Capacity planning in a network of healthcare providers in Twente

Master Thesis

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Preface

Before you lies my master thesis ‘Capacity planning in a network of healthcare providers in Twente”, which is the result of the study I performed at Ziekenhuis Groep Twente. This thesis marks the end of my master Industrial Engineering & Management at the University of Twente. I am grateful for everything I have learned and all the interesting courses I have followed. I am still very happy with my choice for this master and the focus on Operations Management in Healthcare, as I discovered that this is where my passion lies. I am grateful for the opportunity to have gained work experience in this field during my master's program at ZGT, and I am happy that I can continue working in it.

I thank Marleen Engelbertink and Michel Kats for their supervision from within ZGT. Thank you for giving me the opportunity to graduate in this interesting field, by setting up the idea for this research together. Also, I appreciate your willingness to brainstorm, connect me with the right people and provide valuable feedback. I also thank Martine Jongbloed for her critical view and valuable feedback.

Furthermore, I thank my supervisors from the University of Twente, Erwin Hans and Daniela Guericke. Thank you for your feedback and input during our meetings, for your feedback on the intermediate versions of my report and for all your general tips and advice.

Jorieke Havinga
Enschede, June 2023

Management Summary

Problem definition

This study focuses on the care that patients need after being in the hospital. The study is embedded at the transfer agency of hospital group Twente (ZGT, Dutch: Ziekenhuisgroep Twente). The transfer agency arranges care for patients after they reached the end of their hospital treatment, but are not ready to go home on their own. From the hospital point of view, it is important that the care for a patient can be transferred to an aftercare institution as soon as possible, after a patient has finished medical treatment. The number of days that a patient is in the hospital after the patient has finished the medical treatment, are labeled as alternate level of care days (ALC days, Dutch: verkeerde beddagen). ALC days cost the hospital time and money, the estimated loss for the hospital is 200 euro per day for long-term care patients (WLZ, Dutch: Wet Langdurige Zorg) and 100 euro for other ALC patients. From the aftercare point of view, it is important to have a high bed occupation, as empty beds may lead to financial difficulties. The core problem we address in this study is: *The healthcare providers in the transfer chain of Twente do not know how much capacity is needed when and where in the system and how the demand should be optimally allocated between them.*

Method

We chose to use Discrete Event Simulation. The most important model inputs consist of the patients' characteristics, discharge rates, length of stay and capacity in the aftercare. The scope of the model consists of the transfer of patients from the hospital to extramural aftercare. The object of our simulation model is to analyze the effects of interventions and scenarios on the system performance on a strategical and tactical level. As KPIs, we use the average waiting time in the hospital, the probability of waiting and the bed occupation rate in the aftercare. On a strategical level, we explore the effect of the bed occupation in aftercare on the waiting time in the hospital and experiment with options to lower the bed occupation. Further, we explore the effects of capacity pooling and a redistribution of the beds between the care types. On a tactical level, we explore the effects of adding more admission possibilities and the influence of the estimation of the discharge date in the hospital.

Results and conclusions

As expected, the average waiting time in the hospital is lower with a lower bed occupation in the aftercare institutions. However, it differs per type of care how high the bed occupation in the aftercare can be for a certain waiting time. For WLZ, the bed occupation can be around 95% to have a very low waiting time, while for ELV Palliative, the waiting time is only low with an average bed occupation of 70%. To halve the waiting time for each type of care, the capacity of ELV Low should be increased by 5% or the length of stay decreased by 5%. For ELV High and GRZ, an increase in capacity or decrease in LOS of 3% is enough for halving the waiting time. Looking at ELV Palliative, an increase of 1 bed would already be enough to halve the waiting time. At last, for the WLZ an increase in capacity of 1% or a decrease in LOS of 1% would already be enough. Although the average waiting time can get very low, the probability of waiting always remains around 10% the lowest.

Using the simulation model we show that capacity pooling, i.e. adding some flexibility in who can be admitted to which bed, has a large impact on the average waiting time and the probability of waiting. More than 30 flexible beds are not necessary as there is no significant improvement anymore in the waiting time. The average waiting time for ELV and GRZ together decreases with 30 flexible beds from 2.4 to 0.4 days. We could not find a significantly better distribution of the beds between the types of care when capacity pooling is not possible.

Currently, there are no admission possibilities during the weekend. By adding one admission possibility per location, the average waiting time decreases for all types of care, except for the WLZ. With two admission possibilities, there is no significant improvement anymore relative to one admission possibility. Adding more admission possibilities on weekdays only gives an improvement at ELV high. Also in this case, one additional admission possibility would satisfy. When there are no admission restrictions at all the average waiting time for ELV high decreases from 4.5 to 3.1 days.

In the current situation, it is not very important to focus on a better and early estimation of the discharge date. The current estimation is already quite good and on time. However, when capacity is less of a problem in the transfer chain, we showed that a good and early estimation of the discharge date becomes more important, especially for ELV. For ELV palliative, it is most important to focus on a good and early estimation of the hospital discharge date.

Discussion

Modeling in healthcare is an emerging field, but most of the current work focuses on the optimization of a specific healthcare provider (e.g. a hospital) or even a specific department (e.g. the operating theatre). Little work is performed on how to integrate the care need between different healthcare providers. By analyzing the effects of bed occupation in aftercare on ALC days in the hospital, this study provides a nuanced understanding of the relationship between bed occupation in the aftercare and waiting times and ALC days in the hospital. Next, by evaluating the effects of pooling capacity between different types of aftercare, our study addresses the issue of fragmentation in capacity and their impact on system performance. Overall, the theoretical contribution of this research lie in the exploration of various interventions in a detailed discrete event simulation, which is able to handle more details and stochasticity than an explicit mathematical model formulation as used in other studies. The insights gained from this research can also be applied to other regions or countries facing similar challenges. Also, the conceptual model can be used to set up a similar simulation model.

The results of this research align with the expectations of the managers of the aftercare institutions and the capacity manager of ZGT. Specifically, they acknowledge the lack of admission possibilities during weekend, which leads to unnecessary prolonged hospital stays and ALC days. Moreover, they found it to be a common experience that a shorter length of stay for the ELV and GRZ contribute to better patient outcomes and a decrease in ALC days. This research underscores the importance of optimizing the length of stay. For the hospital, it is a valuable finding that the current estimation of the discharge date is quite good, so it is not necessary to put a lot of effort in improving this. Finally, the managers acknowledge that the concept of flexible capacity, allowing for easy scalability, is a great solution. However, implementing this solution is complex in terms of personnel planning and financing, but it is worth further investigation.

We used some assumptions and simplifications in our study. Unfortunately, we do not have all the needed data available. Therefore, we make assumptions about the length of stay in the aftercare per type of care and the demand for places in the aftercare institutions not coming from ZGT. Other limitations are that we do not have information about all reasons why a patient has to wait in the hospital, how often patients switch locations when they are in an aftercare institution and the impact of the length of stay in the hospital on the length of stay in the aftercare.

Recommendations and further research

We recommend also performing research from the aftercare institution perspective, as this would give a different perspective which is also valuable for the transfer chain. Second, we recommend broadening this study by also including smaller aftercare institutions and care at home. When incorporating home care into the study, the focus of analysis expands beyond physical locations in aftercare, as personnel planning becomes an aspect to be taken into account. Third, we recommend using the developed simulation model for testing other situations and options than explored in this study. For example, we focus on exclusively increasing capacity or decreasing the length of stay or demand, while also a combination of these options can be tested. Further, when there is reliable data, the foundation of the model assumptions can be explored. It would, among others, be important to explore the behavior of the patient's length of stay and recovery in the aftercare. Next, we recommend further investigating how the aftercare institutions, the insurers and the hospital can collaborate to share the financial burden properly to keep the care for the elderly affordable, also in the future.

This research is meant to be a starting point for better collaboration in terms of capacity planning between ZGT and aftercare providers. We showed the bottlenecks, where the most profit can be made and how this can be done. Achieving a perfect collaboration is challenging due to the complexity of the healthcare system. We describe a roadmap that aims to provide a path to a successful collaboration between the hospital and aftercare institutions. The goal is to optimize resource utilization, reduce waiting times, and provide better patient care. The roadmap consists of the following steps:

1. Create a foundation for collaboration
2. Conduct joint capacity planning
3. Continuously monitor and evaluate performance
4. Develop a perfect information system
5. Create a culture of collaboration in Twente

Table of contents

Glossary

ELV	First-line stay (Dutch: Eerstelijnsverblijf)
WLZ	Long-term care law (Dutch: Wet Langdurige Zorg)
GRZ	Geriatric Rehabilitation care (Dutch: Geriatische Revalidatie Zorg)
ALC days	ALC days (Dutch: Verkeerde beddagen)
POINT	Information system used for the communication related to patients transferring (Dutch: Punt voor Overdracht, Informatie, Naslag en Transfers)
LOS	Length of stay
MDO	Multidisciplinary consult
CIZ	Care Assessment Center (Dutch: Centrum Indicatiestelling Zorg)

1. Introduction

This chapter introduces the topic of this study. Section 1.1 provides background information on the context of the study. Section 1.2 and 1.3 present the problem and our approach to solve it.

1.1 Background information

The healthcare system in the Netherlands is known to be one of the best healthcare systems in the world. However, the costs are increasing rapidly, especially in long-term care (Ministerie van Volksgezondheid). The costs for the long-term care increased in 2021 by 10.8%. The statistics show that more long-term care is delivered at home. The costs for care at home increase more rapidly than the costs at aftercare institutions (Ministerie van Volksgezondheid). Therefore, it becomes more important to manage healthcare cleverly and efficiently. The government of the Netherlands focuses more on senior housing, life-cycle housing, informal care, digital care, domotics and fall prevention.

This study focuses on the care that patients need after being in the hospital. The study is embedded at the transfer agency of hospital group Twente (ZGT, Dutch: Ziekenhuisgroep Twente). The transfer agency arranges care for patients after they reached the end of their hospital treatment, but are not ready to go home on their own. The care patients need differs per patient. It could be care at home, care according to the long-term care law (WLZ, Dutch: Wet langdurige zorg), first-line stay (ELV, Dutch: Eerstelijnsverblijf), geriatric rehabilitation care (GRZ, Dutch: geriatische revalidatie zorg) or hospice. Within these categories, the demand for care also differs.

From the hospital point of view, it is important that the care for a patient can be transferred to an aftercare institution as soon as possible, after a patient has finished medical treatment. This is not always possible, because the capacity in the aftercare institutions is limited. As long as a patient cannot be transferred, he or she will remain in the hospital. The number of days that a patient is in the hospital after the patient has finished the medical treatment, are labeled as ALC days (ALC days, Dutch: verkeerde beddagen). ALC days cost hospitals time and money, as ALC patients block beds for other patients. It has also negative consequences for the patients to stay longer in the hospital than necessary (Jasinarachchi, 2009).

Internal confidential research has shown that the bed occupancy of the WLZ beds in the region of Twente is about 95-99%. A logical consequence of such a high bed occupancy is that the waiting time is long. In the coming years, due to the aging population, the number of elderly people in the Netherlands will increase and thereby the demand for care. Given the current bed occupancy and long waiting times, the current system is not sustainable. In 2019, ZGT reached a record number of ALC days. In 2020 and 2021, the number of ALC days was lower, probably due to the corona crisis. In 2022, the ALC days are increasing again. The expectation is that the ALC days will increase further, due to the above-mentioned increase in the demand for care.

The project group "The transfer chain of Twente" (Dutch: De Twentse Transfer Keten), an initiative of ZGT and three large aftercare institutions in Twente (Trivium Meulenbelt Zorg, ZorgAccent and CarintReggeland), aims to achieve an optimal flow of patients within the transfer chain. The aim is to organize the transfer of patients as well as possible in a process-based manner, so that, for example, duplication of work is prevented. The expected outcome of this project is also a decrease in the number of ALC days. However, the internal confidential research performed by Zonderland (2019) has shown that there is no overview of current and future supply and demand. This part is not included in the project "the Transfer chain of Twente". It is not clear where the bottlenecks between supply and demand are and how the chain can be set up in such a way that this is future-proof. With our research, we want to contribute to the project group at this part.

1.2 Problem identification

Figure 1 depicts the problems and the consequences ZGT and the aftercare institutions face.

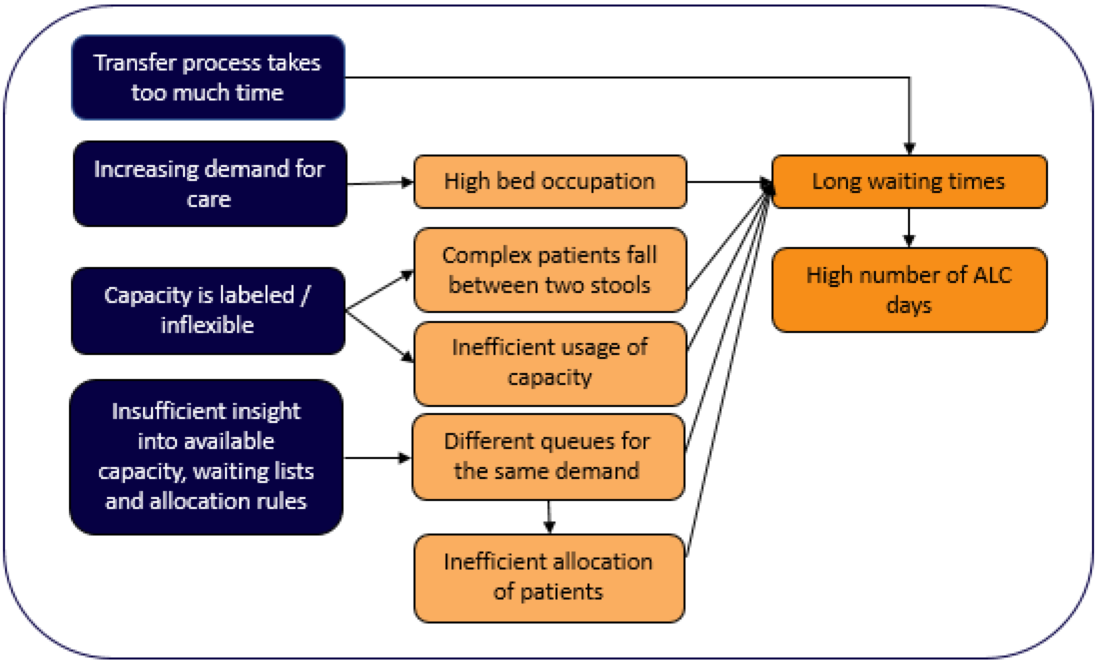

Figure 1: Problem cluster

The first problem is that the process of transferring a patient from hospital to aftercare takes a long time. A lot of people are involved before the right indication for aftercare is made, and this indication is sometimes made by multiple people. Also, many phone calls are needed before a patient can be placed at an aftercare institution. The project group "The transfer chain of Twente" is already tackling this problem.

The second problem is that, due to the aging population, the demand for care increases. The result of this increasing demand is that bed occupation is currently quite high, namely 95-99% for the WLZ. The current system is not yet adapted to this increase, and it is not clear what is needed for the system to be sustainable.

The third problem is that the capacity at the aftercare institutions is labeled and inflexible. This means that the beds in the aftercare institutions have a label of a certain care type, and they cannot be used by patients with another care type. Sometimes it is hard to fit a complex patient into a certain care type, whereby this patient does not fit into any bed. Therefore, transferring these patients to an aftercare institution takes a long time, which results in a high number of ALC days.

The fourth problem is that there is insufficient insight into the available capacity, waiting lists and allocation rules. The available capacity in the system of POINT is not always up-to-date and hard to interpret. Sometimes the available indicated capacity in the system is zero, while there is capacity in reality. Or the other way around, according to the system there is capacity, but after a phone call, it turns out that this place cannot be used. Further, patients are currently offered to the aftercare institutions one by one. If the first refuses, the request goes to the next, and so on. Next to that, the aftercare institutions receive demand from various sides, e.g. from various hospitals, general practitioners and other aftercare institutions. In this way, many different queues arise for the same demand and it is not clear how the requests are prioritized and whether this is done in the most efficient way. Also, the different waiting lists are not feasible for all parties.

1.2.1 Core problem

We discussed four problems that have consequences for the flow of patients between the hospital and the aftercare. The first problem is that the transfer process takes too much time, there is already a project group dealing with this problem. The second one, which is the increasing demand for care, is something we cannot influence. The third problem is that the capacity is labeled and inflexible, this is something we want to consider, as tackling this problem could lead to a better usage of capacity. The fourth problem is that there is insufficient insight into available capacity, waiting lists and allocation rules. Tackling the last two problems are possible ways to get a better match between demand and supply. Therefore, the core problem we address in this study is:

The healthcare providers in the transfer chain of Twente do not know how much capacity is needed when and where in the system and how the demand should be optimally allocated between them.

1.3 Problem approach

To solve this problem, we need to take multiple steps. Hence, we define several research questions.

