0.574764
66	5	0.974477	5.352167569	0.023172
70	0	0.98929	2.725509276	2.725509
74	3	0.995974	1.22990482	2.547544
78	0	0.998647	0.491808749	0.491809
82	2	0.999594	0.174267449	19.12749
More	0		**TotalError**	**37.07966**
			TestStatistic	**22.36203**

Appendix F: Cumulative Probabilities for Care Demand of each level and shift

In Appendix F, the calculated cumulative probabilities for the occurrence of different number of patients in Cluster Noord in high demand months on a Sunday are presented.

NrOfPatients	Morning	L3IG P	Prob	L4 P	Prob	L5 P	Prob	L3IG UNP	Prob	L4 UNP	Prob	L5 UNP	Prob
0		1	0.03571429	10	0.35714286	14	0.5	3	0.107142857	18	0.642857	21	0.75
1		0	0.03571429	4	0.5	8	0.7857143	1	0.142857143	7	0.892857	5	0.928571429
2		0	0.03571429	6	0.71428571	5	0.9642857	2	0.214285714	2	0.964286	1	0.964285714
3		1	0.07142857	3	0.82142857	0	0.9642857	1	0.25	1	1	0	0.964285714
4		1	0.10714286	2	0.89285714	1	1	4	0.392857143	0	1	1	1
5		0	0.10714286	2	0.96428571	0	1	5	0.571428571	0	1	0	1
6		2	0.17857143	1	1	0	1	1	0.607142857	0	1	0	1
7		1	0.21428571	0	1	0	1	0	0.607142857	0	1	0	1
8		1	0.25	0	1	0	1	1	0.642857143	0	1	0	1
9		2	0.32142857	0	1	0	1	2	0.714285714	0	1	0	1
10		2	0.39285714	0	1	0	1	0	0.714285714	0	1	0	1
11		1	0.42857143	0	1	0	1	0	0.714285714	0	1	0	1
12		7	0.67857143	0	1	0	1	1	0.75	0	1	0	1
13		1	0.71428571	0	1	0	1	1	0.785714286	0	1	0	1
14		0	0.71428571	0	1	0	1	3	0.892857143	0	1	0	1
15		4	0.85714286	0	1	0	1	1	0.928571429	0	1	0	1
16		2	0.92857143	0	1	0	1	0	0.928571429	0	1	0	1
17		0	0.92857143	0	1	0	1	1	0.964285714	0	1	0	1
18		1	0.96428571	0	1	0	1	0	0.964285714	0	1	0	1
19		1	1	0	1	0	1	1	1	0	1	0	1
20		0	1	0	1	0	1	0	1	0	1	0	1
21		0	1	0	1	0	1	0	1	0	1	0	1
22		0	1	0	1	0	1	0	1	0	1	0	1
23		0	1	0	1	0	1	0	1	0	1	0	1
24		0	1	0	1	0	1	0	1	0	1	0	1
25		0	1	0	1	0	1	0	1	0	1	0	1
26		0	1	0	1	0	1	0	1	0	1	0	1
27		0	1	0	1	0	1	0	1	0	1	0	1

NrOfPatients	Evening	L3IG P	Prob	L4 P	Prob	L5 P	Prob	L3IG UNP	Prob	L4 UNP	Prob	L5 UNP	Prob
0		0	0	14	0.5	15	0.535714	2	0.071429	8	0.285714	21	0.75
1		1	0.035714	5	0.678571	4	0.678571	1	0.107143	6	0.5	4	0.892857
2		1	0.071429	7	0.928571	6	0.892857	5	0.285714	7	0.75	2	0.964286
3		1	0.107143	1	0.964286	2	0.964286	2	0.357143	4	0.892857	1	1
4		0	0.107143	0	0.964286	0	0.964286	4	0.5	1	0.928571	0	1
5		4	0.25	0	0.964286	0	0.964286	2	0.571429	2	1	0	1
6		2	0.321429	0	0.964286	0	0.964286	2	0.642857	0	1	0	1
7		0	0.321429	0	0.964286	1	1	0	0.642857	0	1	0	1
8		2	0.392857	0	0.964286	0	1	4	0.785714	0	1	0	1
9		2	0.464286	0	0.964286	0	1	2	0.857143	0	1	0	1
10		1	0.5	1	1	0	1	0	0.857143	0	1	0	1
11		3	0.607143	0	1	0	1	1	0.892857	0	1	0	1
12		1	0.642857	0	1	0	1	1	0.928571	0	1	0	1
13		2	0.714286	0	1	0	1	1	0.964286	0	1	0	1
14		0	0.714286	0	1	0	1	0	0.964286	0	1	0	1
15		1	0.75	0	1	0	1	1	1	0	1	0	1
16		1	0.785714	0	1	0	1	0	1	0	1	0	1
17		3	0.892857	0	1	0	1	0	1	0	1	0	1
18		0	0.892857	0	1	0	1	0	1	0	1	0	1
19		1	0.928571	0	1	0	1	0	1	0	1	0	1
20		1	0.964286	0	1	0	1	0	1	0	1	0	1
21		0	0.964286	0	1	0	1	0	1	0	1	0	1
22		0	0.964286	0	1	0	1	0	1	0	1	0	1
23		0	0.964286	0	1	0	1	0	1	0	1	0	1
24		0	0.964286	0	1	0	1	0	1	0	1	0	1
25		0	0.964286	0	1	0	1	0	1	0	1	0	1
26		0	0.964286	0	1	0	1	0	1	0	1	0	1
27		1	1	0	1	0	1	0	1	0	1	0	1

