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Master Thesis

EXPLORING THE POSSIBILITIES FOR AN EMERGENCY DEPARTMENT NURSES FLOAT POOL IN THE EUREGIO USING STOCHASTIC PROGRAMMING.

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Exploring the possibilities for an Emergency Department nurses float pool in the Euregio using Stochastic Programming.

Master Thesis

Industrial Engineering and Management

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Management summary

The following document contains the results of the research performed at the three hospitals in the Euregio, Medisch Spectrum Twente in Enschede (MST), Streekziekenhuis Koningin Beatrix in Winterswijjk (SKB) and Ziekenhuisgroep Twente in Almelo (ZGT). This research was commissioned by Acute Zorg Euregio (AZE), as part of a master thesis assignment Industrial Engineering and Management at the University of Twente.

Research design

The research aims to answer the following main research question:

"At which planning level and with which design choices will instating a float pool be beneficial for the Emergency Departments (EDs) that are part of AZE?"

In order to answer this research question the following sub-questions have been formulated:

- *"What are the logistical possibilities and boundaries for a float pool for EDs for AZE?"*
- *"What possibilities exist for float pooling in literature that are applicable to EDs and how can they be modelled?"*
- *"How is the ED demand and nursing capacity characterized across AZE?"*
- *"In what way can the effectiveness of an ED float pool best be modelled?"*
- *"What will the optimal configuration and performance be of relevant float pool designs compared to the current situation at AZE?"*

Float pool decision moments

Based on literature, an overview is created of all decision moments relevant for designing a float pool that could be considered by the stakeholders, which can be summarised by the following figure:

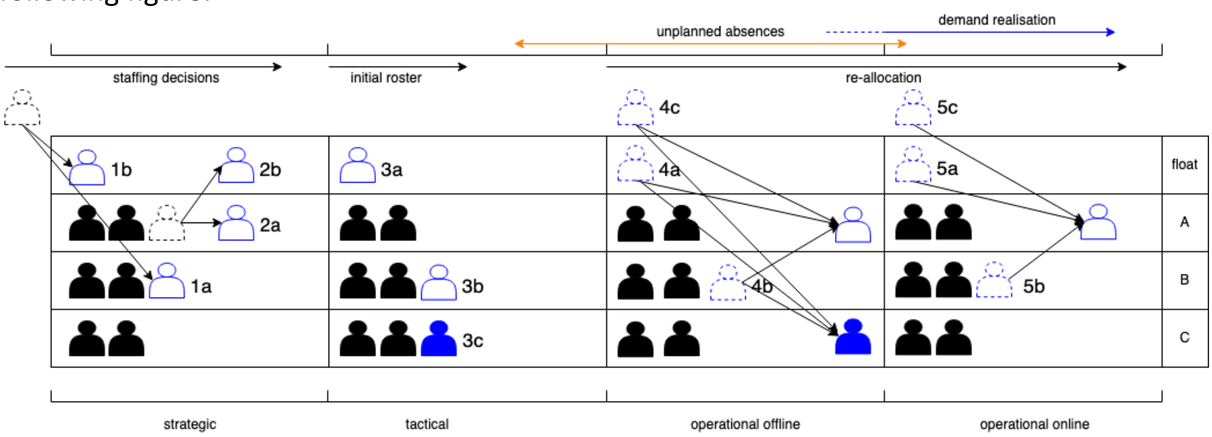


Figure i: Float pool Decision moments

Other relevant considerations are the cross-training policy, flexibility ratio and decision making. Cross-training policy concerns the question of which nurses will be trained for which hospital and the depth of this compatibility. Flexibility ratio is how much of the capacity allocated in a region should be able to float. Decision making involves the question on which conditions floating should be initiated.

For the situation in the Euregio, it is deemed most applicable to work with choice (2a), (3b), (4b) and (5b) from Figure i. This means asking existing nurses to participate in a float pool, planning them to a shift but not to a fixed location and floating if needed before or during demand realisation. However, choice (4c) and (5c) can be worth investigating as well, meaning adding the float pool to existing unplanned absenteeism or unexpected demand responses.

Data analysis

Data analysis is performed on patient arrival and departure data of 2022, where care load is approximated using NTS-triage values. The data proves that variability across the region is lower than when considering the hospitals individually. This indicates that a float pool could be worth investigating further. Additionally, the data analysis shows some similarities but also large differences in patient mix across the region, as outlined below:

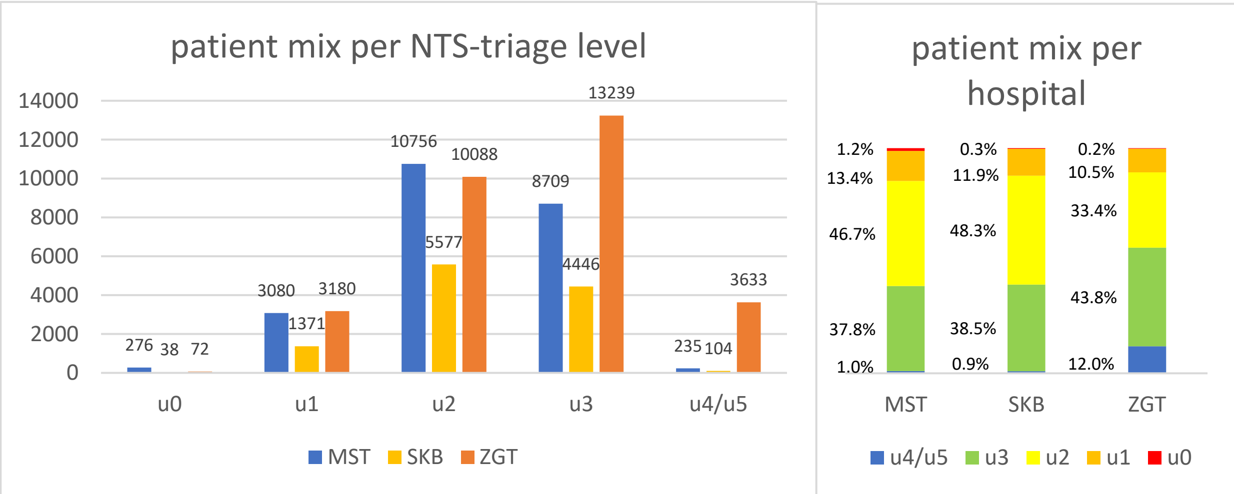


Figure ii: Patient mix per NTS-triage and per hospital

The data analysis also shows some misalignment of schedules with care load throughout the day at MST and ZGT, best illustrated by the following figure:

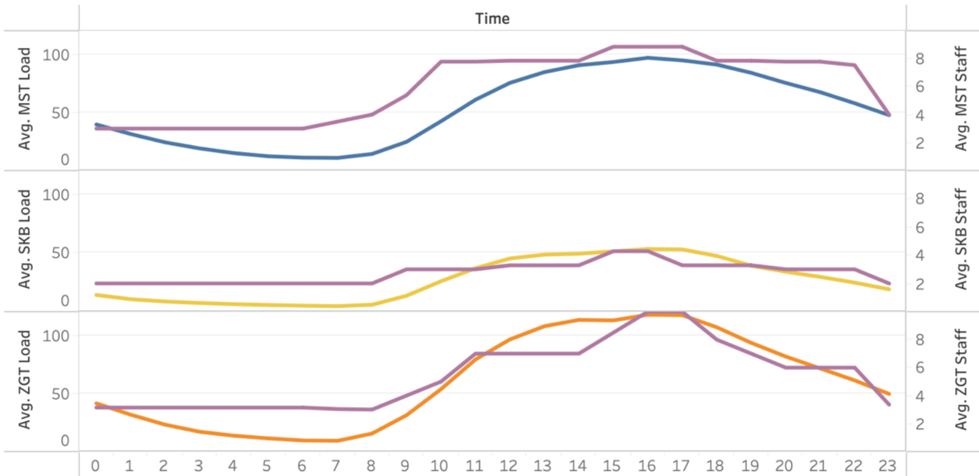


Figure iii: Care load compared to staffing per hour

Experimentation

The situation of the EDs in the Euregio was modelled using a stochastic programming model that minimises the expected maximum care load experienced across the region across a day. The model was run in different configurations as part of the experimentation, with 0,1,3 and 5 float nurses, and with full cross-training as well as cooperation between only MST and ZGT. The results of the experiments show that after a certain point, additional flexibility does not yield significantly better performance. Based on the results, it is recommended to have three float nurses per day spread across the region. This can decrease the maximum observed care load in the region with approximately 70%. More float nurses will only decrease the maximum observed care load additionally by less than 5%. Should it be decided to only create a float pool with only Enschede and Almelo, it is recommended to have only one float nurse, as no noteworthy benefits are achieved by deploying more float nurses in this configuration. The model gives the following schedules as best option for the chosen configuration:

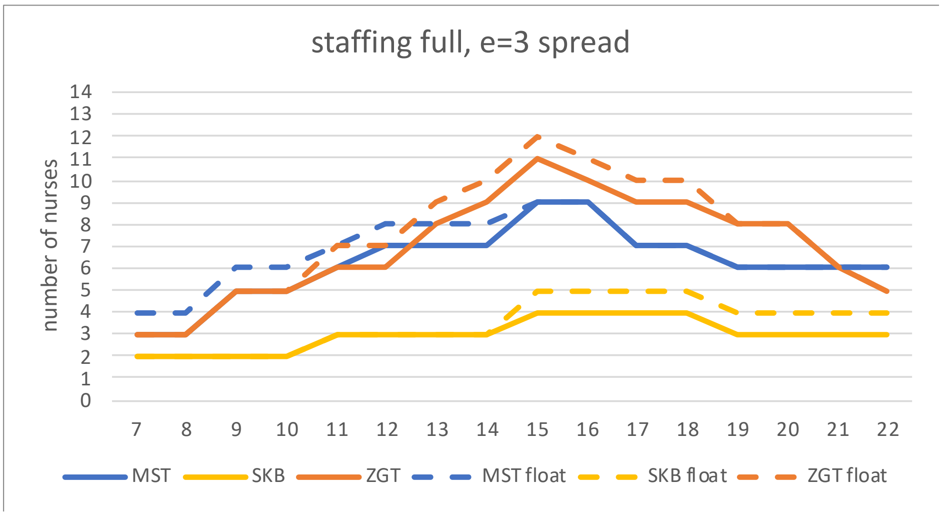


Figure iv: Proposed schedule for e=3 spread

The most prominent features of the proposed schedules are the fact that at each moment in time a float nurse is present in the region, with an overlap in the afternoon. The planning of dedicated nurses is more sloped for MST and flatter for ZGT. The peak of staff at ZGT is also moved forward a few hours.

Further recommendations

Next to the results regarding the float pool, other main recommendations to the stakeholders include:

- Consider deploying nurses across the region on the basis of filling in for illnesses or other absenteeism, or as part of the Multi-bel system that all three hospitals have in place.
- Take a conscious stand towards demand fluctuations at the ED and have contingencies in place, rather than rely on last minute action for extra capacity.
- Let the staffing at MST and ZGT be more closely aligned with the care load pattern throughout the day. For MST this means sloping the schedule more, as for ZGT this means flattening the schedule.

Management Samenvatting (NL)

Het volgende document bevat de resultaten van het onderzoek dat heeft plaatsgevonden in de ziekenhuizen van de Euregio, Medisch Spectrum Twente in Enschede (MST), Streekziekenhuis Koningin Beatrix in Winterswijk (SKB) en Ziekenhuisgroep Twente in Almelo (ZGT). Het onderzoek is gedaan in opdracht van Acute Zorg Euregio (AZE), als onderdeel van een master afstudeeronderzoek Technische Bedrijfskunde aan de Universiteit Twente.

Onderzoeksopzet

Het doel van het onderzoek is om de volgende hoofdvraag te beantwoorden:

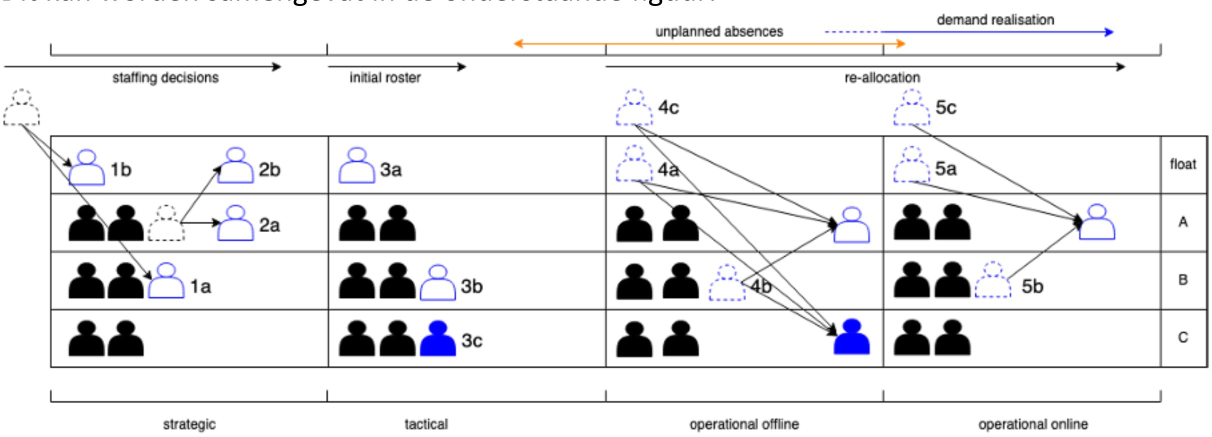
“Op welk planningsniveau en met welke ontwerpkeuzes is het opzetten van een float pool de moeite waard voor de Spoed Eisende Hulp afdelingen (SEHs) die vallen onder AZE?”

Om deze hoofdvraag te beantwoorden, zijn de volgende deelvragen opgesteld:

- *“Wat zijn de logistieke mogelijkheden en obstakels voor een SEH float pool voor AZE?”*
- *“Welke mogelijkheden voor float pooling worden genoemd in de literatuur die toepasbaar zijn op SEHs en hoe kunnen deze gemodelleerd worden?”*
- *“Hoe is de SEH zorgvraag en personeelsinzet gekarakteriseerd binnen AZE?”*
- *“Hoe kan de effectiviteit van een SEH float pool het beste gemodelleerd worden?”*
- *“Wat is de optimale configuratie voor relevante float pool ontwerpen, en hoe presteren deze ten opzichte van de huidige situatie?”*

Float pool beslissingsmomenten

Op basis van literatuur is er een overzicht gemaakt van alle relevante beslissingsmomenten voor het ontwerpen van een float pool die de betrokken ketenpartners kunnen overwegen. Dit kan worden samengevat in de onderstaande figuur:



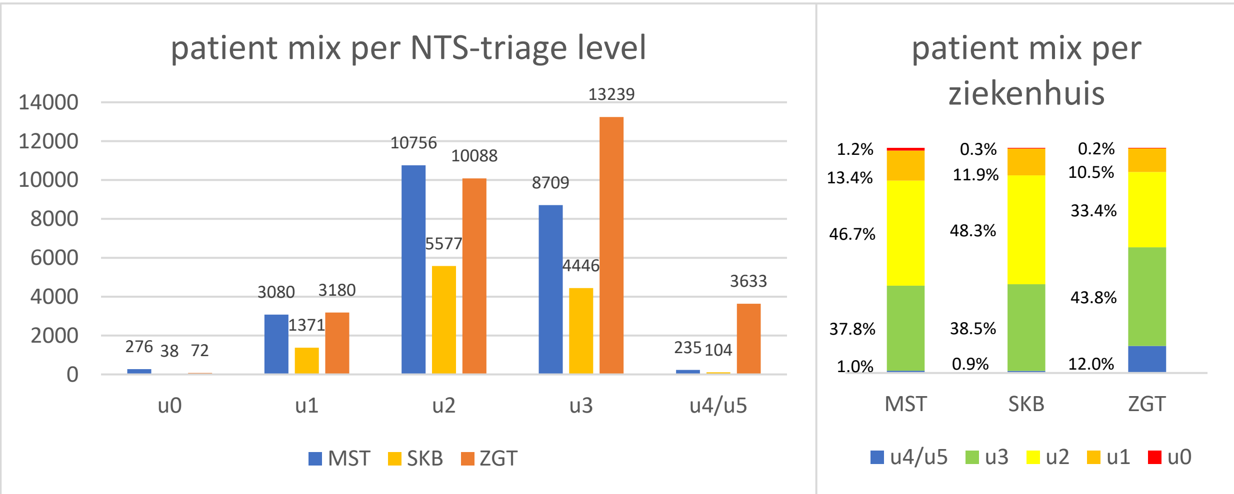
Figuur i: Float pool beslissingsmomenten

Andere relevante beslissingen zijn die over “cross-training” beleid, flexibiliteitsratio en de besluitvoering. “Cross-training” gaat over het vraagstuk welke verpleegkundigen worden opgeleid voor welk ziekenhuis en de uitvoerigheid van deze kruisinzetbaarheid. Flexibiliteitsratio gaat over hoeveel van de capaciteit in de regio flexibel ingezet moet worden. Besluitvoering betreft de vraag over welke situaties moeten leiden tot het verplaatsen van verpleegkundigen.

Voor de Euregio is het het meest toepasbaar om te werken met keuzes (2a),(3b),(4b) en (5b) van figuur i. Dit houd in dat verpleegkundigen die al in dienst zijn gevraagd word deel te nemen in de float pool. Vervolgens worden zij ingepland op een dienst met de kennis dat het ziekenhuis nog kan veranderen. Deze verpleegkundigen kunnen vervolgens verplaatst worden voorafgaand of tijdens de dienst. Echter zijn keuzes (4c) en (5c) mogelijk ook de moeite waard om te overwegen. Dit houdt in dat de float pool ook wordt ingezet in bestaande methodes voor het opvangen van ziekteverzuim of onverwachte drukte.

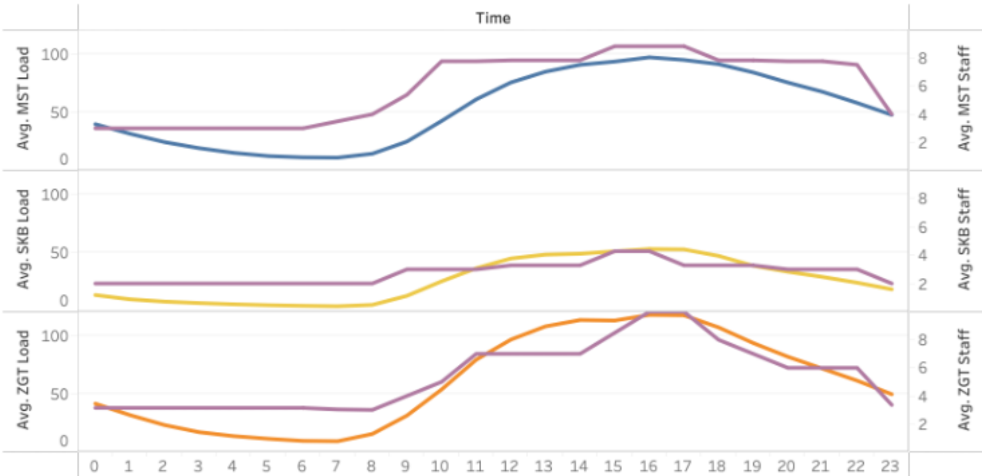
Data-analyse

De data-analyse is uitgevoerd op gegevens van aankomst en vertrek van patiënten gedurende 2022. Hierbij wordt de zorglast per patiënt benaderd op basis van NTS-triage waardes. De data bevestigd dat de variabiliteit over de hele regio lager ligt dan wanneer er naar elk ziekenhuis individueel gekeken wordt. Dit geeft aan dat een float pool de moeite waard is om verder te onderzoeken. Verder geeft de data-analyse aan dat er gelijkenissen maar ook verschillen bestaan in de patiënten mix in de regio, zoals beschreven in de volgende figuur:



Figuur ii: Patiënten mix per NTS-triage en per ziekenhuis

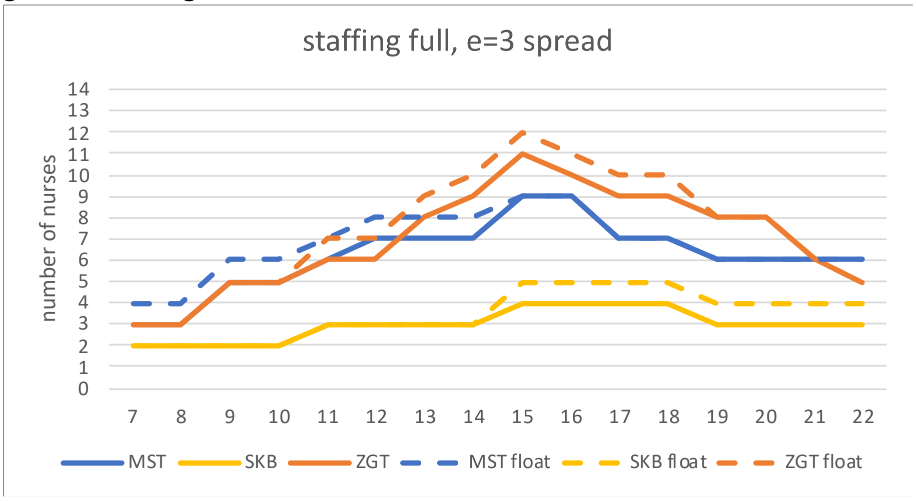
De data-analyse legt ook een aantal mismatches van zorgvraag en personele bezetting bloot, zoals gezien kan worden in de onderstaande figuur:



Figuur iii: zorg vraag vergeleken met personele bezetting door de dag

Experimenten

De situatie van de SEHs in de Euregio is gemodelleerd met een stochastic programming model met als doel het minimaliseren van de verwachte maximale zorgvraag ervaren in de regio op een gegeven dag. Als deel van het experiment zijn verschillende configuraties getest met het model, namelijk met 0,1,3, en 5 float diensten, en met zowel volledige cross-training als samenwerking enkel tussen MST en ZGT. De experimenten tonen aan dat boven een bepaald punt extra flexibiliteit geen significante verbetering meer oplevert. Gebaseerd op de resultaten wordt aangeraden om 3 float diensten per dag in te plannen gespreid over de regio. Dit kan de maximaal ervaren zorgvraag verminderen met ongeveer 70%. Nog meer float diensten zal de maximaal ervaren zorgvraag met minder dan 5% extra verbeteren. Wanneer besloten wordt om enkel samen te werken tussen Enschede en Almelo, wordt het aangeraden om een enkele float dienst in te plannen, aangezien meer diensten geen noemenswaardige verbetering oplevert. Het model adviseert het volgende roosters als beste optie voor de gekozen configuratie:



Figuur iv: Voorgesteld rooster voor e=3 spread

De meest noemenswaardige kenmerken van het voorgestelde rooster zijn dat er op elk moment op de dag een float dienst actief is in de regio, met een overlap in de middag. De planning van vaste verpleegkundigen is ook meer oplopend voor MST, en vlakker voor ZGT. De piek van aanwezig personeel bij ZGT is ook een paar uur eerder dan in het huidige rooster.

Verdere aanbevelingen

Naast de resultaten over de float pool, zijn er nog andere aanbevelingen voor de ketenpartners voortgekomen uit het onderzoek. Deze zijn onder andere:

- Overweeg het regiowijd inzetten van verpleegkundigen voor het invullen van diensten voor ziekteverzuim, of als onderdeel van een regionaal Multi-bel systeem.
- Neem een bewuste en actieve houding in tegenover variatie in zorgvraag op de SEH, en stel vaste methodes in om hiermee om te gaan in plaats van te rekenen op last-minute methodes om extra capaciteit te verkrijgen.
- Pas de roosters van MST en ZGT aan om beter aan te sluiten op het zorgvraag patroon door de dag heen. Voor MST betekend dit het rooster minder vlak maken en voor ZGT betekend dit het rooster juist vlakker maken.

Preface

Dear reader,

Before you lies my master thesis: *"Exploring the possibilities for an emergency department nurses float pool in the Euregio using stochastic programming.".* This work is not only the result of a six month research at Acute Zorg Euregio, but also marks the end of my studies. Therefore, I wish to use this section to express my thanks.

I want to say thank you to Derya and Melanie for being my UT supervisors. Through turbulent times you've given me the guidance that was needed to make this thesis academically sound. This project wouldn't have been the same without your clear and honest feedback. Furthermore, I'd like to extend my gratitude to the countless staff at the UT that have made me realise this work is my passion during my six years on campus.

I also want to express thanks to the whole team at Acute Zorg Euregio, as well as the ED teams at MST, SKB and ZGT. The work you do is very important to everyone in the region, and I've found it humbling to be a small part of it. A special thanks has to go out to Saskia. Not only has your feedback and guidance always been impeccable, but I can also say that you've helped me a lot by just being another IEM graduate working in the -sometimes confusing- world of healthcare.

Lastly, I want to say some less tangible thanks: To the Roosters for taking me in as a kiddo and giving me a place in Enschede. To 45 for helping me Dive In to student life to the fullest. To Hermes for giving me a home and not only a bed. To the boys for offering perspective and an escape far away from the UT. And finally, to my parents for being there every step of the way.

Daniël Snieder
28-08-2023

Readers guide

The following document details the research performed at Acute Zorg Euregio to investigate the under which conditions it would be beneficial to start a float pool for Emergency Department nurses across the three hospitals in the region. The document is structured as follows:

1: Introduction

The introduction chapter gives insight into the background and motivation behind the research. It also details the way the research has been structured, and which research questions will be answered by the thesis.

2: Context

In this chapter, the logistical possibilities and boundaries that exist within the context of the Euregio are discussed. This covers Acute Zorg Euregio as an organisation and the hospitals involved and their Emergency Departments. Relevant aspects regarding the nurses themselves, the planning at EDs and the response to demand fluctuations are also presented in this chapter.

3: Literature review

Within the literature review, the theoretical motivation behind float pools is covered first. After that, the various decision-making moments regarding float pools identified in literature are described and combined into an overview. This is followed by other considerations that have been brought up in literature for float pools. The chapter also covers how float pools have been modelled in the past and motivates the model type chosen for this research.

4: Data analysis

The data analysis chapter includes an analysis on care load and patient mix across the region over time. This is compared to the schedules that the hospitals currently have in place. Next to information required for the modelling of the situation in the Euregio, this chapter also includes broader observations on the care load and patient mix.

5: Model

This chapter gives a detailed description of the model formulated to represent the situation of the EDs in the Euregio. This includes a motivation, a theoretical definition and a linearisation which can be implemented in a linear solver.

6: Experimentation

The experimentation chapter covers how the model has been setup for experimentation. It also covers the experimental design that was executed, as well as the results of these experiments. These results include both performance as well as proposed schedules.

7: Recommendations

The recommendations chapter includes all further recommendations to Acute Zorg Euregio and the hospitals. These are not strictly related to the research questions defined at the start of the research. Many of these recommendations are thus not strictly related to the float pool but came forward during other phases of the research as relevant for the stakeholders.

8: Conclusion

The conclusion chapter answers the main research question, based on the results of the previous chapters. It also covers the contributions to theory and practice limitations of the research and suggests opportunities for further research.

Contents

List of abbreviations

AZE	Acute Zorg Euregio
DES	Discrete Event Simulation
ED	Emergency Department
EVPI	Expected Value of Perfect Information
IC	Intensive Care
JDT	Jones Dependency Tool
MST	Medisch Spectrum Twente
NEDOCS	National Emergency Department Overcrowding Scale
NTS	Nederlandse Triage Standaard
ROAZ	Regionaal Overleg Acute Zorg
SAA	Sample Average Approximation
SKB	Streekziekenhuis Koningin Beatrix
VSS	Value of Stochastic Solution
ZGT	Ziekenhuis Groep Twente

List of Figures

List of Tables

1 Introduction

The following document details the research that was performed at Acute Zorg Euregio (AZE) into the quantitative aspects surrounding a nursing float pool for Emergency Departments (EDs). The research aims to give insight into when instating such a float pool is worthwhile.

The current chapter discusses the motivation behind the research and the research design. First, the context from the perspective of the commissioners is given. After that, the main motivator is given a broader overview. The reason why this research focusses specifically on float pools is also given. After the context is given, the main research question is presented, which is followed by the sub research questions and corresponding methods which were used to answer the main research question.

1.1 Context

This research was commissioned by AZE, so that the results can be used by the hospitals that fall within the Euregio. The hospitals in the region are interested in the subject of float pools due to the nursing shortage in the region, which is especially prevalent in the EDs. It is hypothesised that a float pool can enrich the working environment of their nurses, as well as make the use of nursing capacity in the region more efficient. The former stems from the idea that nurses would want to experience what other hospitals are like culturally and would enjoy the variety. Furthermore, due to the different functions that the hospitals fulfil in the region, nurses could learn a lot from the other types of cases that they might be confronted with at the other hospitals. Literature supports the idea that job enrichment can lead to higher staff retention with nurses, with float pools being one of the ways to achieve this (McDonald et al., 2019). In terms of efficiency gains, one can intuitively determine that a float pool could aid, but this has not been researched in this setting.

This is why AZE has commissioned various research projects. Whilst qualitative aspects, like the opinions of the nurses have been researched before (Elferink, 2022), as well as in parallel with this thesis (Weelink, 2023), the hospitals also wish to gain more insight into the logistical aspects of a float pool, as well as its potential quantitative benefits. With this information, they can decide on whether it is worthwhile to start working with a float pool, and in what fashion this can best happen.

1.1.1 Nursing shortage

The basis of this research is the shortage of ED nurses that is currently present in the Euregio and is expected to become worse in the coming years. The nursing shortage that the Euregio is dealing with is not limited to the region. Rather, the nursing shortage can be viewed as global issue birthed by the aging population and various other social and economic reasons (Marc et al., 2019). In the Netherlands, the number of people aged above 75 is projected to increase by 86% between 2019 and 2040 which will increase the demand for care immensely (RIVM, 2019). At the same time, the fraction of people able to work in the healthcare system will decrease in comparison. For the ED specifically, it is projected that until 2029 351 ED nurses will need to be trained annually to be able to satisfy demand, but currently a lot of vacancies have trouble being filled (Capaciteits Orgaan, 2023).

While demand is increasing, AZE is also faced with a large number of nurses leaving. Across The Netherlands the outward flow of ED nurses for the coming years is projected at 9,4% for nurses above 60 years old, and 5,1% for the rest. Often named reasons are the low wages, high work pressure, long and irregular working hours and low appreciation. While some of these nurses leave the profession entirely, it is also reported that many of them leave their hospital to start working as a self-employed, or staffing agency nurse. This phenomenon is observed across the healthcare system of the Netherlands, and has become more significant in recent times (CBS, 2022), with currently 4.7% of ED nurses not being employed by hospitals (Capaciteits Orgaan, 2023). Due to the staff shortages, EDs are currently forced to hire back these self-employed or agency nurses for their regular schedules, but against a large premium compared to what a nurse on payroll would cost.