1. Background research (Chapter 2)

At first, we do background research into how the transfer chain is currently organized. This includes the following research questions:

1.1 Which types of aftercare exist and what are the differences between them?
1.2 What does the process of transferring a patient from hospital to aftercare look like?
1.3 Which providers are there in Twente and what is their capacity?
1.4 What is the current demand, number of ALC days and waiting time?

2. Literature research (Chapter 3)

Once the current situation is clear, we do literature research into the optimal allocation of demand and supply in a network of healthcare services.

2.1 What can we learn from the literature regarding the allocation of demand and supply in a network of healthcare services?
2.2 What models are available to match supply and demand in a network of healthcare services?

3. Modeling approach (Chapter 4)

To determine the capacity needed when and where in the transfer chain and to evaluate methods to improve the allocation of demand and supply in the transfer chain, we develop a model. The research questions we answer are:

3.1 What kind of model should we use?
3.2 Which assumptions and simplifications are needed?
3.3 Which KPIs are relevant in the model?
3.4 How do we validate the model?

4. Experiments (Chapter 5)

Using the developed model, we evaluate the effects of various interventions. We answer the following questions:

4.1 What factors can improve the match between demand and supply in the transfer chain of Twente?
4.2 What are the effects of having a more flexible capacity?
4.3 Are the beds currently correctly divided between the care types?
4.4 What are the effects of admission restrictions to the aftercare institutions?
4.5 What are the effects of having an earlier and better estimation of the discharge date?

5. Sensitivity analysis and financial impacts (Chapter 6)

At last, we perform a sensitivity analysis and consider the financial consequences.

5.1 What is the impact of the input parameters on the experiment results?
5.2 What are the financial consequences of the various interventions?

1.3.1 Scope

This research focuses on the demand for intramural care in the three large aftercare institutions in the region of Twente: Trivium Meulenbelt Zorg, ZorgAccent and CarintReggeland. The other smaller institutions will be outside the scope of this study.

1.4 Conclusion

The transfer agency at hospital group Twente arranges care for patients after they reached the end of their hospital treatment, but are not ready to go home on their own. As long as a patient cannot be transferred, he or she will remain in the hospital. The number of days that a patient is in the hospital after the patient has finished the medical treatment, is labeled as ALC days. ALC days cost hospitals time and money. The expectation is that the ALC days will increase, due to the aging population and thereby increase in the demand for care. As bed utilization is already quite high, the current system is unsustainable. The healthcare providers in the Transfer Chain of Twente do not know how much capacity is needed when and where in the system and how the demand should be optimally allocated between them. In this study, we address this problem by developing a model and evaluating various interventions.

2. Context

This chapter elaborates on the context of this study. Section 2.1 explains the existing types of aftercare Section 2.2 describes the process of transferring patients from hospital to aftercare. Section 2.3 gives an overview of the stakeholders in the transfer process and their interests. At last, Section 2.4 shows the current performance of the transfer process.

2.1 Types of aftercare

The transfer nurse arranges the care for patients after they are ready to leave the hospital. The transfer nurse indicates which kind of care the patients need, often in consultation with a medical specialist, and ensures the transfer of the patients' data. Which type of care is needed, depends on multiple factors. Figure 2 shows the decision tree that the transfer nurses use. In the next sections, we give some background information on the types of aftercare.

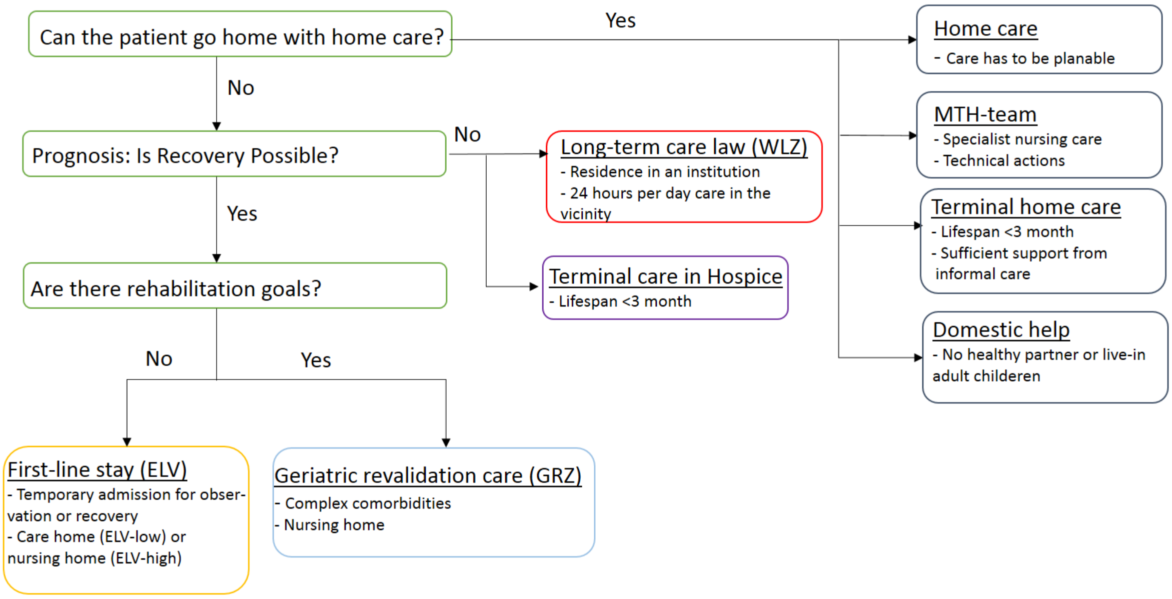

Figure 2: Decision tree used by a transfer nurse to determine the type of aftercare needed for a patient

2.1.1 Care at home

If there is no reason why a patient should have 24 hours per day surveillance or nursing in the vicinity, a patient can go home. How the reimbursement of care at home is arranged, depends on what type of home care is needed at home. The care can be reimbursed out of the basic insurance, social support law (WMO, Dutch: Wet Maatschappelijke Ondersteuning) or long-term care law (WLZ, Dutch: Wet Langdurige Zorg).

The basic insurance is an insurance in the Netherlands that each person above 18 years is obliged to have. The municipality provides support at home through the WMO. Municipalities must ensure that people can continue to live at home for as long as possible. Section 2.1.2 explains WLZ. Table 1 shows via which insurance the various types of care at home are insured.

Table 1: Types of home care and reimbursement (source: UnitedConsumers, 2022)

Type of home care	Explanation	Reimbursement
District nursing	Care by nurses in the area. Only when there is a need for medical care.	Basic insurance
Personal care	Support when a disease or physical limitation withhold you from, for example, dressing and washing yourself.	WMO
Guidance in independent functioning	Support in the household and daily functioning for people with a psychosocial disability	WMO
Domestic support	Support for people who are no longer able to do the household themselves due to medical reasons	WMO
Terminal care	For patients with a life expectancy of 3 months or less	Basic insurance
Day and night care	Care or nursing during the night and/or day on medical grounds.	WLZ

2.1.2 Long-term care law

If the prognosis is that recovery is not possible anymore, the care for patients is provided through the long-term care law (WLZ). This mainly concerns elderly people with advanced dementia or people with serious mental or physical. To receive care from the WLZ, a WLZ indication is required from the Care Assessment Center (CIZ, Dutch: Centrum Indicatiestelling Zorg). An indication gives you access to care in an institution or at home. Where and how the client receives care is determined by the patients themselves as much as possible (Ministerie van Volksgezondheid, 2018). At the institutions, a distinction is made between somatic and psychiatric care. At a psychiatric department, patients usually have to stay behind closed doors.

2.1.3 First-line stay

If a patient cannot go home, but recovery is still possible and there are no rehabilitation goals, the patient goes to a first-line stay place (ELV). The prognosis is that the patient will recover in the short-term and the purpose of the stay is that the patient can live independently at home again. ELV is reimbursed from the basic insurance. There are two types of ELV, namely ELV high and ELV low. ELV low is given at a care home, when there is a single disease or disability and the care can be given under the guidance of one person. ELV high is given at a nursing home when the care is more complex and multidisciplinary (Ministerie van Volksgezondheid, 2017).

2.1.4 Geriatric rehabilitation care

Geriatric rehabilitation care (GRZ) is intended for vulnerable elderly. The aim is to help them return to their home so that they can continue to participate in social life as well as possible. To be eligible for GRZ, according to the regulations, the patients must have a vulnerability, complex multimorbidity and decreased learnability and trainability. GRZ is reimbursed from the basic insurance. When the patient has a WLZ indication, receiving GRZ is not possible anymore (ministerie van volksgezondheid, 2016).

2.2 Process description

The hospitals and the aftercare institutions both have a department that focuses on giving patients the right care in the right place. This section describes the transfer process between these institutions. Figure 3 depicts the transfer process, which we explain below.

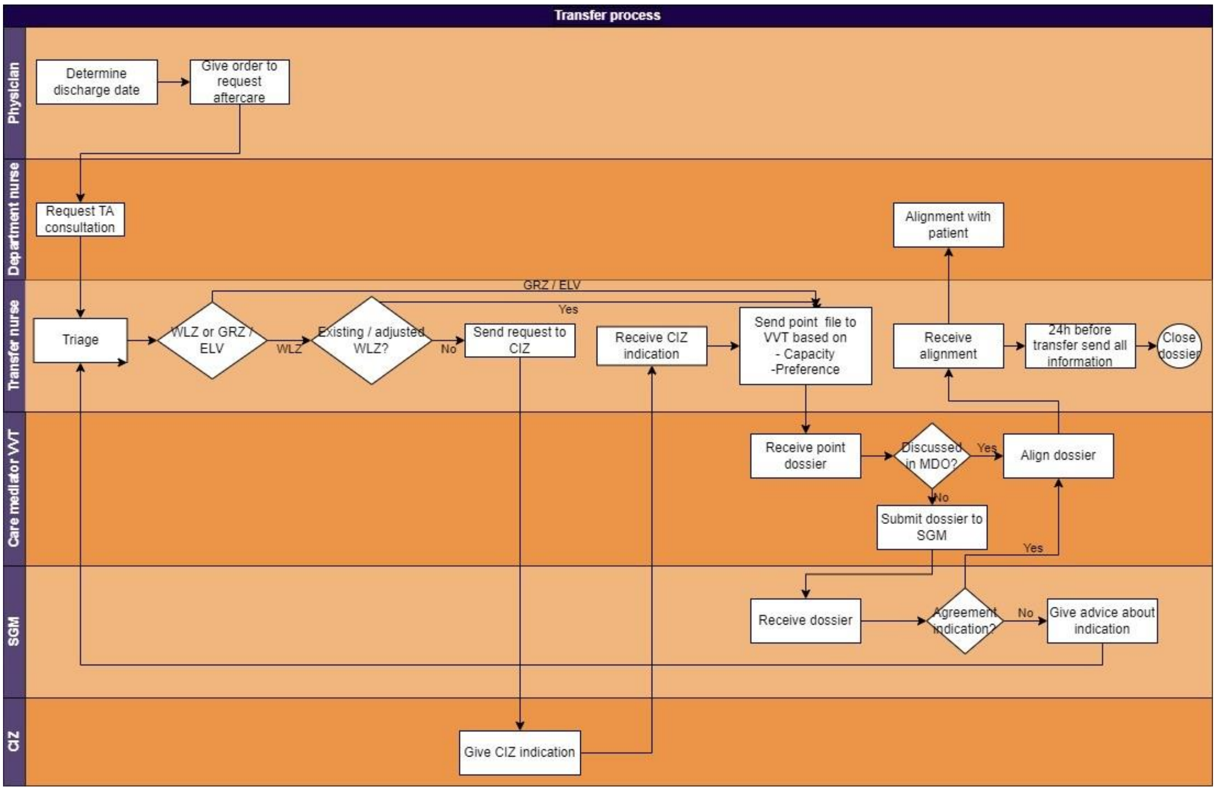

Figure 3: Transfer process of intramural care

During the patient visits with the physician, the physician determines the initial discharge date and decides if a patient needs aftercare. When this is the case, a nurse from the department opens a request for a consultation at the transfer agency and informs the patient. On average, this request is made 3 days before the initial discharge date of the patients. A transfer nurse does the triage about which type of care is needed, where the nurse uses the decision tree as depicted in Figure 2. The transfer nurse does this often in consultation with a specialist geriatric medicine (SGM), or the physician during a multidisciplinary consult (MDO, Dutch: multidisciplinair overleg). The transfer nurse also exports the patient dossier to POINT. When the transfer nurse decides that WLZ is the right type of aftercare, the nurse has to check if there is already an indication. To receive care from the WLZ, a WLZ indication is required from the Care Assessment Center (CIZ, Dutch: Centrum Indicatiestelling Zorg). After this indication is signed by a patient or family, the arrangement of aftercare can continue. The transfer nurse uses POINT to search for a suitable place with capacity. If a patient has a preference for a location, this is taken into account as long as there is capacity at the preferred location. The transfer nurse sends the POINT dossier to the chosen aftercare institution. The care mediator at the aftercare institution reviews the dossier and decides if the patient is suitable for the offered place. If a patient is already discussed in an MDO, the care mediator aligns the dossier and sends it back to the transfer nurse at the hospital. The transfer nurse gives the information to the nurse at the department, who informs the patient. 24 hours before the transfer, the transfer nurse has to make sure that all information, such as medication is sent to the aftercare institution. After that, the transfer nurse closes the dossier. Only when a patient is not discussed at a MDO, the care mediator submits the dossier to the specialist geriatric medicine (SGM), who checks the dossier and has to agree with the indication.

2.3 Stakeholders

In Section 2.3 we described the transfer process, which includes different stakeholders. In this Section, we explain which stakeholders there are and the interests of the stakeholders.

1. Patient

The first stakeholder is the patient. The patient wants a minimal length of stay in the hospital, as staying longer in the hospital than necessary has negative consequences for the patient (Jasinarachchi, 2009). Further, the patient wants the highest quality of care and wants to receive care close to their relatives. In this research, we only include patients that need care after hospital treatment.

2. Hospital

The second stakeholder is the hospital, which includes the hospital management, the physicians, the department nurses and transfer nurses. In this research, we focus on ZGT as the hospital. At first, they all want high patient satisfaction. Further, the hospital management wants low costs and a high profit. This is reached when the length of stay in the hospital is minimal, and the number of ALC days low. Also, the physician and department nurses want bed availability to admit new patients. The transfer nurse wants a smooth transfer process, without having to do duplicate work and many phone calls.

3. Aftercare institutions

In Twente, there are many providers of aftercare to which patients go after staying in the hospital. In this research, we focus on three large institutions, namely ZorgAccent, CarintReggeland and Trivium Meulenbelt Zorg. 83% of the patients from ZGT that go to ELV, WLZ or GRZ go to a location of one of these three institutions. All other institutions are small and only a small percentage of patients go to each of these locations.

Figure 4 shows the municipalities in Twente and the municipalities where each organization operates. The grey regions are all municipalities in Twente that we consider, and the blue regions are the municipalities where CarintReggeland operates. All providers have places for WLZ, GRZ, ELV-low and ELV-high.

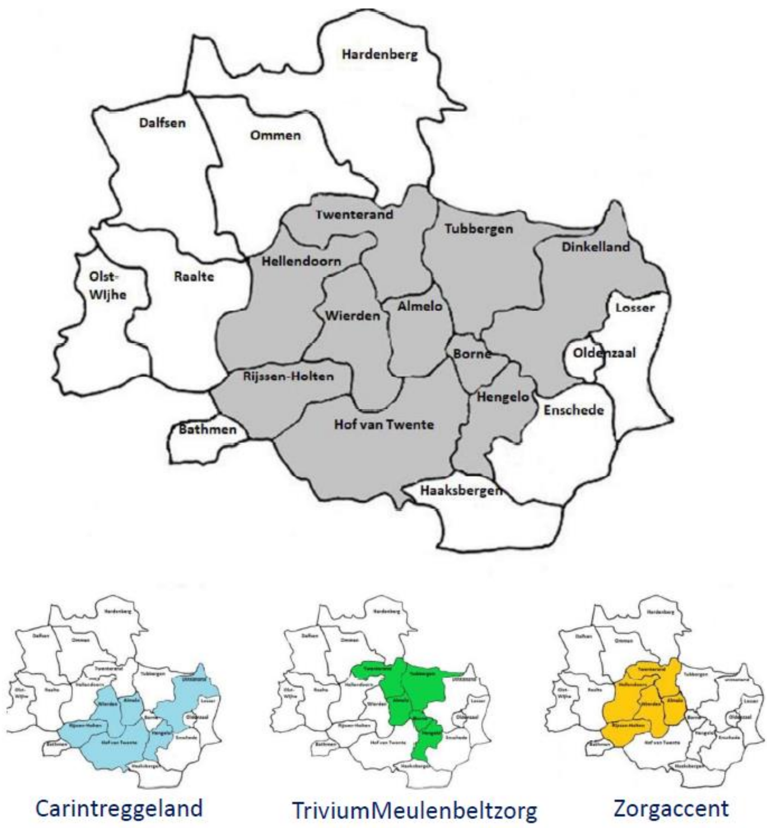

Figure 4: Healthcare providers in the region of Twente

The aftercare institutions also aim at high patient satisfaction. The care mediators want a smooth transfer process. The management of the institutions wants high bed occupation, as empty beds may lead to financial difficulties. When having a short throughput time at the aftercare, it is likely that the occupation decreases. Therefore, aftercare institutions benefit more from longer throughput times.