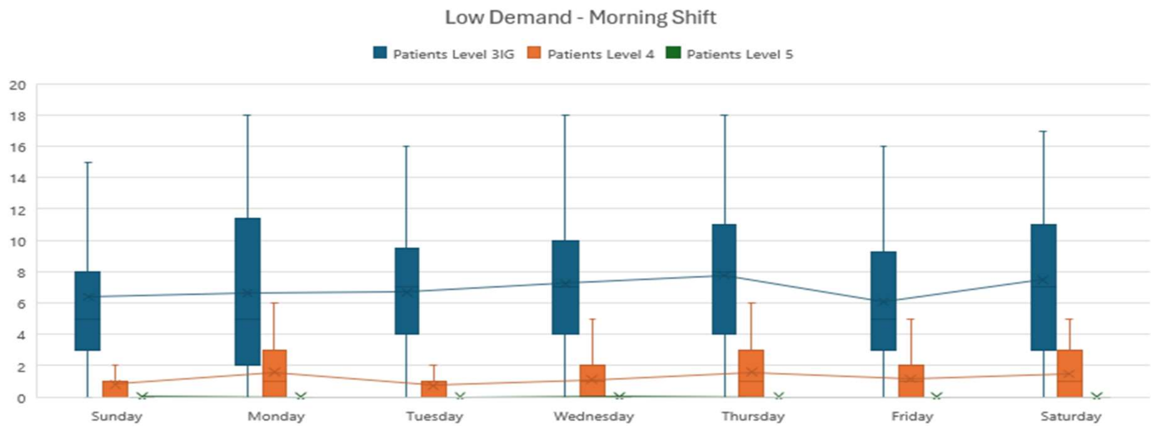
Appendix G: VBA Code for Monte-Carlo Simulation

In this Appendix, we present the VBA code that we have written for the Monte-Carlo simulation.