1.1.2 Float pools

With the unpredictable nature of demand at the EDs, and the shortage of staff that is already present having a shared pool of people available intuitively makes sense. The principle commonly referred to as risk pooling in supply chain theory dictates that the reserve capacity required to meet a service standard diminishes with increasing mean demand (Utley & Worthington, 2012). Thus, plainly viewed, if the demand for nurses is shared, the required number of nurses will always be the same or smaller than a rigid system (Landau et al., 1983). A float pool is thus often seen as one way of dealing with demand fluctuations without having to increase staff levels across all departments involved with the float pool (Fagefors et al., 2020). Other options for dealing with demand fluctuations with staffing could be using nurses from external agencies, or ask nurses to work overtime, but these are generally less desirable than float pools (Dall'Ora & Griffiths, 2017). Other flexibility measures like denying patients or referring them to other departments or hospitals are deemed less desirable as well, due to the urgency and speciality of the care that is required for ED patients. Therefore, this is not done at the EDs in the Euregio.

Potential is seen in having a float pool of nurses available for long term planning, incidental planning (due to illness for example) as well as dealing with peak demand. However, little is known on which of these levels, and with which policies the float pool can function and be beneficial.

1.2 Research design

Based on the context presented, the following main research question has been formulated:

1.2.1 Main research question

At which planning level and with which design choices will instating a float pool be beneficial for the EDs that are part of AZE?

In this instance, the planning level refers to the moment decisions are made regarding the allocation of staff to and from the float pool. The design choices reflect on how the float pool will be build up and used. This means decisions on the number of staff, the cross-training policy, set of rules for staff allocation and possibly other choices will be included.

1.2.2 Sub questions and methods

To be able to answer the main research question, 5 sub questions have been formulated. These sub questions follow each other chronologically with the aim that the answers of each can narrow down the scope of the further questions and aid in their answering.

1.2.2.1 What are the logistical possibilities and boundaries for a float pool for EDs for AZE?

To be able to say which float pool designs are applicable to the situation for AZE, as well as which modelling method can be applied, the logistical possibilities and boundaries of the EDs are explored. Through interviews with the ED managers and analysis of the planning and capacity scaling processes at the three hospitals, it is determined which of the theoretical designs could be applied in practice at AZE. This also concerns the number of staff available, and the skill requirements they might have. The willingness for staff to be allocated at other hospitals is informally explored as well. This is important to know for selection of the types of pooling that will be investigated further.

1.2.2.2 What possibilities exist for float pooling in literature that are applicable to EDs and how can they be modelled?

It is important to place the setting that this research focusses on in the context of the wider literature on float pools. This research focusses on EDs, within a setting with a relatively small number of hospitals with a non-neglectable amount of travel time between them. Furthermore, the timeframe in which the demand changes, and thus can be predicted is quite small. This makes for a challenging combination of factors. Existing literature on float pools that have been proposed or implemented across various healthcare settings is consulted. Using this, it can be determined which of these float pool designs, or parts of the designs can be applied to EDs. Ways to model float pools are also inventoried, so that an adequate method can be chosen.

1.2.2.3 How is the ED demand and nursing capacity characterized across AZE?

To find the optimal way in which the float pool can improve the care in all three hospitals, the characteristics of the care demand, and allocation of staff is analysed. By looking at the data from the patient arrivals the amount of fluctuation in demand, as well as the patterns can be identified. These fluctuations and patterns can span over multiple time periods as well as hospitals. Using the historical data on staff allocation in combination with the input from the ED managers the demand data can be translated into the number of nurses needed. The way care demand relates to nurse capacity in the current situation can then be investigated further as well.

1.2.2.4 In what way can the effectiveness of an ED float pool best be modelled?

Based on the literature on float pools, an overview has been made on what modelling methods have been applied to model float pools in the past. This overview is supplemented with other relevant methods from the broader area of operations research. Based on the results of the previous research questions, an adequate modelling method is chosen and a general model is formulated.

1.2.2.5 What will the optimal configuration and performance be of relevant float pool designs compared to the current situation at AZE?

Using the results of the literature, the data analysis and the information gathered at the hospitals the relevant float pool designs have been determined. These are incorporated into the model alongside the current situation. The model is used to experiment on the designs on current patient demand as well as projected future patient demand.

After answering the sub questions, the optimal solution found by the model serves as a basis for answering the main research question. Based on the theoretical optimum found, as well as the findings from the context, literature and data, recommendations to AZE are formulated in Chapter 7. Chapter 8 covers the overall conclusion of the research and answers to the main research question. This chapter also details the implications for float pooling research and identifies further research opportunities.

2 Context

This chapter answers the first research question: *"What are the logistical possibilities and boundaries for a float pool for EDs for AZE?".* First, an overview is given of the organisations involved in the research and their capabilities. After that, more light is shed on EDs and their functioning by discussing nursing, planning and dealing with demand fluctuations at the ED.

2.1 Acute Zorg Euregio

This research assignment was commissioned by AZE, but this organisation does not employ nurses themselves. Therefore, most of the research is focussed on the hospitals that are located in the region of AZE. How this organisation functions will be discussed in the following section. This is followed by a description of the hospitals that are involved in the research.

2.1.1 Organisation

AZE is the bureau responsible for coordinating and facilitating the "Regionaal Overleg Acute Zorgketen" (ROAZ) in the Euregio. This is one of ten regions in which the Netherlands is divided. The various ROAZ organisations are tasked with coordinating the cooperation between all acute care providers in a given region (Acute Zorg Euregio, n.d.-c). This includes various specialty organisations, general practitioners, ambulance services as well as hospitals. AZE is charged with coordinating this collaboration in the Euregio region. This region covers Twente, the east of the Achterhoek and the border region with Germany (Acute Zorg Euregio, n.d.-b).

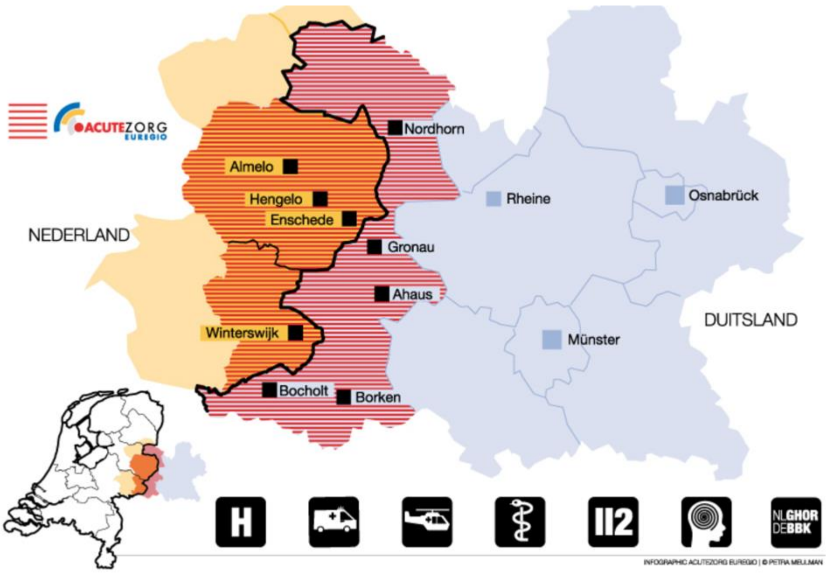


Figure 1: Overview of the Euregio

It is important to note that AZE does not get involved in the operations of the hospitals. The tasks that AZE performs are strictly to support the region in improving the care in the Euregio by training, research and facilitating cooperation amongst the partners. Thus, the day-to-day management of a float pool would not logically fall under the tasks of AZE but rather the hospitals. However, the government has expressed the wish for a more integrally managed care system. Not a lot is known yet about how this will take form, and if centralised decision making would become an option in that situation.

2.1.2 Hospitals

Within the Euregio, there are three hospital organisations: Medisch Spectrum Twente (MST) in Enschede, Ziekenhuis Groep Twente (ZGT) in Almelo/Hengelo and Streekziekenhuis Koningin Beatrix (SKB) in Winterswijk (Acute Zorg Euregio, n.d.-a). The Hengelo location of ZGT does not have an ED, and thus there are three EDs in the Euregio.

With 20 rooms and 23 beds available, the ED at MST is one of the larger two. To staff the ED, 3 to 13 nurses are deployed at the same time on a regular day. MST is classified as a level 1 hospital, meaning it can provide the most advanced care of the region. ZGT is a level 2 hospital and has a capacity of 21 rooms with 24 beds available. ZGT is staffed by 3 to 13 nurses. This ED can provide live saving care but does not have the means to administer all types of specialised care. SKB is the smallest of the three hospitals. It is classified as a level 3 hospital and has a capacity of 12 beds with 2 to 5 nurses present**.** Patients for which the ZGT or SKB cannot provide care due to specialised requirements are referred to the MST. (Nederlandse Vereniging voor Traumachirurgie, 2020). This can happen either directly by their general practitioner or ambulance personnel, or when the patient has initially arrived at ZGT or SKB and the need for advanced care is identified there.

2.2 Emergency departments

An ED (Dutch: "Spoedeisende hulp") is a department in a hospital that is charged with providing immediate care to patients that arrive to the hospital unplanned and is obligated to have a certain amount of specialised doctors and nurses scheduled at any time (werkgroep Kwaliteitsindeling Spoedeisende Hulp, 2009). Patients can arrive at an ED on their own accord, as well as via an ambulance or, if the hospital has the capability, via trauma helicopter. In case of ambulances and trauma helicopters, the ED will be warned a short time in advance, but generally, demand can be considered unplannable. The EDs in the Euregio cannot deny patients care in case of overcrowding. Thus, the EDs need to be equipped for large amounts of patients should the occasion present itself.

After the patient arrives at the ED, the severity of their condition will be assessed, and care will be provided by the ED doctors and nurses. The care needs of these patients vary greatly, both in terms of urgency as well as intensity. A person with a sprained ankle does not need a lot of nursing capacity and does not have to be treated immediately. Contrarily, a person that has just received CPR in the ambulance has to be seen immediately and requires a large number of staff to be present. After initial care is provided and a further treatment plan has been determined, the patient will either be referred to a different part of the hospital or a different care provider or be send home if the situation allows. This means that a patient will spend a period of a few minutes to a few hours in treatment at the ED. Detailed patient characteristics will be discussed in section 4.3.

2.2.1 Nurses

ED nursing is a specialisation that requires dedicated education separate from basic nursing school. Next to the on-paper requirements, most of the staff is also of the opinion that ED nursing requires a certain mindset. This can be attributed to the fact that working on the ED can be stressful and chaotic when compared to other, less acute units in the hospital. However, this stress is also why some nurses choose to leave the department. The stress currently being experiences is only partly attributed to the nature of the work at the EDs.

Especially at MST and ZGT, the EDs experience systematic staff shortages. This means that longer, or more frequent shifts are being made, or higher work pressure is needed to fulfil demand.

Another measure taken is the deployment of contract or agency nurses. These nurses have the right qualifications for EDs but are not employed by a hospital. They are either self-employed or work for an agency that flexibly deploys nurses across various hospitals. However, these contract or agency nurses are, counterintuitively, often less flexible than nurses that have a contract with the hospitals. Whilst hospital employed nurses not only have the obligation, but also feel the responsibility to make sure every shift is covered, contract or agency nurses dictate their own terms. This means that a contract or agency nurse cannot always be deployed on a nightshift, or that they might decide to take other contracting opportunities elsewhere for a week. A situation now exists where the extra capacity that contract or agency nurses offer does not translate to more flexibility, but rather puts extra constraints on regular staff. The planning staff of MST and ZGT report this requires the regular staff to work more unfavourable shifts to work around the contract or agency nurses.

When asked about the possibility of a float pool, nurses saw both opportunities as well as conditions and hesitations. Some of the nurses have expressed that it would be an exciting opportunity to work in another hospital to broaden their perspective. Others recognise how the availability of staff from other hospitals could aid in solving the staffing issues they're facing. Overall, nurses almost unanimously expressed that joining the float pool should be done on a voluntary basis.

One of the limitations identified by the nurses is the experience on the specific ED. Whilst all ED nurses have had the same education, the general opinion is that one should also know the logistical and practical aspects of that specific ED well to be able to function and not be a burden. Furthermore, some nurses doubt whether all nurses could adapt to working everywhere instantly due to the different levels of care that the hospitals provide. Thus, for a nurse to be able to function well at the other EDs, a thorough work-in period would be beneficial. This means that preparing a nurse to be floated will take a non-neglectable time investment.

Although initially thought to be a limiting factor, geographic considerations do not appear to be one of the main concerns of the nurses (Weelink, 2023). Many nurses live spread across the Euregio, and thus travel distance would not always differ greatly. Furthermore, with 28km, the distance between ZGT and MST is also not extreme. A slight hesitation exists for travelling to SKB. This can be explained because it is geographically the furthest away from the other hospitals with 36km and 59km to MST and ZGT respectively. SKB is also situated in a more rural area when compared to the other hospitals. Compensation for travel should be adequate for the nurses to consider the float pool.

A more crucial factor is that of time. Many of the nurses have families, and next to that are of course entitled to a private life and healthy work-life balance. Thus, one of the conditions most stated is that it should be known well in advance when a nurse should work (Weelink, 2023). This counts for both regular shifts and potential float shifts. Due to what's mentioned above, knowing when to work the shift on time is more important than knowing where to work the shift.

2.2.2 Planning

Planning at all three hospitals is generally done three months in advance, with the exception of summer due to vacations. The desired number of staff is based on a rolling schedule that generally stays the same, with small deviations per hospital. MST deploys slightly fewer nurses on Sundays, whilst ZGT deploys more staff during Sunday night. SKB systematically deploys more staff on Mondays and Fridays as these have been identified as the busiest days. The roster of the MST is also different during summer, where less staff is deployed.

At all three hospitals initial planning happens based on nurse preference. After gaps remain in the planning after the preference phase, the planners will fill in the gaps with regular nurses. If gaps still exist in the planning after using all existing manhours, the planners will attempt to fill the rest of the hours with contractors. Should gaps come up again in the planning due to illness for example, the planners will send out a request via text message to all nurses. This shift is generally then filled by regular nurses willing to work extra shifts.

2.2.3 Response to demand fluctuations

Demand fluctuations are part of the nature of an ED, therefore the EDs have certain measures in place for dealing with these fluctuations already. However, no direct patterns can be identified on which conditions which measure is deployed.

The most concrete measure that is deployed at ZGT and MST is referred to as a “multi-bel”. When this measure is executed, all regular staff that is not currently active is alerted that the ED is in need of assistance until two nurses have indicated that they’re able to come and assist. These hours are then counted as overtime. This measure is deployed around 10 times a year at MST and around once in two weeks at ZGT. SKB also has a multi-bel system in place but indicates that it has only been deployed once since it has been installed. The rationale behind this is that if deployed too often, it will not be taken serious anymore and thus it is only used in extreme situations.

In some instances, nurses that are scheduled to arrive in a few hours are asked to come in earlier in case of large demand spikes. This takes care of the large demand, but also means that nurses work longer shifts. This is an option that is mostly deployed at ZGT and SKB, with MST indicating that this is one of the least favourable options. SKB only deploys this option within a short timespan before the start of a shift.

In some cases, staff from other parts of the hospital are asked to help on the ED as the response time to this is the fastest. This is often regarded as a suboptimal solution as this staff will lack the specialisation that ED nurses have and thus can only aid in menial tasks. At SKB this is arranged differently, since most staff are cross-trained as both an intensive care (IC) and ED nurse. Thus, a large portion of staff working at the IC is fully qualified to aid at the ED in full capacity. This is consequently also one of the first methods of dealing with higher demand that is deployed at SKB.

Generally, contract or agency nurses are not deployed as a way to deal with unexpected demand. However, the most prevalent way of dealing with extra demand appears to be continuing with the staff at hand but working harder. This has drawbacks as well, as the quality of care, as well as the well-being of the staff can be influenced by the high workload.

2.3 Conclusion

Based on the information presented in this chapter, we can answer the first research question: *"SQ: What are the logistical possibilities and boundaries for a float pool for EDs for AZE?".*

There are three main areas where a float pool could be beneficial in the Euregio: during the planning phase, leading up to the shift due to illnesses and during the shifts. These time periods show a need for extra nursing capacity. In the first case this is plainly because of the shortage of nurses. This could partly be solved by leveraging the added flexibility of float nurses to allocate staff more efficiently and lowering the baseline staff levels. In the second case, benefits can be achieved by having a larger pool of people to ask to do an extra shift, but it does not create higher efficiency.
In the third case, the most benefits can be realised from float nurse allocation after demand is realised which does not usually span multiple shifts in the case of EDs. Therefore, these benefits can be best realised when nurses can be floated during a shift and not only for a full shift.

In terms of boundaries, it is important that, if the float pool is used to aid in filling existing rosters, or for dealing with extra demand, in both cases the nurses wish to know when to work the shift well in advance. The timeframe given for this corresponds to the timeframe in which the regular planning is made as well. Nevertheless, this still leaves space for solutions where the shift is known but the allocation is still open for when demand is realised. Furthermore, because being able to float to a different hospital will take a time investment and because not every exchange is desirable, creating too many combinations with too many nurses will be unrealistic. Thus, this needs to be critically chosen. Lastly, in the current setting centralised decision making on the allocation of float nurses is not viable, thus decision rules or other governance methods would be needed. However, in the future centralised decision making could become possible.

3 Literature review

The following chapter aims to answer the research question "*What possibilities exist for float pooling in literature that are applicable to EDs, and how can they be modelled?".* To answer this research question a literature review was performed on nursing and operations research literature. From the literature, various motivations and factors have been identified that differentiate different possibilities for float pool designs. The most notable of these are the planning level, the flexibility ratio and the cross-training policy used. Another key factor, namely the decision making for the allocation of staff needs to be considered as well. The factors and considerations for this will be discussed first in this chapter.

Next to the possibilities, this chapter will also discuss the various methods found to model float pools. This will be discussed after the factors have been outlined. Many authors propose models to cover one, or multiple of the identified factors. Based on the overview of factors, it can be determined which of these are important for EDs. This information can then be used to choose an adequate modelling method.

3.1 Motivations for decision making

(Mendez de Leon & Stroot, 2013) make a distinction between using float staff for coverage of predictable unfilled hours and using float staff for unpredictable spikes in volume. While not using specific terms for the decisions, (Dziuba-Ellis, 2006) also argues that float pools can be used for two reasons. These are for filling in shifts that have no assigned nurse before the start of the shift, and for aiding with excessive demand that allocated staff can't cope with anymore.

3.2 Float pool decision moments

Across the literature, two frameworks for categorising planning decisions for float pools are used. The taxonomy of (Hulshof et al., 2017) divides planning decisions into "strategic", "tactical", "operational offline" and "operational online". Other authors divide planning decision for nurses into "planning", "scheduling" and "allocation". Both of these frameworks are cited by authors to identify their decision-making moment. The various stages identified in the frameworks carry different names but in practice represent similar timeframes. Since the framework of Hulshof is more comprehensive, the decision moments will be classified according to this framework.

In the next section, different planning levels and decisions for EDs as described in Hulshof are briefly discussed along with the relation to float pools as already identified in Hulshof. From the broader literature review, two schools of thought regarding strategic and tactical decision making are identified which are discussed after the overview. On the one hand, authors give example of various isolated decisions, while other authors argue that the strategic and tactical decisions are impacted by the operational implications and thus require a wholistic approach. The last prominent aspect regarding float pool decision moments is the difference between offline and online operational decision making.

3.2.1 Definitions

Strategic decisions in this framework comprise the long-term decisions regarding facilities, coverage and service mix and capacity dimensioning. In the context of float pool staffing, The capacity, hence the number of nurses is decided on the strategic level. At this level one can also consider scale of flexibility, and thus amount of float nurses that the organisation should strive for. At the tactical level, decisions regarding staff-shift scheduling are made, meaning the required staffing level for each time interval should be determined. This in turn can result in a block schedule. At this stage, part of the block schedule can already be chosen to be fulfilled by float nurses. At the offline operational planning level, individual staff members are given a shift to perform before the start of the shift. At this stage it can also in some cases be seen which shifts in the block schedule cannot be fulfilled by regular staff and thus require other ways of fulfilment. At the online operational planning level, that is during demand realisation, (Hulshof et al., 2017) mentions that one can decide to react to unexpected higher demand by rescheduling staff or by calling in additional staff.

3.2.2 Partial decision making

Various authors only partially outline decision making. (Mendez de Leon & Stroot, 2013) propose that one can choose to source staff for nursing resource teams well in advance as a strategic decision, and either hire them internally (as dedicated float pool nurses) or only come into contact with them (as contractor or agency nurses). Another choice that is proposed is whether this staff should have committed hours but not units, or have no committed hours or units. (Ward et al., 2015) mentions the strategic choice of cross training existing staff so that they can be allocated to multiple tasks but does not outline further decision making. (Otegbeye et al., 2015) describes a situation where the tactical decision was made to move existing ED staff from fixed shifts to flexible allocation when demand becomes higher than expected. However, when this allocation is done is not mentioned. (Fagefors et al., 2020) identifies float pools as one of the more promising methods of dealing with short-term demand and supply fluctuations in healthcare but does not detail whether this can be best done on an operational offline or online level.

3.2.3 Wholistic decision making

The authors of (Maenhout & Vanhoucke, 2013) observe that the closer to demand a float nurse is allocated, the more effective the float pool will function. However, they also argue for the need to integrate the implications of the short-term allocation into the long-term planning. In this case, they refer to the staffing question on the strategic level. (Winasti et al., 2022) give a clear overview of the interconnectivity of decisions. they indicate that deciding on how many nurses are needed, and how many of those should be float nurses is a decision that a hospital has to make on a strategic level. The allocation of individual (float) nurses based on rosters is then an operational offline decision. After this, the authors identify the re-allocation of float nurses based on demand as an operational online decision that can be taken additionally. Under the assumption that staffing decisions are made ones a year, (Gnanlet & Gilland, 2009) outline the question of simultaneous or sequential decision making. This means that the option exists to decide on the number of float nurses when making an initial strategic staffing decision. Alternatively, this decision can also be made after the initial staffing has been set, so on the tactical level. The authors assume that the actual allocation of float pool nurses will happen on the operational online level, after demand has been realised.

3.2.4 Operational offline

The authors of (Paul et al., 2018) model the choice of determining the roster for regular, float and agency nurses to EDs in three week periods based on demand predictions. (Campbell, 1999) argues that float nurse allocation should happen either a few weeks in advance to the shift, or at start of the shift. The authors of (Kortbeek et al., 2015) formulate a model that addresses how many employees should be assigned to each care unit during a given planning horizon, while also taking into account float nurses. This tactical planning should in turn inform the staffing decision making at the strategic level. In this case, the allocation of float nurses happens at the start of a shift. Focussing on wards, (Fügener et al., 2018) propose a model for allocating float nurses on the operational offline level, as part of their tactical planning method. In this method, the authors also propose to plan nurses to a shift, but not yet to a unit during tactical planning. The allocation to the unit then happens at the start of the shift. This model is used to create insights into the strategic or tactical choice of choosing a cross-training policy

3.2.5 Operational online

The analysis of (Inman et al., 2005) serves to decide on a the number of nurses from existing staff that have to be trained to float, as well as the way they are cross trained on a strategic level. The analysis on the benefits works under the assumption that the actual floating of nurses happens after demand has been realised, similarly to Gnanlet & Gillands work.

The authors of (Griffiths et al., 2021) also work with a given amount of staff and only introduce the float pool as a fraction of this staff. To test the effectiveness of a variety of ratios, experiments are done on a model that assumes that the float nurses can be allocated on the online planning level. The model of (Schoenfelder et al., 2020) also works from the principle that float nurses will be actually allocated once demand has been realised. However, they also take the float nurses into account when creating a planning for several weeks on the tactical level. The float nurses are given a shift and potential starting location, however where the shift is actually executed is determined later on based on the realised demand.

More examples of how to respond when demand realization is becoming larger than forecast are more prevalent in other industries than healthcare but could be applicable to our situation (Hur et al., 2004). The possibility of re-allocating staff after demand realization is seen here as one of the best options for dealing with unexpected demand.

3.2.6 overview

Based on the sources discussed above, the decision moments found literature can be summarised per planning level to create a full overview of decisions that can be made. The overview outlines the moments at which a decision can be made, and the scope of the decisions.

Strategic

Choice 1: how much staff do you hire from the labour market?

- (only hire fixed staff)
- 1a: fixed staff with option to float
- 1b: staff specifically for the float pool

Choice 2: do you ask existing fixed staff to become float staff?

- 2a: fixed staff with option to float
- 2b: staff specifically for the float pool

Tactical
Choice 3: how do you create your roster?
- 3a: allocate float nurses to time-slot, not hospital ("stand-by")
- 3b: allocate float nurses to time-slot and hospital for shift with option to float still open
- 3c: allocate float nurses to time-slot and hospital for fixed shift

Operational offline
choice 4: how to fill gaps in existing roster before shift? (or predicted excessive demand?)
- 4a: allocate from "stand-by" allocation (needs 3a)
- 4b: re-allocate from other hospitals (needs 3b)
- 4c: request float staff from pool without pre-allocation

For this decision, one can choose to allocate the float staff to a dedicated fixed shift, or choose to allocate staff to a float shift, meaning the staff can be floated still ones demand manifests.

Operational online
Choice 5: how to deal with excessive demand?
- 5a: allocate from "stand-by" allocation (needs 3a)
- 5b: re-allocate from other hospitals (needs 3b or the float variants of 4a/4b/4c)
- 5c: request float staff from pool without pre-allocation

For clarity, an overview of how the choice moments could be applied in the situation of AZE is provided in Figure 2. In this figure, fixed staff is indicated in black, and float staff indicated in blue. If a shift is fixed, it is indicated by being coloured in, while a float shift only has a border.

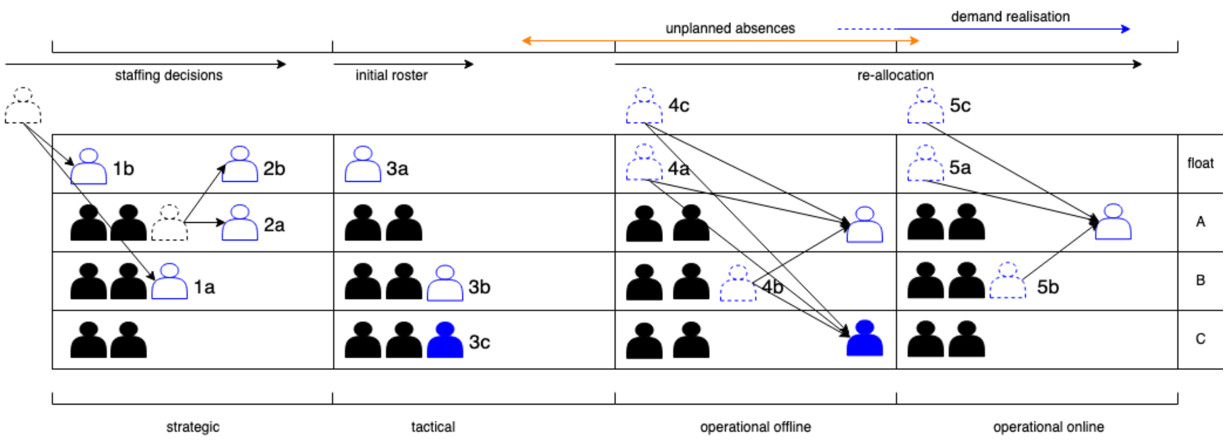


Figure 2: decision moments for float pools

3.3 Other considerations

Next to the decision moments that can be considered for instating a float pool, another set of factors are important to consider. Most notably, one should decide on which nurses will be prepared to work at which other location. This is often referred to as the cross-training policy. Furthermore, another decision that is to be made is the number of nurses that will be asked to be available as float nurses. This is referred to as the flexibility ratio. Both these considerations have been covered by various authors and multiple approaches exist to make a decision on these considerations.

3.3.1 Cross-training policy

(Dziuba-Ellis, 2006) warns against using float pools without taking into account the competencies of the nurses in the area that they are floated towards. Other authors have also identified the need to sufficiently prepare nurses to work at different hospitals or departments than their usual location. To this end, (Inman et al., 2005) have proposed a framework of cross-training policies. This framework outlines policies on which it can be decided which nurses should be trained for which locations, namely “chaining”, “reciprocal pairs” and “N-to-all” (with as a special case the “all-to-all” policy). (Fügener et al., 2018) expand this framework by proposing the “one for each” policy. The difference between the policies is best explained by the illustration by Fügener et al. in Figure 3.

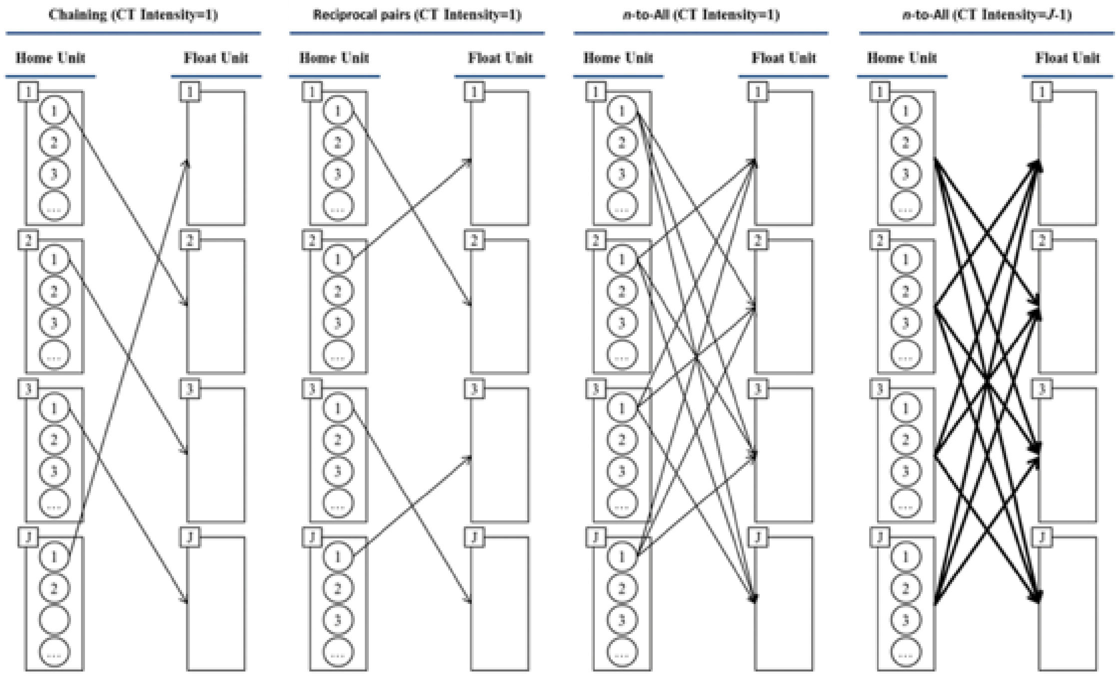


Figure 3 : Overview of cross-training policies

The degree to which training can and should lead to full effectiveness at the EDs is often doubted. However, it has been shown that partial effectiveness by floated workers can also have a positive impact on the performance of the total pool (Campbell, 1999).