The stakeholders have some shared interests, they all want the highest quality of care for the patient and a high patient satisfaction. Also, all stakeholders benefit from a smooth transfer process without duplication of work. However, there is also a contradiction in interests. The hospital benefits from a minimum length of stay in the hospital and a high throughput, whereas aftercare institutions benefit from a high bed occupation, which is more likely to be reached with longer throughput times. A higher occupation in the aftercare also leads to longer waiting times in the hospital.

2.4 Current performance

In this section, we measure the current performance of the transfer process, in terms of demand, waiting times and ALC days.

2.4.1 Demand

First, we define the number of patients that flow out of the hospital on a yearly basis and what the ratio is between the types of care.

Table 2 and Figure 5 show the number of requests ZGT made for the types of care between September 2021 and August 2022. 66% of the requests are for home care, 20% for GRZ, 9% for ELV and 5% for WLZ. For ELV, GRZ and WLZ in total there were 1674 requests between September 2021 and August 2022.

Table 2: Number of requests per care type (source: POINT)

Care type	Number	%
ELV Low	124	2%
ELV High	245	5%
ELV Palliative	45	1%
GRZ	1000	20%
WLZ	259	5%
Home care	3384	66%
Other	68	1%

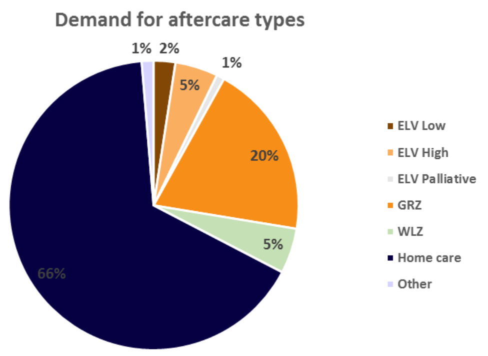

Figure 5: Pie chart of demand for aftercare types

2.4.2 Waiting time and ALC days

The number of ALC days per patient can also be seen as the waiting time, as these are the days the patient is waiting in the hospital before they can go to a follow-up institution. Table 3 depicts the average waiting time and the percentage that must wait longer than one day per type of care for the period September 2021 to August 2022.

Table 3: Average waiting time per type of care (N=5705, source=POINT)

Care type	Average waiting time	% that has to wait > 1 day
ELV Low	0.9	27%
ELV High	4.3	68%
ELV Palliative	1.6	43%
GRZ	1.9	42%
WLZ	3.5	54%
Home care	0.2	2%

The average waiting time for WLZ is the longest, 3.5 days. Only 54% of the WLZ patients do have to wait, the other patients can leave immediately. The average waiting time increases for some patients with a very long waiting time. For home care, only 2% of the patients have to wait, wherefore the average waiting time is very low. For intramural care, the average waiting time and percentage of patients that have to wait is the lowest for ELV Low. Table 3 shows that the number of patients that leave the hospital within one day after reaching the end of medical treatment is currently far below the norm. Figure 6 shows the number of ALC days of the patients that have at least one ALC day per type of care.

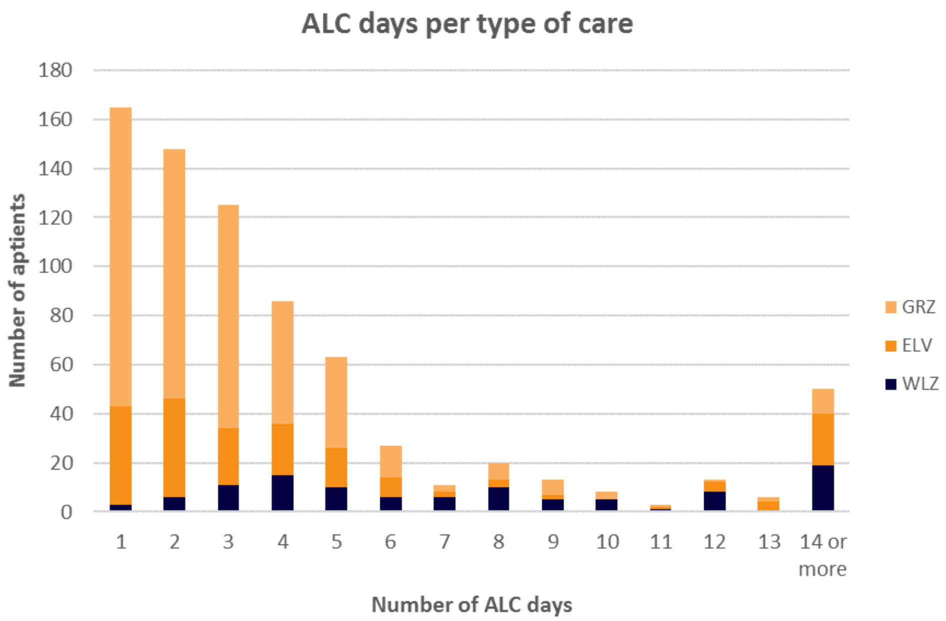

Figure 6: ALC days per type of care for ALC patients

For ELV and GRZ, most patients can leave after one day. Only a few patients have to wait for more than five days. For the WLZ, we see that if a patient has to wait, many have to wait more than 14 days. However, the number of patients that have to wait long is low.

Between September 2021 and August 2022, there were on average 17.3 ALC patients per day in the hospital, see Figure 7. This means that on average, 17.3 beds were occupied with patients that did not necessarily have to stay in the hospital. Out of them, 7.4 beds were occupied by GRZ patients, 4.1 by ELV patients and 3.4 by WLZ patients. Figure 7 also shows that 45% of the ALC days are from GRZ patients, 24% from ELV patients and 21% from WLZ patients.

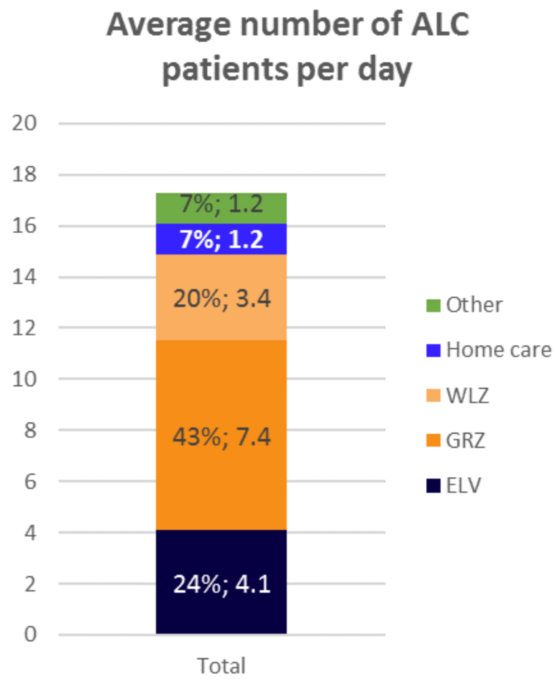

Figure 7: Average ALC patients per day per type of care (n=365 days, source = POINT)

2.4.3 Financial consequences

ALC days have financial consequences for the hospital. The hospital receives compensation per ALC day, but this compensation does not cover the costs of ALC days. Moreover, ALC patients are blocking beds for new patients. No new patients can be admitted to these beds, which means lost sales for the hospital.

On average, the expected costs (fixed and variable) for one hospital day is 500 Euro. The hospital receives compensation of about 300 euro per day for WLZ patients and on average about 400 Euro for other ALC patients. This means a loss of 200 Euro per day for WLZ patients and 100 Euro for other ALC patients. The average bed occupation in the hospital is 85%. Concerning on average 17.3 ALC patients per day, of which 3.4 are WLZ patients, the expected loss per day for the hospital is (3.4*200+13.9*100)*0.85 = 1,759 Euro.

2.5 Conclusion

The transfer nurse at the hospital assesses which type of aftercare suits the patient. Often, the nurse does this in consultation with a physician or specialist geriatric medicine. The types of aftercare can be divided into four categories, namely care at home, long-term care law, first-line stay and geriatric rehabilitation care. Especially within the first-line stay, there are still differences. The transfer nurse at the hospital confers with the care mediator at the aftercare institution to find the right place for the patient. The communication mainly goes via the ICT system POINT. In Twente, there are many providers of aftercare to which patients go after staying in the hospital. In this research, we focus on three large institutions, namely ZorgAccent, CarintReggeland and Trivium Meulenbelt Zorg. 83% of the patients from ZGT that go to ELV, WLZ or GRZ go to a location of one of these three institutions. For intramural care, 54% of the patients have to wait for more than one day in the hospital before the transfer to the aftercare takes place. On average, there are 17.3 ALC patients per day in the hospital, these ALC patients have negative financial consequences.

3. Related Literature

The goal of this chapter is to provide a theoretical framework for ALC days and capacity planning in a network of healthcare services. Section 3.1 provides an overview of research conducted into ALC days, the causes and solutions. Section 3.2 shows which research is already performed in the field of capacity planning in a network of healthcare services and what kind of models and techniques are used. Appendix A provides the search method.

3.1 ALC days: causes and solutions

ALC days are the days that a patient remains in the hospital after the medical treatment has ended. This problem occurs not only in the Netherlands but over the whole world. This section provides some research into the causes and solutions for ALC days.

First, we provide some insights into the causes of alternate levels of care days. In the literature, we found four studies into possible causes of ALC days. We discuss these five studies and their conclusions. At first, Travers et al. (2008) try to understand the dynamics of ALC days in Australian public hospitals by analyzing data and utilization patterns in hospitals and aged care services. They conclude that the main reason for ALC days in hospitals is a mismatch between demand and supply, and cannot be understood by viewing the hospital system in isolation. Secondly, Koizumi et al. (2005) conclude that congestion in a system is not always a cumulative effect of shortages across all facility types. They suggest that shortages in one specific facility type are often the cause of system-wide congestion. Therefore, the most cost-efficient way to reduce congestion in the system is often the removal of a bottleneck in a specific facility type. Third, Benson et al. (2006) conclude that the lack of social care provision is the major cause of delayed discharge. Due to problems in defining ALC days, governments often underestimate the true numbers. They also point out that ALC patients are often elderly and are more likely to be admitted to the hospital as an emergency patient. At last, Gridley et al. (2022) examined the local transfer arrangements in six English local authority sites and present the findings about the causes of delayed transfers. Their analysis points out that there is often a mismatch between the available capacity and the need of people leaving the hospital. Gridley et al. (2022) show the significance of the alignment of service capacity, including the type and location of provision, with the needs and preferences of patients leaving the hospital.

Next, we point out some research into possible solutions to reduce ALC days. Steenstraten (2021) conducted research into improving the flow of patients from hospitals to follow-up care. Steenstraten (2021) mentions some improvements that are already applied in hospitals. The first one is giving priority to hospital patients when allocating nursing home places. The second one is providing clear insight into available nursing home capacity. The last one is realizing a transfer department in the hospital where patients 'wait' until they can go to a nursing home. Steenstraten (2021) points out that the greatest achievements can be reached by working in a more discharge-oriented manner and by making better use of the flexibility of follow-up care institutions. There are three interventions required to achieve integration. First, internal optimization: by streamlining the internal process there is a better view of supply and demand, whereby the transfer process can be started earlier with the right information. Second, optimizing existing collaborations: by coordinating supply and demand with all partners, the usage of the available capacity can be improved. At last, system-wide innovations: by connecting demand and capacity at a regional level, integrated solutions are found. Another possible solution for ALC days is described by Haraden and Resar (2004). They suggest that hospitals should make a nursing home "reservation". Most hospitals use a "push system", where hospitals start searching for a bed close to the discharge date of the patients. According to Haraden and Resar (2004), it is more efficient to synchronize hospital and nursing home needs by establishing a reservations system. In such a system, hospitals can reserve beds in nursing homes once the care need of a patient is determined. The nursing home should still receive a payment if the reservation is canceled and the bed stays unused.

3.2 Capacity planning in a network of healthcare services

Some research is already performed into capacity planning in a network of healthcare services. Most studies focus on predicting future demand and determine the optimal capacity in long-term care facilities. We give an overview of these studies and the kind of models they used.

Patrick (2011) presents a Markov decision process model that determines the required access in order to keep the number of patients waiting for long-term care in hospitals to remain a given threshold. The decision made is which part of the available capacity should be allocated to hospital patients, and which part to demand from the community. A lower threshold for the hospitals results in higher waiting times in the community. They performed a sensitivity analysis on the impact of three changes in the current policy. The first topic is the impact of the length of stay; reducing the length of stay results in shorter waiting times. The second topic is the impact of letting patients wait on a place of their preference; there is only a minor difference in the hospital census if fifty percent of the patients wait until a place of their preference compared to zero percent. However, if a hundred percent of the patients wait, the hospital census increases enormously. At last, the impact of giving priority to internal transfer is studied; this is disastrous for the waiting time in the community. Lin et al. (2012) tackled the problem in a different way, namely by modeling the problem as an optimal control problem. This model determines the optimal capacity for home care and community-based service, from a societal expenditure-saving viewpoint. In this model, it is assumed that the nursing homes have infinite capacity.

Another way of tackling the capacity planning problem that is used in literature is making use of a mixed integer linear programming (MILP) model. Intrevado et al. (2015) present a dynamic, large-scale MILP for long-term care network design that focuses on the expansion of an existing long-term care network. The model decides for each time period the addition or removal of capacity and how patients should be assigned to the available capacity. This research concludes that there is no credible financial evidence to suggest that it is better to serve patients inappropriately in an acute-care hospital bed instead of in an appropriately assigned long-term care facility. Cardoso et al. (2015) propose a stochastic mixed integer linear programming model for planning long-term care service within a network of care. The objective is to minimize the expected costs while respecting satisfactory levels of equity, for access and utilization. The proposed model can be used by planners to decide when and where to locate services with which capacity and how to distribute this capacity across patient groups. Also, Bidhandi et al. (2019) make use of a MILP model. This model minimizes the total costs subject to constraints on the amount of blocking at each stage and is solved by a simulated annealing approach. All three MILP models described make use of the costs as a minimization variable.

The next type of model used in literature is modeling the situation as a queuing network. In literature, we found four studies that make use of queuing models. Next to a MILP model, Bidhandi et al. (2019) also use a queuing model. They propose a queuing network approach to capacity planning for a network of healthcare services. They consider six types of services, namely home care, assisted living, long-term care, chronic care, rehabilitation and acute care. By making use of a heuristic algorithm from Bretthauer et al. (2011) they determined the blocking probability for a network with known capacity at each stage. Weiss and Mcclain (1987) also use a queuing network by developing a state-dependent service rate model that can be used to make predictions about various decisions, such as discharge planning and extending care facilities. The model predicts the average ALC census and the impact on ALC patients for the hospital. The model considers one hospital and one extended care facility. However, the model focuses on the rate at which patients enter the long-term care system rather than this entrance rates effect on the capacity at any given point. So, the effect of decisions on the arrival rates and placement decisions must be estimated. At last, Zychlinski et al. (2019) develop a mathematical fluid model. This model consists of 4 stages, namely the hospital and three different types of geriatric revalidation stages. The model takes into account arrival rates, transition probabilities, readmission to hospital, mortality rates and blocking probability. The goal of the model is to determine the number of beds needed in the hospital and geriatric rehabilitation institutions to minimize the costs of over-and underage capacity.

Avkiran and McCrystal (2014) demonstrate how dynamic network data envelopment analysis can be used to evaluate the changing productivity of residential aged care networks over time. Results indicate that an optimal bed capacity is reached at the end of year 7.

At last, discrete event simulation is used as a method to evaluate the performance of a network of healthcare services. In the literature, we found five studies that made use of discrete event simulation in a network of healthcare services. Bidhandi et al. (2019) used discrete event simulation to verify the results of the optimization of the queuing network. Cardoso et al. (2012) propose a simulation model based on a Markov cycle tree structure to predict annual demand. This is for example based on the incidence and prevalence of chronic diseases. The resources required for the predicted demand are also taken into account, but that is not the main focus of this research. Zhang et al. (2012) use discrete event simulation to determine the capacity for long-term care over a multi-year planning horizon, to achieve target wait time service levels. As input, arrival distributions, length of stay distributions and a pre-loaded level of existing clients are used. The output is a percentage of patients who receive care within a certain amount of time. To find the minimum capacity that is needed to meet the norm, a heuristic is implemented in the simulation. Zhang and Puterman (2013) describe a refined version of this methodology, where the required capacity levels per year depend on the state of the system. The state of the system is the service level in the previous year. At last, Bae et al. (2017) also use a discrete event simulation model to forecast the demand for LTC and determine the required number of beds to maintain a service quality requirement. The service quality is measured as the probability that a patient, who needs care in an LTC facility, is to be placed in a bed within a desired number of days.