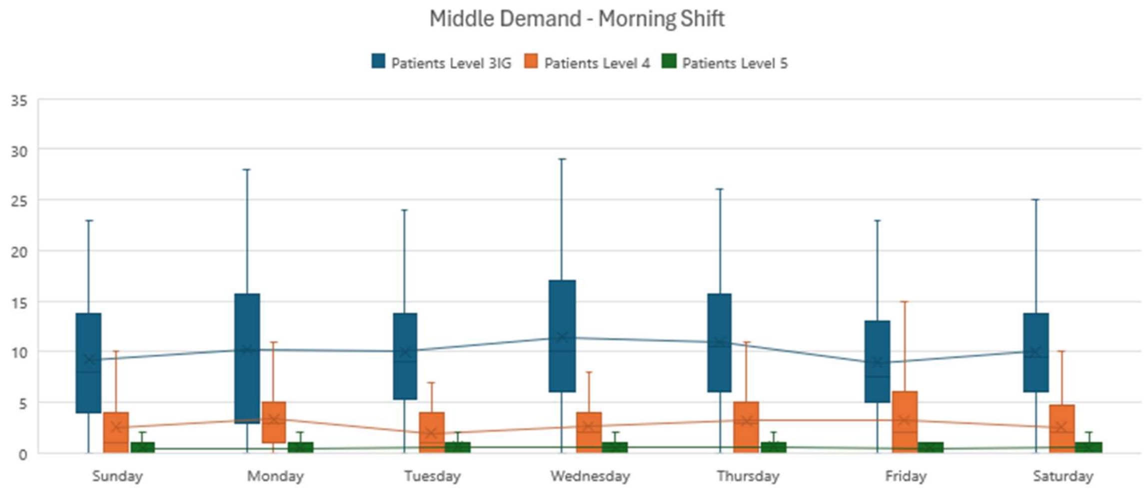
```
Option Explicit
Sub randomNumber()
' RandomNumber Macro
    Range("A45").Select
    ActiveCell.FormulaR1C1 = "=RAND()"
End Sub

Function NumberOfPatients(randomNumber As Double, inputRange As Range, outputRange As Range) As Long
    Dim i As Long
    Dim threshold As Double

    ' Loop through the input range to find the corresponding number of patients
    For i = 1 To inputRange.Cells.Count
        threshold = inputRange.Cells(i).Value
        If randomNumber <= threshold Then
            NumberOfPatients = outputRange.Cells(i).Value
            Exit Function
        End If
    Next i

End Function

Sub MonteCarlo()
    Dim numSimulations As Integer
    Dim i As Integer, j As Integer, k As Integer
    Dim outputArray() As Double
    Dim outputRange As Range

    numSimulations = 1000

    ' Define size of array
    ReDim outputArray(1 To numSimulations, 1 To 12)

    Set outputRange = Range("H40")

    ' Run MCS and fill array
    For i = 1 To numSimulations
        Call randomNumber
        For k = 4 To 15
            outputArray(i, k - 3) = Cells(34, k).Value
        Next k
    Next i

    ' Print array to worksheet
    outputRange.Resize(numSimulations, 12).Value = outputArray
End Sub
```

Appendix H: Care Demand in Cluster Zuid

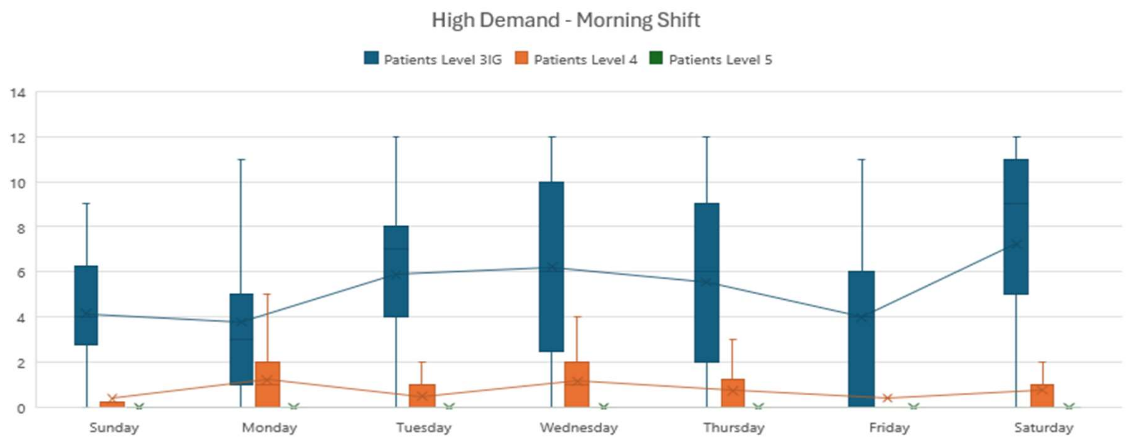
Appendix H contains an overview of how the care demand in cluster Zuid is fluctuating in different demand classifications for both the morning and the evening shift.