3.3.2 Flexibility ratio

Asking every ED nurse employed in the Euregio to be available for the float pool would be unrealistic due to various reasons discussed in the context chapter. However, most authors argue that only a fraction of staff will be needed to for flexible deployment for it to be beneficial (Campbell, 1999; Landau et al., 1983). Campbell also argues that above a certain flexibility ratio no more additional value will be achieved, while still incurring the costs of increasing the flex ratio. Thus, one should critically determine the flexibility ratio.

Using a broader mathematical intuition, Landau proposes that under randomly variable demands, reserve capacity should be proportional to the square root of the capacity required for average demand. (Mendez de Leon & Stroot, 2013) propose that float pools should cover 15% of a hospitals total nursing staff needs, but do not offer a quantitative reasoning for this figure. Contrarily, (Griffiths et al., 2021) use an agent based simulation to analyse the effect of various flexible to fixed staff ratios and conclude that, in an average setting fixed staff should be able to handle up to 90% of the expected care demand to get optimal results. (Winasti et al., 2022) report that between 7% and 20% of nurses planned to work should be allocated flexibly and not to one specific ward at the start of their shift. However, all of these results were based on inpatient wards and not on EDs.

3.3.3 Decision making

The actual decision making for the allocation of staff, given the chosen design of the float pool is treated in a number of ways in literature. A selection of authors choose to allocate staff optimally by using either linear program using a forecast or actual picture of care demand across the float pool departments (Fügener et al., 2018; Morris, 2021; Paul et al., 2018) or by using stochastic programming (Gnanlet & Gilland, 2009; Schoenfelder et al., 2020).

In addition to exact methods, the authors of Schoenfelder propose a heuristic that can be applied which approaches the results of their stochastic programming model. (Winasti et al., 2022) propose a set of algorithms which can be used to allocate the nursing staff based on demand across all float pool departments. Similar algorithms or heuristics for resource re-allocation are proposed in (Hur et al., 2004). All these methods can be seen as centralised decision making, where the allocation of staff is done with full information regarding demand across all involved departments.

Alternatively, (Griffiths et al., 2021) proposed simulation model works from with the assumption that each department will individually request float pool staff without taking the rest of the float pool into account. It should be noted that this model also simplifies where the float pool nurses come from, and thus also the interaction between departments is not crucial to model in this instance.

Due to the geographical distance between the EDs in the Euregio, as well as the fact that the hospitals have their own management and patient and staff planning, it will be interesting to investigate decentralised or cooperative decision making. Using a mathematical model to allocate the float pool staff might not be practical should a float pool be instated across the Euregio, especially when the option to request or allocate float pool staff during a shift is considered. The same goes for heuristics or algorithms that require a full overview of information and centralised decision making.

3.4 Modelling methods

The use of float pools has been modelled in various ways that could be applicable to the situation presented in this research. Most prominently, mathematical modelling is applied. This has been done both deterministically as well as stochastically. Other works have used simulation techniques to model float pools. Furthermore, some authors have used analytical methods to show the usefulness of float pools.

3.4.1 deterministic mathematical modelling

To better test the various cross-training policies (Fügener et al., 2018) create a deterministic linear programming model with a planning horizon of multiple days. In this model, the cross-training policies can be included as constraints, and the performance is judged on historic nurse demand data. To investigate a similar design question, namely that of partial cross-training, (Campbell, 1999) have also used linear programming. In this case, the model was solved for various levels of effectiveness for float nurses deployed at a different unit.

(Maenhout & Vanhoucke, 2013) define a deterministic mathematical model that aims to solve both the staffing as well as the allocation problem of nursing staff. However, they propose solving the problem with heuristics due to the size of the problem prohibiting solving it in reasonable time.

Specifically focussed on EDs, (Paul et al., 2018) propose a patient inflow model based on forecasting with exponential smoothing, which is used as the input for a deterministic linear program to allocate fixed, float and agency nurses optimally.

3.4.2 stochastic mathematical modelling

(Gnanlet & Gilland, 2009) use a two-stage stochastic programming model to determine the optimal resource levels (beds and staff) for two nonhomogeneous hospital departments under uncertain demand with a continuous, general distribution. Next to the resource levels, the number of flexible staff is also determined before demand is realised in this model. After demand is realised, the resources made available after the first decision moment will be optimally allocated. (Schoenfelder et al., 2020) also propose a two-stage stochastic programming model. In their model, the first stage represents the initial staff allocation for a given shift, including a certain amount of float pool nurses. These nurses know that they will work that shift, but not yet at which department. The actual allocation to a department of the float nurses will then happen in the second stage, after demand is realised. The authors of (Schoenfelder et al., 2020) also verify the theoretical performance of the two-stage stochastic model by developing a heuristic based on the models results and testing the heuristic in a simulation.

(Kortbeek et al., 2015) present a mathematical model that allocates nurses to a collection of hospital wards under uncertain demand with the aim of ensuring a set nurse-to-patient ratio, which contains an option for the allocation of float pool nurses which are allocated after demand is realised. However, the authors propose alternative heuristics for solving this problem as it is too large to solve to optimality.

3.4.3 simulation

The authors of (Ward et al., 2015) propose that an ED could be modelled using Discrete Event Simulation (DES) but do not compare this to other Operations Research methods or give reasons on why DES would be the best option to use. To evaluate a variety of float pool designs within of a hospital, (Winasti et al., 2022) use DES in combination with a Markov-based demand prediction. For the allocation of float staff after demand prediction has been done, a set of reallocation algorithms that take the whole system into account are proposed and evaluated. To model a float pool for use in neonatology, (Morris, 2021) uses DES to model the amount of patients per shift, after which a deterministic linear program is used to optimally allocate patients and nurses at the start of a shift. To investigate the effectiveness of real time decision making heuristics for re-allocation during a shift, (Hur et al., 2004) also use DES. The authors of (Thorwarth & Arisha, 2012) also apply DES to model flexible task allocation in an ED, along with (Munavalli et al., 2020). However, for both these works float pools are not the main focus of the research.

To gain insight into the ratio of fixed to flexible nurses (Griffiths et al., 2021) develop an agent based simulation. In this simulation, the hospital units are the agents that transition between over, under and adequately staffed based on the situation that they're in at that time. The agents transition between these states based on the demand that they're presented with and the staff that they currently have. Should the unit be understaffed, then staff from the float pool or from an agency is requested.

3.4.4 analytical methods

One of the more early works on float pooling, (Landau et al., 1983) focus on the mathematical properties of stochastic nurse demand to give a theoretical proof of the benefit of float pools. Using hospital data, they're also able to give a statistical analysis on a hypothetical float pool giving empirical proof of its usefulness.

In an attempt to create a generalised and easy to use method to evaluate the value of various cross-training policies (Inman et al., 2005) propose a set of analytical approximations. These can be executed in Microsoft Excel and use statistical properties of probability distributions of demand to approximate the numerical benefit of the policies.

3.5 Conclusion

This chapter aims to answer the following research question: "*What possibilities exist for float pooling in literature that are applicable to EDs, and how can they be modelled?".* An overview of the decision moments for float pooling has been created. By taking a set of decision moments and options presented, in combination with a cross training policy, flexibility ratio, and allocation strategy/model a design for a float pool can be presented.

The decision moments identified by the staff at the EDs correspond to the strategic choice of asking existing staff to float (2a), which is more realistic than hiring new staff due to the nursing shortage. Furthermore, this will also ensure that staff will keep their connection with their own ED, as is often requested.

At the tactical level, the choice to allocate float staff to a fixed shift (3c) is an option for filling gaps but will not yield efficiency gains. This choice can however be made to systematically familiarise nurses to the other EDs. Alternatively, choice (3a) and choice (3b) do give the opportunity for improved efficiency by allocating float staff to only a shift but no hospital, or an initial hospital with option to float respectively. The decision that could follow from this is best made on the operational online level, because not a lot can be said about demand before the start of a shift. Because this would mean that a nurse would start a shift without a location in the case of choice (3a), it would be more logical to go with choice (3b). This ensures there's a default place to start the shift should no extreme care load be observed.

The consequence of this is that on an operational offline level, the choice to relocate planned float staff (4b) and to request aid from unplanned float staff (4c) remain. Benefits can be achieved by filling in for illnesses out of the pool with option (4c), in a similar fashion to how this is now filled out of the regular staff that is not planned. However, due to the drawbacks of those solutions (overtime, irregular workload etc.) it might be more favourable to consider choice (4b). One could decide to then allocate the float nurse to a fixed shift, but this sacrifices the floating opportunity at demand realisation and thus obstructing efficiency gains. Thus, it is most beneficial to choose to allocate the float nurse to a float shift. On an online level, this means that choice (5b) to relocate planned float staff remains alongside choice (5c) to request extra float staff from unplanned staff. That said, choice (5c) could be viewed as an expansion of the “multibel” system currently in place meaning it has the same drawbacks. It does however expand the pool from which people can respond to the request. Choice (5b) has the most potential benefit over the current situation by moving the allocation of staff towards demand realisation.

Full cross-training could be applied, but it would be costly due to the large time investment for nurses to get used to a different ED. Therefore, one could consider moving forward with another cross-training policy like chaining, or pairs. The flexibility ratio also must be determined, but nothing can be stated about this as of yet except for that it should remain low. Literature shows that a too big flexibility ratio will lead to diminishing returns, while enabling the ratio will take significant time investment as discussed in the context chapter. Intuitively, centralised decision making will yield optimal results. However, in the current way EDs are organised this would not be feasible to implement for online re-allocation. This decision making would then fall onto ED staff themselves.

To see the impact of the chosen float pool design, models can be created. The best model to work with depends on the questions that one wishes to answer.

To answer globally whether a float pool will be beneficial to implement with the current design choices, a stochastic programming approach can be applicable. With this method, holistic planning decisions can be made across the various stages of uncertainty and compared to baseline decision without a float pool. This can be used to determine the desired flexibility ratio at a strategic level for example or compare different cross-training policies with each other. Such a model would require certain simplifications and assumptions that would make it deviate from real life. For example, online decision making, travel time between EDs and specific peaks in demand due to unfortunate combinations of patient arrivals and departures will have to be simplified. However, for a strategic and tactical model to show the potential benefits of a float pool, such assumptions may be warranted.

Should one wish to get a detailed perspective on the functioning of a float pool a DES could be created. A simulation can serve to better model performance of a given float pool design compared to baseline in detail with all interacting factors. Additionally, a simulation can also be used to model the online decision making, be it centralised or decentralised, more accurately. This could be used to determine concrete policies that can be put in place should a float pool be created.

4 Data analysis

The following chapter answers the research question: *How is the ED demand and nursing capacity characterized across AZE?* To answer this question, a dataset was made available by AZE and the three hospitals. Based on patient characteristics, an estimation of care demand for various time periods has been created.

4.1 methodology

The dataset provided for the research includes the arrival times, start times of triage, start times of treatment and departure times of all patients that visited the EDs in the region along with their diagnosis and Nederlandse Triage Standaard (NTS) level. The datasets of the three hospitals vary in length, but due to the Covid-19 pandemic a lot of data is not representative. Therefore, the analysis is based on the data of 2022. For the staffing data, input from the planning departments was used.

4.1.1 care demand

By aggregating the data on patients across timeframes of 15 minutes, the number of patients per time period is determined. This is based on the logged time of triage, which is the first contact nurses have with a patient and the time of departure from the ED. Crucial for analysis is the way the characteristics lead to a certain care demand.

Due to the diverse nature of patients arriving at the ED, it would not be accurate to directly correlate the number of patients present to the workload for nurses. Various methods are applied to approximate or estimate the workload for EDs in practice. For AZE these are most notably the National Emergency Department Overcrowding Scale (NEDOCS), the Jones Dependency Tool (JDT) and the NTS.

NEDOCS is a validated method that works based on a linear regression to estimate the workload at EDs that includes patients present and patient arrivals compared to the number of beds present at the ED as well as in the rest hospital, combined with statistics on waiting times of patients (Hoot & Aronsky, 2006). However, NEDOCS is only based on the number of beds available and number of patients. Thus, it does not have a lot of direct correlation with number of staff available. Furthermore, except for patients requiring ventilators[1], NEDOCS does not include the variety in care intensity that different patients might require at lower levels of care intensity. It should be noted that while the number of patients is taken relative to the number of beds and thus scale of the hospital, the value for ventilators is not normalised and thus the impact of this characteristic will vary per hospital.

The JDT is a tool specifically designed to determine individual patient care requirements at an ED (Crouch & Williams, 2006). The software in use at MST and ZGT uses the cumulative Jones Dependency scores of all patients divided by the cumulative “amount of care” one nurse can provide to give an indication of workload at that moment in time. The JDT takes various factors into account among which triage, mobility and health characteristics, but also communication, personal care and health and safety aspects. While this can offer a good picture of care need, the historic JDT values, or the factors required to calculate the JDT are not readily available at

[1] Since Dutch hospital systems do not all log the number of ventilators, in practice all patients with NTS u0 and u1 are used as input for this factor.

MST and ZGT. At SKB, the software is not yet configurated to calculate the JDT and thus also does not log its historic values or input characteristics.

Triage at the EDs in the Netherlands happens via the NTS standard, which contains 6 levels of care urgency (Nederlandse Triage Standaard, 2014). In the standard, “u0” or 1 in the data set means that the patient is in a life-threatening condition and needs care immediately while “u5” or 5 means the patient requires care between now and the following weekday. The standards’ primary goal is to assess how quickly a patient has to be seen by a doctor to start treatment. The value assigned to a patient depends on various medical factors observed by a trained professional. This means that the NTS is only based on medical factors and no social or logistical factors.

Using NTS-triage as way of measuring workload can be considered a good approximation, as correlations exist between the urgency that a patient needs care, and the severity of their case and thus requirements for care. Furthermore, NTS serves as input direct input for JDT and indirect input for NEDOCS. In the case of JDT, out of 18 possible “points” a patient can score, between 1 and 3 comes from the NTS level, with u5 and u4 resulting in a value of 1, u3 and u2 resulting in 2 and u1 and u0 resulting in 3. This relates back to the nurses by the given figure that a nurse can be responsible for 30 JDT points. In the case of NEDOCS, a patient with u0 or u1 has a higher influence on the NEDOCS score than a patient with a lower NTS level. In NEDOCS, the relative impact of a patient on a ventilator is larger for large hospitals as the impact for all patients is normalised by the number of beds (Vergeer, 2023). In the situation of AZE, this means that the calculation will be significantly different for SKB, as the number of beds is significantly lower.

Based on the characteristics of the approximation methods in use in the Euregio, and in collaboration with ED staff the following formula has been chosen to approximate the care intensity based on NTS level:

$$C_p = 5 + (4.75 - NTS_p)\hat{}2$$

where NTS_p represents the numerical representation of the NTS level (the integers 1 to 5). Because not all hospitals report u5 urgencies (as these patients are technically not in need of care at the ED), and the care load is comparable to u4 patients according to the nurses, u4 and u5 are grouped in the dataset with integer value 5. The resulting Care intensity C_p can be considered a JDT equivalent value. The behaviour of this formula compared to JDT and NEDOCS[2] can be seen in Figure 4. This formula allows for differentiating between all NTS levels separately. Furthermore, it conforms to the idea that the highest levels of urgency correlate to the most workload from NEDOCS due to the quadratic term. The values that are gained from the formula also span the whole range of possible values of the JDT, with more space above as well as below the regular values the JDT can take. As the JDT groups the NTS levels, it is intuitively logical that slightly higher and slightly lower values could in practice be applicable. This has also been confirmed by the ED staff. Correlation between higher NTS and other factors of influence for the JDT (like ability to communicate or care for oneself) were also mentioned by the ED staff, and is represented by this formula as well. Because the values of the formula adhere to the scaling of the JDT, we can also use the figure of 30 JDT “points”

[2] The derivation of the NEDOCS formula to this form is included in Appendix A

per nurse to create an approximation of workload at the ED. A sensitivity analysis on this approximation is included in Appendix B.

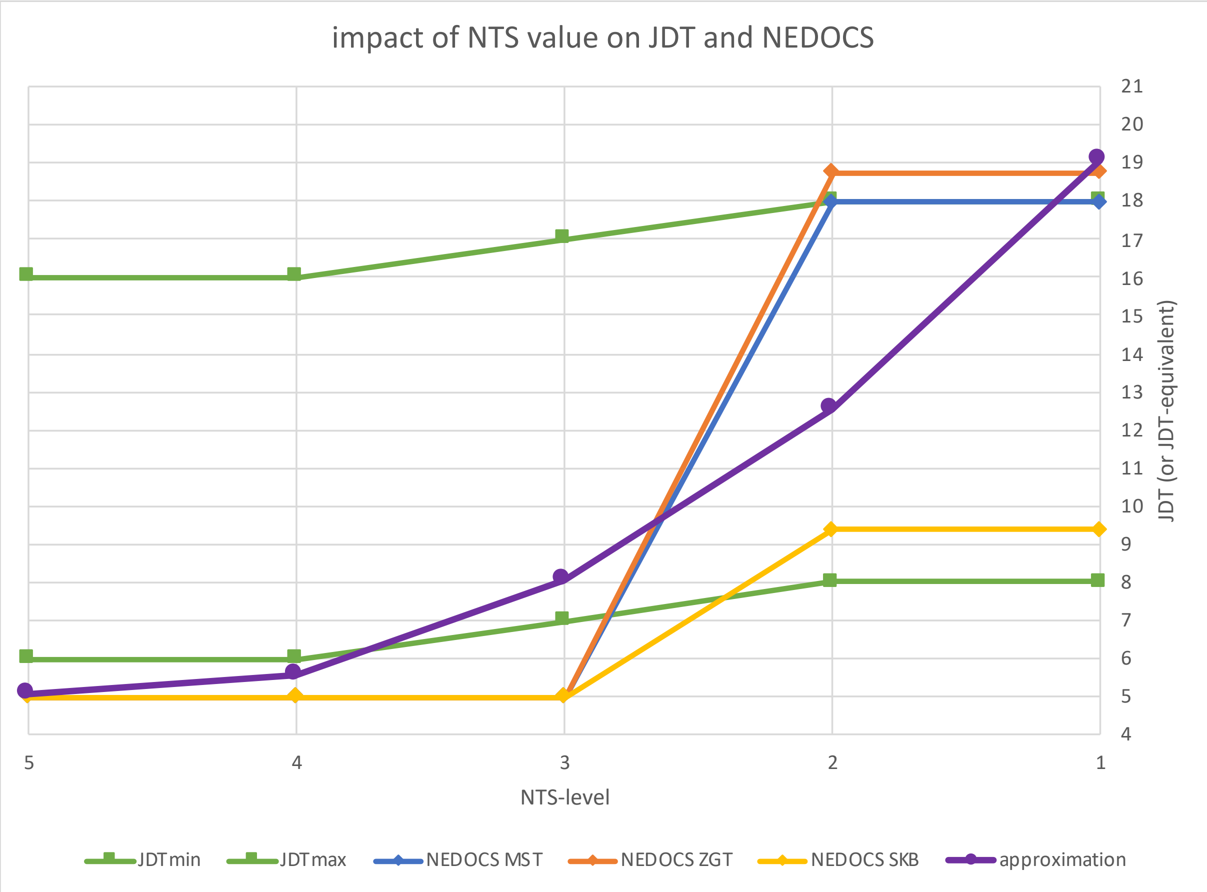


Figure 4: approximation of care demand based on JDT and NEDOCS

4.1.2 Staffing

To compare the care demand with staffing, information was gathered from the planning departments of all three EDs. All three hospitals work with layered schedules with various starting points for shifts. This is done to cover expected demand peaks based on experience. Although all three hospitals have a fairly constant base planning, a few deviations exist. ZGT works with the same layered schedule throughout the year, with a deviating schedule on Sundays. MST also works with a standard schedule, but also has a deviating schedule for Sundays with one nurse less. Furthermore, MST also has a separate schedule for during the summer (week 30 until week 35) with a lower number of nurses during the day. Based on the shift start and end times, it can be determined how much nursing staff is present at the ED at every 15-minute interval. In the case of all three hospitals, shift overlaps of 15 to 30 minutes occur. However, because of patient transfers and start-up activities it would be inaccurate to count this overlap as additional operational nursing staff. Therefore, the number of nurses was smoothed over to the average from before and after the spike due to overlap and rounded to a full nurse. A comparison of the regular staffing levels can be found in Figure 5.

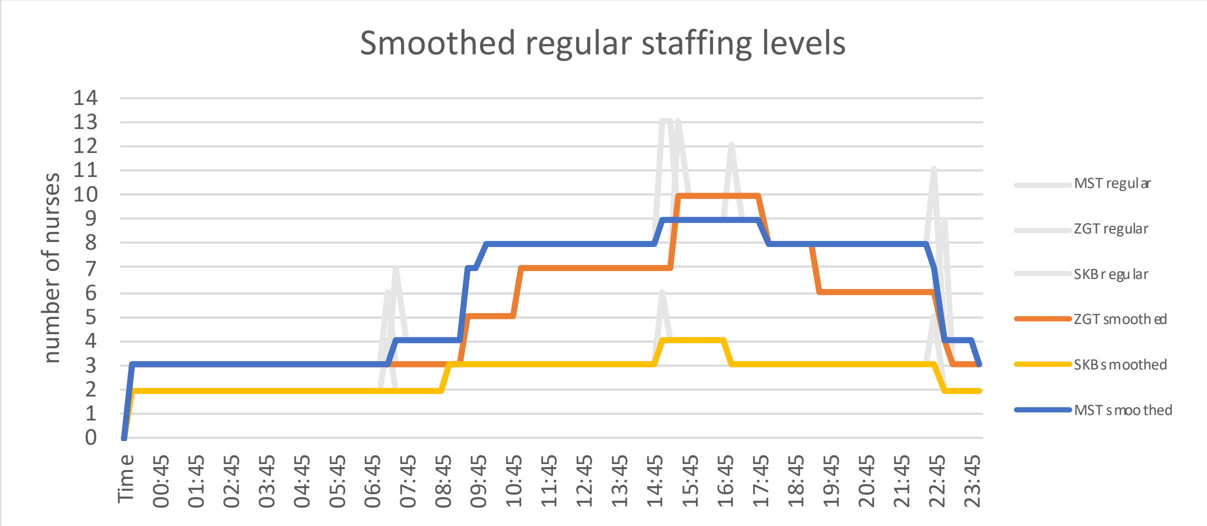


Figure 5: smoothed regular staffing levels throughout the day.

4.2 Data cleaning

In preparation of the data analysis, some of the data points had to be altered due to missing, incorrect or corrupt data. The changelog before data analysis is included in Table 1.

Table 1: changelog of data cleaning

issue	#MST	#SKB	#ZGT	solution
Missing start of treatment time	62	46	45	Substituted with triage time
Missing triage time	175	64	609	Substituted with start of treatment time
Missing start of treatment and triage	11	11	23	Substituted with arrival time of patient
Data point at 28-03-2022 02:55:00 (moment in time doesn't exist due to summer/wintertime)			1	Substituted with 28-03-2022 03:55:00

4.3 Findings

The following section outlines the findings from the data analysis. First, the overall patient mix is discussed. After that, the demand across time is analysed on various levels and compared to staffing. An analysis on the variability in care load is included to see whether pooling would theoretically be beneficial. Lastly, a distribution is fitted to the care load per hour for use in the model.

4.3.1 Patient mix

When looking at the statistics of all patients as presented in Figure 6, some things that are to be expected become apparent. First, SKB sees significantly fewer patients than MST and ZGT, with 11,536 versus 23,056 and 30,212 in 2022 respectively. Second, MST sees significantly more patients with u0 status, which is in line with its role as a level 1 hospital. However, with fewer than one patient per day with this status and the other hospitals also still receiving a non-neglectable number of patients with this status the difference is smaller than some stakeholders perceive it to be.

Conversely, it is of interest to mention that ZGT sees significantly more patients with lower triage levels (u3,u4 and u5). Both in absolute numbers, as well as in relative percentages a significant difference compared to SKB and MST can be identified. A potential explanation mentioned by the nursing staff is the large number of elderly patients that ZGT sees, but this is not supported by data. Furthermore, some ambiguity exists on what criteria are used to give patients a certain NTS-triage level across the different hospitals in the Euregio even though it is standardised. Nurses have expressed that the patients with u5 could often also be seen by a general practitioner

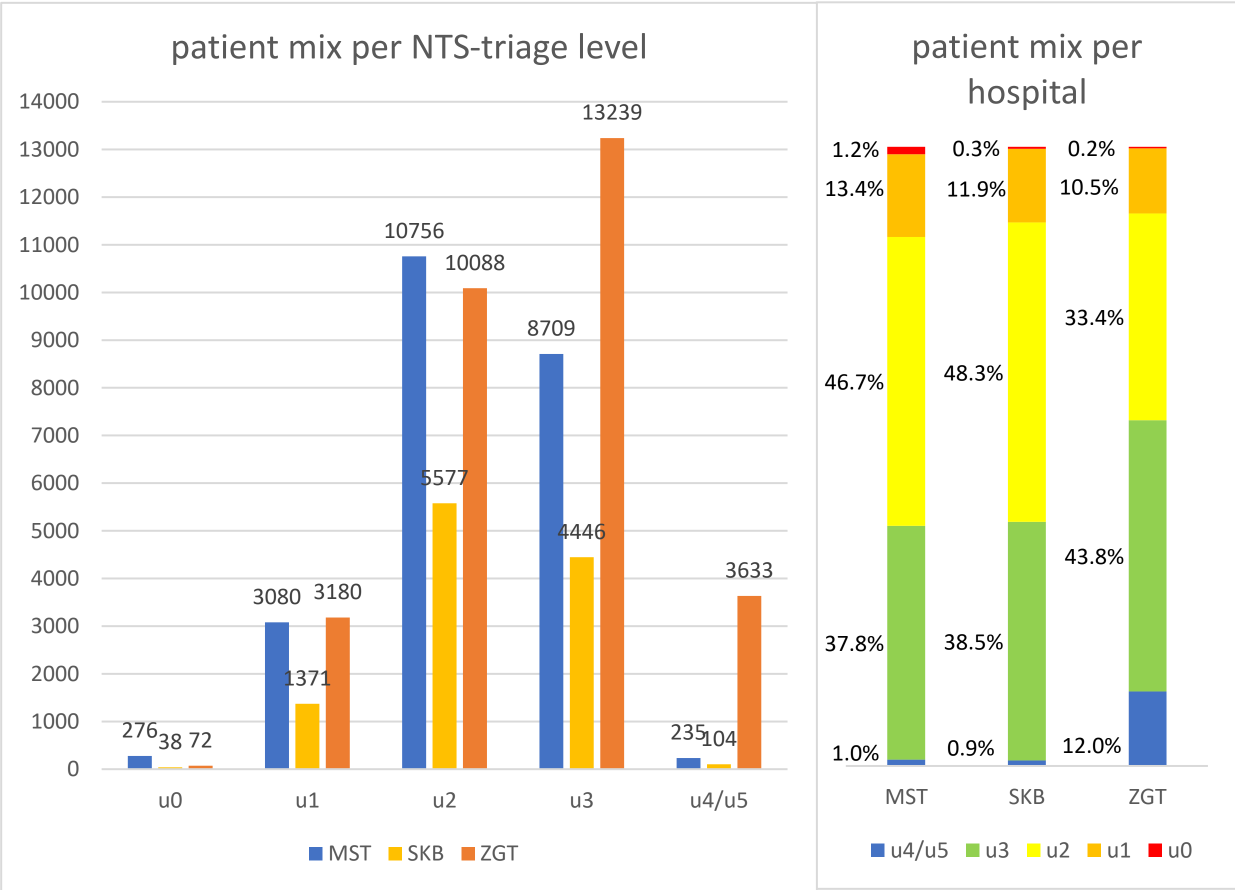


Figure 6: Patient mix per NTS-triage and per hospital

4.3.2 Demand across time

Because the dataset is only complete for one year, it is hard to draw conclusions regarding demand patterns throughout the year. When looking at the average care load across the year in Figure 7, large fluctuations can be observed. Except for a potential decrease in demand during the summer holidays, no clear patterns appear to be present. This ties in with the special summer holiday rosters that MST has.

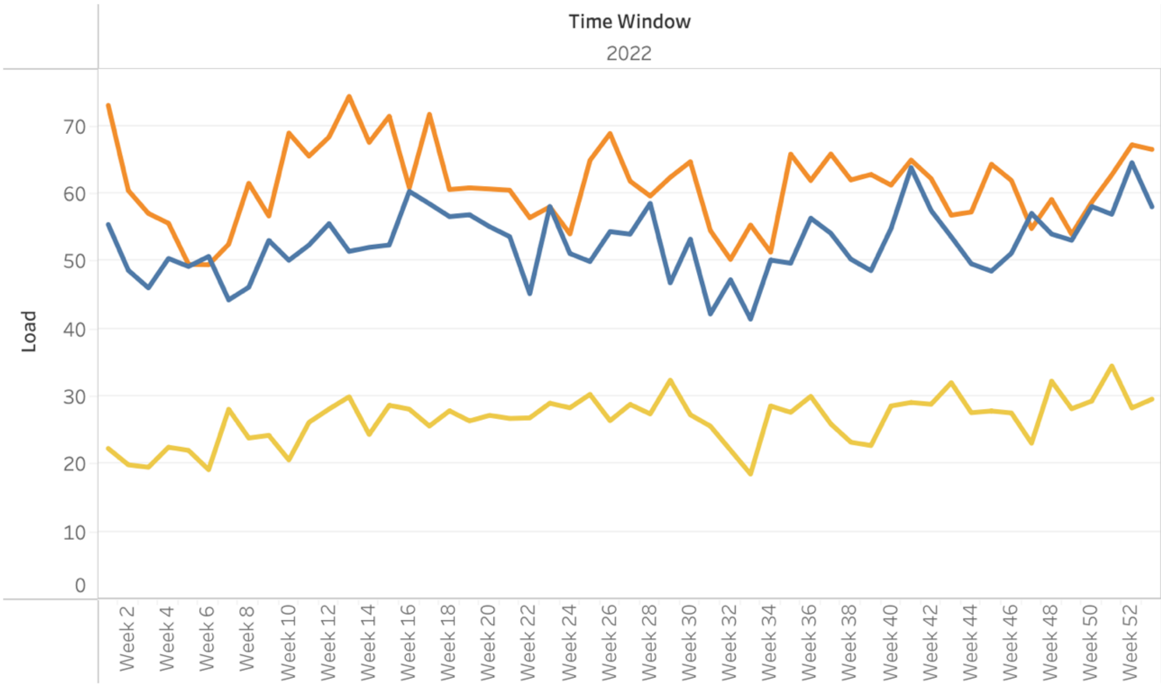


Figure 7: Average Care load per week for MST (blue), SKB (yellow) and ZGT (orange)

When looking at the week level, which is the level most relevant for creating the nursing schedules, more patterns can be identified. In Figure 8, it becomes apparent that the demand follows a similar pattern throughout each day. A distinction between weekdays and the weekend can be identified, but within these two groups the demand per hour is similar. Slightly more demand is observed on Mondays and Fridays at ZGT and SKB, which aligns with SKBs decision to deploy extra staff during these days. During the weekend, the peak demand is earlier than on weekdays. This is to be expected due to regular working hours of most potential patients not being applicable on these days.