3.2.1 Conclusion and our study

We presented an overview of the techniques and models employed in existing literature. The models used most frequently for capacity planning in a network of healthcare services are Markov decision process models, optimal control models, MILP models, queuing network models and discrete event simulation.

Our primary focus is twofold: determining the necessary capacity to meet demand and optimizing the allocation of this demand. Moreover, we aim to explore various interventions to improve the system's performance. By using discrete event simulation, we can model the situation in detail, thereby generating the most reliable and accurate results. This approach aligns with Harper and Shahani's (2002), who state that simplistic deterministic models fail to provide adequate decision-making insights, making simplifications an unfavorable choice. We aim to develop a simulation model similar to the simulation model method of Zhang et al. (2012).

We explored the possibility of using mathematical models but found them unsuitable for our specific scenario. Markov decision process models and optimal control models, which are used for analyzing the trade-off between community and hospital demand, do not align with the primary focus of our study. Furthermore, the MILP models we encountered emphasize cost considerations, which are not available to us in sufficient detail, and fail to capture the intricate complexities of our model.

Additionally, it is hard to incorporate all necessary details in a mathematical model, such as a queuing model. The arrivals of patients vary between the days of the week and the week of the year. This is important to incorporate in the model, as this affects the accuracy of the model's outcome regarding waiting times and the effects of admission capacity, for example. Queuing models typically assume constant arrival rates or require simplifying assumptions that do not capture the reality of the arrival patterns. In contrast, in a simulation model, it is possible to incorporate these variations directly, allowing for a more accurate representation of the system's behavior. Moreover, it is hard to incorporate all process steps in detail in a mathematical model. In our study, the process at the transfer agency is an important aspect, where the priority rules play a role in determining the order of patient transfers. These rules influence the flow and allocation of resources, affecting the overall system performance. In a simulation model, we can incorporate the detailed process steps, including the priority rules at the transfer agency, which provides a more realistic presentation of the system's dynamics and allows an evaluation of interventions and their impact on system performance. In summary, the challenges of incorporating variable arrival rates and detailed process steps within a mathematical model underline the suitability of a simulation model for our study.

3.2.2 Contribution to literature

Modeling in healthcare is an emerging field, but most of the current work focuses on the optimization of a specific healthcare provider (e.g. a hospital) or even a specific department (e.g. the operating theatre). Little work is performed on how to integrate the care need between different healthcare providers. Our contribution to the literature mainly lies in testing new interventions in a detailed simulation model. Such interventions are challenging to evaluate using other mathematical models, making our approach distinctive. Further, we offer a nuanced understanding of the relationship between bed occupation in the aftercare and waiting time and ALC days in the hospital. Next to that, it provides guidance on strategies to reduce ALC days. To the best of our knowledge, only a limited number of interventions for a network of healthcare providers have been tested within a comprehensive simulation model. The insights gained from these interventions can also be applied to other regions or countries facing similar challenges. The conceptual model can be used to set up a similar simulation model.

4. Simulation model

The objective of this study is to evaluate various interventions to match demand and supply in a network of healthcare services. Section 4.1 describes the model choice and Section 4.2 the conceptual model, which includes the model objectives, input and outputs, the scope and level of detail and the assumptions and simplifications. Finally, Section 4.3 describes the experimental design, which includes the warm-up period and run characteristics and model validation.

4.1 Model choice

We use a discrete event simulation model, which we will from now on refer to as 'simulation', as motivated in Section 3.2.1. Robinson (2014) defines computer-based dynamic simulation as: "An imitation (on a computer) of a system as it progresses through time". Discrete-event simulation is particularly used for modeling *dynamic* queuing systems. A queuing system is represented as entities flowing from one activity to another. These activities are separated by queues (Robinson, 2014). The transfer chain of Twente can also be seen as a queuing system. We develop the model using the simulation software Technomatix Plant Simulation version 13.

4.2 Conceptual model

This section describes the conceptual model of the simulation. We use the framework of Robinson (2014) as a guideline for developing the conceptual model. The conceptual model is a non-software-specific description of the computer simulation model, including the objectives, inputs, outputs, scope and assumptions and simplifications.

4.2.1 Modeling objectives

The objective is to analyze the effects of interventions and scenarios on the system's performance. To specify this objective, we need to know which interventions and scenarios we want to test and which performance on this system we want to measure. We explain the latter in section 6.2.3. We want the model to be able to:

1. *Analyze the effects of bed occupation in aftercare on ALC days in the hospital*
   Currently, the bed occupation in aftercare is quite high. Empty beds have high costs for the aftercare institutions, therefore they want their bed occupation to be high. However, the effect of a high bed occupation is also a longer waiting time, which results in ALC days in the hospital. The variability of demand has influence on the extent to which the waiting time increases by a higher bed occupation. Figure 8 shows this relation, where c represents different levels of the coefficient of variation. To lower the waiting time and thereby the ALC days, there are two options, namely a) lower the bed occupation and b) lower the variation. Lowering the bed occupation can for example be done by decreasing the length of stay, lowering the demand or increasing the capacity. Lowering the variation can for example be done by taking into account the outflow to aftercare by planning elective patients. We test the effects of these options in the simulation model, to make clear what is necessary to lower the waiting time.

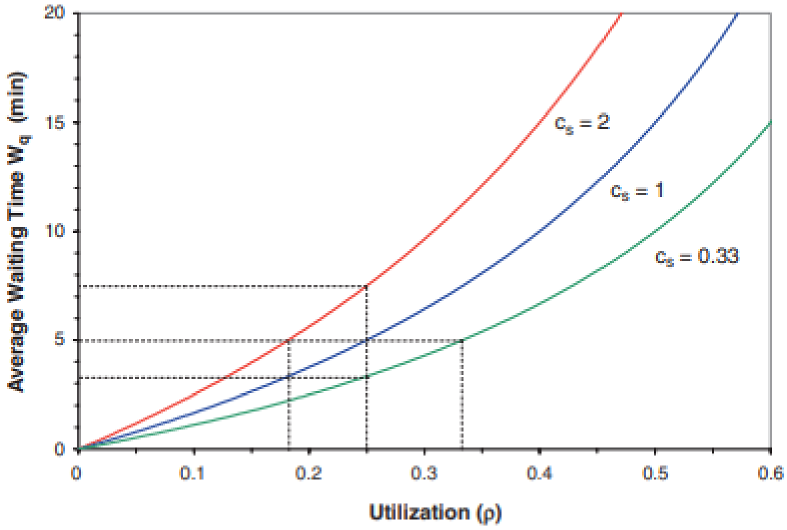

Figure 8: Trade-offs between variability reduction, waiting time and utilization, source: Dilip Chhajed & Lowe, 2010

2. *Analyze the effects of pooling capacity between the types of care*
   As explained in Chapter 2, there are differences between the types of aftercare. The beds in the institutions are also labeled with a certain care type, namely ELV-low, ELV-high, ELV-palliative, GRZ or WLZ. We evaluate the effects on the system performance when the distinction between the types of beds is less hard.

3. *Analyze the effect of other bed distributions*
   We analyze the effects of other bed distributions between the types of care in the aftercare. We try different distributions and look if the total waiting time can be improved.

4. *Analyze the effects of admission restrictions*
   Currently, no patients are transferred on the weekend. So, if a patient ends medical treatment on the weekend, the patient has to wait until Monday before the transfer can take place. Further, the admission capacity per day in the aftercare institutions is limited, because a new admission takes a long time. We analyze the effect on the system performance when transfers also take place on the weekend or the admission capacity is increased. This gives guidelines to decide if this option is worth considering.

5. *Analyze the effects of a better and earlier estimation of the discharge date*
   When there is an indication of when a patient is ready to leave the hospital and it is clear that aftercare is needed, the process of searching for a place can start. We analyze the effect on the system performance when this process starts earlier or the estimation is better.

4.2.2 Model inputs

This section explains the input parameters of the simulation model

1. *Patient characteristics*

In the simulation model, patients occur according to a seasonal pattern (see point 2). These patients have two characteristics, the aftercare type and nature. The aftercare type of patients occurs according to the division in Table 4.

Table 4: Occurrence of care types (n= 1500, Source=POINT)

Type	Occurrence
GRZ	61%
WLZ	13%
ELV High	15%
ELV Palliative	5%
ELV Low	6%

A patient can be admitted to the hospital as an elective or as an emergency patient. The ratio between emergency and elective patients differs per aftercare type. Table 5 shows the percentage of emergency patients per type of aftercare.

Table 5: Percentage of emergency patients per type of aftercare (n=1500, source=POINT)

Type	% Emergency
ELV Low	68%
ELV High	88%
ELV Palliative	90%
WLZ	92%
GRZ	80%
Total	83%

2. Discharge rates

On average 4.1 patients with one of the included aftercare types are discharged per day from ZGT. The number of discharges follows a seasonal pattern and differs between the weeks of the year and the days of the week. Especially during the weekend, there are fewer discharges. The number of discharges on weekdays, follows a Poisson distribution, see Appendix B. So, a number of discharges is determined randomly from the Poisson distribution: x. The number of discharges is then determined as: $x * factor\ weekday * factor\ weeknumber$. We determine the seasonal factors per weekday and week number with data from 2019 to 2022, following the Holt-Winters method, as presented in Silver et al. (2016). Figure 9 and Figure 10 show the seasonal factor per week number and per weekday. The seasonal factor per week shows an erratic course, where no clear seasonal pattern is recognized. The seasonal factors per weekday show that on the weekend there are fewer discharges and most discharges take place on Friday.

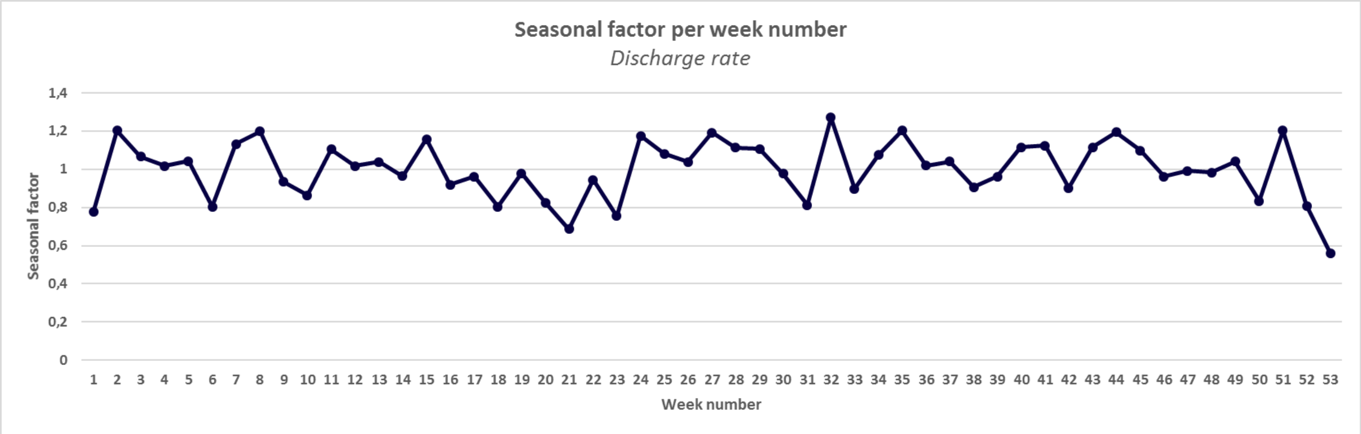

Figure 9: Seasonal factor discharge rate week number

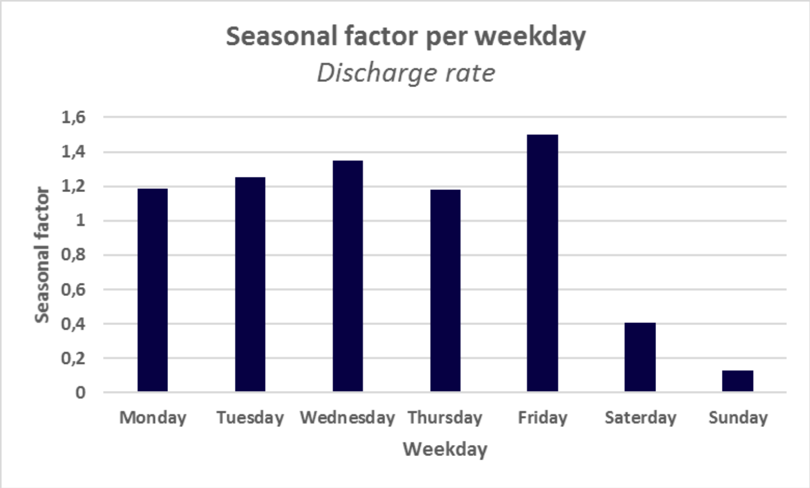

Figure 10: Seasonal factor discharge rate weekday

Next to the hospital patients, the simulation model also generates patients from "other parties". This could be other hospitals or patients from home. It is necessary to generate these patients, as they also take capacity in the region. However, we have no complete data about these patients. As we do not have complete and reliable data about the patients in the whole region, we make an estimation of the arrival rate from other parties. To make this estimation, we assume the system per type of care to be an M/M/C queue. According to Tijms (2008), the properties of an M/M/C queue are as follows:

- Customers arrive following a Poisson process with an average of λ customers per unit of time.
- A customer's service time is exponentially distributed with an expected value of 1/µ units of time.
- There are c servers, with one common queue.
- There is an infinite waiting room.

As we know the probability that a patient has to wait and the average waiting time, we can make an estimation of the arrival rate using queuing theory. As the arrival rate is not constant over time, but varies between weekdays and week of the year, the M/M/C queue is not a perfect fit. Probably, we underestimate the arrival rate. Further, we assume that there is one department with c servers, while there are different locations patients can go to. Also, we do not take into account admission restrictions. For these reasons, we can overestimate the arrival rate. The arrival rate we determine using queuing theory is a starting point for the arrival rate in the simulation model. By validating the simulation model, we adjust the arrival rate until it has a good fit with the real situation.

Tijms (2008) gives the formula for the probability that a patient has to wait in an M/M/c queue, which is as follows:

$$C(c,\rho) = \frac{(c\rho)^c}{c!\,(1-\rho)}\left[\frac{(c\rho)^c}{c!\,(1-\rho)} + \sum_{j=0}^{c-1}\frac{(c\rho)^j}{j!}\right]^{-1}$$

Where $\rho = \frac{\lambda}{c\mu}$

The average waiting time is calculated with the following formula (Tijms, 2008):

$$W_q = \frac{1}{c\mu(1-\rho)} C(c,\rho)$$

We calculated the probability of waiting and average waiting time for different arrival rates and compared them to the values measured in the real system. Figure 11 shows the values for the GRZ; the dashed line shows the measured values and the solid line the calculated values. For the GRZ at an arrival rate of 3.4, the calculated average waiting time is almost the same as the measured value. However, the calculated probability of waiting time is a bit lower at an arrival rate of 3.4 than the measured value. We think that the probability of waiting is increased in the real system because, for example, transfers cannot take place on the weekend. This also affects the average waiting time, but we expect that this effect is lower. Therefore, we look at the arrival rate that has the best match with the average waiting time, which is at an arrival rate of 3.4 for the GRZ. For ELV and WLZ, we did the same analysis. Appendix C contains these graphs.

Table 6 shows the arrival rates we chose as starting point for the simulation model.