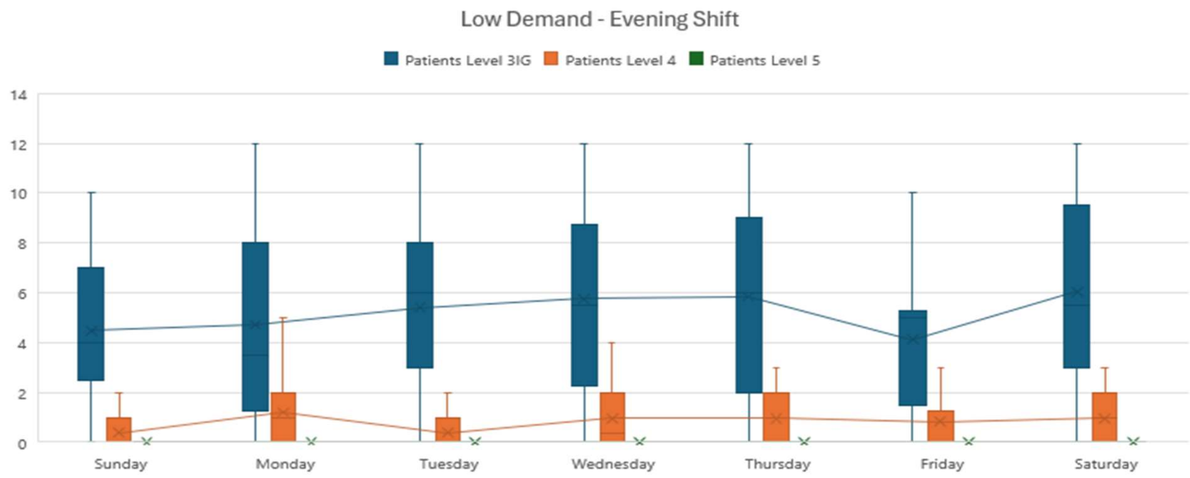
Demand pattern for months August, December – Morning Shift



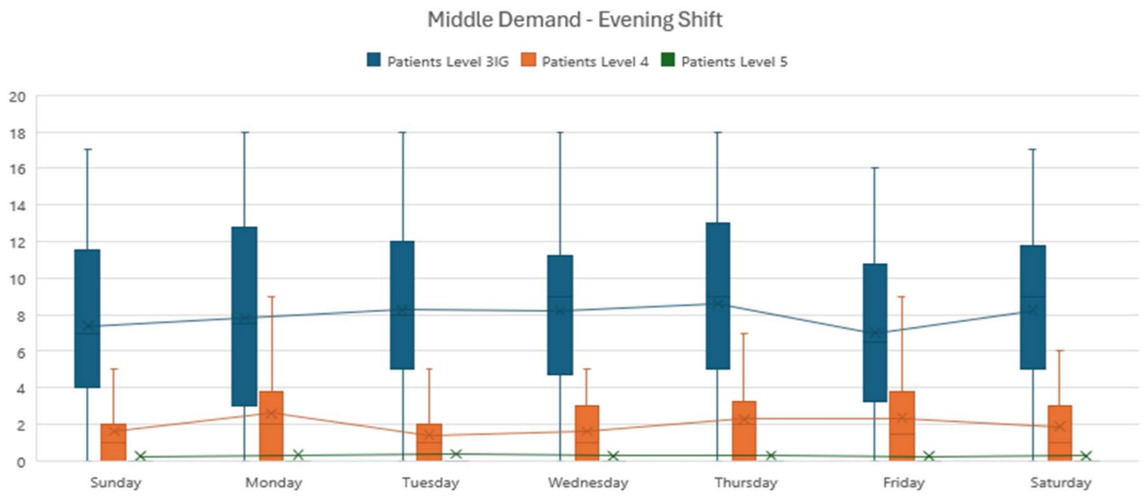
Demand pattern for months January, February, April, June, September, October, November – Morning Shift



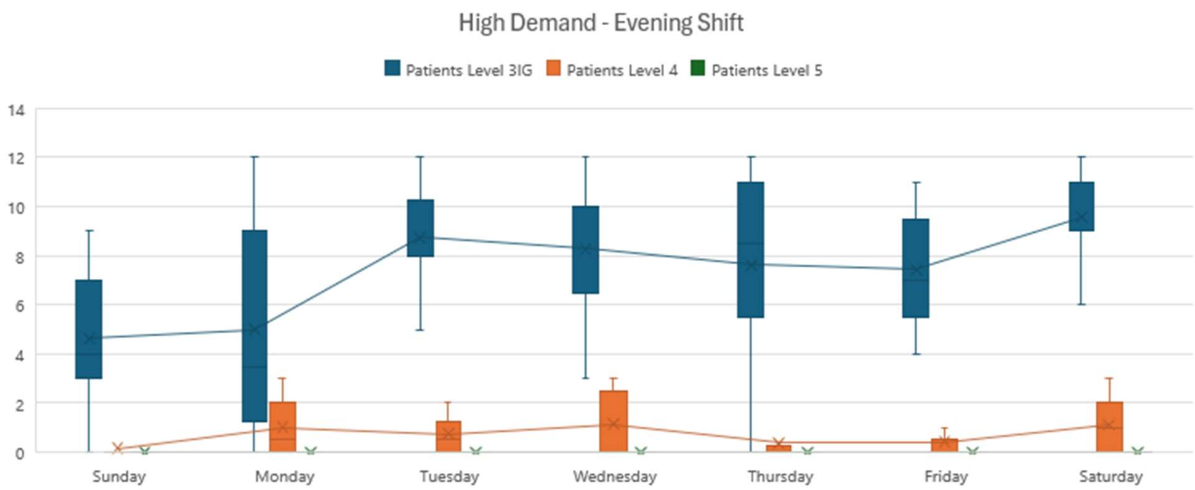
Demand pattern for months March, May, July - Morning Shift