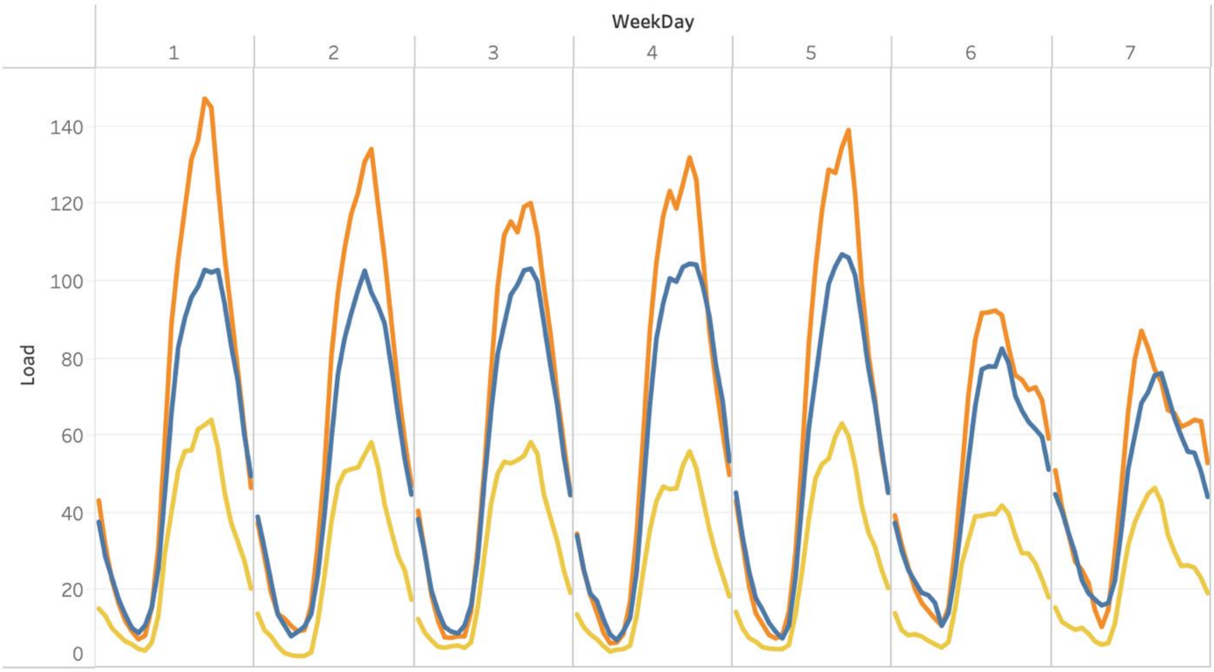


Figure 8: Average Care load per weekday for MST (blue), SKB (yellow) and ZGT (orange)

When looking at the demand per hour in Figure 9, the three hospitals again show similar patterns. The largest peak of patients is at the end of the afternoon for all hospitals. This then sharply decreases as the evening progresses. The low point for all hospitals is during the early morning between 5:00 and 7:00, after which demand slowly increases again. Both ZGT and MST experience a slight dip in the increase around 15:00. This could be linked to the way general practitioners refer their patients at certain moments in time. Although not entirely the same, it is safe to say that demand across the hours follows similar patterns for all hospitals.

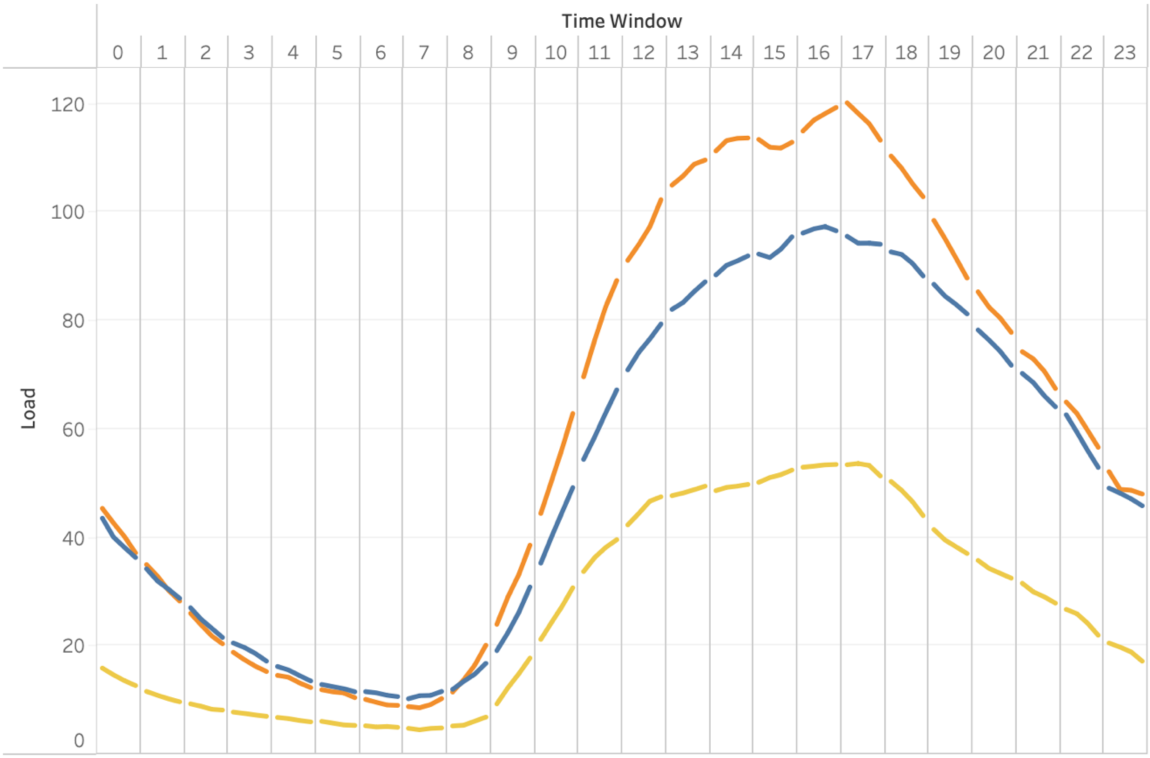


Figure 9: Average Care load per hour for MST (blue), SKB (yellow) and ZGT (orange)

When comparing the demand to the staffing levels of each hospital in Figure 10, we can see that even though the demand is very similar, the staffing response is different in each hospital. Most notably, the staffing increase throughout the day at ZGT is more aggressively sloped where MST and SKB choose to have a more stable staffing level. This ensures that ZGT's staffing levels follow the demand curve more closely. However, starting from around 12:00 care load is almost as high as the rest of the afternoon until 17:00 whilst staffing is significantly lower at that point. Conversely, MST could be considered "overstaffed" during the early morning and late afternoon when compared to their peak hours. Expectedly, the variations in both demand and staff at SKB are less pronounced than at the larger two hospitals. It appears that the extra shift for Mondays and Friday during the day follows the demand pattern almost exactly. However, the standard overlap in shifts to account for the afternoon peak appears to take place just before the actual peak.

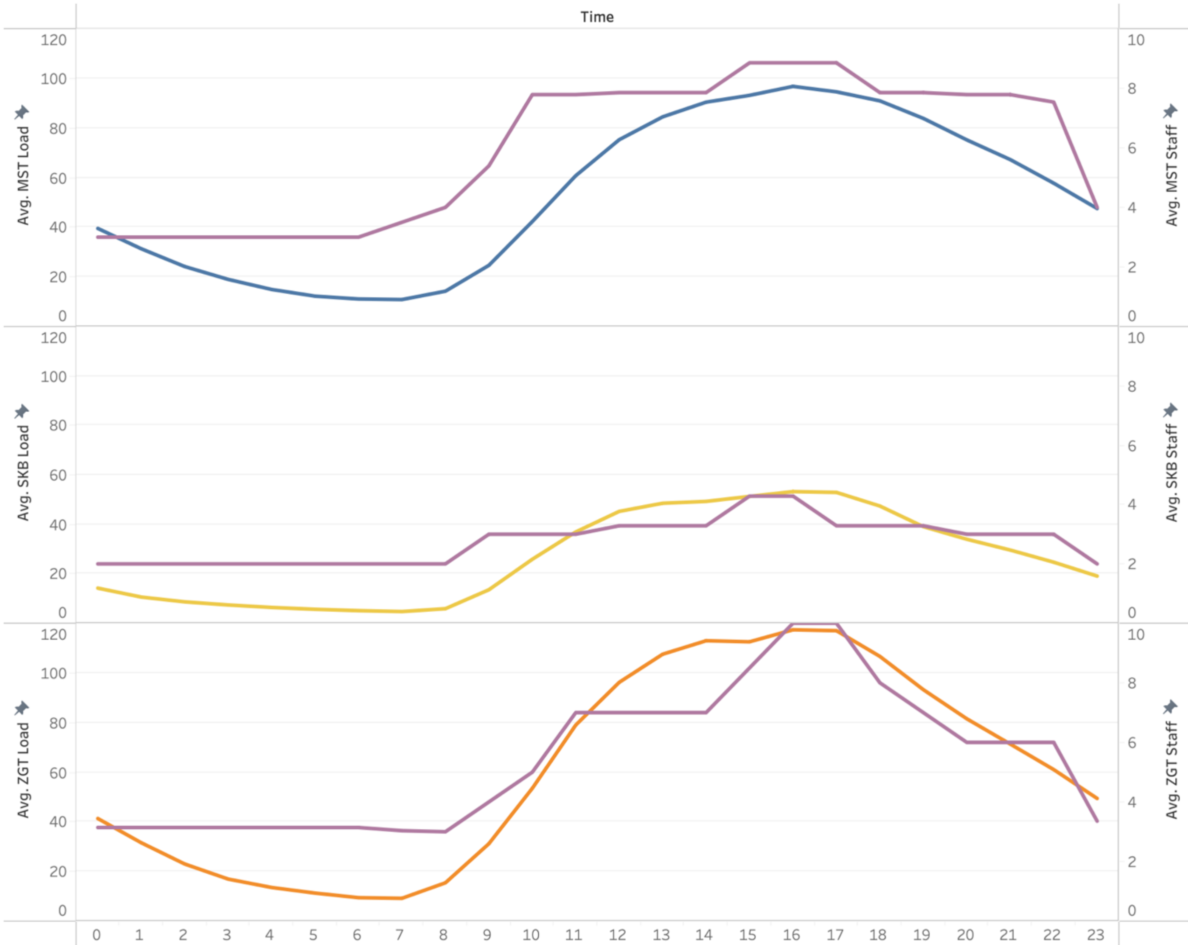


Figure 10: Care load (in blue for MST, yellow for SKB and orange for ZGT) compared to staffing per hour in purple

4.3.3 Analysis on variability

To compare the variability across the hospitals and across time and evaluate the theoretical benefit of risk pooling, the standard deviation of care load is plotted in Figure 11. Next, the pooled standard deviation of the total care load in the Euregio is plotted. This can be considered the variation if we were to regard the whole region as one big hospital. The corresponding formal expression is:

$$\sqrt{\frac{1}{size(t)} * \sum_t \left(E\left(\sum_h l_{h,t}\right) - \sum_h l_{h,t}\right)^2}$$

Where t is a set of given time windows, h the set of hospital and $l_{h,t}$ represents the observed care load at that h and t. Additionally, the cumulative standard deviation of the hospitals is calculated by adding the variances of each hospital and taking the square root, which can be expressed as:

$$\sum_h \sqrt{\frac{1}{size(t)} * \sum_t \left(E(l_{h,t}) - l_{h,t}\right)^2}$$

This way, an assessment can be made on the benefits in terms of variability should one consider the EDS in the Euregio as one pooled system rather than three separate hospitals.

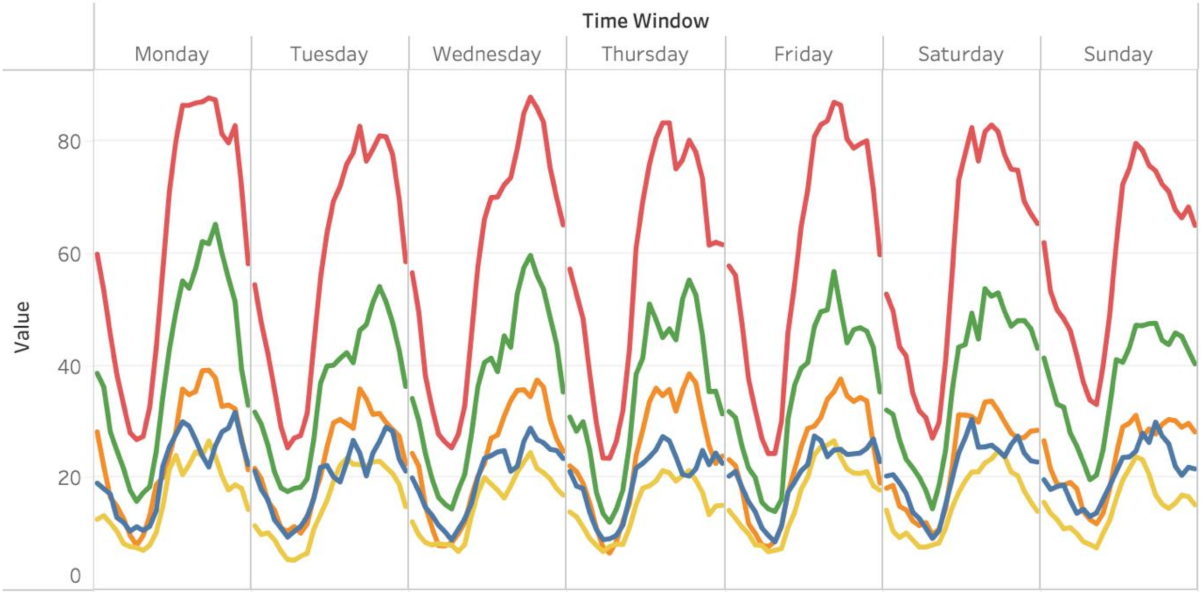


Figure 11: Standard Deviation of care load per weekday for MST (blue), SKB (yellow), ZGT (orange), pooled load (green) and cummulative standard deviations (red)

From Figure 11 we can see that the pooled variability of the region in green is significantly lower across each moment in time than the cumulative variability in red. However, the greatest differences appear to be present during the afternoon. This corresponds with the demand patterns identified earlier. Even though demand is significantly lower during the weekend as seen in Figure 8, cumulative variability during the weekend appears to be only marginally lower. Pooled variability in the weekend is lower in comparison as well. The least amount of theoretical benefit from pooling can be achieved on Mondays, as the pooled variability remains comparatively high. Notable in Figure 11 is the fact that even though the mean care load in in SKB is significantly lower, the standard deviation appears to be close to MST on most days. Consequently, the coefficient of variation, as presented in Figure 12 is noticeably higher at SKB. This can partly be explained by the fact that the number of patients at SKB is significantly lower, and thus the standard deviation and coefficient of variation is higher. When looking at absolute numbers, for example in Figure 13, the range at SKB is still comparatively small, but it does show some extreme outliers.

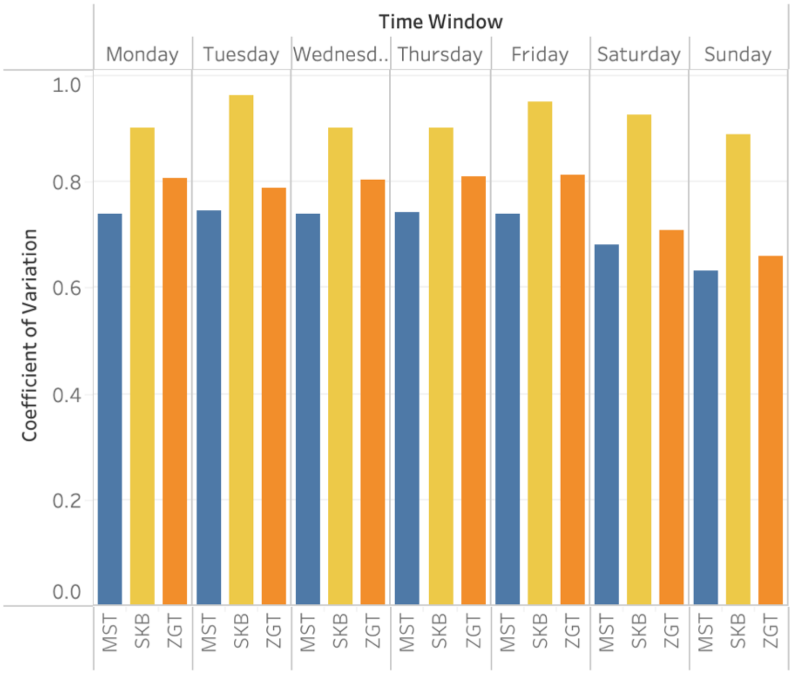


Figure 12: Coefficient of variation per weekday, per hospital

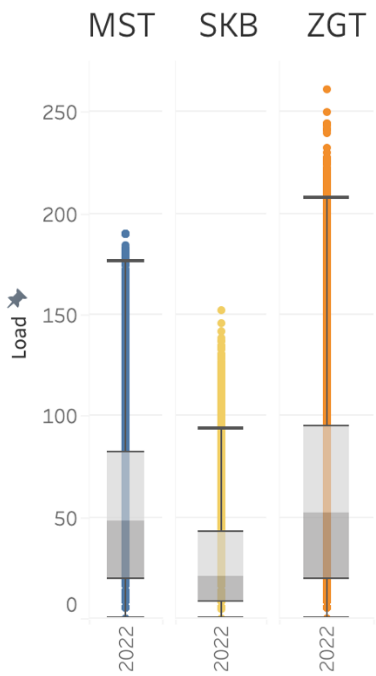


Figure 13: Boxplot on individual care load observations

4.4 Distribution per hour

To be able to model the situation of AZE mathematically in such a way that it remains solvable in acceptable time, the data is analysed per hour. For each of the hours in a day at each hospital a Gamma distribution can be fitted. The choice for the Gamma distribution is made due to multiple characteristics. The fact that it accepts values starting from 0 and up to infinity as the probability approaches 0 fits the nature of care load. Furthermore, the parameters can be chosen as such that the peak of care load can move around whilst still including 0 and infinity in the distribution. Lastly, conceptually a Gamma distribution can be considered applicable as it can be used to model the accumulation of independent stochastic events (Larsen & Marx, 2012). In our case this would be the accumulation of the care load of individual patients present at the same time.

When attempting to fit the distribution to various time periods, the goodness of fit was judged based on a histogram, Q-Q plot, P-P plot and Cumulative density function plot as included in Figure 14. From these figures, it can be concluded that the Gamma distribution offers a good fit to the data. Some slight irregularities exist for time windows with a low number of patients, which can be explained by the way the care load was approximated. The care load per patient knows a minimal value and is not continuous. This causes the observed care load to jump where the theoretical distribution is smooth. However, in reality the care load can also be considered a continuous curve.

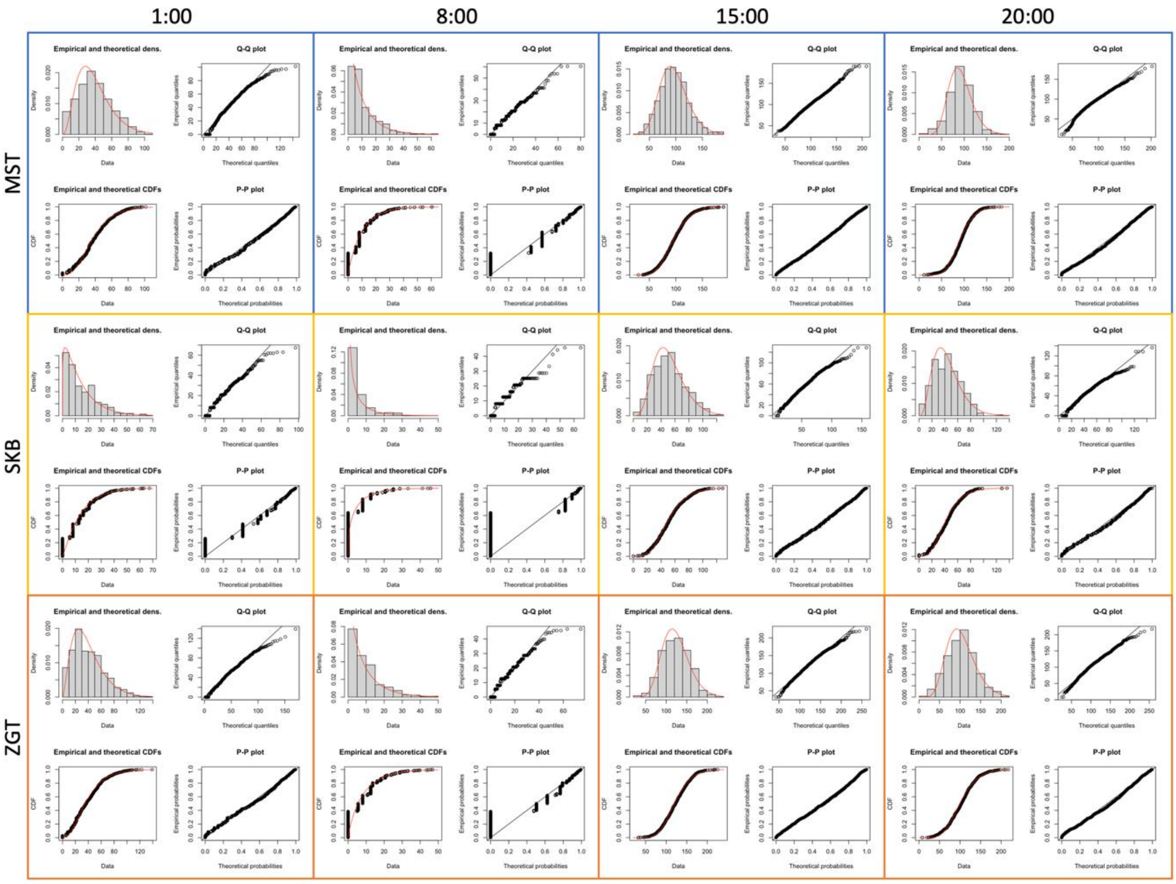


Figure 14: Gamma distribution fitting for weekdays at 1:00, 8:00, 15:00, 20:00 (x-axis) for MST, SKB and ZGT (y-axis)

4.5 Conclusion

The data shows that the hospitals in the Euregio experience different patient mixes. Most notably, ZGT sees vastly more patients with low urgency. Second, the fraction of patients at MST with u0 and u1 seems lower than generally thought. Lastly, SKB has a significantly lower care load, which is to be expected from the regional hospital. When looking at care load across time, the hospitals have comparable patterns. On a per day level, the largest peak exists in the afternoon, which is to be expected. The weekend days appear to be less busy for all three hospitals and the peak of care load appears to be slightly earlier. Due to the limited data set no real conclusions can be drawn on seasonality across the year. When comparing the care load across a day to staffing, some slight mismatches can be identified. Analysis on the standard deviation across a week shows that theoretically a float pool could make use of the reduced pooled variability. It is to be expected that different results will be achieved during the weekend as opposed to during weekdays. For modelling demand across an hour, using the Gamma distribution is applicable.

5 Model

The following chapter aims to answer the research question *In what way can the effectiveness of an ED float pool best be modelled?* First, the choice for the model that has been formulated will be explained. After that the definition of the model is given and remarks regarding the model are discussed.

5.1 Model choice

Based on the literature review, analysis of the processes at the EDs and the characteristics of demand two modelling options remain that would be most interesting for researching the effectiveness of an ED float pool: stochastic programming and discrete event simulation. Since AZE is in the early stages of considering an ED float pool, the strategic and tactical insights that a stochastic programming model can offer are considered more relevant at this time.

The model presented in this chapter is able take the demand per time period, and the staff available across the set of EDs as input to create an optimal, or near optimal roster. At the same time, it can evaluate various decisions. Firstly, the model can evaluate the benefit of varying flexibility ratios. The model can also be executed using different cross-training policies. Since EDs have varying starting moments for shifts to accommodate for demand fluctuations and staffing structure varies across EDs, the model is formulated in such a way that it can optimally decide on when shifts should start.

The model works under the assumption that the float pool design as discussed in chapter 4 will be implemented. This means that the choice for number of float nurses and cross training policy will be decided beforehand. The allowed number of float shifts will then be placed optimally in the rosters of the EDS. Because these schedules repeat per day, shifts can start at any moment and continue into the next day for their full duration. After demand is realised, the decision to move a float nurse can also be taken. Other mentioned measures of dealing with fluctuation in demand are not incorporated into the model. As discussed before, these are often considered less favourable. Furthermore, the aim is to research the impact of a float pool, which is better achieved when isolating this option.

To model the relocation decisions after demand has been realised, the model is formulated as a two-stage problem, which is illustrated in figure 15. The first stage decisions are at which time and to which hospital to allocate nursing shifts, both dedicated as well as float. The second stage decisions are if and how to relocate available float staff after demand realisation.

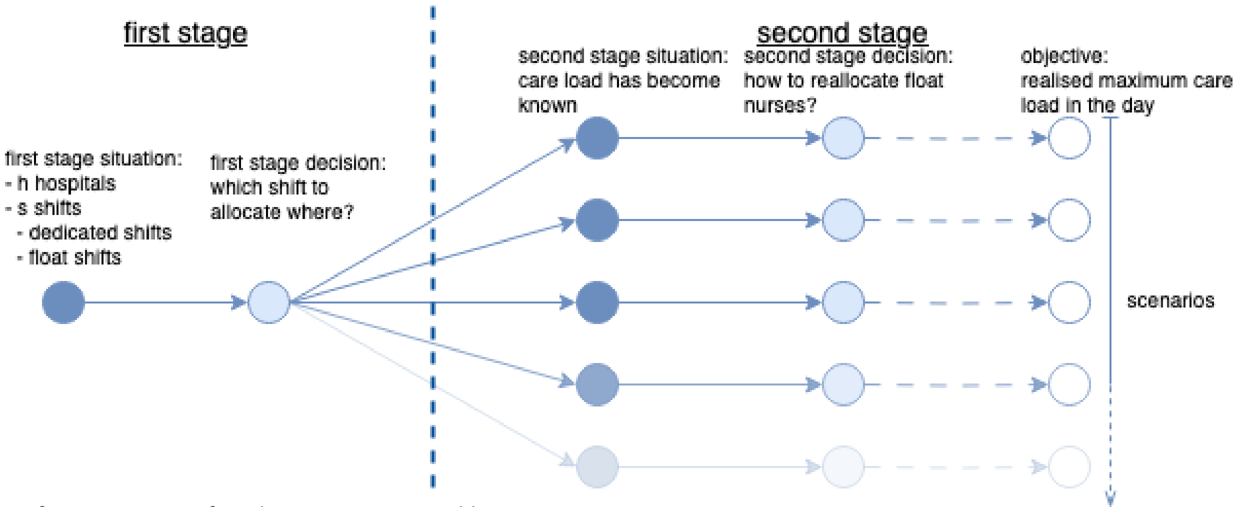


figure 15: Setup of stochastic two-stage problem

To incorporate the effects of different flexibility ratios, the model is formulated as a multi-objective problem using an epsilon constraint. The main objective is to minimise the maximum workload observed across all time windows and hospitals as expressed in workload minus nursing capacity. This relates to JDT load, the (non-linear) KPI that the hospitals are used and can be derived in the following manner:

$$JDT_{load} = \frac{objective\ value}{(w * n)} + 1$$

With *w* representing the workload a nurse can be responsible for, and *n* representing the number of nurses present. The JDT load as shown in the hospital is the cumulative JDT scores divided by the cumulative nursing capacity available. This yields a score from 0 to 1[3]. Our linear objective function will take on non-normalised values, where negative values imply that JDT load is not exceeding 1, and the more negative the value is, the better the JDT load KPI would perform as well.

The secondary (epsilon) objective is to minimise the number of float shifts that is allowed. The applicable cross-training policy can be incorporated via a cross-training matrix that is used in a constraint in the model.

5.2 Model definition

5.2.1 Mathematical model

5.2.1.1 Objective function

Minimise the maximum expected care load minus all types of capacity allocated across all hospitals and time windows:

$$\min \max_{h \in H, t \in T} E\left[l_{h,t} - (w * d_{h,t} + w * (f_{h,t} - \sum_{h'} r_{h,h',t}) + w * a * \sum_{h'} r_{h',h,t}) \right]$$

5.2.1.2 Sets

T: time windows
H: hospitals
S: nurse shifts available

5.2.1.3 Parameters

$l_{h,t}$: care load at hospital h at time window t
c_h: capacity of hospital h
a: inefficiency factor for floating
w: care load that a nurse can be responsible for
M: sufficiently large integer
$minn_h$: minimum number of nurses at hospital h at any time
SL: maximum shift length

[3] In theory, the value could exceed 1 if the ratio of load and capacity becomes too small, but the visual meter which is shown in the hospitals does not account for this.

RMax: maximum number of relocations allowed per shift
epsilon: amount of float shifts allowed (for multi-objective analysis)
$e_{h,h'}$: 1 if cross-training between h and h' is enabled, else 0.