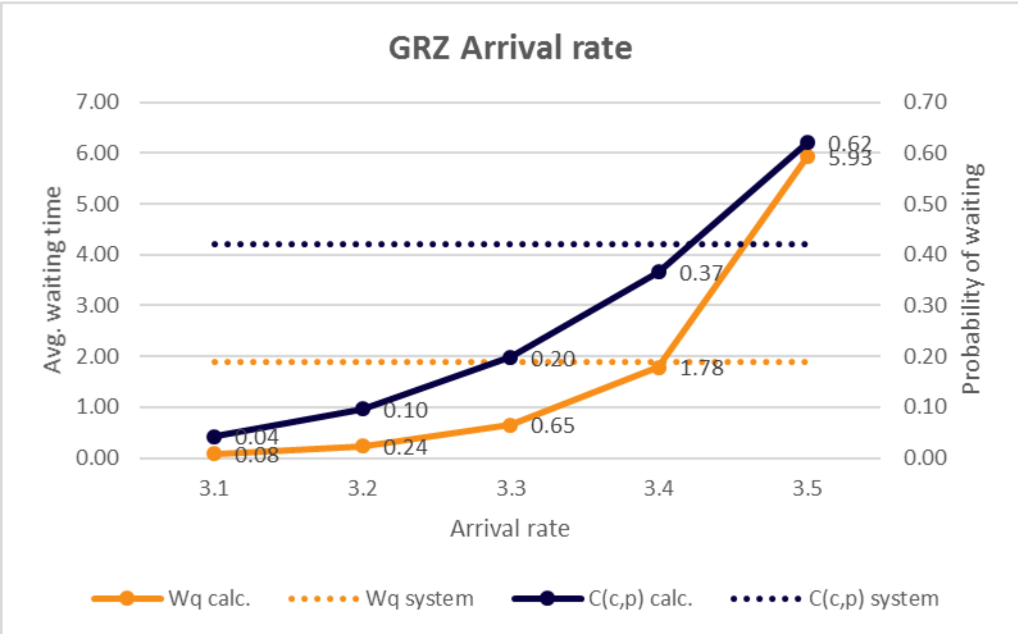

Figure 11: Average waiting time and probability of waiting for different arrival rates of GRZ

Table 6: Start values of arrival rate in simulation model

Care type	Start value arrival rate simulation	Arrival rate ZGT	Arrival rate other parties
GRZ	3.40	2.50	0.90
ELV Low	1.40	0.25	1.15
ELV High	1.85	0.62	1.24
ELV Palliative	0.73	0.21	0.53
WLZ	3.40	0.53	2.87

The arrival rate from the other parties is derived by subtracting the arrival rate from ZGT from the total arrival rate.

3. *Length of stay*

An important input variable for the simulation model is the distribution of the length of stay in the aftercare institutions. Unfortunately, we could not get data for this from the aftercare institutions in Twente. Therefore, we use research that is performed in the Netherlands and assume that this will also apply to the institutions in Twente. Actiz (2018) provides data on the length of stay per type of ELV, however, clients with a long length of stay are underrepresented in this research. Vektis (2020) provides insights into the average length of stay of all ELV clients. From Actiz (2018) we use how the length of stay differs per type of care. From Vektis (2020) we use the average length of stay of all ELV clients and GRZ clients. Combining these sources, we have an estimation of the average length of stay. Next to an average, we also need a probability distribution. Xie et al. (2005) used the framework of aggregated Markov processes to derive a procedure for fitting a model to observed data. The parameters are estimated using the overall joint likelihood function. Their approach is applied to four year data from the social services department of a London borough. For residential home care, they suggest a single-exponential distribution. So, we use the single-exponential distribution, with the mean as presented in Table 7.

Table 7: Average length of stay GRZ and ELV

Care type	Average length of stay
ELV - High	36.9
ELV - Low	32.9
ELV - Palliative	19.0
GRZ	43

For the WLZ clients, it is harder to fit a distribution, as the length of stay can vary widely. For the length of stay of WLZ, we use the publication of the healthcare data bank (Dutch: Zorg cijfers data bank). We use the data of 2019, such that COVID does not influence the data. The data includes an empirical distribution, which shows the percentage with which a range of length of stay occurs. We assume that length of stay is uniformly distributed within a range and we assume a maximum length of stay of five years. Figure 12 depicts the distribution for the length of stay of WLZ clients.

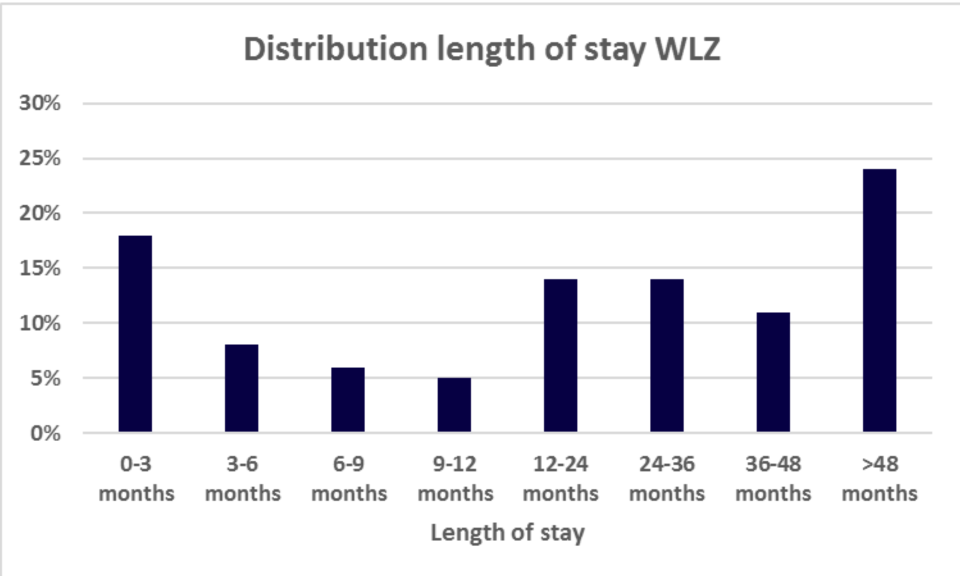

Figure 12: Distribution length of stay WLZ

4. Resources and capacity

In the simulation model, we take the hospital as one resource, so we do not distinguish between different departments, as this is not relevant for our model. The capacity of the hospital is infinite in the simulation model. Regarding aftercare, there are 38 resources. We have 5 types of care, 3 organizations and 10 municipalities. However, not all organizations have locations for each type of care in each municipality. Appendix C contains the capacity of all these resources.

5. Difference between first initial discharge date and initial discharge date

When a patient is registered at the transfer agency, the patient has a first initial discharge date. This date can change when for example the patient needs more treatment. In 68% of the cases, the first initial discharge date remains the same. The date will be later in 29% of the cases, with an average of 5 days. In 3% of the cases, the date will be earlier with an average of 2 days. As we cannot fit a proper distribution to this data, we use these percentages and averages.

6. Days between registering and initial discharge date

On average, a transfer is registered at the transfer agency 3.2 days before the initial discharge date. A gamma distribution with alpha 1.7 and beta 1.9 fits the data best, so we use this distribution in the simulation model. See Appendix B.

4.2.3 Model outputs

To measure the system performance, we define performance indicators, based on stakeholder interests.

1. Number of ALC patients per day: The total number of ALC patients in the hospital per day.
2. Average waiting time: The average time a patient has to wait in the hospital after the medical treatment is finished.
3. Probability of waiting: The probability that a patient cannot transfer immediately to aftercare when medical treatment is finished.
4. Occupation: The bed occupation in aftercare institutions.

4.2.4 Scope and level of detail

In the simulation model, only the process of transfer is included. So the process in the hospital, for example going from the operating room to a hospital ward, is not included. Also, only patients that are admitted to the hospital and need aftercare after hospital treatment are included. Patients that go home are not relevant and outside the scope of the model. Patients that need care at home are also not included, as they have a different process and also cause only a few ALC days. Further, transfers between different aftercare institutions are not included, as there is no data available about these transfers. At last, we do not model readmissions to the hospital. In fact, they are already in the data, but as new patients. Figure 13 shows the simplified simulation process. This figure makes clear what is in scope and out of scope of the simulation process. Appendix E shows the detailed flowchart of what the simulation model does at which events. Appendix F contains a screenshot of the interface of the simulation model.

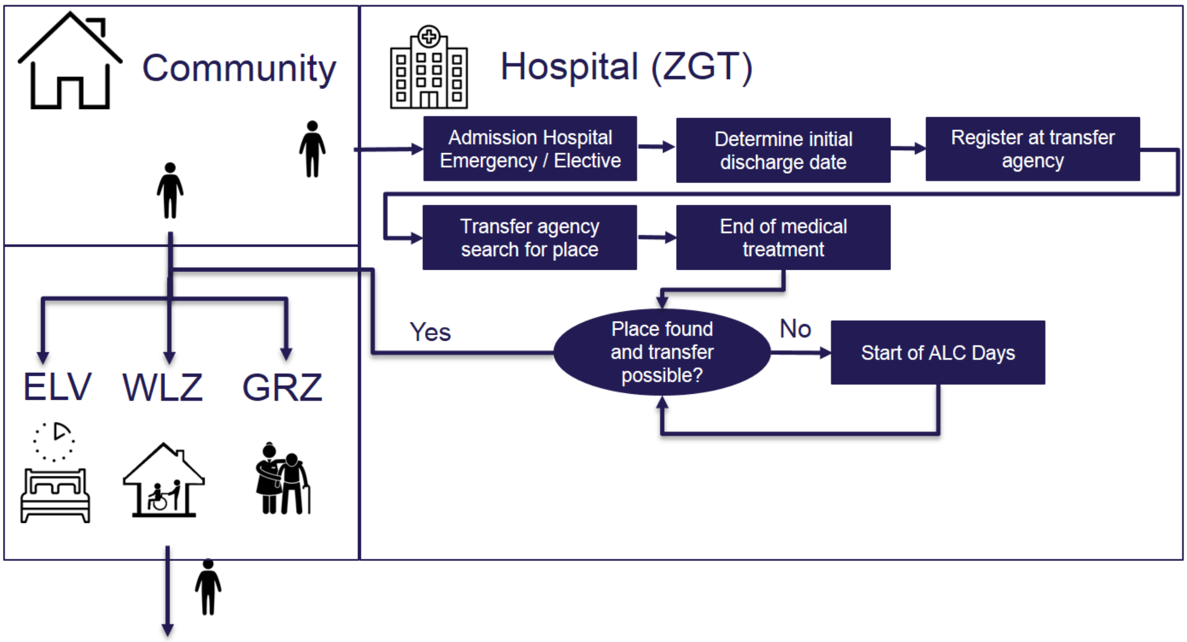

Figure 13: Simplified simulation process

4.2.5 Assumptions

In the simulation model, we make the following assumptions:

1. *Patients flow only downstream*

In the simulation model, patients only flow in the downstream direction. So, patients are not re-admitted to the hospital and patients do not move between aftercare institutions.

2. *No transfers on the weekend and at most two admissions per day per institution*

No transfers take place from the hospital to any aftercare institution on the weekend. Further, for each aftercare institution, there is a maximum of two transfers per day.

3. *No differences in places per care type*

As explained in Section 2.1 we distinguish between five care types. We assume that within these care types, there are no differences between beds and there are no reasons why a patient is not accepted on a bed.

4. *No delay due to the transfer agency*

When a patient is registered at the transfer agency before 14:00 and there is a place at an aftercare institution, patients are always transferred the next day. So, there is never a delay due to the transfer agency when a patient is registered before 14:00.

5. *After a discharge a place is released the next day for ELV and GRZ, 3 days for WLZ.*

When a patient is discharged from a place in an aftercare institution, the place is released for the next person on the next day for ELV and GRZ. For the WLZ, we use an average of 3 days.

6. *First come, first served based on the first initial discharge date*

The transfer agency searches for a place for a patient based on the first come, first served rule, based on the first initial discharge date. If the initial discharge date changes, the priority does not change.

7. The number of beds determines the capacity

The number of beds determines the capacity, so personnel and other resources are not accounted for.

8. Length of stay aftercare not influenced by waiting time in hospital

When a patient waits in the hospital for a place in aftercare, the length of stay in aftercare does not change.

4.3 Experimental design

4.3.1 Warm-up period and run characteristics

Before performing our experiments, we need to determine the warm-up period, run length and number of replications to execute (Appendix D). Using Welch's graphical procedure (Law, 2015), we choose a warmup period of 5 years. Additionally, we use as a rule of thumb that the run length is ten times as large as the warm-up period, which gives us a run length of fifty years. To determine how many replications we should do, we run the model with the initial arrival rates. We apply confidence intervals to the simulation output per replication and look when the interval becomes sufficiently narrow, where we choose a significance level (α) of five percent. With five replications, the confidence interval is small enough for all KPIs. According to Robinson (2014), ensuring that enough output data have been obtained from the simulation, can be addressed in two ways. The first is to perform a single long run with the model. As we have a non-terminating simulation, this is an option for us. We have a warm-up period of five years, therefore we chose to do a single long run, to avoid having many warm-up periods. The run length is the warm-up period plus five replications of fifty years, which corresponds to $5 + (5 * 50) = 255$ years.

4.3.2 Experiments for validation

Before we can validate the model, we first have to tune the model with the right parameters. As explained in Section 4.2.2, we do not know the exact arrival rate from other parties. We made an estimation in Section 4.2.2, which we used as start values. As a tuning KPI, we chose the average waiting time per type of care. Table 8 shows the result of the average waiting time with these parameters.

Table 8: Average waiting time in simulation model at start values

Type of care	Start value arrival rate	Avg. Waiting time	Avg. Waiting time simulation model
ELV Low	1.15	0.9	0.21
ELV High	1.24	4.3	0.27
ELV Palliative	0.53	1.6	0.49
GRZ	0.9	1.9	0.28
WLZ	2.87	3.5	0.19

Table 8 shows that the average waiting time in the model is too low compared to the measured average waiting time. Therefore, we tried different values of the arrival rates with an accuracy of two decimal places to find the values that correspond to the waiting time closest to the measured waiting time (Appendix G). This gave us the following values for the arrival rates from other parties, see Table 9. The deviation of the average waiting time is at most 9%, this deviation is measured at the average waiting time for GRZ. This gap of 0.2 days does not make a difference in practice. Both the target values and the simulation results show a high standard deviation (SD), so we do not see this as a problem. However, the standard deviation in the simulation model is a bit higher, which we should take into account. With these values, we validate the model with another KPI, namely the percentage of patients that have to wait.

Table 9: Average and standard deviation (SD) waiting time in simulation model

		Avg. Waiting time				
Care type	**Arrival rate other parties**	**Target value**	**SD target value**	**Simulation result**	**SD Simulation result**	**Deviation**
ELV Low	1.52	0.9	3.3	0.9	2.8	2%
ELV High	1.60	4.3	6.5	4.5	8.3	4%
ELV Palliative	0.71	1.6	2.9	1.5	3.8	7%
GRZ	1.36	1.9	3.1	2.1	4.3	9%
WLZ	3.05	3.5	6.7	3.5	8.4	1%

Table 10 shows the percentage of patients that have to wait. This KPI is lower in the simulation model than measured in the data. A reason for this could be that in the real system, there are more reasons why a patient is not transferred directly when there is space in aftercare institution. For example, it happens sometimes that a patient does not fit on a free spot, due to the care level for example. However, agreements are made that this cannot be a reason for rejection and it is not measured how many times this happens. So, in our simulation model, we have fewer reasons why a patient should wait. Therefore, we have a lower percentage of patients that have to wait. However, the average waiting time is quite similar in the simulation model. This means that when a patient has to wait, it has to wait longer, due to capacity restrictions. This is something we should take into account when drawing conclusions from the simulation model. Further, looking at the percentage of patients that have to wait, we should only compare the result of the simulation model with each other, and not with the real system.

Table 10: Percentage of patients that have to wait, simulation result and target value

Care type	Target value	Simulation result
ELV Low	27%	20%
ELV High	68%	45%
ELV Palliative	43%	28%
GRZ	42%	34%
WLZ	54%	28%

In terms of the percentage of patients that have to wait, the simulation model already paints a positive picture of reality, therefore we do not overestimate positive effects.

4.4 Conclusion

In this research, we chose to use a discrete event simulation. The model objective is to be able to analyze the effects of interventions and scenarios on the system performance. The most important model inputs consist of the patients' characteristics, discharge rates, length of stay and capacity. The performance indicators we look at in the model are the average number of ALC patients per day, the average waiting time, the percentage of patients that have to wait and the bed occupation in aftercare institutions. To get stable results, we use a warmup period of five years in the simulation model and a run length of 255 years. The simulation model results give a similar average waiting time as the measured value for the real system, but a lower average number of patients that are waiting and a lower percentage of patients that have to wait. A reason for this could be that in the real system, there are more reasons why a patient is not transferred directly when there is space in aftercare institution.

This is something we should keep into account by drawing conclusions out of the simulation model. Further, we should only compare the result of the simulation model with each other, and not with the real system.

5. Experiments

In this chapter, we present the results of the experiments we performed with our simulation model. In section 4.2.1, we explained the experiments we want to perform with the simulation model. We compare the results to the results of the 'base scenario', with the input parameters as explained in section 4.2.2.

5.1 Effect of bed occupation in aftercare on waiting time in the hospital

As explained in Section 4.2.1, a high bed occupation in aftercare institutions results in long waiting times in the hospital. By performing experiments in the simulation model, we give insight into the effects of options to lower the bed occupation. Also, we show what occupation rate results in which waiting time in the hospital. At first, we look at the simulated bed occupation in the base scenario.