Demand pattern for months August, December - Evening Shift



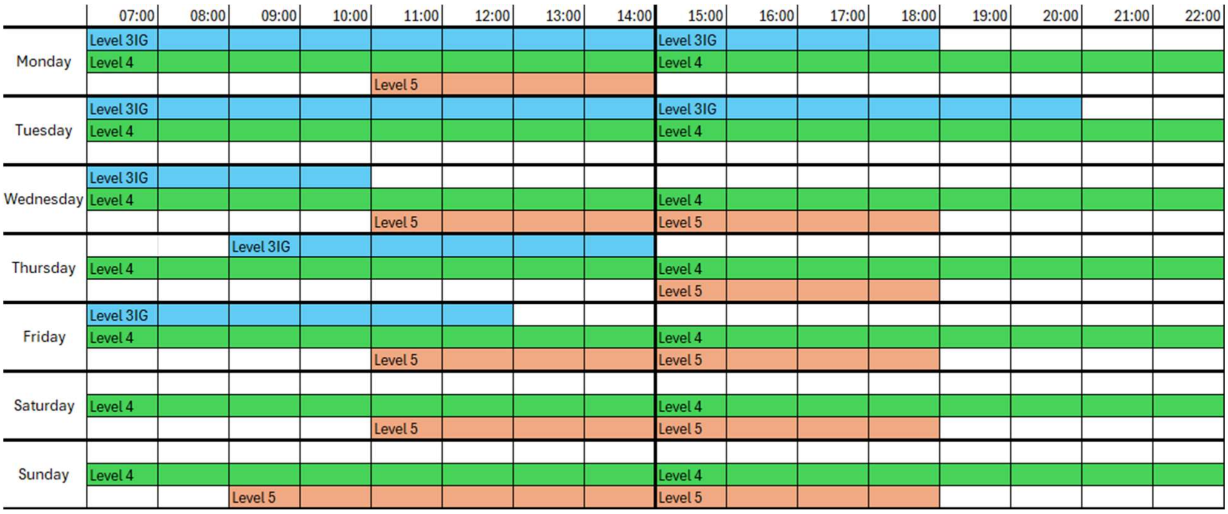
Demand pattern for months January, February, April, June, September, October, November – Evening Shift



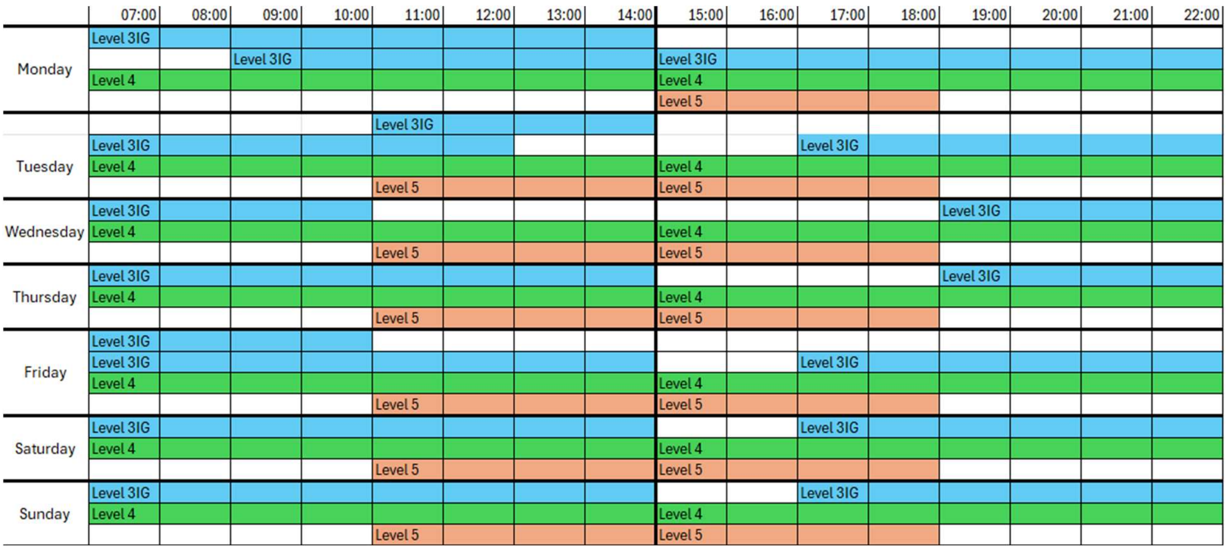
Demand pattern for months March, May, July - Evening Shift