5.2.1.4 Decision variables

$s\_d_{s,h,t}$: 1 if nurse s is starting a dedicated shift in hospital h at timewindow t, else 0
$s\_f_{s,h,t}$: 1 if nurse s is starting a float shift in hospital h at timewindow t, else 0
$s\_r_{s,h,h',t,}$: 1 if nurse s is relocated from hospital h to h' in at timewindow t, else 0

$p\_d_{s,h,t}$: 1 if nurse s is present as dedicated shift at timewindow t in hospital h, else 0
$p\_f_{s,h,t}$: 1 if nurse s is present float shift at timewindow t in hospital h, else 0
$p\_r_{s,h,h',t,}$: 1 if nurse s is present via relocation at timewindow t from hospital h to h' in scenario k, else 0

$d_{h,t}$: number of nurses as a dedicated shift at timewindow t in hospital h
$f_{h,t}$: number of nurses as a float shift at timewindow t in hospital h
$r_{h,h',t,}$: number of nurses relocated at timewindow t from hospital h to h'

5.2.1.5 Constraints

Number of staff constraints

Number of staff can't be more than staff present:

$$d_{h,t} \leq \sum_s p\_d_{s,h,t} \;\forall\, h,t \;(1)$$

$$f_{h,t} \leq \sum_s p\_f_{s,h,t} \;\forall\, h,t \;(2)$$

$$r_{h,h',t} \leq \sum_s p\_r_{s,h,h',t} \;\forall\, h,t\; h' \neq h \;(3)$$

Number of dedicated nurses allocated cannot be lower than set threshold:

$$d_{h,t} \geq \; minn_h \;\forall\, t \;(4)$$

Shift allocation constraints

A shift can only be started once:

$$\sum_h \sum_t s\_d_{s,h,t} + \sum_h \sum_t s\_f_{s,h,t} \leq 1 \;\forall\, s \;(5)$$

Including float staff, no more staff than the total available staff can be allocated:

$$\sum_s \sum_h \sum_t s\_d_{s,h,t} + \sum_s \sum_h \sum_t s\_f_{s,h,t} \leq \sum_h c_h \;\; (6)$$

Hospitals can't deploy more staff than their own staff:

$$\sum_s \sum_t s\_d_{s,h,t} \leq \; c_h \;\forall\, h \;(7)$$

Number of float shifts can't exceed epsilon:

$$\sum_s \sum_h \sum_t s\_f_{s,h,t} < \varepsilon \ (8)$$

Shift allocation to present constraints

A nurse can only be present in a time window if already present before, or when starting at that time window:

$$p\_d_{s,h,t} \leq p\_d_{s,h,t-1} + s\_d_{s,h,t} \ \forall \ s,h,t > 1 \ (9)$$
$$p\_f_{s,h,t} \leq p\_f_{s,h,t-1} + s\_f_{s,h,t} \ \forall \ s,h,t > 1 \ (10)$$
$$p\_d_{s,h,t} \leq p\_d_{s,h,t_{max}} + s\_d_{s,h,t} \ \forall \ s,h,t = 1 \ (11)$$
$$p\_f_{s,h,t} \leq p\_f_{s,h,t_{max}} + s\_f_{s,h,t} \ \forall \ s,h,t = 1 \ (12)$$

Number of time windows allocated cannot exceed maximum shift length:

$$\sum_h \sum_t p\_d_{s,h,t} + \sum_h \sum_t p\_f_{s,h,t} \leq SL \ \forall \ s \ (13)$$

Relocation constraints

Relocation can only happen if cross-training is enabled:

$$s\_r_{s,h,h',t} \leq M * e_{h,h'} \ \forall s,t \ (14)$$

Number of relocations per shift is limited to RMax:

$$\sum_h \sum_{h'} \sum_t s\_r_{s,h,h',t} \leq Rmax \ \forall \ s \ (15)$$

Float staff is only floated to one hospital if reallocation has already happened, or relocation choice is made at this time window:

$$p\_r_{s,h,h',t} \leq p\_f_{s,h,h',t-1} + s\_r_{s,h,t} \ \forall \ s,h, \ h' \neq h, t > 1 \ (16)$$
$$p\_r_{s,h,h',t} \leq p\_f_{s,h,t_{max}} + s\_r_{s,h,h',t} \forall \ s,h,h' \neq h, t = 1 \ (17)$$

Staff can only be reallocated to one hospital and if present as relocated staff at time window t if already planned as float staff:

$$\sum_{h'} p\_r_{s,h,h',t} \leq p\_f_{s,h,t} \ \forall s,h,t \ (18)$$

Sign constraints

Positive variables:

$$maxW \geq 0 \ (19)$$

Integer variables:

$$d_{h,t} \ , f_{h,t} \geq 0, integer \ \forall h,t \ (20)$$
$$r_{h,h',t} \geq 0, integer \ \forall h,h',t \ (21)$$

Binary variables:

$$p\_r_{s,h,h',t} \ , s\_r_{s,h,h',t} \ \in (0{,}1) \ \forall \ s,h,h',t \ (22)$$
$$p\_d_{s,h,t} \ , \ s\_d_{s,h,t}, \ p\_f_{s,h,t}, \ s\_f_{s,h,t} \ \in (0{,}1) \ \forall \ s,h,t \ (23)$$

5.2.2 Linearisation

The model formulated is not linear, and thus cannot be solved by a linear solver. Since finding an optimal solution to the objective function is best done with a linear solver, the model is linearised as follows.

Original objective:

$$\min \max_{h\in H, t\in T} E\left[l_{h,t} - (w * d_{h,t} + w * (f_{h,t} - \sum_{h'} r_{h,h',t}) + w * a * \sum_{h'} r_{h',h,t})\right]$$

To deal with the stochasticity, the model is transformed into a scenario-based model. For this the set k, containing all second stage scenarios on which decision making should be based is added. Each scenario that is included will be multiplied by the probability p_k, which is equal to 1 divided by the size of the set k. The demand will now be different for each scenario k, along with the second stage decision variables r and its helping variables s_r and p_r, since in every scenario a different decision will be made. The objective function thus becomes:

$$\min \max_{h\in H, t\in T} \sum_{k} p_k * (l_{h,t,k} - (w * d_{h,t} + w * (f_{h,t} - \sum_{h'} r_{h,h',t,k}) + w * a * \sum_{h'} r_{h',h,t,k}))$$

To linearly reflect the minimax objective, the variable $maxW_k$ is introduced, along with constraint (i). This changes the objective function into:

$$\min \sum_{k} p_k * maxW_k$$
$$s.t.$$
$$\left(l_{h,t,k} - \left(w * d_{h,t} + w * \left(f_{h,t} - \sum_{h'} r_{h,h',t,k}\right) + w * a * \sum_{h'} r_{h',h,t,k}\right)\right) \le maxW_k \ \forall\, h, t, k \ (i)$$

The added set k also has influence on constraints (3), (14), (15), (16), (17),(18),(22) and (23). The fully linearised model is included below.

5.2.3 Scenario based linear model

5.2.3.1 Objective function

Minimise the maximum expected care load minus all types of capacity allocated across all hospitals and time windows:

$$\min \sum_{k} p_k * maxW_k$$
$$s.t.$$
$$\left(l_{h,t,k} - \left(w * d_{h,t} + w * \left(f_{h,t} - \textstyle\sum_{h'} r_{h,h',t,k}\right) + w * a * \textstyle\sum_{h'} r_{h',h,t,k}\right)\right) \le maxW_k \ \forall\, h, t, k \ (i)$$

5.2.3.2 Sets

T: time windows

H: hospitals
S: nurse shifts available
K: scenarios

5.2.3.3 Parameters

$l_{h,t,k}$: care load at hospital h at time window t in scenario k
c_h: capacity of hospital h
a: inefficiency factor for floating
w: care load that a nurse can be responsible for
p_k: probability of scenario k
M: sufficiently large integer
$minn_h$: minimum amount of nurses at hospital h at any time
SL: maximum shift length
RMax: maximum amount of relocations allowed per shift
epsilon: amount of float shifts allowed (for multi-objective analysis)
$e_{h,h'}$: 1 if cross-training between h and h' is enabled, else 0.

5.2.3.4 Decision variables

$maxW_k$: maximum workload observed across all hospitals and timewindows in scenario k
$s\_d_{s,h,t}$: 1 if nurse s is starting a dedicated shift in hospital h at timewindow t, else 0
$s\_f_{s,h,t}$: 1 if nurse s is starting a float shift in hospital h at timewindow t, else 0
$s\_r_{s,h,h',t,k}$: 1 if nurse s is relocated from hospital h to h' in at timewindow t in scenario k, else 0

$p\_d_{s,h,t}$: 1 if nurse s is present as dedicated shift at timewindow t in hospital h, else 0
$p\_f_{s,h,t}$: 1 if nurse s is present float shift at timewindow t in hospital h, else 0
$p\_r_{s,h,h',t,k}$: 1 if nurse s is present via relocation at timewindow t from hospital h to h' in scenario k, else 0

$d_{h,t}$: number of nurses as a dedicated shift at timewindow t in hospital h
$f_{h,t}$: number of nurses as a float shift at timewindow t in hospital h
$r_{h,h',t,k}$: number of nurses relocated at timewindow t from hospital h to h' in scenario k

5.2.3.5 Constraints

Number of staff constraints

Number of staff can't be more than staff present:

$$d_{h,t} \leq \sum_{s} p_{d_{s,h,t}} \ \forall\, h,t\ (1)$$

$$f_{h,t} \leq \sum_{s} p_{f_{s,h,t}} \ \forall\, h,t\ (2)$$

$$r_{h,h',t,k} \leq \sum_{s} p_{r_{s,h,h',t,k}} \ \forall\, h,t,k\ h' \neq h\ (3)$$

Number of dedicated nurses allocated cannot be lower than set threshold:

$$d_{h,t} \geq\ minn_h \ \forall\, t\ (4)$$

Shift allocation constraints

A shift can only be started once:

$$\sum_{h}\sum_{t} s\_d_{s,h,t} + \sum_{h}\sum_{t} s\_f_{s,h,t} \leq 1 \; \forall \; s \; (5)$$

Including float staff, no more staff than the total available staff can be allocated:

$$\sum_{s}\sum_{h}\sum_{t} s\_d_{s,h,t} + \sum_{s}\sum_{h}\sum_{t} s\_f_{s,h,t} \leq \sum_{h} c_h \;\; (6)$$

Hospitals can't deploy more staff than their own staff:

$$\sum_{s}\sum_{t} s\_d_{s,h,t} \leq \; c_h \; \forall \; h \; (7)$$

Number of float shifts can't exceed epsilon:

$$\sum_{s}\sum_{h}\sum_{t} s\_f_{s,h,t} < \; \varepsilon \; (8)$$

Shift allocation to present constraints

A nurse can only be present in a time window if already present before, or when starting at that time window:

$$p\_d_{s,h,t} \leq \; p\_d_{s,h,t-1} + s\_d_{s,h,t} \; \forall \; s, h, t > 1 \; (9)$$
$$p\_f_{s,h,t} \leq p\_f_{s,h,t-1} + s\_f_{s,h,t} \; \forall \; s, h, t > 1 \; (10)$$
$$p\_d_{s,h,t} \leq p\_d_{s,h,t_{max}} + s\_d_{s,h,t} \; \forall \; s, h, t = 1 \; (11)$$
$$p\_f_{s,h,t} \leq \; p\_f_{s,h,t_{max}} + s\_f_{s,h,t} \; \forall \; s, h, t = 1 \; (12)$$

Number of time windows allocated cannot exceed maximum shift length:

$$\sum_{h}\sum_{t} p\_d_{s,h,t} + p\_f_{s,h,t} \leq SL \; \forall \; s \;\; (13)$$

Relocation constraints

Relocation can only happen if cross-training is enabled:

$$s\_r_{s,h,h',t,k} \leq M * e_{h,h'} \; \forall s, t, k \; (14)$$

Number of relocations per shift is limited to RMax:

$$\sum_{h}\sum_{h'}\sum_{t} s\_r_{s,h,h',t,k} \leq Rmax \; \forall \; s, k \; (15)$$

Float staff is only floated to one hospital if reallocation has already happened, or relocation choice is made at this time window:

$$p\_r_{s,h,h',t,k} \leq \; p\_f_{s,h,h',t-1,k} + s\_r_{s,h,t,k} \; \forall \; s, h, k, h' \neq h, t > 1 \; (16)$$
$$p\_r_{s,h,h',t,k} \leq \; p\_f_{s,h,t_{max},k} + \; s\_r_{s,h,h',t,k} \; \forall \; s, h, k, h' \neq h, t = 1 \; (17)$$

Staff can only be reallocated to one hospital and if present as relocated staff at time window t if already planned as float staff:

$$\sum_{h'} p\_r_{s,h,h',t,k} \leq p\_f_{s,h,t} \; \forall s,h,t,k \; (18)$$

Sign constraints

Positive variables:

$$maxW_k \geq 0 \; \forall k \; (19)$$

Integer variables:

$$d_{h,t}\,, f_{h,t} \geq 0, integer \; \forall h,t \; (20)$$

$$r_{h,h',t,k} \geq 0, integer \; \forall h,h',t,k \; (21)$$

Binary variables:

$$p\_r_{s,h,h',t,k}\;, s\_r_{s,h,h',t,k} \;\in (0,1) \;\; \forall\, s,h,h',t,k \; (22)$$

$$p\_d_{s,h,t}\;,\; s\_d_{s,h,t},\; p\_f_{s,h,t},\; s\_f_{s,h,t} \;\in (0,1) \; \forall\, s,h,t \; (23)$$

5.3 Conclusion

The model proposed in this chapter can offer insights into the strategic and tactical decisions regarding a float pool for ED nurses. However, it has some limitations. First, even though the time windows are modelled separately from each other, the model assumes that demand is known fully after the first stage. The relocation after initial planning is thus made under perfect information. Furthermore, the travel time associated with relocation is neglected in the model as well. The inefficiency factor for relocation is included to partly account for these two factors. However, the implications of these simplifications could be further explored in a separate model.

6 Experimentation

The current chapter answers the research question: *What will the optimal configuration and performance be of relevant float pool designs compared to the current situation at AZE?* To do so the model formulated in chapter 5 is used with a setup that is related to the situation in the Euregio. This setup is described first. After that, it is discussed which method has been chosen to create statistically useable results, as well as how the model has been implemented and solved. The experimental design is discussed afterwards. This is based on the conclusions of the previous chapters, and discussion with stakeholders at AZE on which situations are of most interest. The conclusions of the experiments are discussed last.

6.1 Setup

The general model formulated in chapter 5 needs to be implemented for the situation of the Euregio and solved. This means that the sets and parameters need to be defined to reflect the situation in the Eurgio. Some minor changes were made to the model as well. Furthermore, the model has been implemented in a solver and a solver strategy was chosen.

6.1.1 Configuration

To reflect the situation of the Euregio, the sets and parameters were defined as follows:

T:	[7 .. 23]
H:	[MST,SKB,ZGT]
S:	[1 .. 36]
K:	[1 .. 20]

$L_{h,t,k}$	~Gamma($shape_{h,t}$,$rate_{h,t}$)
c_h:	[16, 6, 14]
a:	0.9
w:	30
p_k:	1/20
M:	sufficiently large integer
$minn_h$:	[3,2,3]
SL:	8
RMax:	1

Epsilon and $e_{h,h'}$ are experiment specific, and thus discussed in 6.2. Scenario generation and related parameters are discussed in 6.1.2.

The time windows are set to one-hour intervals. This is not the full granularity on which the hospitals create their schedules but is deemed a justified simplification since working on half hours or 15-minute time windows would double or quadruple the model scale. This would in turn increase runtimes by an estimate of 10 or 20-fold. Furthermore, as the model is used to give strategic insights to AZE and the hospitals, a full level of detail is not strictly required.

The decision has also been made to exclude the night shifts from experimentation. Initial testing shows that the model will in almost all instances choose not to deviate from the baseline night schedules that the hospitals have in place. This is logical, since the data analysis has shown that care demand is lowest during the night, and variation is not excessively large as well. Furthermore, in many instances the care load is not the limiting factor at night, but rather the minimum staffing levels that the hospitals must adhere to. This decision was deemed favourable since it decreases runtime drastically. Consequently, this leaves more time for other experiments that AZE deems of more interest, like situations with different cross training policies, or demand based on weekends.

The parameter a is set to 0.9 to globally account for inefficiencies by floating nurses, like travel or starting up in a new hospital. This is of course a simplification, but in discussion with the nurses it was deemed a valid approximation. A sensitivity analysis on the effect of this parameter on the overall results is included in appendix C.

Because the model does not cover night shifts, the circularity of the planning needs to be broken. This is done by removing the unique constraints for t=1: (11),(12) and (17).

6.1.2 Scenario generation

As a basis for the scenario generation and further testing, the principles of the Sample Average Approximation (SAA) method are applied. SAA is a method proposed in Ahmed and Shapiro (2002) to solve two-stage stochastic programs such as ours. The method has seen widespread application in various forms. The method proposes to solve problems by solving the model for an increasing number of randomly drawn scenarios, and for an increasing number of replications to generate candidate solutions. By increasing the number of scenarios, and thus samples from the distribution, the full distribution is approximated. Using the law of large numbers, it can be stated that at a certain number of scenarios, the scenarios accurately represent the full, continuous distribution. Increasing the number of replications increases the number of candidate solutions that are found, which in theory will all converge to a single true optimal solution given enough scenarios. However, since the runtime of models increases (more than) exponentially when increasing the number of scenarios, and linearly for increasing the number of replications, it is often more beneficial to add more replications and base conclusions on patterns identified across runs.

Based on the results of the various runs, one can judge whether the configuration used generates solutions of a high enough quality. This can be judged both in terms of the statistical spread of the found objective values, the homogeneity of the candidate solutions and the performance of candidate solutions on larger sets of scenarios. From this pool of candidate solutions, one can then chose a candidate solution that is believed to be (closest to) the true optimal solution based on various criteria. A chosen candidate solution can then be evaluated more accurately by fixating the first stage variables and solving for a significantly larger number of scenarios.

As discussed in Chapter 3, the Gamma distribution is applicable to model the care load across the hospitals in the Euregio and different time windows. Thus, the care load is randomly sampled from these distributions.

To determine the number of scenarios and number of replications that will give us solutions of high enough quality to draw conclusion on, an initial experiment was conducted with various setups. Critical to consider in this instance is also the runtime of the experiments. The quality of the candidate solutions is judged by the confidence interval width of the objective value. The stability of objective values as well as of the decision variables is also taken into consideration. Lastly, the performance of the candidate solutions on a larger scenario set is compared as a final test.

In Figure 16 it can be seen that, for all number of scenarios, the confidence interval on the objective value seems to stabilise around 15 runs. The confidence interval of 10 and 15 scenarios seems tighter than for 20 and 25 scenarios. However, when looking at the decision variables in the solver, no consistency or patterns were identified. Thus, one can conclude that these setups do not represent the full stochasticity of the underlying situation and are overfitting to the scenarios they're presented with.

Alternatively, the decision variables of 20 and 25 scenarios did show patterns and many duplicate solutions across runs. The differences between the two sets of decision variables were largely neglectable. Furthermore, the size of the confidence interval is largely comparable, even though slightly different values have been observed. The runtime difference between 20 and 25 scenarios is more than half an hour per run. Due to the exponential growth of the runtime, running even more scenarios would theoretically approach multiple hours per run, while our current results show that gains would be minimal. This is not deemed a worthwhile time investment for the level of detail that we wish to achieve for this research. Thus, we concluded that a setup with 15 replications of 20 scenarios will give us stable solutions in reasonable computational time which can be evaluated in detail later. To see how much benefit a larger scenario set could have if more computational resources would make this feasible, a sensitivity analysis on a small scale instance of the model is included in appendix D.

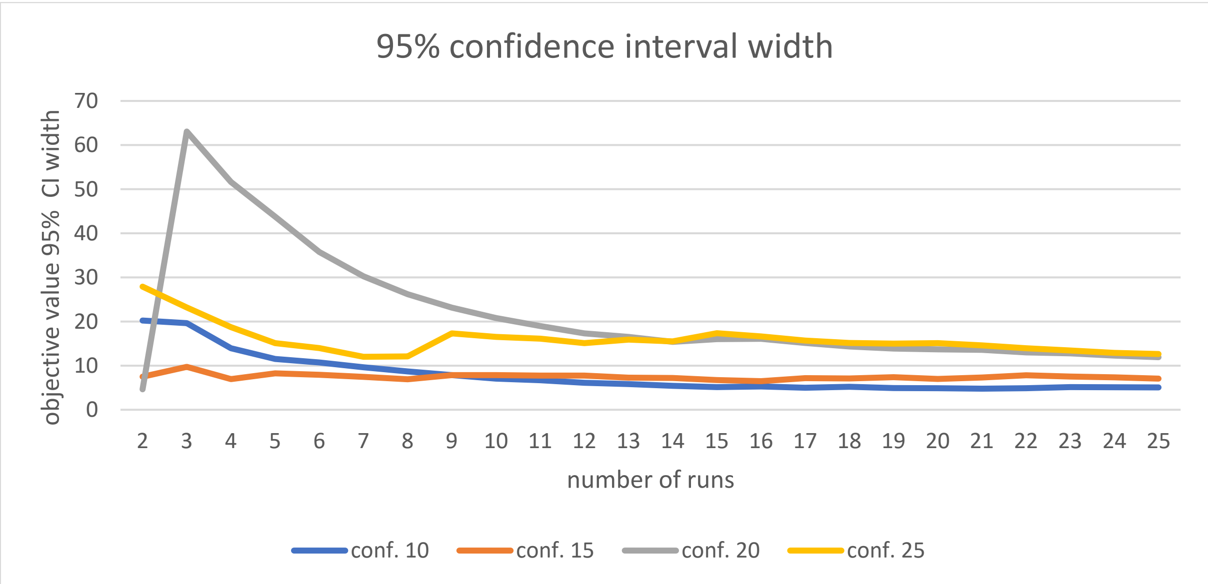


Figure 16: 95% confidence interval of objective values across runs for various numbers of scenarios.

The choice for using 20 scenarios is further validated by judging the quality of solutions on a larger scenario set. In this test, the first stage decision variables are fixed to the candidate solution, after which the second stage decision are made by the solver. This is performed with the same steps as is done for the true experiments. For each configuration, the candidate solution that appears the most in the set of candidate solutions is chosen for further evaluation. The performance of these configurations can be found in Figure 17. It should be disclosed that the most frequently appearing candidate solutions for k=20 and k=25 are in fact identical, hence the similar performance on the larger set. This strengthens the notion that there is limited benefit for using 25 scenarios.

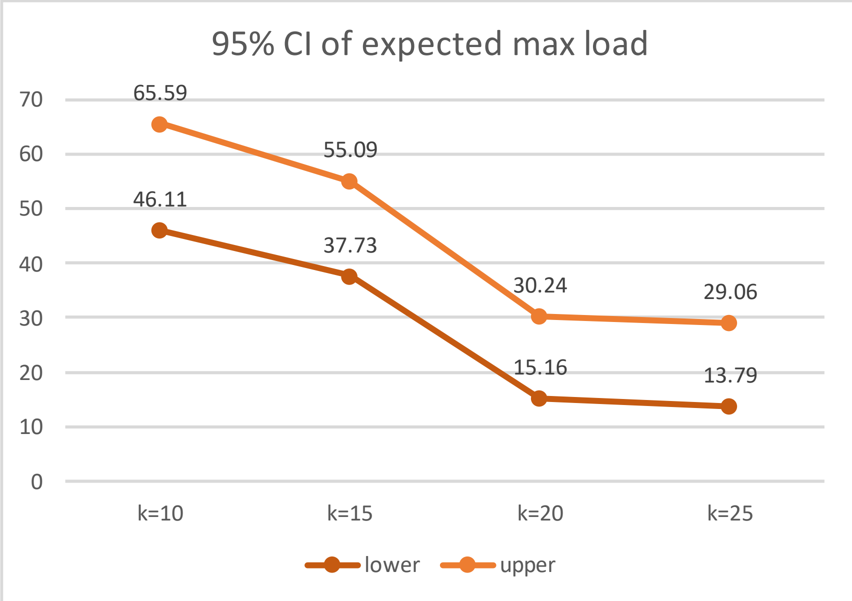


Figure 17: 95% CI for expected max load based on k=100 for candidate solutions with k=10,15,20,25

With the chosen configuration of 15 runs with 20 scenarios, the 15 runs per experiment yield 15 individual candidate solutions. Based on the frequency of candidate solutions and very similar solutions one candidate is chosen per experiment as the chosen schedule. These are believed to be the true optimal schedule, or closest to the true optimal schedule which we can achieve with the current number of scenarios. A full detailing of this process is included in appendix E. The chosen schedules are then re-evaluated. This is done by fixating the first stage decision variables, and creating a new scenario set k=[1..100] for 15 runs. In essence, this transforms the model into a Monte-Carlo simulation, where only the second stage decisions remain. This enables us to analyse the performance of the chosen schedules more accurately. Based on the resulting objective values, confidence intervals of the different configurations can be created and compared. For this, confidence intervals are created with the normal distribution at 95% confidence level.

Solving

The model was implemented in the AIMMS optimisation software and solved using the CPLEX 20.1 solver. The decision was made to let the solver make use of a starting solution, namely either the current schedules of the hospitals, or the optimal solution of the previous run, in combination with an LP relaxation as basis for the branch and bound. For 15 runs and 20 scenarios, with full cross-training and *e*=5, the model solves in 1.24 hours on average per run using an Intel i7 6-core 2.6ghz processer. With lower values for *e* the runtime decreases.

6.2 Experimental design

The model is used to evaluate various configurations that came forward from the conclusions of the previous chapters. An overview of all design choices that were chosen for experimentation is included in Table 2 and explained in the following section.

Table 2: Overview of experiments.

exp number	Number of flex nurses	cross training	day
baseline	na	na	weekday
1	na	na	weekday
2	1	all	weekday
3	3	all	weekday
4	5	all	weekday
5	1	MST+ZGT	weekday
6	3	MST+ZGT	weekday
7	5	MST+ZGT	weekday
8	best	best	weekend

6.2.1 Current situation and baseline

To establish a baseline for the performance of various configurations, two configurations were tested. First, the current staffing schedule of the hospitals was evaluated under uncertain demand by fixing all decision variables to reflect the current situation. Second, the model was solved with epsilon set to 0. This means that only fixed shifts will be allocated optimally. By comparing the results to both these baselines, we can isolate the benefit that can be achieved by enabling float nurses. Furthermore, we can also identify which improvements could still be made to the current schedules without using a float pool.

6.2.2 Flexibility ratios

The first factor that is used for experimentation is changing the flexibility ratio. As stated in the literature review, the general consensus is that after a certain level of flexibility, one is confronted with diminished returns. Thus, we experiment with various flexibility ratios, namely epsilon = [1,3,5]. This is in line with the flexibility ratios identified in literature of between 5% and 15% (as 36*0.05=1.8 and 36*0.15=5.4). Additionally, this range is also what AZE deems the feasible level of floating that could be achieved given staff opinion and logistics.

6.2.3 Cross-training policies

Due to the limited number of hospitals present in the Euregio, extensive evaluation of various cross-training policies is not the most significant matter. However, it is deemed of interest to investigate the performance of the region if SKB is not participating in the float pool. This is due to various reasons, namely:

- The fact that SKB is geographically the least favourable location to travel to and from.
- The system SKB already has in place with their IC nurses to deal with peaks in demand.
- The different size and variation of care demand when compared to the other hospitals.
- The opinions on feasibility from the staff.

6.2.4 Time periods

As a last factor that is experimented with, the care demand is considered. As mentioned in the data analysis, the weekend shows other characteristics in care demand than the weekdays. These deviations span the scale and variation of care demand, as well as the curve throughout the day. Furthermore, staffing schedules also deviate during the weekends in some cases. Thus, it is not unforeseeable that different results can be found when experimenting with care demand and staffing levels during the weekend as opposed to weekdays.

6.3 Results

The following section covers the results from the experiments. Section 6.3.1 focusses on experiments 1 to 7 and aims to draw conclusions on the various flexibility ratios that were tested based on the objective values. The following section makes observations on the schedules that are being proposed by the model for experiments 1 to 7. Based on these results, an additional experiment was performed which is discussed in section 6.3.3. After that, the experiments concerning the weekends are discussed.

6.3.1 Performance

The effect on expected max load of the multiple flexibility strategies and cross training policies can be seen in Figure 18, alongside the performance of the two baseline runs. Between the current schedule of the hospitals, and the baseline proposed by the model, a slight performance gain can be identified, both in terms of absolute numbers as well width of the confidence interval and thus stability.

When looking at the performance curve, one can see that the performance increases the most when comparing no float nurses to one float nurse. This comes down to around 30 units of care load, or between 41% and 45% in the full cross-training configuration and 20 units, or around 32% in the MST+ZGT configuration. Considering 30 units is what one nurse could be considered responsible for, this improvement can be viewed as significant. This aligns with the often-mentioned phenomenon that the first small increase in flexibility will have the largest results (Fügener et al., 2018); Griffiths et al. (2021), and at a certain point more flexibility will add little to no additional value (Campbell, 1999), also known as diminishing marginal returns. The performance of three float nurses is expectedly better than none and one float nurse but the effect is reduced. With around 20 additional units, or around 70% in total in the full cross-training configuration and less than 10 units in the MST+ZGT configuration. Following the trend, the performance of the configurations with 5 float nurses performs only marginally better than the configurations with 3 float nurses at less than 5% additional improvement.

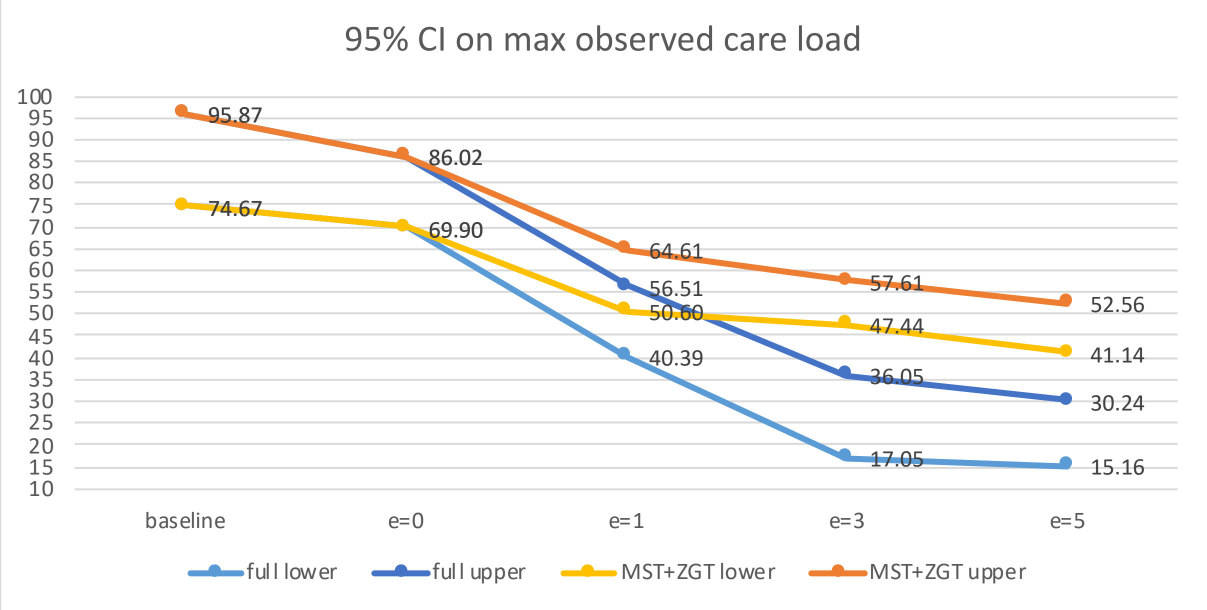


Figure 18: 95% confidence interval on expected max load for experiments 1 to 7.