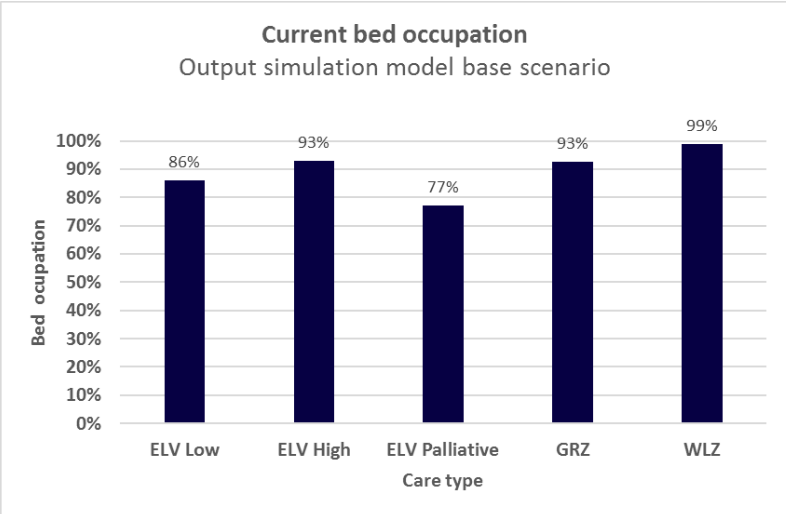

Figure 14: current bed occupation (output simulation model)

Figure 14 shows the bed occupation in the simulation model in the base scenario. Unfortunately, there is no data about the bed occupation in the real situation, so we cannot compare this. The bed occupation for the WLZ is estimated in previous confidential research at 97-99%. In the simulation model, the bed occupation for WLZ is 99%. We see that for the care types with higher throughput, e.g. ELV Palliative and ELV low, the bed occupation is lower. For ELV Palliative, the bed occupation in the simulation model is the lowest, namely 77%. Next, we perform experiments to lower the bed occupation and analyze the effect. We look at three different options, namely a) increasing capacity, b) decreasing the length of stay and c) decreasing the demand. Regarding the latter, demand can be lowered by for example treating more patients at home. Further, we analyze the option of lowering the variation in demand.

5.1.1 Increasing capacity

The first option to lower the bed occupation is by increasing the capacity. We experimented with an increased capacity of 1, 3, 5 and 10%. Because ELV Palliative has a low number of beds, we experimented with an increase of 1 and 2 beds. Table 11 shows how many beds we increased the capacity with. We discuss the results per type of care.

Table 11: Number of increased beds per type of care

	ELV Low	ELV High	GRZ	WLZ
+1%	1	1	2	27
+3%	2	2	5	80
+5%	3	4	8	133
+10%	5	7	16	267

1. *ELV Low*

We increased the capacity for ELV Low with 1, 3, 5 and 10%, which corresponds to 1, 2, 3 and 5 beds respectively. Figure 15 shows per expansion of the number of beds, the average bed occupation, waiting time and the probability that a patient has to wait. The error bars show the 95% confidence interval of the experimental results.

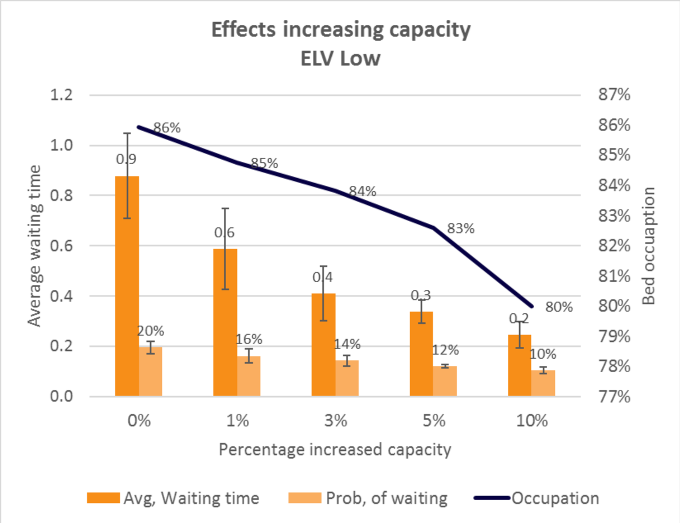

Figure 15: Effects of increasing capacity of ELV Low with a 95% confidence interval

As expected, we observe that the bed occupation, average waiting time and probability of waiting drop when the capacity increases. At an increase of 5% bed capacity, the average waiting time is halved and the probability of waiting is decreased from 20% to 14%. The bed occupation decreased from 86% to 83%. Even if the capacity increases by 10%, the probability of waiting is still 10%.

2. *ELV High*

We increased the capacity for ELV High with 1, 3, 5 and 10%, which corresponds to 1, 2, 4 and 7 beds respectively. Figure 16 shows per expansion of the number of beds, the average bed occupation, waiting time and the probability that a patient has to wait.

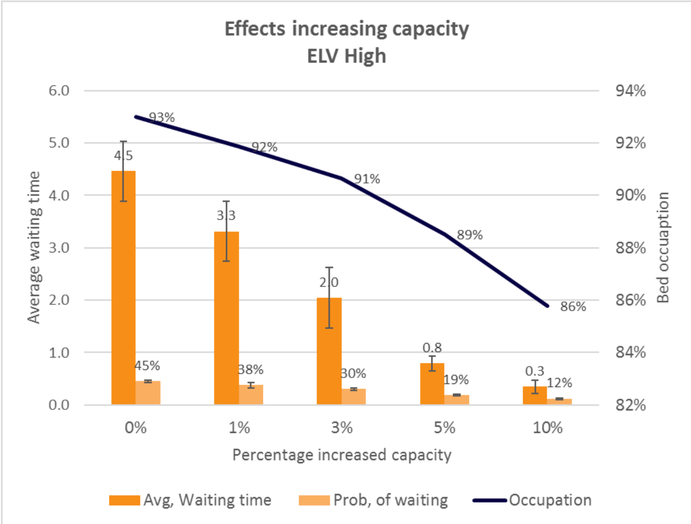

Figure 16: Effects of increasing capacity of ELV High with a 95% confidence interval

As expected, we observe that the bed occupation, average waiting time and probability of waiting drop when the capacity increases. At an increase of 3% bed capacity, the average waiting time is already halved. However, the probability of waiting is still quite high, namely 29%. For a maximum probability of waiting of 15%, a 10% increase in capacity is needed. However, the average waiting time is then very low, namely 0.4 days. With a 3% and 10% increase in capacity, the bed occupation decreases from 93% to 91% and 86% respectively. Even if the capacity increases by 10%, the probability of waiting is still 10%.

3. ELV Palliative

We increased the capacity for ELV Palliative with 1 and 2 beds. Figure 17 shows per expansion of the number of beds, the average bed occupation, waiting time and the probability that a patient has to wait.

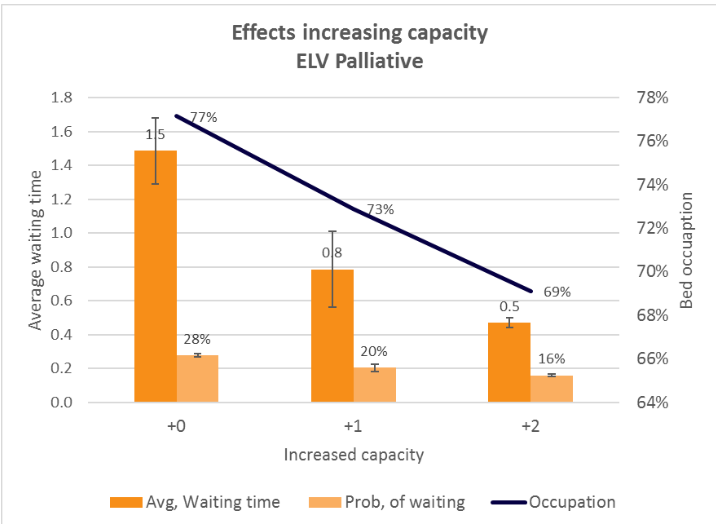

Figure 17: Effects of increasing capacity of ELV Palliative with a 95% confidence interval

With one extra bed, the average waiting time is almost halved and the waiting probability is decreased to 20%. With two extra beds, the average waiting time is at one-third of the current situation and the probability of waiting is decreased to 16%. However, with 2 extra beds, the bed occupation decreases to 69%. For ELV Palliative a lower bed occupation is needed to obtain a low probability of waiting, compared to the other care types. The length of stay for ELV palliative is the shortest, therefore this type of care has the highest throughput, which can explain this. According to the managers of the aftercare institutions, an increase in capacity for ELV Palliative might not be necessary, as there is, for example, only a high waiting time for ELV Palliative in Almelo and not in Hengelo. Therefore, shifting capacity may be a solution. We did not include preference for locations in our research.

4. GRZ

We increased the capacity for GRZ with 1, 3, 5 and 10%, which corresponds to 2, 5, 8 and 16 beds respectively. Figure 18 shows per expansion of the number of beds, the average bed occupation, waiting time and the probability that a patient has to wait.

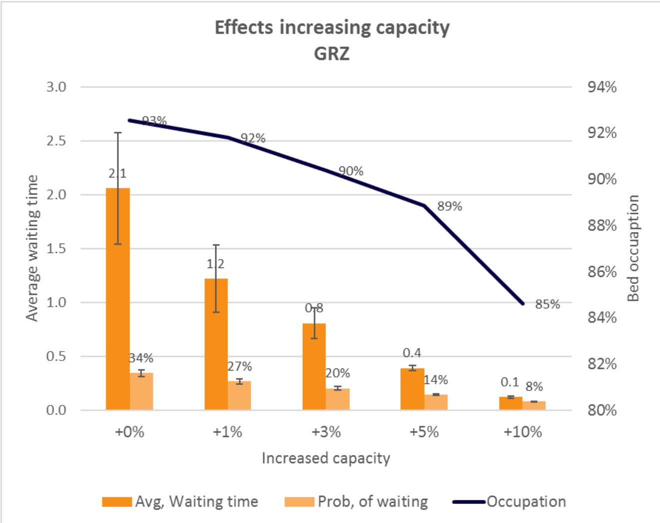

Figure 18: Effects of increasing capacity of GRZ with a 95% confidence interval

With a capacity increase of 3%, the average waiting time is halved and the waiting probability is decreased to 20%. With a capacity increase of 5%, the waiting probability is decreased to 14%. When the capacity is increased by 10%, the average waiting time is very low, namely 0.1 days. However, still 8% of the patients have to wait.

5. WLZ

We increased the capacity for WLZ with 1, 3, 5 and 10%, which corresponds to 27, 80, 122 and 267 beds respectively. Figure 19 shows per expansion of the number of beds, the average bed occupation, waiting time and the probability that a patient has to wait.

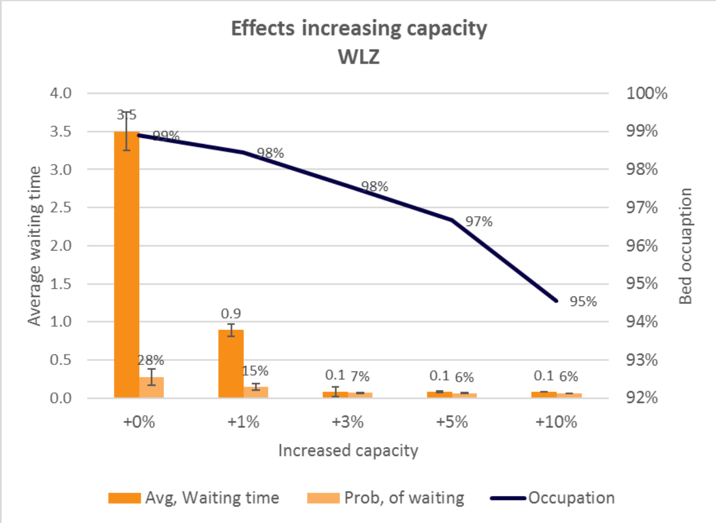

Figure 19: Effects of increasing capacity of WLZ with a 95% confidence interval

Due to the high bed numbers, the percentage increase corresponds with a high number of beds. With a one percent increase in capacity, the average waiting time is more than halved and the probability of waiting is decreased to 15%. The bed occupation in this case is still 98%. So for the WLZ, it is possible to have a high bed occupation with a low waiting time. We see that there is almost no difference in waiting time between an increase of 3%, 5% and 10%, while the occupation does decrease. Therefore, we can conclude that it is not necessary to increase the bed occupation with more than 3%.

5.1.2 Decreasing length of stay

The next experiments we performed are decreases in the length of stay. We experimented with a decrease in the length of stay with 1, 3, 5 and 10%. Table 12 shows the length of stay for the care types for each experiment. For the WLZ, we do not have an average LOS, but an empirical distribution, see section 4.2.2. For each category, we decrease the LOS by 1, 3, 5 and 10%. We do not perform this experiment for ELV Palliative, as it is not desirable or possible to steer on a shorter length of stay. For the WLZ, a shorter length of stay could be realized by focusing on making it possible for more elderly to stay longer at home. For ELV high and ELV low, the focus could be on a quicker recovery and trying to become independent as soon as possible. Overall, it could be possible to focus on a quicker outflow to home.

Table 12: Length of stay per care type for each experiment

	ELV Low	ELV High	GRZ
0%	32.9	36.9	43.0
-1%	32.6	36.5	42.6
-3%	31.9	35.8	41.7
-5%	31.3	35.1	40.9
-10%	29.6	33.2	38.7

We discuss the results per type of care.

1. *ELV Low*

Figure 20 shows per decrease in the length of stay, the average bed occupation, waiting time and the probability that a patient has to wait.

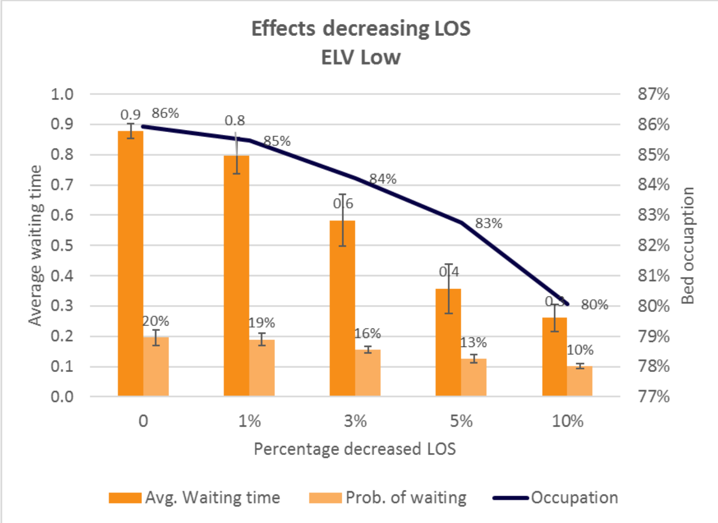

Figure 20: Effects of decreasing LOS of ELV Low with a 95% confidence interval

As expected, we observe that the average waiting time, probability of waiting and the bed occupation decrease when the length of stay decreases. Further, we observe that the effects of a decrease in LOS of a certain percentage results in the same decrease in bed occupation as an increase in capacity of the same percentage. However, the average waiting time and the waiting probability decreases a bit less. At a decrease of 5% in the length of stay, which corresponds to a decrease of 1.6 days, the average waiting time is halved and the probability of waiting is decreased to 13%.

2. *ELV High*

Figure 21 shows per decrease in the length of stay, the average bed occupation, waiting time and the probability that a patient has to wait.

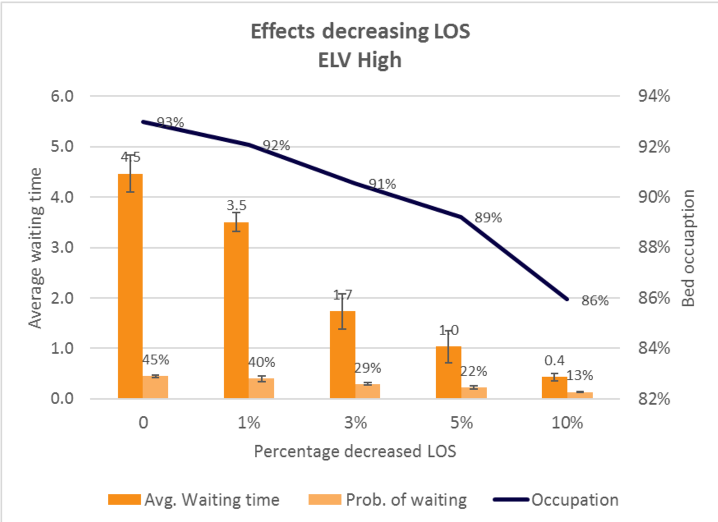

Figure 21: Effects of decreasing LOS of ELV High with a 95% confidence interval

Compared to the increase in capacity of a certain percentage, we see almost the same result. With a decrease in LOS of 3% the average waiting time is halved, but the waiting probability is still quite high, namely 29%. At a decrease in LOS of 10%, the probability of waiting is decreased to 13%.

3. GRZ

Figure 22 shows per decrease in the length of stay, the average bed occupation, waiting time and the probability that a patient has to wait.