Appendix I: Possible Schedules from Results

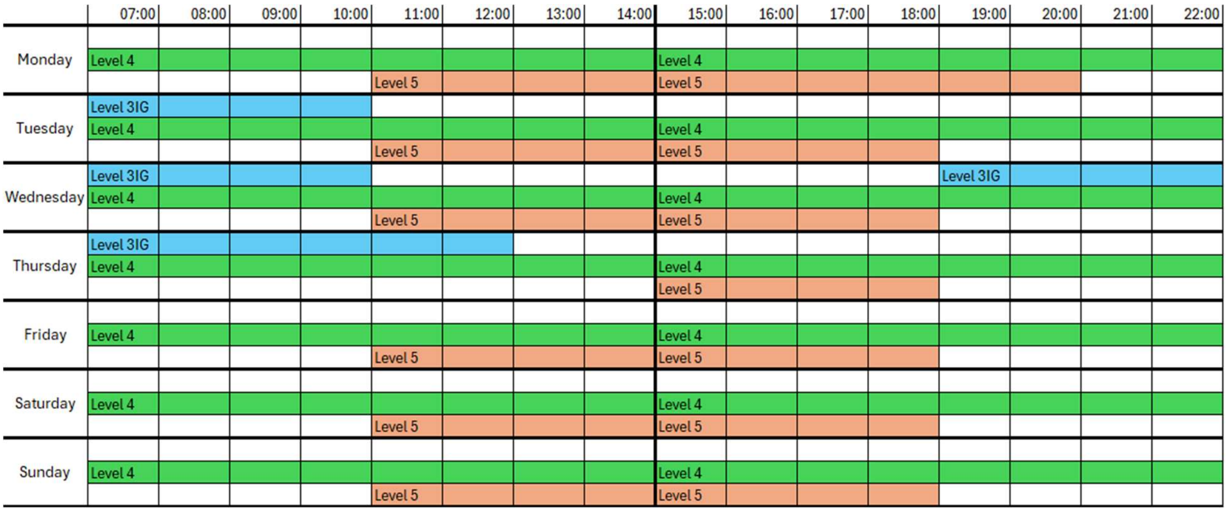
In this Appendix, we present possible schedules that could be used by TWB in the future which are based on our recommendations.



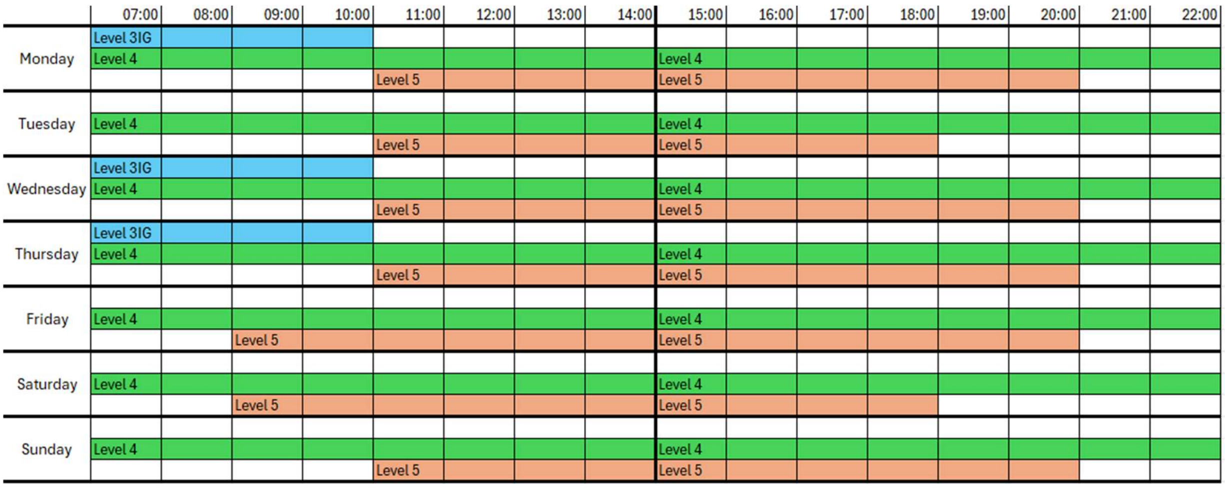
Possible Schedule - Cluster Noord - Low Care Demand