When comparing the configurations that include SKB and the ones that do not, a significant difference can be observed. This is to be expected, as having more participants and thus more patients in total means that the pooling effect can be exploited to a greater extend. From the results, it can be observed that having one float nurse for the entire region will most probably offer equal, if not better performance than having five float nurses for MST and ZGT only. Furthermore, whereas the performance gains remain significant for the 3 float nurses configuration with full cross-training, one could conclude that the improvements for the MST+ZGT configurations with more than one float nurse are not significant.

6.3.2 Schedules

Figure 19 show the staffing schedules that the model has created for configurations of experiments 1 to 7. From these figures we can make a few observations.

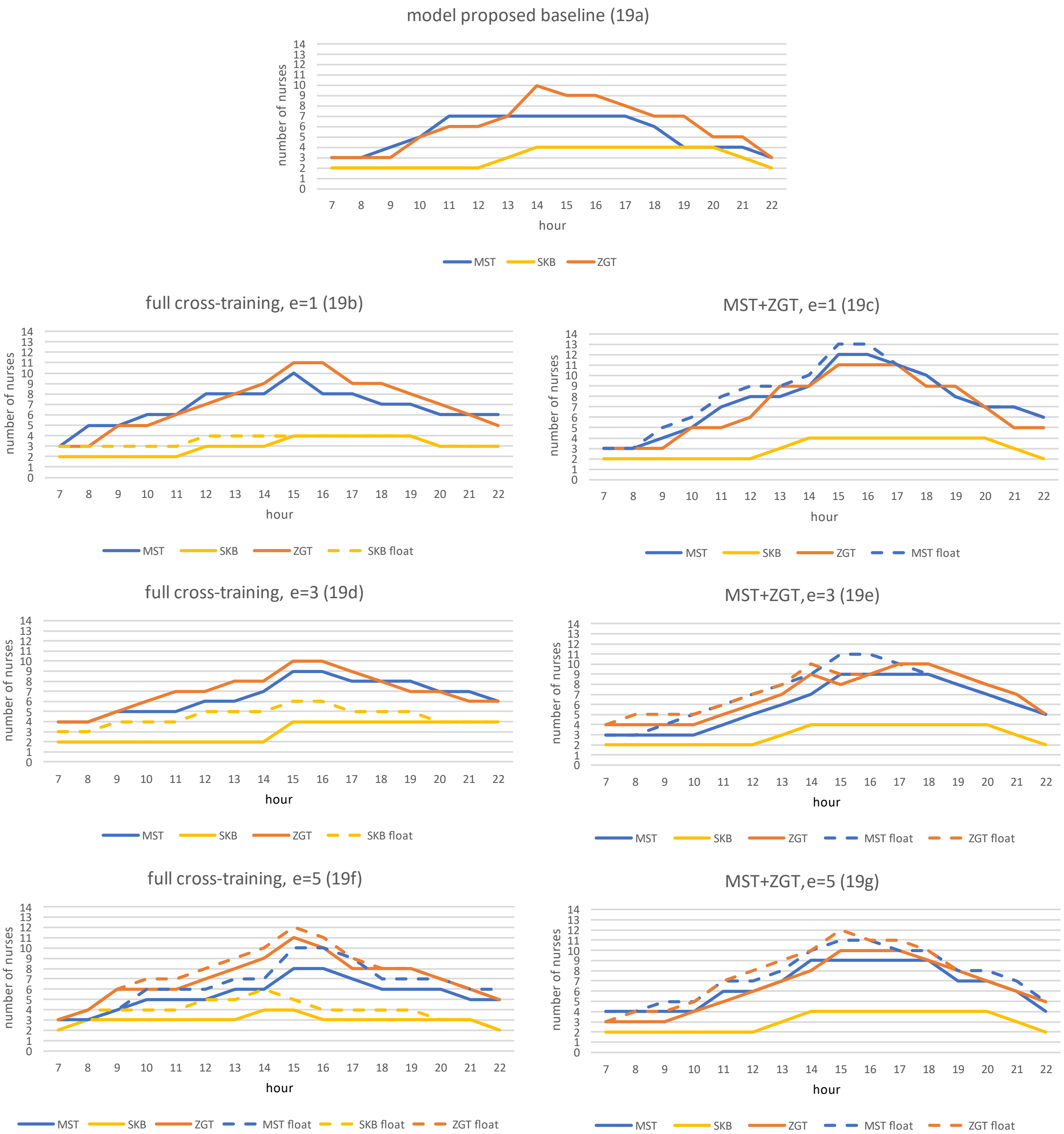


Figure 19: Schedules created in experiments 1 to 7

First, in both the e=1 and e=3 full cross-training configurations, the model finds a solution that lets all float nurses start their shift at SKB, as shown in figure 19b and figure 19d. This intuitively makes sense, since the relatively low absolute variation in care load at SKB means that letting a float nurse leave SKB to go to MST or ZGT would not have great negative impact in many scenarios. At the times where no large peaks are present in the other hospitals, the added shifts have a relatively big impact to the care load per nurse at SKB due to the smaller number of nurses usually present. That said, practically it is less ideal to have all float nurses operate out of SKB due to the geographical drawbacks. Furthermore, it can be considered unfavourable to have all float nurses based at the same hospital. When looking at the configurations without SKB, it seems the model favours allocating float nurses to MST. As MST has lower care demand as well as lower variation, the same logic as for the SKB allocations appears to be applicable here.

Second, it appears that the larger variation in care load at the ZGT during the day causes the model to also propose having an aggressively sloped staffing schedule when e=0 and e=1 for both the full cross-training as well as the MST+ZGT configuration. However, when compared to the current staffing schedule in Figure 5, this peak is placed a few hours earlier. This corresponds with the observation made during the data analysis that the actual peak in demand and variation of demand is observed earlier than the peak in staffing at ZGT. Furthermore, in the e=3 and e=5 configurations, the schedule at all hospitals, but especially ZGT appears to be smoother. This can be explained by the fact that, due to the availability of float nurses it is less necessary to account for peaks with dedicated staff.

Looking at the e=5 full cross-training configuration, it appears this is the first time the model decides to allocate float nurses to all three hospitals. This is logical, since with the large number of float nurses available, having float nurses at all three hospitals means that at demand realisation a nurse can be moved from the quietest hospital to the busiest. This minimises the impact of penalty factor “a” experienced by moving a float nurse away.

It can also be seen that at both configurations with e=5, the model decides to have a float nurse available at each point in the day. Because the model does not experience penalties for not floating nurses, but having the option is often beneficial and because it has the shifts available to fill the full timespan, this decision intuitively makes sense. It can be observed in e=3 that, in contrast, it is not deemed worthwhile to have a float nurse in the late evening hours. When looking at both the decrease in demand at all three hospitals in Figure 9, as well as the stark decrease in variation Figure 11 one can understand why this trade-off is being made.

When looking at the baseline proposed by the model, it can be observed that the schedule for MST is still flatter than the schedule for ZGT. However, this is not as extreme as in the schedule currently in use. When comparing the proposed baseline with the configurations that include float nurses, the schedule at MST becomes more sloped. It appears that the float nurses that are deployed to the region in the early afternoon take away much of the extreme situations there. Thus, more nurses can be allocated to time windows where care load is higher. When looking at the schedules proposed for ZGT across all configurations, the schedules are all less extremely sloped when compared to the current situation. In the configurations where a peak in the schedule exists, it is earlier than in the current schedule as well.

In one configuration a peak can be observed that could be considered extreme, namely in the 1 float nurse MST+ZGT configuration. Here, partly due to the float nurse being deployed to MST, the staffing peaks at 13 nurses during the afternoon. This aligns with when the most care load is observed. It appears that in the other cases, due to the higher flexibility of the system, such extreme peaks are not optimal.

6.3.3 Extra spread experiment

From the initial set of experiments, it came forward that having three float nurses across all regions would be one of the most promising configurations to consider. However, given the choice, the model allocates all float nurses to SKB. Since this is not desirable to implement in reality, it is regarded interesting to further analyse solutions with three float nurses. As an additional experiment, the model has been tasked to solve the e=3, full cross-training scenario again.

This experiment includes the constraint that all three hospitals in the region should provide one float nurse, to ensure that not all float nurses are placed in one location. As can be seen in Figure 21, the performance of the chosen solution is remarkably close to the original solution for e=3. It appears that the spread of the expected max load is even lower than the original solution. However, as can be seen by the higher lower bound, appears to perform well in favourable situations, but worse in less favourable situations in terms of care load. This might also explain why the model did not arrive to this solution in the first place.

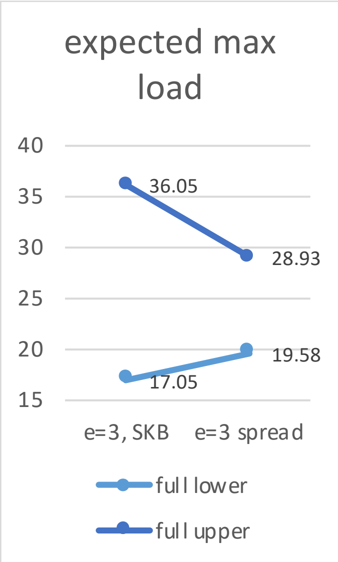


Figure 21: 95% CI on expected max load for e=3, SKB only and spread

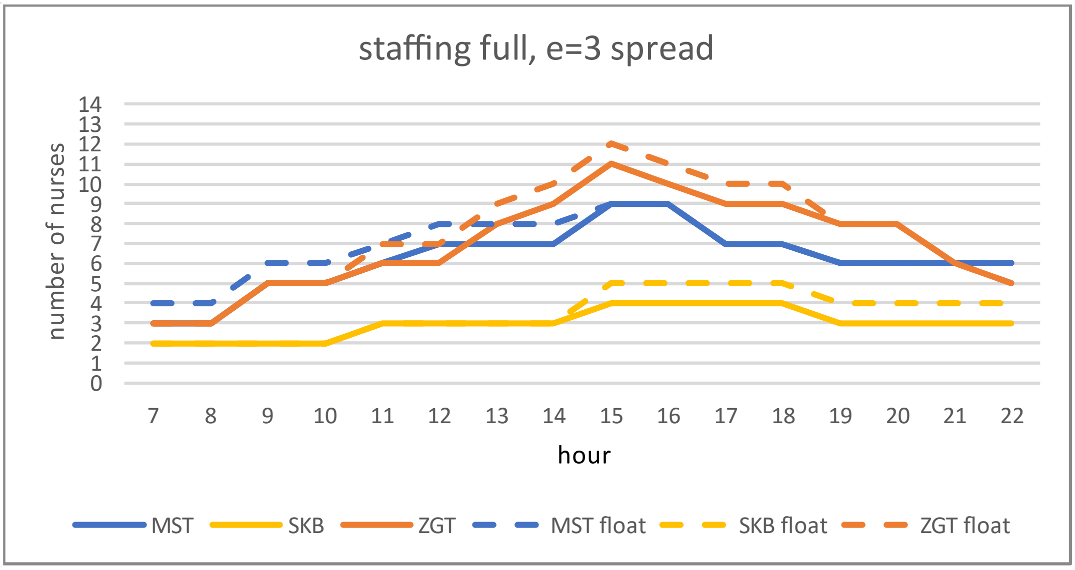


Figure 20: Proposed schedule for e=3 spread

When looking at the proposed schedule for this situation, it can be seen that a slightly different approach is taken. It appears that in this situation, it would be beneficial to have full coverage of float nurses throughout the day. This can be explained by the fact that the trade-off in terms of having float nurses stay at their own hospital working at 100% efficiency or having them float for 90% efficiency lies differently. It can be that due to this setup, more movements could be expected. In terms of dedicated staff, this schedule shares the likeness of the original e=3 full cross-training solution, as well as that of the proposed baseline and e=1 full cross-training solution.

6.3.4 Weekends

The configuration of having three float nurses was also tested for weekends. This means different distributions were used to sample care load from and the deviating staffing levels were applied. During the data analysis, it was concluded that the care load was lower during the weekend across the region. Furthermore, the variation was also determined to be slightly lower during the weekend. Thus, the results as presented in Figure 22 can be considered predictable. From these results it can be concluded that having float nurses during the weekend will still have some effect, the but the benefits will be lower than during weekdays. Combining this with the knowledge that extreme care load is already less prevalent in the weekend, it would be logical to not prioritise weekends when setting up a float pool.

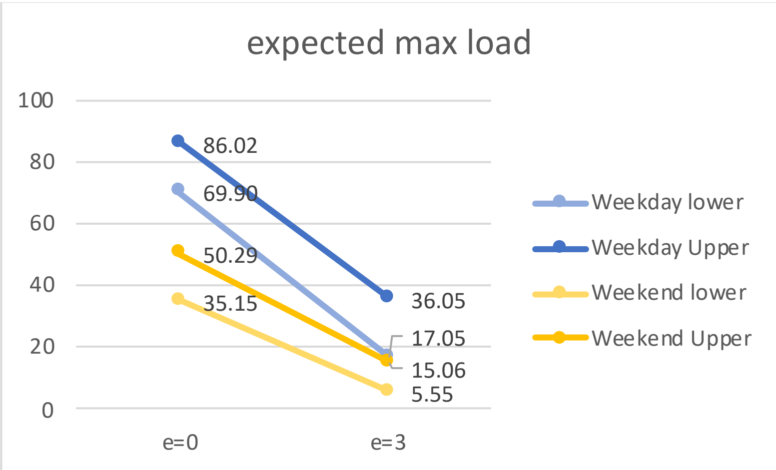


Figure 22: 95% CI on expected max load for weekdays and weekends.

When looking at the schedules that the model proposes in Figure 23 both the e=0 and e=3 configurations show similar characteristics as the schedules proposed for the weekdays. The proposed baseline appears flatter for ZGT and more sloped for MST. Furthermore, the proposed schedule for 3 float nurses is flatter for both these hospitals. The configuration with 3 float nurses again proposes to allocate float nurses to SKB, but in this case also allocates one float nurse to MST in the morning. This schedule also has full coverage of float nurses across the day.

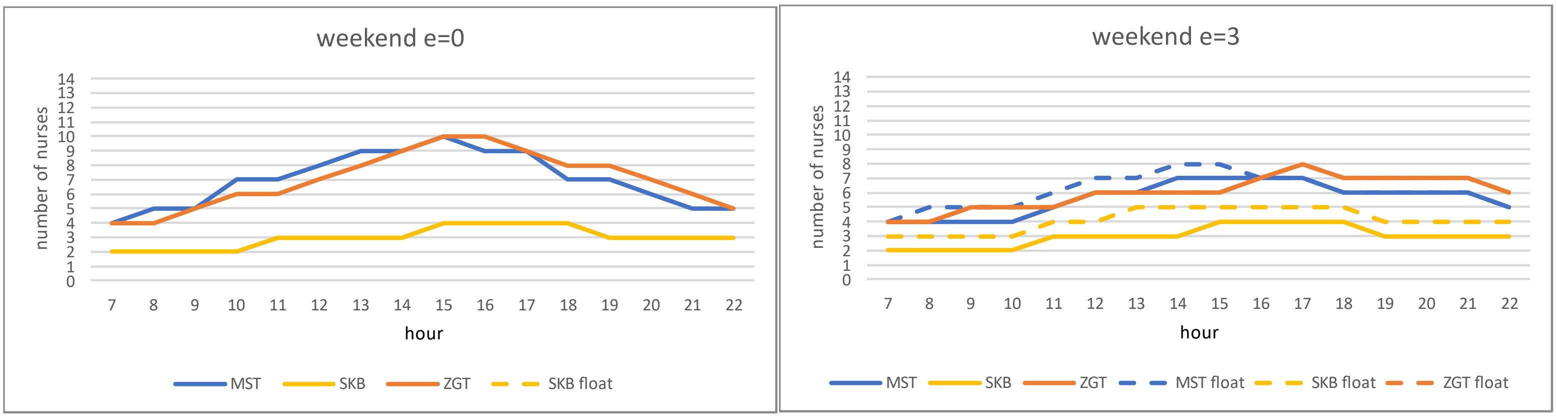


Figure 23: Proposed schedule for e=0 and e=3 during weekends.

6.4 Analysis on model

To evaluate the theoretical and practical benefits of two-stages models like the one used in this thesis, two often used indicators are the Value of the Stochastic Solution (VSS) and the Expected Value of Perfect Information (EVPI) (Birge & Louveaux, 1997). An analysis on these two indicators was performed on the favoured solution from the first set of experiments, namely the e=3 full cross training configuration without forced spreading of the float nurses. The results can be found in Figure 24.

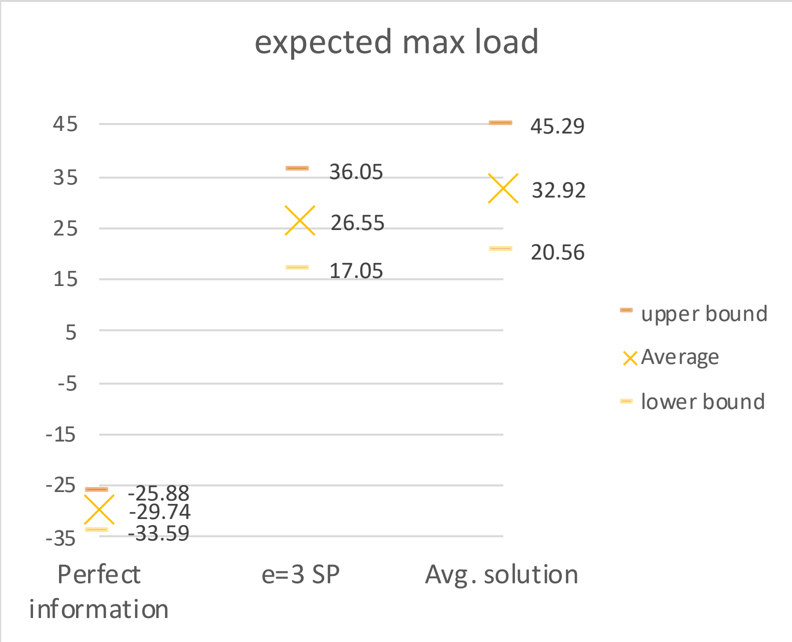


Figure 24: 95% CI on e=3 under perfect information, the regular stochastic program and using an average policy

6.4.1 VSS

The VSS is an indicator of what the optimality gap is between using a model that takes second stage decisions into account when making first stage decision and using a model that makes first stage decisions solely based on the average situation. Currently, the model presented in this thesis calculates the second stage decision of re-allocation when deciding where to allocate float nurses. Alternatively, one could base the first stage decision on the known distributions of care load without looking at the actual consequences in terms of re-allocations. The re-allocations are then executed as a separate decision and evaluated on a set of scenarios much like how the second part of SAA is performed.

When performing these steps, the mean expected max care load came out to be 32.92. The VSS is thus: *32.92 - 26.55 = 6.38*. This can be viewed as low when considering the scale of improvements that the proposed configuration gives over the baseline is a tenfold larger. It should be noted that a large drawback of the solution offered by the average solution method is that it does not consider float movements and their inefficiencies, as well as the benefits achieved in extreme cases. The effects of this are not as great here, since the average solution follows a similar reasoning as given in 6.3.2, and allocates all float staff to SKB. To verify the results, the VSS was also calculated for the configuration with equal floating across the region as described in 6.3.3. The results, which can be seen in Figure 25, show that here the VSS is noticeably higher at *49.27 - 24.25 = 25.02.*

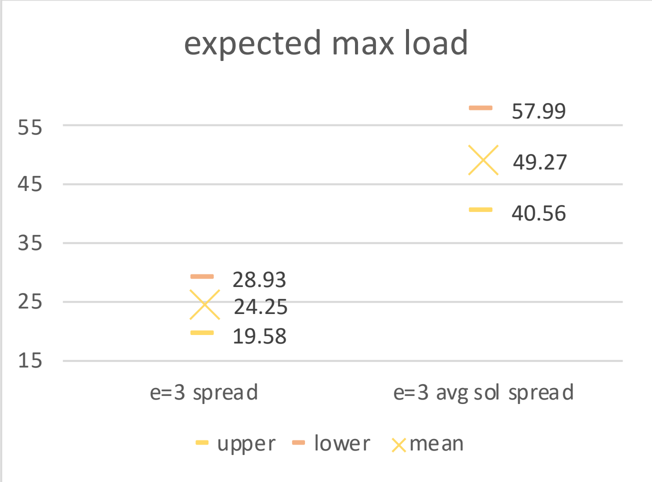


Figure 25: 95% CI on e=3 with spread constraint for the regular stochastic program and using an average policy

This shows that one could choose to use an average solution method instead of using the stochastic model without sacrificing all performance of the model. Considering the significantly larger computational capacity needed for the stochastic model, this might be an option to consider. However, it is also shown that the average solution approach is not guaranteed to give a solution that performs close to optimal. Thus, it is highly advised should one decide to move forward with using an average solution method, to always carefully evaluate the results using for example a Monte-Carlo or Discrete Event Simulation.

6.4.2 EVPI

Where the VSS is used to see the value of a stochastic solution over a simpler average approach, the EVPI can be used to see the value of perfect information. Mathematically this means modifying the first stage decisions for each scenario to already account for the realisation presented in the second stage. Practically it would represent a system wherein initial staff allocation could always be done using exact knowledge of what care load is going to be. While this can never fully happen in practice, it can serve to illustrate what a theoretical lower bound of performance could be should flexibility measures be incorporated.

In this case, the EVPI is: *26.55 - (-29.74) = 56.28.* This figure is quite large, which is to be expected from a perfect information setting with as much volatility as the care demand has. However, a perfect information setting will never be possible for ED planning. When regarding the perfect information objective value (-29.74) as a lower bound and the baseline as upper bound (85.27), we can see that the solutions the model currently offers (between 28.93 and 19.58 for the most promising configuration) are quite a significant improvement when considering the scale.

6.5 Conclusion

The research question *What will the optimal configuration and performance be of relevant float pool designs compared to the current situation at AZE?* is answered in this chapter via a range of experiments. From these experiments using the proposed model on the various configurations, it can be concluded higher flexibility constitutes to better performance. However, as often stated in literature, diminishing returns can also be observed. From the results in Figure 18 we can see that the performance improvement becomes insignificant after a certain point for both the full cross-training as well as the MST+ZGT configurations. Keeping in mind that increasing the float pool size will take considerable resources, it would be advisable to not pursue the highest possible level of flexibility. A full cross-training configuration would appear to be most worthwhile to pursue, where the number of float shifts should be around three to still experience large performance increases. Even though it would theoretically be more numerically beneficial to allocate all three float shifts to SKB, spreading the float nurses across the region offers very similar performance. Should full cross-training not be possible due to external factors as mentioned in 6.2.3, it would be advisable to work with one float nurse in the MST+ZGT configuration, as more float nurses do not yield significant performance improvement. In almost all configurations, float nurses should be allocated during the daytime, meaning starting between 7:00 and 9:00 and ending between 15:00 and 20:00. When setting the constraint to spread the float nurses across the region, it should be considered to have full coverage of float nurses throughout the day.

The schedules proposed for weekends show similar patterns as the schedules proposed for weekdays. However, as the performance gain is less significant, it could be considered more interesting to focus on weekdays when implementing a float pool.

In general, the schedules of dedicated nurses should be adjusted accordingly with the float configuration chosen to maximise the performance. A trend observed across all configurations, including the baseline the model proposes is to flatten the schedule for ZGT, and to taper the schedule for MST.

7 Recommendations

Throughout the research, various points of interest have been identified which are not directly part of answering the research question. However, based on the results of the previous chapters, some recommendations can be made that might be of interest to AZE and the hospitals. These are discussed in this chapter.

7.1 Potential changes to fixed schedules

Next to the recommendations made regarding the potential float pool for the region, the results of this research can offer insights into the current fixed staffing schedules at the hospitals.

First, the extra shifts during the day that SKB deploys on Mondays and Fridays are very well placed. During conversations with the management of SKB, it came forward that these shifts are deployed to other days as well if the staffing situation allows for it. Should this be the case, it is recommended to use these extra shifts during weekdays in the same timeframe.

ZGT indicated during the meetings that they have an extra shift on Sunday during the night, which is a change that has been implemented recently. However, when looking at the data both in terms of care load as well as number of patients, it comes forward that this is the quietest moment of the week. Therefore, it might be worthwhile to consider this extra shift per week to a moment where more demand is noticeable. A good example of this would be Monday during the day, which comes forward in the dataset as the busiest moment in the week for ZGT.

When comparing the staffing throughout the day at MST and ZGT, we can identify two different approaches. Namely, having a flatter schedule, or one more steeply tailored to the demand curve of the day. Although the further implications of the two methods can be debated, it is quite clear that in the case of MST care load fluctuates greatly throughout the afternoon and early evening, whilst staffing levels stay the same. It could be worthwhile to consider moving some capacity away from early in the day (10:00 to 12:00) or evening (20:00 to 22:00) towards the middle of the afternoon (12:00 to 20:00). At ZGT, staffing is more adapted to what is probably expected to be the peak in demand. However, when looking at the data we can see that the peak starts a few hours earlier than the peak in staffing (13:00 and 16:00 respectively). Thus, it might be worthwhile to move around the shifts at ZGT to accommodate this.

7.2 Unplanned demand responses

The hospitals in the Euregio make use of calling non-scheduled staff in varying intensities. This is done via the Multi-bel system, or by asking via informal channels. Requests for both extra staff, as well as for planned staff to come earlier are communicated to staff. However, these unexpected sources of overtime lead to much irritation among staff. Furthermore, it also indirectly incentivises staff to consider doing contractor work, as these extra requested shifts are not mandatory within their contract with the hospital but are paid at a premium when taken on by a contractor. Perhaps even more importantly, unexpected overtime for nurses has shown to increase risks for patients (Dall'Ora & Griffiths, 2017).

Regardless of whether the hospitals would wish to implement a regional float pool, it is recommended that they take a conscious attitude towards demand fluctuations. From the data analysis it can be seen that demand fluctuations are part of the nature of the EDs, which is also something that can be confirmed by literature. Therefore, it would be worthwhile to think about more pre-planned methods of dealing with peak demand. Examples of this would be to have dedicated people on call for a shift and to have a clear set of criteria for extra staff requests to take place.

7.3 Local cross-training

As mentioned a few times, SKB is unique in the fact that they have a large portion of cross-trained staff across the IC and ED. While all three hospitals indicate that they sometimes use staff from different departments as a method of dealing with unexpected demand, ZGT and MST mostly have to rely on nurses that do not have an ED certification. This has a few unwanted effects, namely: The efforts of the borrowed nurses will not be as effective as ED nurses would be, risks are increased due to unfamiliarity and most of the responsibilities over patients and thus pressure will remain at the fixed ED nurses. Logically, it would thus be preferred to have ED certified staff available as flexibility measure. This is a large part of the basis behind this thesis.

That said, cross-training nurses from within the hospitals does appear to be an option to seriously consider. A significant part of the literature regarding float pooling focusses around float pools within one hospital (Campbell, 1999; Fügener et al., 2018; Gnanlet & Gilland, 2009). Cross-training within one hospital eliminates the geographical drawbacks of a regional float pool. Furthermore, it can also better ensure a cultural fit between nurses. A drawback would be that the learning opportunities of working in the region would be eliminated. Most prominently however, it is important to note that cross-training staff to a point of ED certification is a long and expensive process. This thus does not only mean more additional costs, but also a large period of absenteeism for the candidates.

7.4 Logging of JDT data

Throughout the research, it has proven both hard as well as important to approximate care load at the EDs. Compared to many other (healthcare) systems, the load experienced by nurses is dependent on a large set of factors, some of which cannot be readily identified or quantified. Two of the three hospitals are already familiar with the JDT score, which is implemented in the software used at the ED. It is expected that this functionality will be available at the last hospital soon as well. Even though both the nurses as well as literature confirm that the JDT score is a functional way of approximating care load, little is done with the scores that the software calculates in real time.

By logging the historical JDT scores, better research can be done, both academically as well as practically, into the workload at the EDs. In the context of this thesis, it is not hard to envision that using JDT scores could have been a better approximation of care load than using NTS values.

Furthermore, the JDT scores could also be used in the implementation of a float pool, or regional cooperation in general. Currently, the shared data across the region regarding EDs is based on NEDOCS. However, as previously discussed this method does not have staffing as main focus and thus says little about the workload that nurses are experiencing. When speaking to the nurses, it came forward that JDT oftentimes gives a good overall estimation of workload at the ED, even though it does not see much use currently.

7.5 Multi-bel usage

As discussed in 2.2.3, the hospitals in the Euregio have various methods of responding to unexpected demand. The method shared by all three hospitals that has the clearest process behind it is the Multi-bel system. This system could be adapted to send out requests to all nurses in the float pool, instead of only the ones employed by the single hospital. This would realise option 5c as discussed in 3.2.6, where unplanned staff is requested from the float pool after demand realisation. Implementing this change would mean that a larger pool of people is contacted for a multi-bel. This both increases the chance that someone responds to the request, as well as lowers the burden on individual nurses because they will have to respond less often per person.

For this to work, the criteria for multi-bel usage would need to be standardised across the region. As mentioned in 2.2.3, usage of the system varies between once in two weeks to ideally never. From a theoretical standpoint, the multi-bel can be viewed as an intrusive method of dealing with demand fluctuations and should thus be deployed sparsely. Regardless of the chosen threshold, the most important thing is that a consensus should be reached on when to use the system.