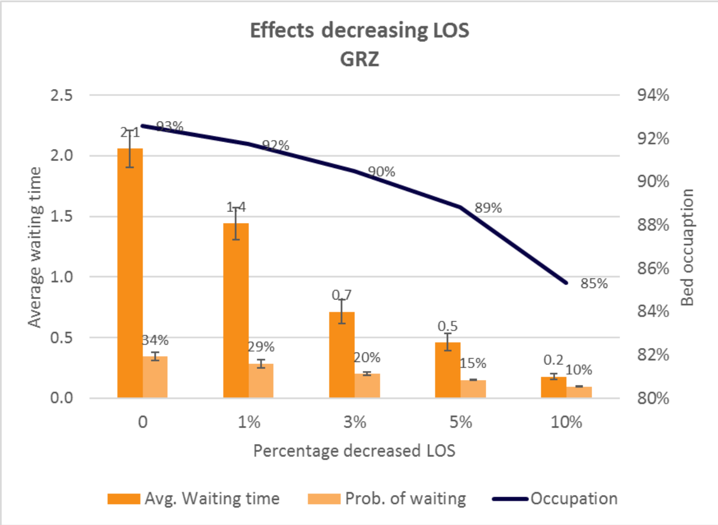

Figure 22: Effects of decreasing LOS of GRZ with a 95% confidence interval

As expected, we observe that the average waiting time, probability of waiting and the bed occupation decrease when the length of stay decreases. At a decrease of 3% in LOS, the average waiting time is halved. Again, we observe that the results of decreasing the LOS with a certain percentage corresponds with increasing the capacity by a certain percentage.

4. WLZ

Figure 22 shows per decrease in the length of stay, the average bed occupation, waiting time and the probability that a patient has to wait.

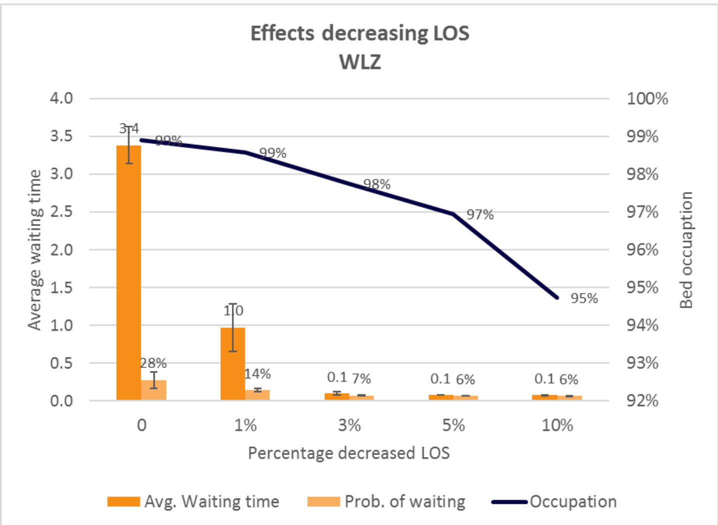

Figure 23: Effects of decreasing LOS of WLZ with a 95% confidence interval

As the WLZ has a long length of stay, a decrease in LOS of 1% already has a huge impact on the average waiting time. We observe that there is no significant difference in average waiting time and probability of waiting between a decrease of 3, 5 and 10%.

5.1.3 Decreasing demand

The next experiments we performed are decreases in the demand for aftercare. This could for example be realized by moving more care to home. We experimented with a decrease in demand of 1, 3, 5 and 10%. We decreased the total on average 4.1 discharges per day. Therefore, we look at the total decrease in average waiting time and probability of waiting. Appendix H shows the results per type of care. Figure 24 shows per decrease in demand, the average bed occupation, waiting time and the probability that a patient has to wait.

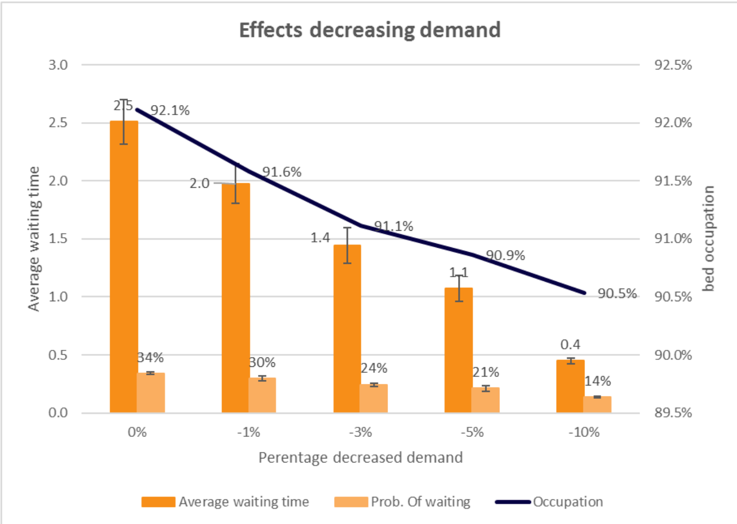

Figure 24: Effects of decreasing demand with a 95% confidence interval

As expected, we observe that the occupation, average waiting time and probability of waiting decreases when the demand decreases. At a decrease in demand of 5% in demand, the average waiting time is halved. The bed occupation decreased in this case from 92.1% to 90.9%.

5.1.4 Lower the variation in demand

As mentioned in Section 4.2.1, another solution to the high bed occupation could be to lower the variation in demand. With a lower variation, the average waiting time can be lower with the same bed occupation.

Only the elective patients are scheduled, so it is only possible to lower the variation in the elective patients. However, 83% of the patients that need aftercare are emergency patients. So, we can only lower the variation of 17% of the patients. As also shown in section 4.2.2, the seasonal patterns are very erratic. Therefore, it is hard to predict when there will be few or many emergency patients. It is therefore very hard to take emergency patients into account when planning elective patients. The option that is left is to spread the elective patients as evenly as possible over the year. This is not a realistic option due to vacation reductions for example. Figure 25 and Figure 26 show the seasonal pattern over the year for the elective and emergency patients. Figure 25 shows the current situation and Figure 26 the situation when we spread elective patients evenly over the year.

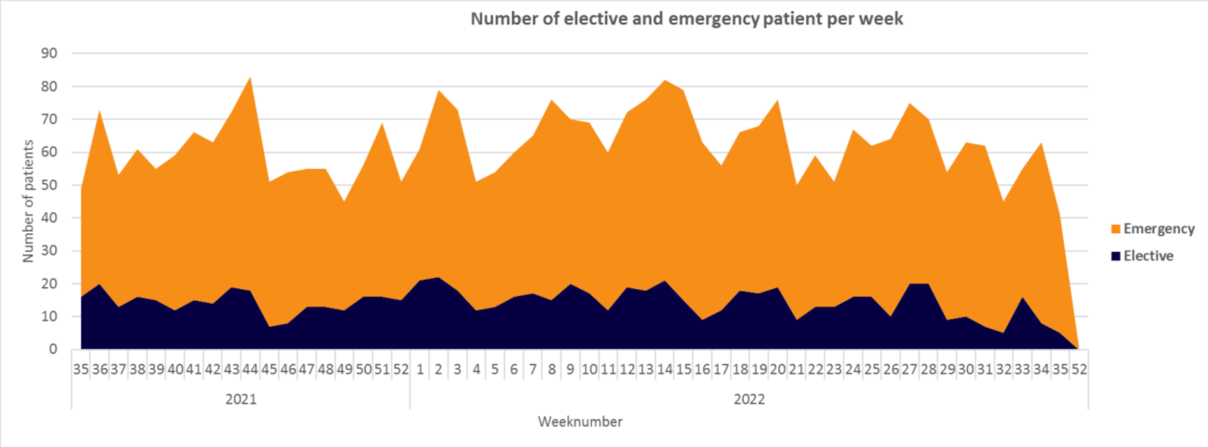

Figure 25: number of elective and emergency patients per week

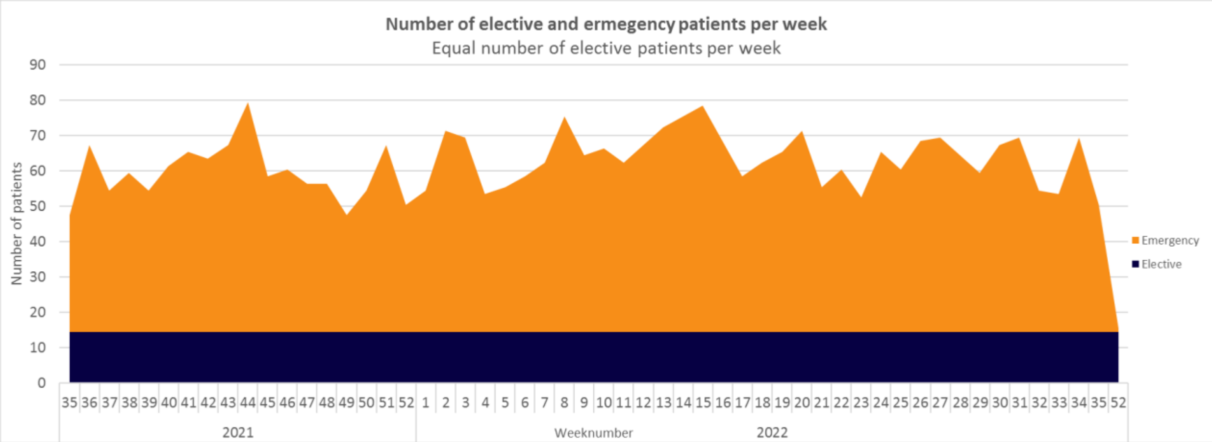

Figure 26: number of elective and emergency patients per week with an equal number of elective patients per week.

We observe that even when we spread the elective patients evenly over the year, the seasonal pattern is still erratic. The standard deviation of patients per week decreases from 10.0 in the current situation to 7.7 in the adjusted situation. As we do not see realistic options to lower the variation in demand, we do not further investigate this option in the simulation model.

5.1.5 Conclusion of experiment

The goal of these experiments is to understand the relationship between the bed occupation in aftercare and the waiting time in the hospital. As expected, with a lower bed occupation, the average waiting time is lower. Options to lower the bed occupation are increasing the capacity, decreasing the length of stay or decreasing the demand. The results show how much the bed occupation and waiting time decrease with each intervention. To halve the waiting time for each type of care, the capacity of ELV Low should be increased by 5% or the LOS decreased by 5%. For ELV High and GRZ, an increase in capacity or decrease in LOS of 3% is enough for halving the waiting time. Looking at ELV Palliative, an increase of 1 bed would already be enough to halve the waiting time. At last, for the WLZ an increase in capacity of 1% or a decrease in LOS of 1% would already be enough. Further, we observe that even with an increase in capacity or decrease in length of stay of 10%, the probability of waiting in the simulation still stays around 10%. In the real situation, the probability of waiting was even higher. The results are in line with the expectations of the managers of the aftercare institutions, but a lower bed occupation leads to vacancy and financial difficulties for the aftercare.

Figure 27: Average waiting time vs. bed occupation per type of care

We observed that it differs per type of care how high the bed occupation can be for a certain waiting time. Figure 27 shows the measurements of the average waiting time and the average bed occupation per type of care. We observe that the bed occupation for WLZ can be quite high and still have a low average waiting time. For ELV Palliative, the average bed occupation must be low. We can explain this by the throughput per type of care, the throughput is the lowest for the WLZ and the highest for ELV Palliative. Looking at Figure 27, we observe that the greatest achievement can be made at the WLZ, ELV High and GRZ, as these lines are the steepest. This means that with a small drop in bed occupation, the average waiting time decreases much.

5.2 Capacity pooling

In this Section, we show the results of the experiments with "capacity pooling". With capacity pooling, we mean that we "unlabel" beds such that it does not matter which care type a patient has to be able to be admitted to a bed. We looked at two situations; in the first situation, only ELV beds are flexible. This means that all types of ELV can be admitted to a flexible ELV bed, but no patients for GRZ or WLZ can be admitted. In the second situation, ELV and GRZ beds are flexible, so all types of ELV and GRZ can be admitted to a flexible but, but no patients for WLZ. We chose to not make WLZ beds flexible with ELV and GRZ beds, as WLZ places can be used for several years. Patients live at a WLZ place, other than a short stay for ELV or GRZ.

5.2.1 Flexible ELV beds

We experimented with making 5, 10, 20, 30, 50 and 100% of the ELV beds flexible. Table 13 shows how many flexible beds there are per percentage of flexible beds. For example, with 5% flexible ELV beds, we have 7 flexible beds. This means that we reduced the number of ELV high, ELV low and ELV palliative beds in proportion to the number of available beds per type of care with 7 and make a new department with 7 beds where all types of ELV can be admitted.

Table 13: Number of flexible beds

Percentage of flexible beds	Number of flexible beds
0	0
5%	7
10%	14
20%	29
30%	43
50%	71
100%	143

We compare the average waiting time and the probability of waiting in the original situation with the situation where there are flexible ELV beds. Figure 28 shows the average waiting time per percentage of flexible beds and Figure 29 shows the probability of waiting.

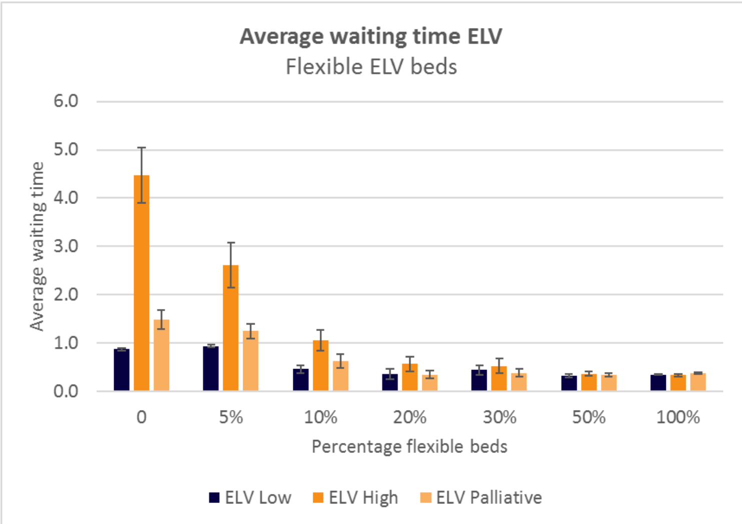

Figure 28: Average waiting time per percentage of flexible ELV beds with a 95% confidence interval

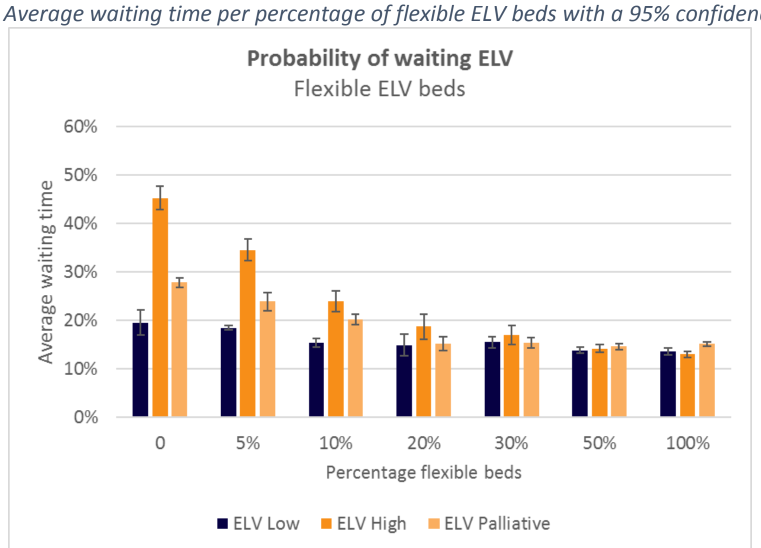

Figure 29: Probability of waiting per percentage of flexible ELV beds with a 95% confidence interval

As expected, we observe that the average waiting time and probability of waiting decrease when there are flexible beds. We observe that with 5% flexible ELV beds, the average waiting time for ELV high is already halved. For ELV Palliative the average waiting time also decreases somewhat with 5% flexible beds, but the average waiting time for ELV low stays almost the same. At 10% flexible beds, the average waiting time for ELV high is again halved compared to 5% flexible beds. Also the waiting time for ELV low and ELV palliative are significantly lower at 10% flexible beds compared to 5% flexible beds. With 20% flexible beds, we still observe a significant improvement in the average waiting time and probability of waiting. At a higher flexibility level than 20% we do not see a significant improvement anymore in the average waiting time or the probability of waiting. Therefore, we can conclude that more than 20% of flexible beds are not necessary.

5.2.2 Flexible ELV and GRZ beds

We experimented with making 5, 10, 20, 30, 50 and 100% of the ELV and GRZ beds flexible. Table 14 shows how many flexible beds there are per percentage of flexible beds. For example, with 5% flexible ELV and GRZ beds, we have 15 flexible beds. This means that we reduced the number of ELV high, ELV low, ELV palliative and GRZ beds in proportion to the number of available beds per type of care with 15 and make a new department with 15 beds where all types of ELV can be admitted.