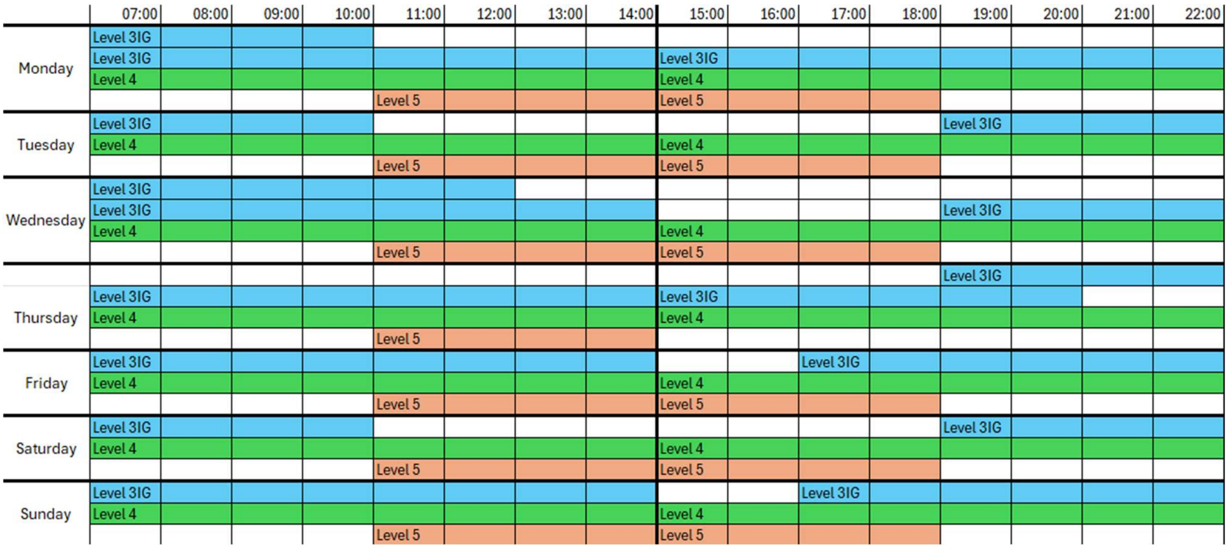
Possible Schedule - Cluster Noord - High Care Demand



Possible Schedule - Cluster Zuid - Low Care Demand



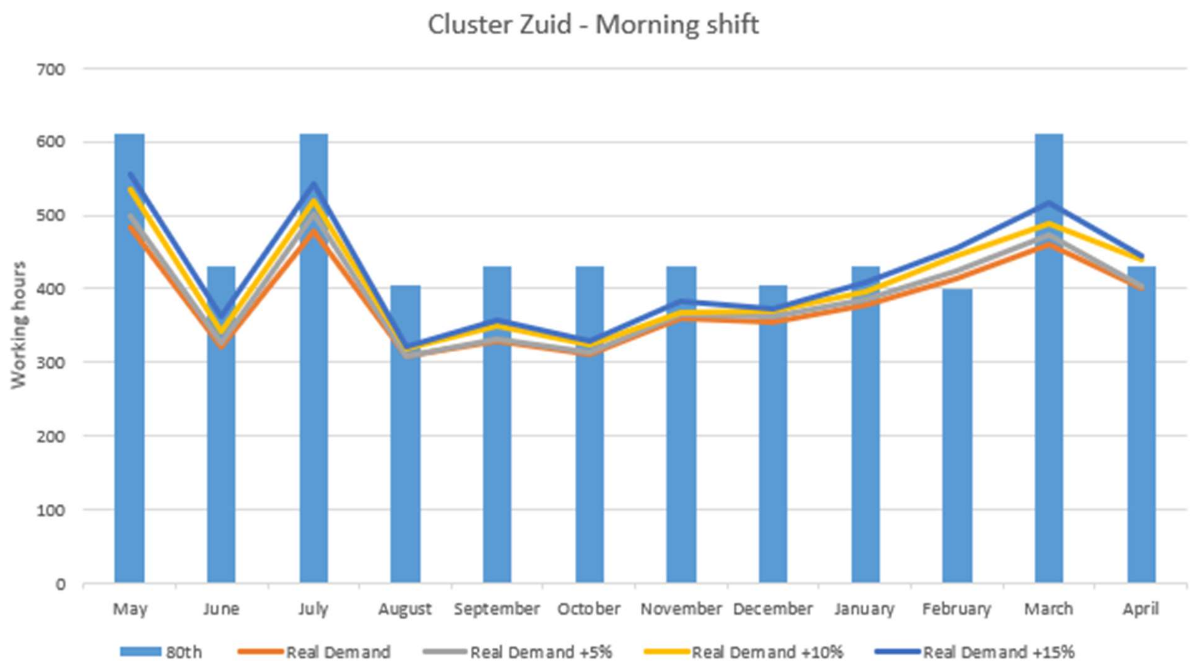
Possible Schedule - Cluster Zuid - Middle Care Demand