7.6 Contractors

As mentioned in 2.2.1, currently MST and ZGT deploy contractors to fulfil shifts that they cannot fill with their own staff. These contractors do not have a fixed hospital at which they're deployed, or only work at a hospital parttime. These contractors complicate planning of inhouse staff due to their volatile availability as well as extra demands, which is an issue recently addressed by the union of healthcare professionals. However, these contractors pose another hurdle to the implementation of an ED float pool. Currently, it is very lucrative as well as convenient to become a contractor, with the main drawbacks being not having a team or fixed location to work at. While becoming a contractor will probably become less convenient in the future due to the union demands, it is not hard to expect that due to the nursing shortage it will remain lucrative. Thus, when implementing a float pool, the hospitals should carefully consider how to handle extra compensation. Becoming part of the float pool shares some of the drawbacks of becoming a contractor, with the latter having the reputation of being highly lucrative among nurses. Becoming part of the float pool should come with compensation that reflects the extra drawbacks experienced by nurses in such a way that it is a valid alternative to becoming a contractor.

8 Conclusion

The research presented in this document aims to answer the research question "*At which planning level and with which design choices will instating a float pool be beneficial for the EDs that are part of AZE?*", which was done by doing a context analysis, a literature review, a data analysis and experimentation on a model. The results of these parts form the basis of an overall conclusion which is discussed first in this chapter. After that, the contributions to theory and practice are discussed, followed by the limitations of the research. Lastly, opportunities for further research are identified.

8.1 Conclusion

Instating a float pool for EDs can yield benefits at the initial planning stage by enabling more efficient use of staff and can be used before the start of a shift to account for illnesses and other absenteeism. The most benefit can however be achieved by using the float pool to respond to demand fluctuations during demand realisation and make use of pooling effect. When instating a float pool for EDs in the Euregio, it is important that nurses know the times at which a shift is to be worked in advance. The geographical location appears to be less important. Furthermore, it should be taken into consideration that there's limited nurses that would be willing to join the float pool. The float pool should be created by asking existing staff to participate in the float pool. These nurses can then be allocated to fixed shifts across the region or used fill in for illnesses. However, the most benefit can be achieved by assigning the nurses to a shift at a hospital with the knowledge that they can be asked to go to a different hospital during this shift.

The data shows that the highest care load, as well as the highest variation can be observed during the afternoon during weekdays with all three hospitals showing similar patterns. It can also be proven that variation across the region is lower than for individual hospitals which supports the notion that the float pool can decrease peak workload without increasing staff. The results of the experiments confirm this, with the most promising schedule achieving an expected peak care load that's two nurses worth of workload lower than the schedules currently in place. Based on this solution, it would be advised to have three float nurse shifts per day. The shifts of these nurses can best be spread out across the day, with overlap during the afternoon. If SKB would not be taking part in the float pool, it is advised to have one float nurse shift during the afternoon for the other two hospitals.

8.2 Contribution to theory and practice

The research presented in this document contains contributions to the literature on float pools as well as practical insights that can contribute to the decision making the hospitals in the Euregio. These are outlined in this section.

8.2.1 Literature

This thesis presents a stochastic programming model to optimise staffing at EDs. While other research has applied stochastic programming to nursing staffing problems (Gnanlet & Gilland, 2009; Schoenfelder et al., 2020), the subject of these models has been wards. Consequently, these models aim to fulfil nurse-to-patient ratios to the highest possible degree. Furthermore, these models work under the pretence that shifts have set starting and ending times and should be floated in their entirety. Alternatively, the model proposed in this research aims to optimise the maximum workload experienced by nurses. More significantly however, the model proposed in this research works on a time window basis. This enables the model to inform decision making on float pools on a per hour level, which creates a more granular decision-making space. Options such as floating a nurse halfway through a shift, or having shifts layered across each other are possibilities that the proposed model can evaluate. To our knowledge, no other mathematical programming models have been proposed for this setting which can do the same.

Most literature on nursing float pools focusses on floating within one hospital across different departments (Campbell, 1999; Dall'Ora & Griffiths, 2017; Landau et al., 1983; McDonald et al., 2019). Only limited literature is available on float pools that operate across different hospitals (Elferink, 2022; Fagefors et al., 2020) and only a small portion of this is quantitatively oriented (Morris, 2021). This thesis adds to the body of knowledge regarding float pools that operate across different hospitals. This is achieved partly by proposing a model which can be applied to these situations, but also by offering insights into the logistical aspects that hospitals are faced with, and design decisions that can be made when considering instating a geographical float pool.

8.2.2 Practice

This thesis offers practical insights into the subject of nursing float pools that AZE and the hospitals in the Euregio can use for their decision making based on literature, data analysis, observations and experimentation on the proposed model. Additionally, some other observations that could aid the EDs in the Euregio are included in the thesis.

Most notably, the results of the experiments show how much benefit can be achieved by creating a float pool in the region. Furthermore, the most promising configurations for this float pool are recommended based on the results of the experiment. The results show that a lot of extreme workload can be relieved without having to bring in additional staff into the region. Furthermore, the results illustrate how only a small portion of staff would need to be made available for the float pool for it to have the desired effect.

Based on literature as well as observations at the EDs, an overview is given of possibilities and design decisions for float pools that the parties involved should consider when deciding to move forward with setting up a float pool. These decisions cover the full spectrum of planning decision making from strategic to operational, and thus can hopefully offer a good framework to base the discussion on should the EDs wish to start collaborating with a float pool.

Next to the contributions on the subject of float pooling, this thesis offers insights into other points of interest for the EDs and AZE as well. The data analysis shows a clear pattern for care demand across the day, as well as throughout the week. The EDs can use these insights to improve their regular schedules by aligning them with care demand more accurately. The data analysis also gives insight into the patient mix across the region and highlights some unexpected differences but also similarities in patient mix.

8.3 Limitations

While the current research delivers insights and conclusions which can aid AZE and the hospitals on a strategic level, it is important to state its' limitations. Most prominently, these are the care load approximation applied, and the way the number of time windows was reduced to make the model solve in acceptable time. It is also discussed what the limitations are with respect to the fact that the research was performed in the Euregio.

8.3.1 Care load approximation

As mentioned in 4.1.1, the care load that a patient causes is approximated by using the NTS-triage value. The logic behind the approximation can be brought back to various other well-known methods and was corroborated by the nurses and AZE. However, it must be stated that it remains an approximation. As discussed in (Williams & Crouch, 2006), (Weiss et al., 2004) and (Hoot & Aronsky, 2006), many factors have been proven to impact the amount of care load a patient causes that are not, or only partly present in the NTS-triage. Among these are age, emotional state and self-sufficiency. unfortunately, these factors were not included in the dataset available for this research. Should data like this become available in the future, it would be beneficial to base a care load approximation on these factors. This could for example be done with JDT values.

Secondly, it is important to note that the care load per patient is not constant across their full stay at the ED. During the first part of a stay of a patient, tests need to be performed and first aid can be required in some cases. After that, a quieter period usually follows where the patient has to wait on test results, or consultation with a doctor. The last part of the stay of a patient is often spend waiting for the patient to go home, or to a different department in the hospital. As the calculations for the model in this research were performed in time windows of one hour and on a more strategic level, the distinction was not deemed most critical. Furthermore, a way to quantify the differences in care load across a stay would need to be researched.

8.3.2 Time windows

Due to the scale of the model, it was decided to not model the time windows that take place during the night. The data analysis has shown that this is the moment in time where the least variation in care load can be observed, so intuitively this would be the least interesting to investigate in the model. Furthermore, the organisational and logistical barriers for a float pool have also been deemed higher during the night. However, due to the minimum staffing levels low variation and peaks elsewhere in the day as well as the removal of circularity in the schedules, it is not possible to state that including the nightshifts will deliver exactly the same results.

The model currently also works with time windows of one hour, which is an additional choice to limit the scale of the model. In reality, the schedules of the hospitals work on 15-minute intervals. This is mostly done so that small overlaps in shifts can exist for transfer of responsibilities between arriving and leaving nurses. Increasing the number of time windows could definitely deliver different results, seeing that the length of stay of patients tends to be relatively short. However, the current model will most probably not solve within acceptable time should the number of time windows be increased to such a level.

8.3.3 Regionality

The research has originally been commissioned by AZE, and thus only covers the hospitals within the Euregio. Therefore, one cannot definitively say that the results of this research can be directly applied to other regions. The Euregio is a relatively small region, in a fairly rural area of the country with a low concentration of hospitals. That said, most of the theory on float pooling shows that larger systems to float within offer larger rewards, as more variation can be reduced, and more nurses can be involved in the system. The results of this thesis also shows significant increases in performance when considering three hospitals instead of two. At a certain point the performance increase is expected to flatten off when incorporating more hospitals into the float pool, much like it flattens when incorporating more float shifts. When considering instating a float pool in a different region than the Euregio, this behaviour should be studied further. However, the positive results in a relatively unfavourable region like the Euregio give a promising indication of performance elsewhere.

It is advised to, should one wish to do research in larger regions with the current model, considerably more computational capacity should be sourced than used in the current research. It has been observed throughout the research that the model scales poorly, and thus solving to optimality for larger regions might become too time consuming. Alternatively, a different modelling approach could be considered, as discussed in 8.4.1 and 8.4.2.

8.4 Further research

Before the hospitals decide to move forward with instating an ED float pool, it is recommended that a few matters are still investigated. These matters are also of interest to the theoretical body of knowledge regarding ED float pooling, as they have not been covered in the past. Based on the results of the research three main further research directions have been identified. In terms of quantitative research these are detailed scheduling as well as an analysis on operational functioning. Both these directions require additional research into care load prediction and approximation. More qualitative matters that are important to consider are those of governance over the float pool and decision making, financial and legal aspects and change management.

8.4.1 Schedule generation

The schedules created by the model in this research have been simplified to hour level to accommodate for computational time. However, realistic schedules at the EDs currently are made on a 15-minute level. Furthermore, overlaps are included in schedules to accommodate for transfer of responsibilities, the model used in this research does not account for this. Thus, it would be beneficial to investigate the scheduling at a higher level of detail. At that point, stochastic programming would no longer be an applicable method as runtimes would become unrealistically large. As an alternative it could be considered to use a (stochastic) heuristic approach. This will not guarantee optimal results and some trouble might be experienced in implementing stochasticity, but computational performance will be significantly better than stochastic programming. Another possibility would be to use deterministic mathematical programming, using service level KPIs like probability of understaffing, or percentage of time with extreme understaffing as part of the objective function. As part of this further research, the matters regarding care load approximation discussed in 8.3.1 could also be addressed.

8.4.2 Operational functioning

Should a float pool be instated for EDs, some critical questions still remain regarding the operational functioning of the float pool that can be researched. A prominent question that lies open is what the criteria should be for initiating a float movement during a shift. Ideally, this decision is made at such a time that the nurse can move to the busier hospital right in time to help for the largest peak in care demand. Furthermore, the relation between the criteria set, and the number of actual relocations that happens per time-period is something that should be investigated. This means incorporating the (stochastic) travel times of nurses, as well as random arrivals of patients. The balance of relocations from and to each hospital can then also be analysed, which is crucial as all hospitals have indicated they wish to have a "fair" collaboration. This analysis would also benefit from more accurate care load estimations that take fluctuating care load per patient into account. Research has already been done on short term care load predictions for EDs (Hoot & Aronsky, 2006), which could be used to inform decision making and is thus also interesting to consider for this follow up research. Due to the large number of stochastic factors required for these detailed analyses, it would be advisable to use a form of simulation for this research.

8.4.3 Qualitative aspects

Even though the opinions on a regional float pool have been researched in the Euregio (Elferink, 2022; Weelink, 2023), it remains important to consider the broader qualitative aspects of instating an ED nursing float pool. Even though it can be researched what the optimal criteria could be for initiating a float movement, it must be stressed that actually making this decision will always be contended. In practice, it would namely also mean that one hospital has to make do with one less nurse. Thus, all involved hospitals would need to come to an agreement. This raises questions regarding centralised or decentralised decision making, creating a governing body, or tasking an existing organisation with this task and mutually beneficial rulesets.

Furthermore, the financial and legal aspects of having someone work in one hospital whilst under contract at another hospital is often mentioned as limiting factors. Even though a float pool would in theory not have to deviate from constructions already in place with contract nurses in these aspects, investigating this can take away a lot of doubt and prove to be an opportunity to research new ways of governance and cross-organisational collaboration within healthcare.

Last, an often-mentioned topic at the EDs has been hospital culture, and the various dimensions that define it (geographical, type of hospital etc.). Starting with an ED float pool would provide a good opportunity to research how these cultural aspects match, and how this change from one hospital to another can best be approached.

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Appendix A: NEDOCS calculation

To gain predict care load at an ED, NEDOCS is calculated using the following formula (Vergeer, 2023):

$$NEDOCS = -20 + 85.8 * \left(\frac{P_{all}}{B_{ED}}\right) + 600 * \left(\frac{w}{B_{all}}\right) + 13{,}4 * P_{u1} + 0.93 * q + 5.64 * t$$

Were P_{all} is the total number of patients at the ED, B_{ED} the number of beds at the ED and P_{u1} are the number of patients at the ED with the highest NTS-triage level of u1.

The factors w, B_{all}, q and t represent other characteristics of the hospital, as well as waiting times of individual patients. Since we're interested in approximating care load per patient based on their own characteristics, we choose to remove these from the formula for our approximation:

$$care\ load = 85.8 * \left(\frac{P_{all}}{B_{ED}}\right) + 13{,}4 * P_{u1}$$

Regarding P_{all} and P_{u1} as variables, and B_{ED} as a constant, the formula can be reformulated as follows:

$$care\ load = \left(\frac{85.8 * P_{all}}{B_{ED}}\right) + 13{,}4 * P_{u1}$$

$$care\ load = \left(\frac{85.8}{B_{ED}}\right) * P_{all} + 13{,}4 * P_{u1}$$

$$care\ load = P_{all} + \frac{13{,}4}{\left(\frac{85.8}{B_{ED}}\right)} * P_{u1}$$

$$care\ load = P_{all} + \frac{13.4}{85.8} * B_{ED} * P_{u1}$$

Using the known number of beds at each ED in AZE, we can calculate the relative impact of a u1 patient at each hospital. This is multiplied by a factor of 5, so that the values are in the same range as JDT values so that an adequate comparison can be made.

Table 3: NEDOCS Triage influence equivalent to JDT

hospital	ED beds	JDT equivalent value <u1	JDT equivalent value u1
MST	23	5	17,96
SKB	12	5	9,37
ZGT	24	5	18,74

Appendix B: Sensitivity analysis on care load approximation

To approximate the care load experienced due to each patient based on their NTS triage value, a method based on JDT and NEDOCS is applied as described in chapter 4. This approximation has quite some influence on the care load calculations and thus the results of both the data analysis as well as the experiments. The approximation also works under the assumption that the care load experienced by nurses can cover (more than) the full range of JDT values, and that this line becomes steeper at higher triage levels. This assumption was made in cooperation with the nurses and is grounded in the theory behind JDT and NEDOCS. Nevertheless, it is important to see what impact this assumption has on the results of the research. To evaluate this, an alternative function was formulated that assumes a less radical influence of NTS triage on care load:

$$C_p = 7 + (0.75 * (5 - NTS_p))^2$$

The behaviour of this alternative function can be observed in Figure 26.

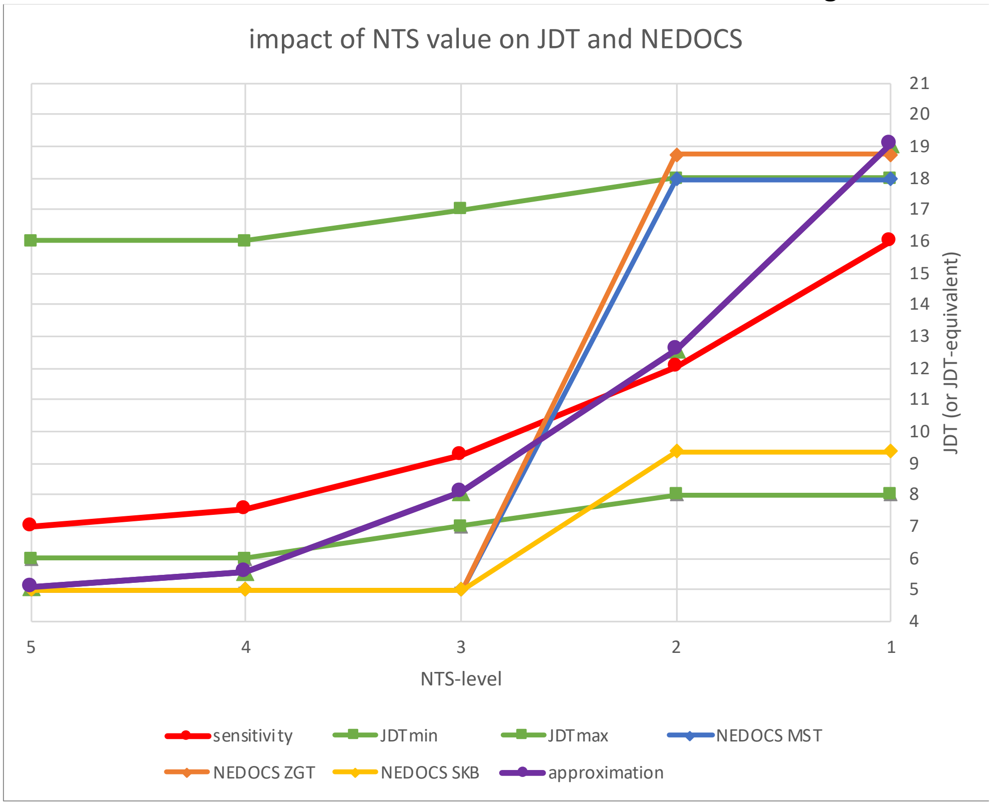
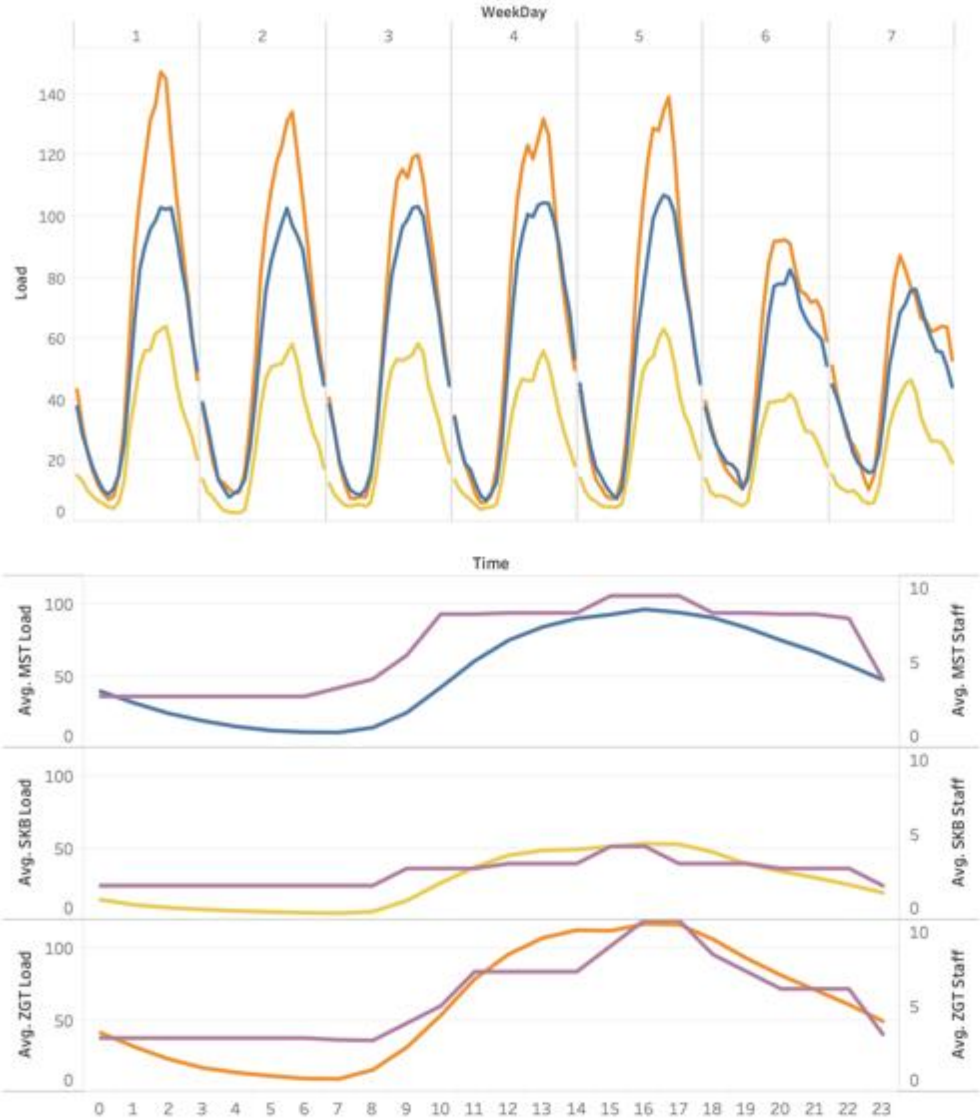


Figure 26: Care load approximation including sensitivity analysis

To see the effect of the application of this adapted formula, some of the figures of the data analysis have been reconstructed with the adapted care load data. From this we can conclude that there would be a consistently higher care load across the day and the region. A deviation from the known patterns is that ZGT would deviate even more from the other hospitals, both in size and variation of care load. This is to be expected, as significantly more patients with lower triage levels are seen at ZGT. Consequently, pooling effect could be less effective during some days when looking at the combined standard deviations, but more effective on others. Other than that, no other significant differences in patterns across time or the region can be identified. To conclude, this sensitivity analysis confirms that the basis of our research still stands, but also affirms that in the future one might consider other care load approximation methods for both research as well as cooperation in the region.

Care load approximation



Sensitivity analysis

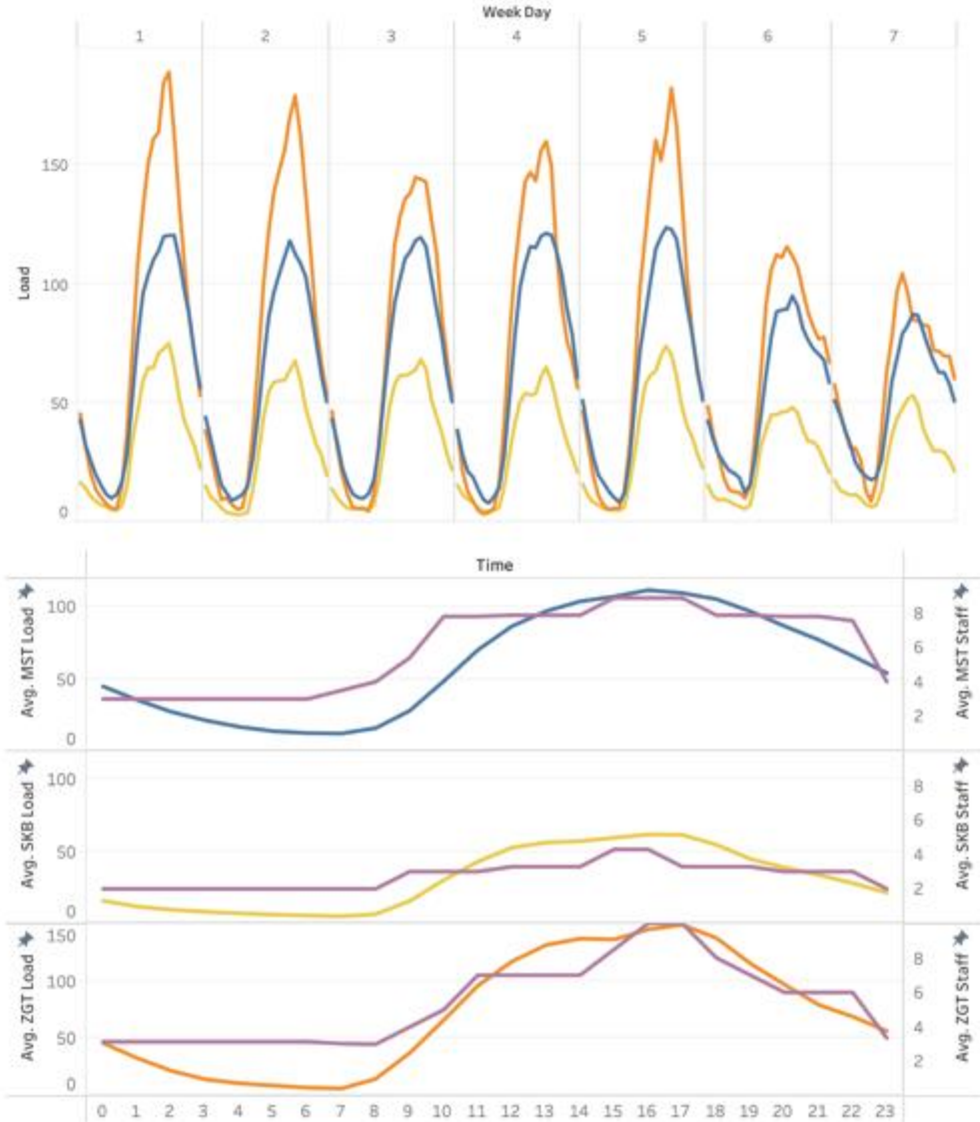


Figure 27: Sensitivy analysis on care load at week and day level

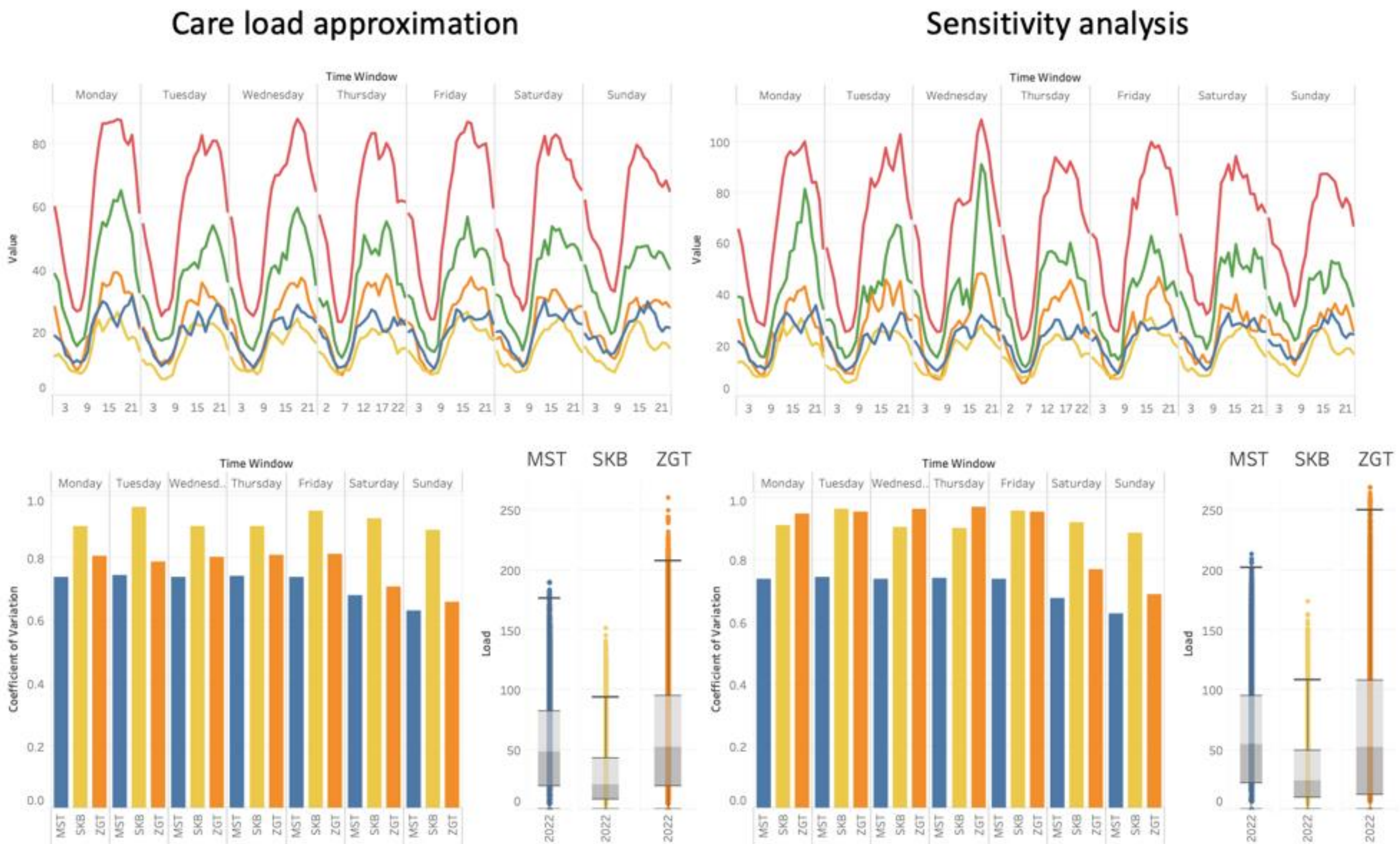


Figure 28: Sensitivity analysis on standard deviation and coefficient of variation across weeks, and box plot of observed care load.

Appendix C: Sensitivity analysis on choice for efficiency penalty

The efficiency penalty factor “a” for having a float nurse work in a different hospital than initially assigned was determined to be 0.9 in discussion with various stakeholders. This is an assumption and simplification of several inefficiencies that could be encountered be float nurses like travel and unfamiliarity with the other hospital. To see how much influence this parameter has on the model, a sensitivity analysis was performed. This analysis included both a more optimistic (a=1) as well as a more pessimistic (a=0.75) value. From the figure below, we can see that assuming no penalty (a=1) appears to have a slight positive impact on the objective. This is to be expected, as floating takes care of more care load. However, the results are not majorly different. For the more pessimistic value (a=0.75), the results also appear to be slightly different, with the lower bound being less low than the original experiments, but the upper bound not exceeding the original experiment by much.

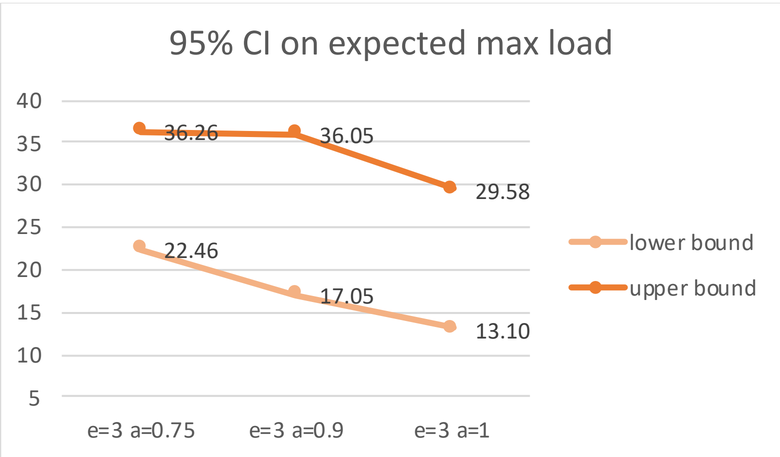


Figure 29: 95% confidence interval on expected maximum care load for e=3 with a= (0.75, 0.9,1)

When looking at the proposed schedules from the sensitivity analysis, we can see a slight deviation from the solutions found for the main experiments in both the optimistic and pessimistic scenario. The pessimistic scenario proposes to have full coverage across the day, much like the configuration where equal floating was enforced across the region. However, in this instance the model proposes to split the float nurses over SKB and ZGT. The proposed schedule also appears to be slightly more sloped than the results of the original experiment. The optimistic scenario proposes to have the float nurses spread across SKB and ZGT as well. However, in this case full coverage is not included. Instead, the model appears to propose flatter schedules across the day. The phenomenon of flatter or more sloped schedules can be considered to behave similarly to how the schedules become flatter the more flexibility is added in terms of float nurse s, as could be observed in the original experiments.

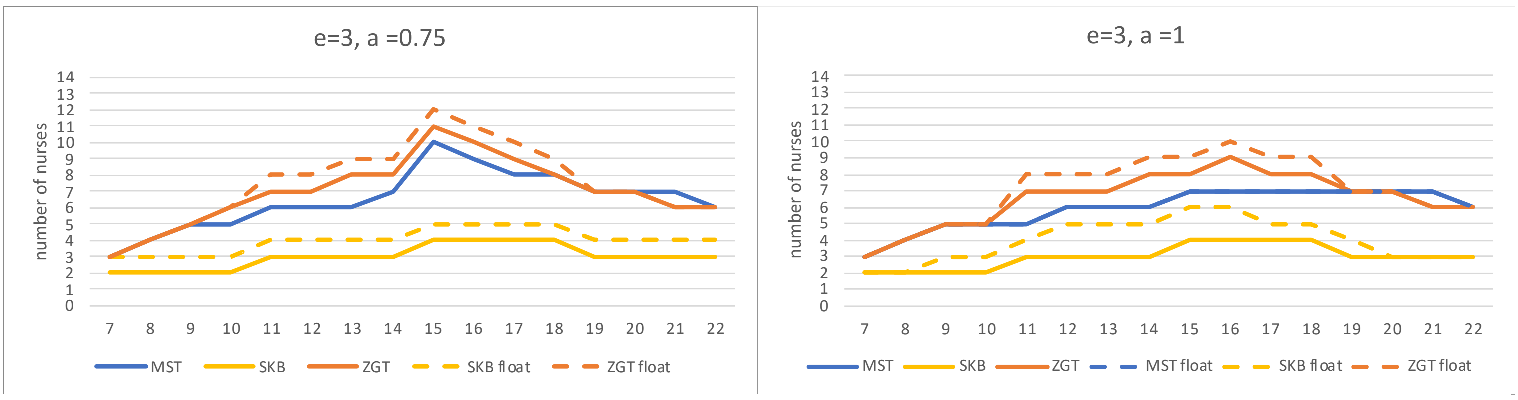


Figure 30: Proposed schedules for e=3 with a= 0.75 and a=1

In conclusion, it appears the parameter "a" does have influence on the optimal schedules. This is to be expected, as there is a trade-off between allocating less efficient float nurses, or dedicated nurses to certain time windows. For future research it will thus be important to get a good insight into the efficiency of float nurses, as well as the optimal moments to start floating considering expected care load. It will then also be important to not see the proposed configurations as set in stone. This however brings a large set of other factors that would also be worthwhile to investigate, as discussed in the conclusion chapter. That said, the parameter "a" does not appear to have the greatest effect on expected benefits of the float pool. Thus, the conclusions for the potential benefits of the float pool as discussed in the research appear to be justified.

Appendix D: small scale experiment on larger scenario sets

During the research, a configuration for the SAA analysis was chosen that made use of 15 runs of 20 scenarios. This decision was based on exploratory experiments with 5, 10, 20 and 25 scenarios. The decision to use 20 scenarios was made because 25 scenarios did not appear to offer significantly better solutions, while increasing runtime noticeably.

The trade-off between solution quality and runtime is present in every situation where SAA is applied, but also subject to the solvers and hardware used. To see if results would change drastically, should better solvers and/or more capable hardware be available to solve larger scenario sets in acceptable time, a small scale experiment was performed. The small scale experiment uses the same model as used in the main experiments, but with the following parameters:

T: [10 .. 16]
H: [MST,SKB,ZGT]
S: [1 .. 9]
K: (experiment specific)

$L_{h,t,k}$ ~Gamma($shape_{h,t}$,$rate_{h,t}$)
c_h: [5, 5, 5]
a: 0.9
w: 30
p_k: 1/size(K)
M: sufficiently large integer
$minn_h$: [1,1,1]
SL: 5
RMax: 1
$E_{h,h'}$: 1

The model was used to perform 15 runs of each experiment, with the experiments differentiating from each other by having 5, 10, 20, 50, and 75 scenarios. From the 15 resulting candidate solutions, the chosen solution was selected using the same methodology as applied in the main experiments. These chosen solutions where then evaluated using 15 runs of 250 scenarios using fixed first stage variables, as was done in the main experiments as well.

The average objective values are presented in **Error! Reference source not found.**, and show that whilst the differences between 5 and 10 scenarios is noticeable, the difference between 50 and 75 scenarios is almost neglectable. When looking at the results using 20 scenarios, it can be seen that some differences exist, especially in the epsilon=1 results, but the results come very close to the 50 and 75 scenario results in the other configurations. Overall however, the differences in values are not extreme in terms of absolute values

Table 4: Average objective value across 15 runs using 250 scenarios for epsilon=1,2,3,4 and k=5,10,20,50,75

Epsilon/k	1	2	3	4
5	114.0502	104.9294	103.3481	86.50115
10	112.4983	111.5086	104.7636	84.17614
20	112.2582	103.47	101.8058	81.67598
50	107.9552	103.458	101.5193	81.25896
75	107.955	103.557	101.6237	81.19591

When looking at the way the confidence intervals are formed throughout the experiments, as shown in Figure 31, we can observe a few things as well. First, it can be seen that the width of the confidence intervals is reasonably steady across all configurations, narrowing slightly at the higher epsilon values. Second, the configurations with k=50 and k=75 appear to have almost the same results, with the difference being almost certainly neglectable for any practical use. The k=20 results appear to be less optimistic than k=50 and k=75 for the epsilon=1 configuration. However, for all the other results, the results look almost indistinguishable from k=50 and k=75.

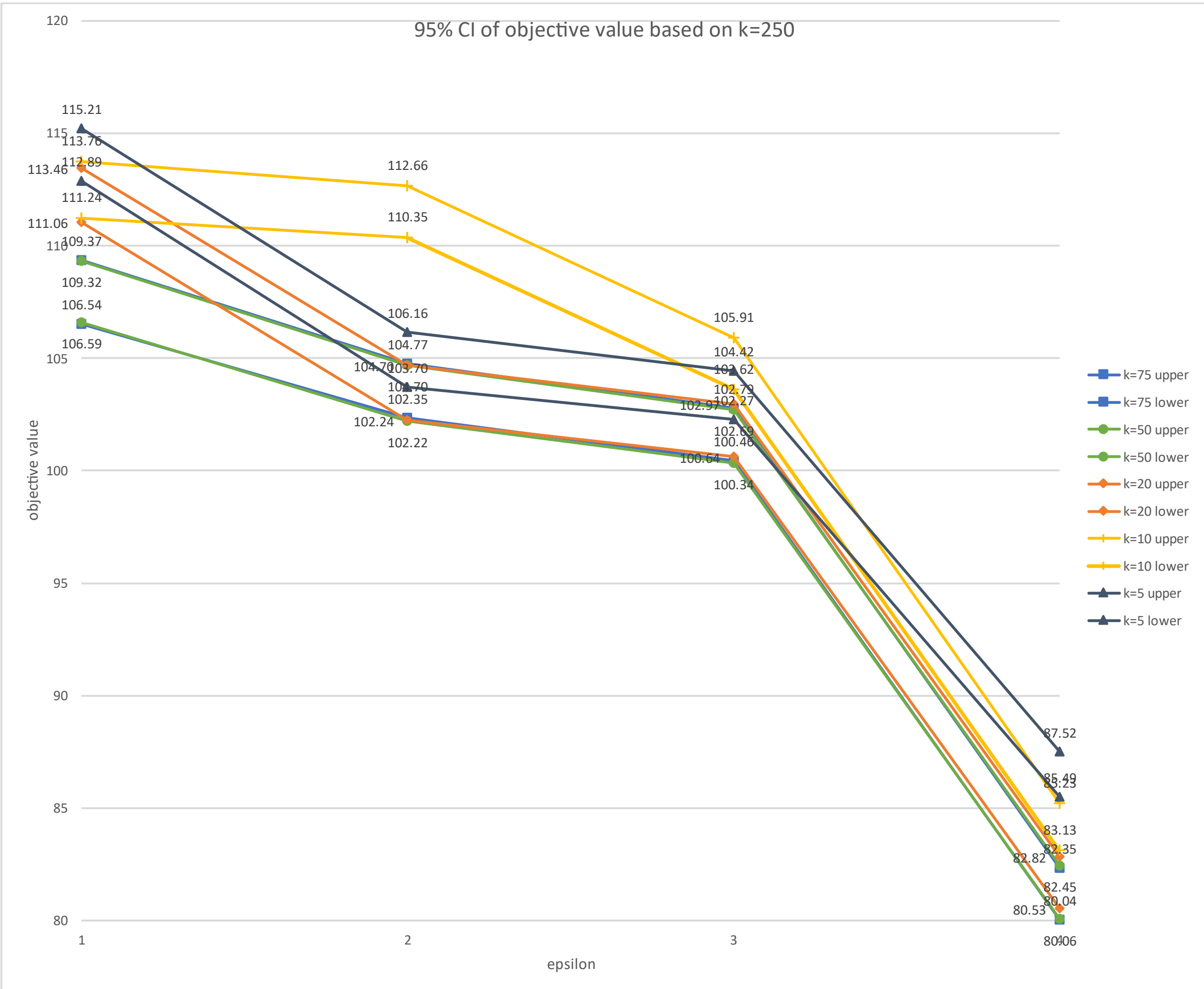


Figure 31: 95% CI of objective value across 15 runs of 250 scenarios with epsilon = 1,2,3,4 and k= 5,10,20,50,75

Based on this analysis, it can be concluded that at lower levels of flexibility, better solutions can potentially still be found by using more scenarios in the model. However, at the level of flexibility that the solutions which were selected in the research (in most cases, epsilon=3), the configuration with 20 scenarios appears to perform equal to when larger scenario sets are applied. It should be noted that this analysis does not reflect the full range of variability that is present in the main research. Therefore, it cannot be said with absolute certainty what the behaviour of the model would be with significantly larger scenario sets. However, it can be concluded that using 20 scenarios is likely not to be significantly handicapping or skewing the results of the main research.

Appendix E: Details on candidate solutions and solution selection

The process used for selecting candidate solutions to evaluate further from the set of runs for each experiment has not been thoroughly described in the main report for the sake of brevity. Therefore, it is discussed in this appendix.

First, it was checked whether a duplicate solution in terms of float nurse allocation meant that the dedicated nurse allocation would also be the same. This turned out to be true for all candidate solution sets. Therefore, selection was done based on the characteristics of the float nurse allocation, except for the e=0 experiments as these do not have float nurse allocation. In these instances, the dedicated nurse allocation was used. Based on these characteristics, all duplicate solutions were identified and colour coded. Furthermore, candidate solutions that shared similarities but no exact match were given similar colours as well. The chosen solution is in most cases the candidate solution with the most duplicates. In case of ties, the candidate solution with the most similar solutions was chosen. In case of further ties, both options were evaluated using a larger set of scenarios and the better performing one was selected.

This process is visualised in the following tables, where the fully green solution is the solution ultimately used in the rest of the research.

dedicated e=0

n	t / h	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22
1	MST	4	5	5	7	7	8	9	9	10	9	9	7	7	6	5	5
1	SKB	2	2	2	2	3	3	3	3	4	4	4	4	3	3	3	3
1	ZGT	4	4	5	6	6	7	8	9	10	10	9	8	8	7	6	5
2	MST	4	5	5	7	7	8	9	9	10	9	9	7	7	6	5	5
2	SKB	2	2	2	2	3	3	3	3	4	4	4	4	3	3	3	3
2	ZGT	4	4	5	6	6	7	8	9	10	10	9	8	8	7	6	5
3	MST	4	5	5	7	7	8	9	9	10	9	9	7	7	6	5	5
3	SKB	2	2	2	2	3	3	3	3	4	4	4	4	3	3	3	3
3	ZGT	4	4	5	6	6	7	8	9	10	10	9	8	8	7	6	5
4	MST	5	4	5	5	6	7	7	6	6	6	7	6	6	5	5	5
4	SKB	2	2	2	2	3	3	3	3	4	4	4	3	3	3	3	3
4	ZGT	4	4	5	5	5	6	6	6	7	7	8	7	7	6	6	5
5	MST	3	3	5	6	8	7	7	7	8	8	7	7	6	6	6	6
5	SKB	2	2	2	2	2	2	3	3	2	2	2	3	2	3	3	2
5	ZGT	3	3	4	5	6	8	7	7	7	9	9	7	6	5	5	5
6	MST	3	3	5	6	8	7	7	7	8	8	7	7	6	6	6	6
6	SKB	2	2	2	2	2	2	3	3	2	2	2	3	2	3	3	2
6	ZGT	3	3	4	5	6	8	7	7	7	9	9	7	6	5	5	5
7	MST	3	3	4	5	7	7	7	6	7	6	7	7	5	6	6	5
7	SKB	2	2	2	2	2	2	3	4	2	2	2	2	3	4	2	2
7	ZGT	3	3	3	4	5	6	7	7	7	9	9	7	7	6	4	4
8	MST	3	3	4	5	7	7	7	6	7	6	7	7	5	6	6	5
8	SKB	2	2	2	2	2	2	3	4	2	2	2	2	3	4	2	2
8	ZGT	3	3	3	4	5	6	7	7	7	9	9	7	7	6	4	4
9	MST	3	3	4	5	7	7	7	6	7	6	7	7	5	6	6	5
9	SKB	2	2	2	2	2	2	3	4	2	2	2	2	3	4	2	2
9	ZGT	3	3	3	4	5	6	7	7	7	9	9	7	7	6	4	4
10	MST	3	3	4	5	7	7	7	6	7	6	7	7	5	6	6	5
10	SKB	2	2	2	2	2	2	3	4	2	2	2	2	3	4	2	2
10	ZGT	3	3	3	4	5	6	7	7	7	9	9	7	7	6	4	4
11	MST	3	4	5	6	8	8	8	9	10	9	8	7	5	5	5	4
11	SKB	2	2	2	2	2	2	4	4	4	4	4	4	4	4	2	2
11	ZGT	3	3	3	5	7	8	9	10	11	11	11	9	7	6	5	4
12	MST	3	4	5	6	8	8	8	9	10	9	8	7	5	5	5	4
12	SKB	2	2	2	2	2	2	4	4	4	4	4	4	4	4	2	2
12	ZGT	3	3	3	5	7	8	9	10	11	11	11	9	7	6	5	4
13	MST	3	4	5	6	8	8	8	9	10	9	8	7	5	5	5	4
13	SKB	2	2	2	2	2	2	4	4	4	4	4	4	4	4	2	2
13	ZGT	3	3	3	5	7	8	9	10	11	11	11	9	7	6	5	4
14	MST	3	4	5	6	8	8	8	9	10	9	8	7	5	5	5	4
14	SKB	2	2	2	2	2	2	4	4	4	4	4	4	4	4	2	2
14	ZGT	3	3	3	5	7	8	9	10	11	11	11	9	7	6	5	4
15	MST	3	4	5	6	8	8	8	9	10	9	8	7	5	5	5	4
15	SKB	2	2	2	2	2	2	4	4	4	4	4	4	4	4	2	2
15	ZGT	3	3	3	5	7	8	9	10	11	11	11	9	7	6	5	4

float e=1

n	t / h	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22
1	MST	1	1	1	1	1	1	1	1								
2	SKB	1	1	1	1	1	1	1	1								
3	SKB	1	1	1	1	1	1	1	1								
4	MST				1	1	1	1	1	1	1	1					
5	SKB	1	1	1	1	1	1	1	1								
6	MST		1	1	1	1	1	1	1	1							
7	MST	1	1	1	1	1	1	1	1								
8	ZGT	1	1	1	1	1	1	1	1								
9	SKB	1	1	1	1	1	1	1	1								
10	SKB	1	1	1	1	1	1	1	1								
11	SKB	1	1	1	1	1	1	1	1								
12	SKB			1	1	1	1	1	1	1	1						
13	SKB			1	1	1	1	1	1	1	1						
14	SKB			1	1	1	1	1	1	1	1						
15	SKB			1	1	1	1	1	1	1	1						

float e=3

n	t / h	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22
1	MST	1	1	2	2	2	2	2	2	1	1						
1	SKB				1	1	1	1	1	1	1	1					
2	MST							1	1	1	1	1	1	1	1		
2	ZGT	1	1	2	2	2	2	2	2	1	1						
3	SKB							1	1	1	1	1	1	1	1		
3	ZGT		1	1	1	2	2	2	2	2	1	1	1				
4	MST	1	1	1	1	1	1	1	1								
4	SKB						1	1	1	1	1	1	1	1			
4	ZGT			1	1	1	1	1	1	1	1						
5	MST				1	1	1	1	1	1	1	1					
5	SKB		1	1	1	1	1	1	1	1							
5	ZGT					1	1	1	1	1	1	1	1				
6	SKB	1	2	2	2	2	2	2	2	1							
6	ZGT								1	1	1	1	1	1	1	1	
7	MST		1	1	1	1	1	1	1								
7	ZGT		1	1	1	2	2	2	2	2	1	1	1				
8	MST	1	1	1	1	1	1	1	1								
8	SKB						2	2	2	2	2	2	2	2			
9	MST		1	1	1	1	1	1	1	1							
9	SKB								1	1	1	1	1	1	1	1	
9	ZGT	1	1	1	1	1	1	1	1								
10	SKB				1	1	1	1	1	1	1	1					
10	ZGT	1	1	1	1	1	1	2	2	1	1	1	1	1	1		
11	SKB	1	1	2	2	2	3	3	3	2	2	1	1	1			
12	SKB	1	1	2	2	2	3	3	3	2	2	1	1	1			
13	SKB	1	1	2	2	2	3	3	3	2	2	1	1	1			
14	SKB	1	1	1	2	2	3	3	3	2	2	1	1	1			
15	SKB	1	1	1	2	2	3	3	3	2	2	2	1	1			

float e=5

n	t / h	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22
1	MST	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
1	SKB						1	1	1	1	2	2	2	2	1	1	1
1	ZGT							1	1	1	1	1	1	1	1		
2	MST	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
2	SKB						1	1	1	1	2	2	2	2	1	1	1
2	ZGT							1	1	1	1	1	1	1	1		
3	MST	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
3	SKB						1	1	1	1	2	2	2	2	1	1	1
3	ZGT							1	1	1	1	1	1	1	1		
4	MST	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
4	SKB						1	1	1	1	2	2	2	2	1	1	1
4	ZGT							1	1	1	1	1	1	1	1		
5	MST	1	1	1	1	1	1	1	1								
5	SKB		1	1	1	1	1	1	1	1							
5	ZGT									3	3	3	3	3	3	3	3
6	MST			1	1	1	1	1	1	1	1						
6	SKB					1	1	2	2	2	2	2	2	1	1		
6	ZGT	1	1	1	1	1	1	1	2	1	1	1	1	1	1	1	
7	MST	1	1	1	1	1	1	1	1								
7	SKB		1	1	1	1	1	1	1	1							
7	ZGT									3	3	3	3	3	3	3	3
8	MST	1	1	1	1	1	1	1	1								
8	SKB	1	1	1	1	1	1	1	1								
8	ZGT					1	1	1	2	3	3	3	3	2	2	2	1
9	MST		2	2	2	2	2	2	2	1							
9	SKB					1	1	1	1	1	1	1	1				
9	ZGT										2	2	2	2	2	2	2
10	MST				1	1	1	1	1	1	1	1					
10	SKB			1	1	1	1	1	1	1	1						
10	ZGT			2	2	2	2	2	2	3	3	1	1	1	1	1	1
11	MST				1	1	1	1	1	1	1	1					
11	SKB				1	1	1	1	1	1	1	1					
11	ZGT	1	1	1	1	1	1	1	1	1	2	2	2	2	2	2	2
12	MST				1	1	1	1	1	2	2	2	1	1	1	1	1
12	SKB	1	1	1	1	1	2	2	2	1	1	1	1	1			
12	ZGT				1	1	1	1	1	1	1	1					
13	MST				1	1	1	1	1	2	2	2	1	1	1	1	1
13	SKB	1	1	1	1	1	2	2	2	1	1	1	1	1			
13	ZGT				1	1	1	1	1	1	1	1					
14	MST				1	1	1	1	1	2	2	2	1	1	1	1	1
14	SKB	1	1	1	1	1	2	2	2	1	1	1	1	1			
14	ZGT				1	1	1	1	1	1	1	1					
15	MST			1	1	1	1	1	1	2	2	1	1	1	1	1	1
15	SKB				1	1	1	1	1	1	1	1					
15	ZGT	1	1	2	2	2	2	2	2	1	1						

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UNIVERSITY OF TWENTE.

ded e=0 weekend

n	t / h	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22
1	MST	4	5	5	7	7	8	9	9	10	9	9	7	7	6	5	5
1	SKB	2	2	2	2	3	3	3	3	4	4	4	4	3	3	3	3
1	ZGT	4	4	5	6	6	7	8	9	10	10	9	8	8	7	6	5
2	MST	4	5	5	7	7	8	9	9	10	9	9	7	7	6	5	5
2	SKB	2	2	2	2	3	3	3	3	4	4	4	4	3	3	3	3
2	ZGT	4	4	5	6	6	7	8	9	10	10	9	8	8	7	6	5
3	MST	4	5	5	7	7	8	9	9	10	9	9	7	7	6	5	5
3	SKB	2	2	2	2	3	3	3	3	4	4	4	4	3	3	3	3
3	ZGT	4	4	5	6	6	7	8	9	10	10	9	8	8	7	6	5
4	MST	4	5	5	7	7	8	9	9	10	9	9	7	7	6	5	5
4	SKB	2	2	2	2	3	3	3	3	4	4	4	4	3	3	3	3
4	ZGT	4	4	5	6	6	7	8	9	10	10	9	8	8	7	6	5
5	MST	4	5	5	7	7	8	9	9	10	9	9	7	7	6	5	5
5	SKB	2	2	2	2	3	3	3	3	4	4	4	4	3	3	3	3
5	ZGT	4	4	5	6	6	7	8	9	10	10	9	8	8	7	6	5
6	MST	4	5	5	7	7	8	9	9	10	9	9	7	7	6	5	5
6	SKB	2	2	2	2	3	3	3	3	4	4	4	4	3	3	3	3
6	ZGT	4	4	5	6	6	7	8	9	10	10	9	8	8	7	6	5
7	MST	4	5	5	7	7	8	9	9	10	9	9	7	7	6	5	5
7	SKB	2	2	2	2	3	3	3	3	4	4	4	4	3	3	3	3
7	ZGT	4	4	5	6	6	7	8	9	10	10	9	8	8	7	6	5
8	MST	4	5	5	7	7	8	9	9	10	9	9	7	7	6	5	5
8	SKB	2	2	2	2	3	3	3	3	4	4	4	4	3	3	3	3
8	ZGT	4	4	5	6	6	7	8	9	10	10	9	8	8	7	6	5
9	MST	4	5	5	7	7	8	9	9	10	9	9	7	7	6	5	5
9	SKB	2	2	2	2	3	3	3	3	4	4	4	4	3	3	3	3
9	ZGT	4	4	5	6	6	7	8	9	10	10	9	8	8	7	6	5
10	MST	4	5	5	7	7	8	9	9	10	9	9	7	7	6	5	5
10	SKB	2	2	2	2	3	3	3	3	4	4	4	4	3	3	3	3
10	ZGT	4	4	5	6	6	7	8	9	10	10	9	8	8	7	6	5
11	MST	5	4	5	5	6	7	7	6	6	6	7	6	6	5	5	5
11	SKB	2	2	2	2	3	3	3	3	4	4	4	3	3	3	3	3
11	ZGT	4	4	5	5	5	6	6	6	7	7	8	7	7	6	6	5
12	MST	5	4	5	5	6	7	7	6	6	6	7	6	6	5	5	5
12	SKB	2	2	2	2	3	3	3	3	4	4	4	3	3	3	3	3
12	ZGT	4	4	5	5	5	6	6	6	7	7	8	7	7	6	6	5
13	MST	5	4	5	5	6	7	7	6	6	6	7	6	6	5	5	5
13	SKB	2	2	2	2	3	3	3	3	4	4	4	3	3	3	3	3
13	ZGT	4	4	5	5	5	6	6	6	7	7	8	7	7	6	6	5
14	MST	5	4	5	5	6	7	7	6	6	6	7	6	6	5	5	5
14	SKB	2	2	2	2	3	3	3	3	4	4	4	3	3	3	3	3
14	ZGT	4	4	5	5	5	6	6	6	7	7	8	7	7	6	6	5
15	MST	5	4	5	5	6	7	7	6	6	6	7	6	6	5	5	5
15	SKB	2	2	2	2	3	3	3	3	4	4	4	3	3	3	3	3
15	ZGT	4	4	5	5	5	6	6	6	7	7	8	7	7	6	6	5

float e=3 weekend

n	t / h	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22
1	MST		2	2	2	2	2	2	2	2							
1	ZGT						1	1	1	1	1	1	1	1			
2	MST		2	2	2	2	2	2	2	2							
2	ZGT						1	1	1	1	1	1	1	1			
3	MST				1	1	1	1	1	1	1	1					
3	SKB		1	1	1	1	1	1	1	1							
3	ZGT					1	1	1	1	1	1	1	1				
4	SKB	1	1	1	1	1	1	2	2	1	1	1	1	1	1		
4	ZGT						1	1	1	1	1	1	1	1			
5	SKB	1	1	1	1	1	1	2	2	1	1	1	1	1	1		
5	ZGT						1	1	1	1	1	1	1	1			
6	SKB	1	1	1	1	1	1	2	2	1	1	1	1	1	1		
6	ZGT						1	1	1	1	1	1	1	1			
7	MST	1	1	1	1	1	1	1	1								
7	SKB				1	1	1	2	2	1	1	1	1	1	1		
8	MST	1	1	1	1	1	1	1	1								
8	SKB				1	1	1	2	2	1	1	1	1	1	1		
9	MST	1	1	1	1	1	1	1	1								
9	SKB				1	1	1	2	2	1	1	1	1	1	1		
10	MST		1	1	1	1	1	1	1	1							
10	SKB	1	1	1	1	1	1	2	2	1	1	1	1	1	1		
11	MST		1	1	1	1	1	1	1	1							
11	SKB	1	1	1	1	1	1	2	2	1	1	1	1	1	1		
12	MST		1	1	1	1	1	1	1	1							
12	SKB	1	1	1	1	1	1	2	2	1	1	1	1	1	1		
13	MST		1	1	1	1	1	1	1	1							
13	SKB	1	1	1	1	1	1	2	2	1	1	1	1	1	1		
14	MST		1	1	1	1	1	1	1	1							
14	SKB	1	1	1	1	1	1	2	2	1	1	1	1	1	1		
15	MST		1	1	1	1	1	1	1	1							
15	SKB	1	1	1	1	1	1	2	2	1	1	1	1	1	1		

float e=3 spread																	
	t	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22
n	h																
1	MST	1	1	1	1	1	1	1	1								
1	SKB									1	1	1	1	1	1	1	1
1	ZGT					1	1	1	1	1	1	1	1				
2	MST				1	1	1	1	1	1	1	1					
2	SKB		1	1	1	1	1	1	1	1							
2	ZGT					1	1	1	1	1	1	1	1				
3	MST							1	1	1	1	1	1	1	1		
3	SKB	1	1	1	1	1	1	1	1								
3	ZGT						1	1	1	1	1	1	1	1			
4	MST	1	1	1	1	1	1	1	1								
4	SKB									1	1	1	1	1	1	1	1
4	ZGT					1	1	1	1	1	1	1	1				
5	MST	1	1	1	1	1	1	1	1								
5	SKB									1	1	1	1	1	1	1	1
5	ZGT					1	1	1	1	1	1	1	1				
6	MST	1	1	1	1	1	1	1	1								
6	SKB									1	1	1	1	1	1	1	1
6	ZGT					1	1	1	1	1	1	1	1				
7	MST				1	1	1	1	1	1	1	1					
7	SKB		1	1	1	1	1	1	1	1							
7	ZGT					1	1	1	≈	1	1	1	1				
8	MST				1	1	1	1	1	1	1	1					
8	SKB		1	1	1	1	1	1	1	1							
8	ZGT					1	1	1	1	1	1	1	1				
9	MST				1	1	1	1	1	1	1	1					
9	SKB		1	1	1	1	1	1	1	1							
9	ZGT					1	1	1	1	1	1	1	1				
10	MST	1	1	1	1	1	1	1	1								
10	SKB									1	1	1	1	1	1	1	1
10	ZGT					1	1	1	1	1	1	1	1				
11	MST	1	1	1	1	1	1	1	1								
11	SKB									1	1	1	1	1	1	1	1
11	ZGT					1	1	1	1	1	1	1	1				
12	MST		1	1	1	1	1	1	1	1							
12	SKB									1	1	1	1	1	1	1	1
12	ZGT					1	1	1	1	1	1	1	1				
13	MST	1	1	1	1	1	1	1	1								
13	SKB									1	1	1	1	1	1	1	1
13	ZGT					1	1	1	1	1	1	1	1				
14	MST					1	1	1	1	1	1	1	1				
14	SKB									1	1	1	1	1	1	1	1
14	ZGT	1	1	1	1	1	1	1	1								
15	MST	1	1	1	1	1	1	1	1								
15	SKB									1	1	1	1	1	1	1	1
15	ZGT					1	1	1	1	1	1	1	1				