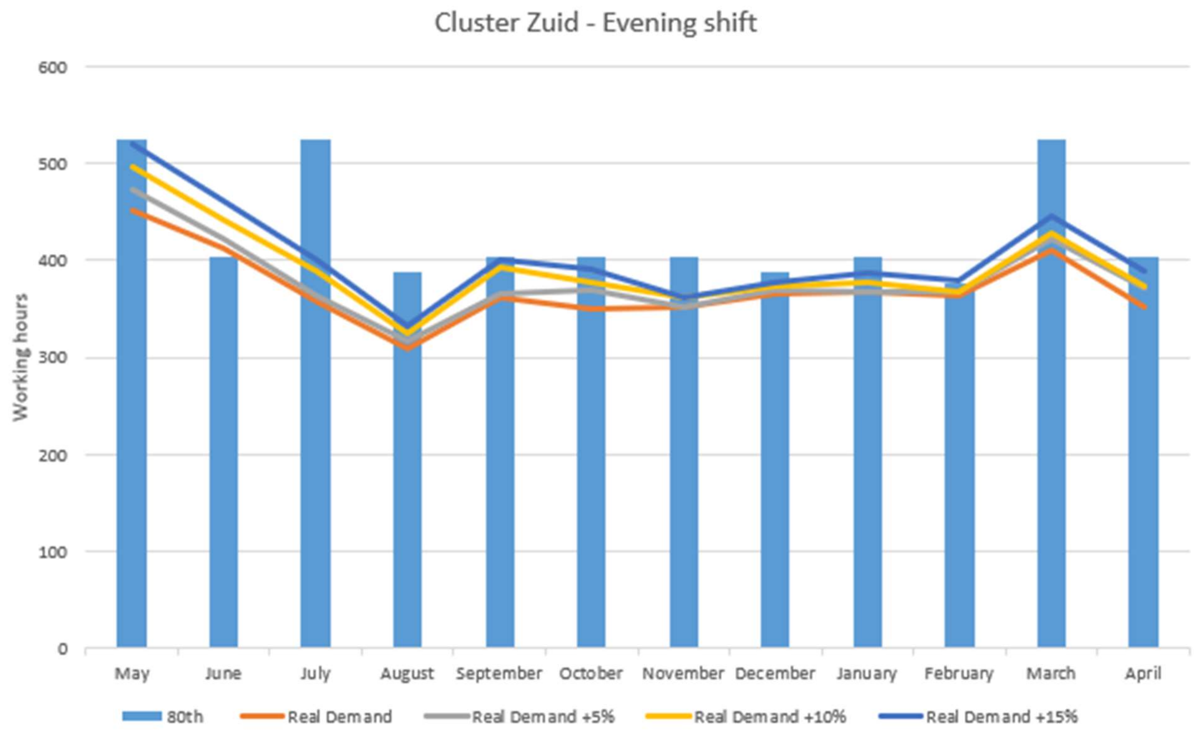
Possible Schedule - Cluster Zuid - High Care Demand

Appendix J: Sensitivity Analysis for Cluster Zuid

Appendix J presents the results of the sensitivity analysis, where the real historical demand has been increased by 5%-15% to check if the recommended schedule would produce undercapacity in cluster Zuid in the future.



Robustness of solution for 80th percentile assuming increase in care demand - Cluster Zuid - Morning shift



Robustness of solution for 80th percentile assuming increase in care demand - Cluster Zuid - Evening shift

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