Table 14: Number of flexible beds

Percentage of flexible beds	Number of flexible beds
0	0
5%	15
10%	30
20%	60
30%	89
50%	149
100%	298

We compare the average waiting time and the probability of waiting in the original situation with the situation where there are flexible ELV and GRZ beds. Figure 30 shows the average waiting time per percentage of flexible beds and Figure 31 shows the probability of waiting.

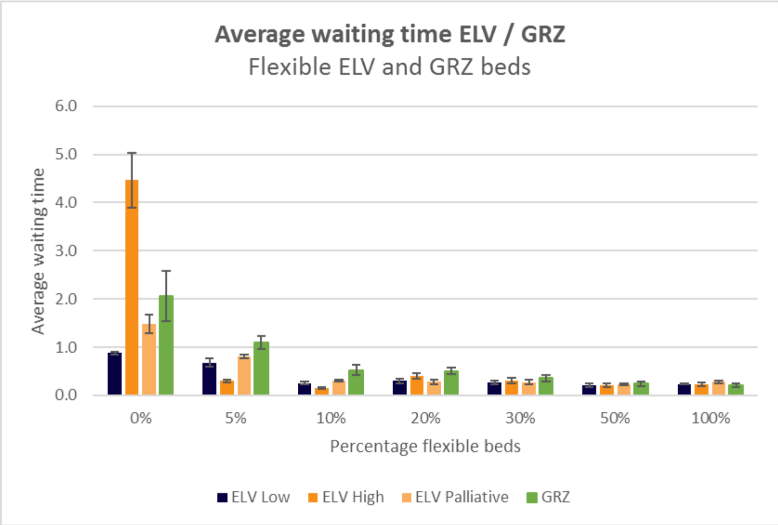

Figure 30: Average waiting time per percentage of flexible ELV and GRZ beds with a 95% confidence interval

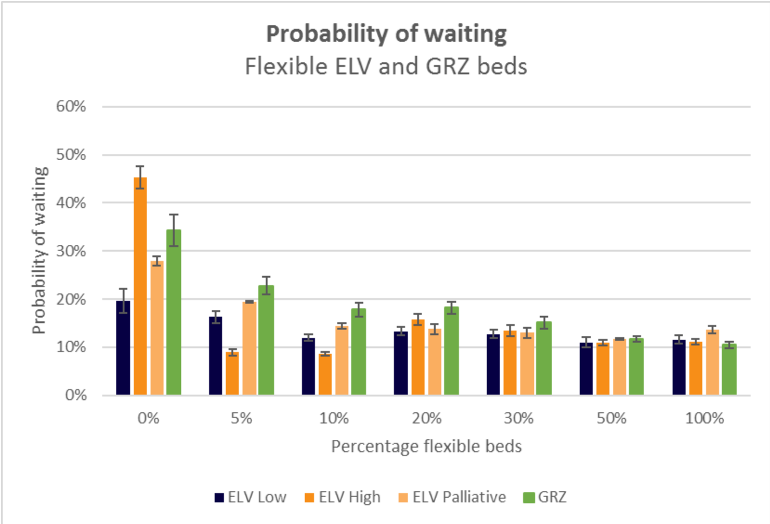

Figure 31: Probability of waiting per percentage of flexible ELV and GRZ beds with a 95% confidence interval

As expected, we observe that the average waiting time and probability of waiting decrease when there are flexible beds. We observe that with 5% flexible ELV and GRZ beds, the average waiting time for ELV high already decreases from 4.5 to 0.3 days. Also for GRZ, we see a large decrease from 2.1 to 1.1 days average waiting time. For ELV Palliative and ELV Low, the average waiting time also decreases somewhat with 5% flexible beds. At 10% flexible beds, the average waiting time and probability of waiting for all types of care decreases compared to 5% flexible beds. With 20% flexible beds, we do not see significant improvements in the average waiting time and probability of waiting anymore. Therefore, we can conclude that 20% or more flexible ELV and GRZ beds are not necessary.

5.2.3 Conclusion of experiment

In this experiment, we showed that some flexibility in who can be admitted to which bed has a large impact on the average waiting time and the probability of waiting. When only ELV beds are flexible, such that each type of ELV can be admitted to the flexible beds, 20% or 29 flexible beds are enough as we do not see improvement when more beds are flexible. When also GRZ patients can be admitted to flexible beds, 10% or 30 flexible beds are enough. The decrease in length of stay and probability of waiting is larger when ELV and GRZ patients can be admitted to flexible beds. The managers of the aftercare institutions believe that flexible capacity, which allows for easy scaling up and down, would be a great solution. However, implementing this solution is complex in terms of personnel planning and financing, but it is worth further investigation.

5.3 Redistribute beds between the care types

In section 5.1 and section 5.2, we showed the results of experimenting with decreasing the bed occupation and capacity pooling. We observed in the results that the improvements differ per type of care. Therefore, we want to know if the number of beds is correctly divided between the care types. We only look at a new division between the ELV and GRZ beds.

5.3.1 New bed distribution according to bed usage

To find a new division, we look at the results of the experiment where all ELV and GRZ beds are flexible and look at which patients use which percentage of the time the beds. Table 15 shows the percentage of time each care type is using the beds and the percentage of beds that are currently available for this care type.

Table 15: Percentage of bed usage and percentage of beds available

	Percentage of bed usage	Percentage of beds available
ELV High	25%	24%
ELV Low	17%	18%
ELV Palliative	5%	6%
GRZ	53%	52%

We observe that there are no large differences between the percentage of beds usage when all beds are flexible and the percentage of beds available. ELV High and GRZ have fewer beds available than they use when all beds are flexible, while ELV Low and ELV Palliative have some more beds. Table 16 shows the current number of beds available per care type and the number of beds they would have according to the percentage of bed usage.

Table 16: Current and new bed division ELV and GRZ

	Current number of beds	New number of beds
ELV High	73	75
ELV Low	53	50
ELV Palliative	17	14
GRZ	155	159

We experimented with the new bed division as shown in Table 16. We compared the average waiting time and bed occupation between the current and new distribution. Figure 32 shows the results.

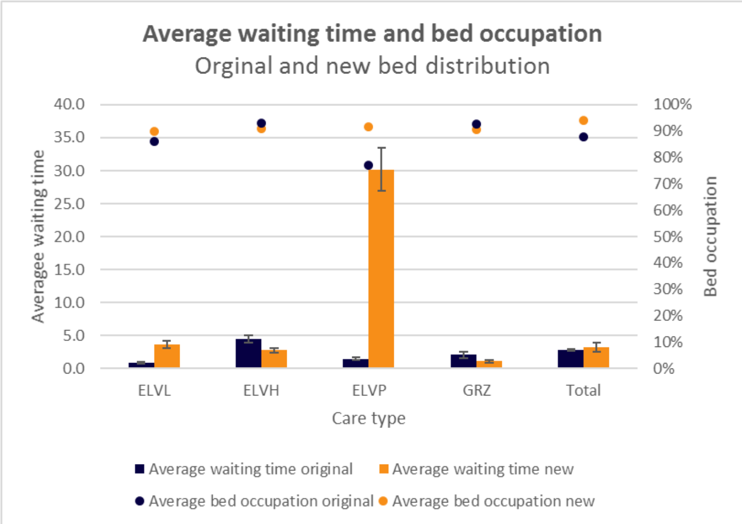

Figure 32: Average waiting time and bed occupation for the original and new bed distribution

We observe that for ELV Palliative, the average waiting time increases much when this care type has three beds less. Also for ELV low, the average waiting time increases with three beds less. For ELV high and GRZ, the average waiting time decreases, as they have more beds. If we look at the total average waiting time, we see only a small difference, however, the average waiting time is higher with the new division. If we look at the bed occupation, we see that the bed occupation is higher in the situation where the average waiting time is also higher. For ELV Palliative, we see the largest increase in bed occupation. We can conclude that the new bed distribution is not better than the original bed distribution.

5.3.2 Other options for bed distributions

As the new bed distribution is not better than the old distribution, we look into two other options. Within these options, we also increase the number of beds for ELV high and GRZ and decrease the number of beds for ELV low and ELV palliative, but less than in the previously tested distribution. Table 17 shows the bed distribution of these options.

Table 17: Bed distribution for option 2 and option 3

	Original bed distribution	Bed distribution option 2	Bed distribution option 3
ELV Low	53	51	52
ELV High	73	75	74
ELV Palliative	17	15	16
GRZ	155	157	156

We experimented with the new bed division as shown in Table 17. We compared the average waiting time and bed occupation between the current and new distribution. Figure 33 shows the results.

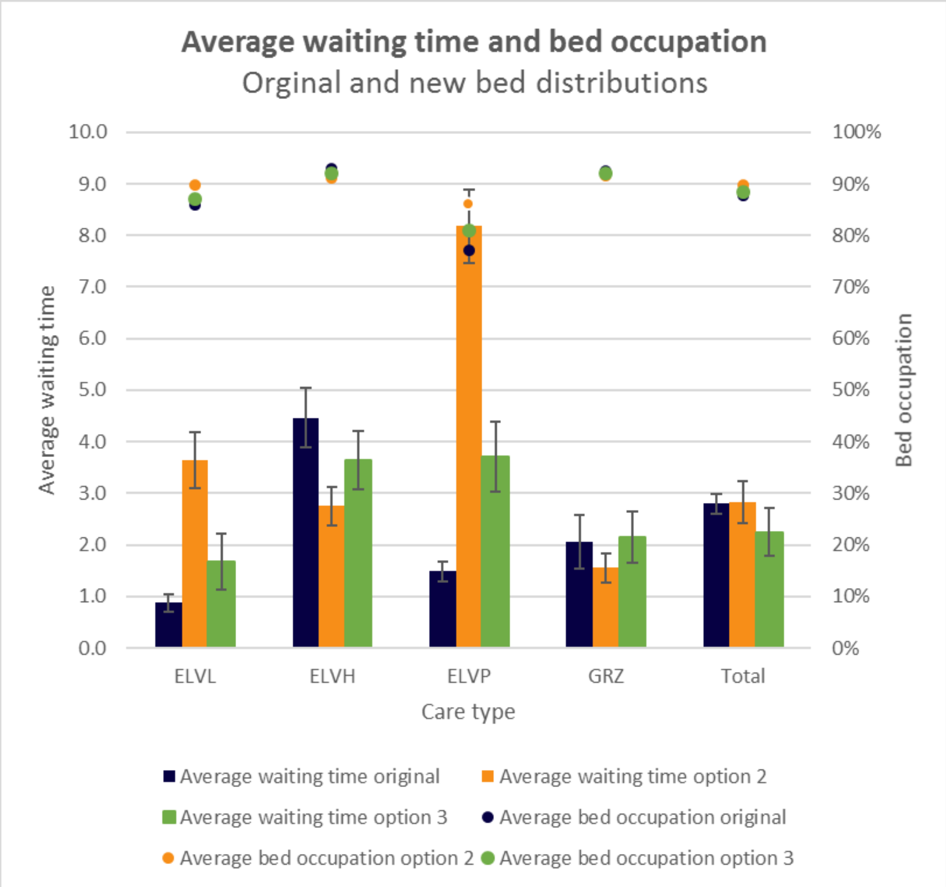

Figure 33: Average waiting time and bed occupation for the original and option 2 and option 3 distribution

If we look at the total average waiting time, we observe that there is no improvement for option 2 compared to the original bed distribution. For option 3, we see a small improvement. If we look at the differences per care type, we observe that only the average waiting time for ELV High improves. For ELV low and ELV palliative the waiting time increases much. Especially for ELV Palliative, with a short length of stay, it is questionable if it is desirable that the waiting time increases.

5.3.3 Conclusion of experiment

We tried three new distributions of beds between the types of ELV and GRZ. In only one option, we see a slight improvement in the total average waiting time. However, this comes with the cost of a large increase in the waiting time for ELV low and ELV palliative. Therefore, we cannot immediately conclude that this bed distribution is better. To conclude, the current bed distribution is quite good.

5.4 Admission restrictions

In this section, we show the results of experimenting with the admission restriction. Currently, there is an admission restriction of 2 patients per location. Also, on the weekend there are no admission possibilities. First, we experiment with admission possibilities on the weekend. Second, we experiment with more admission possibilities on weekdays.

5.4.1 Admission possibilities on the weekend

Currently, there are no admission possibilities on the weekend. We experiment with one and two admission possibilities per location on the weekend. Figure 34 and Figure 35 show the average waiting time and probability of waiting with these admission possibilities on the weekend.

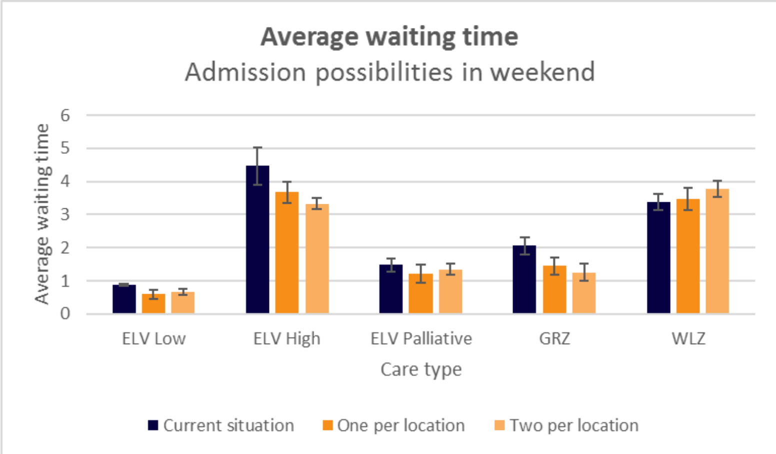

Figure 34: Average waiting time for admission possibilities on the weekend with a 95% confidence interval

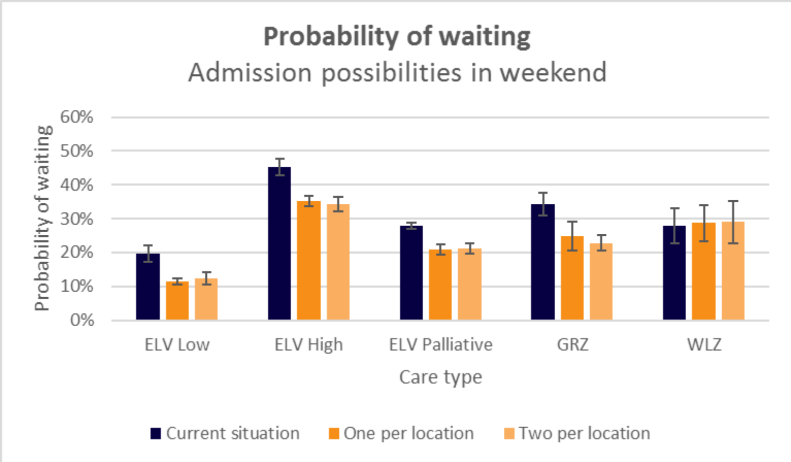

Figure 35: Probability of waiting for admission possibilities on the weekend with a 95% confidence interval

We observe, that with one admission possibility on the weekend, the average waiting time decreases for all types of care, except for the WLZ. With two admission possibilities, there is no improvement anymore relative to one admission possibility. Therefore we can conclude that one admission possibility per location on the weekend would satisfy.

5.4.2 Admission possibilities during weekdays

Currently, there are two admission possibilities on weekdays per location. We experimented with three, four and five admission possibilities per location. Figure 36 and Figure 37 show the average waiting time and probability of waiting with these admission possibilities on weekdays.

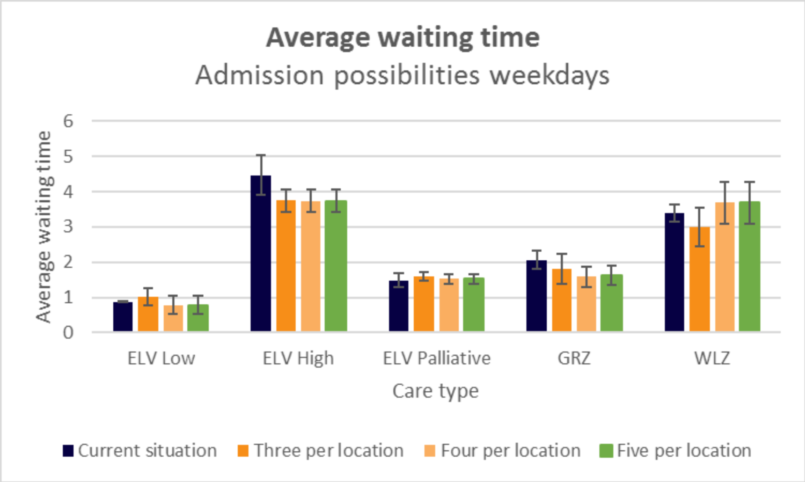

Figure 36: Average waiting time for admission possibilities on weekdays with a 95% confidence interval

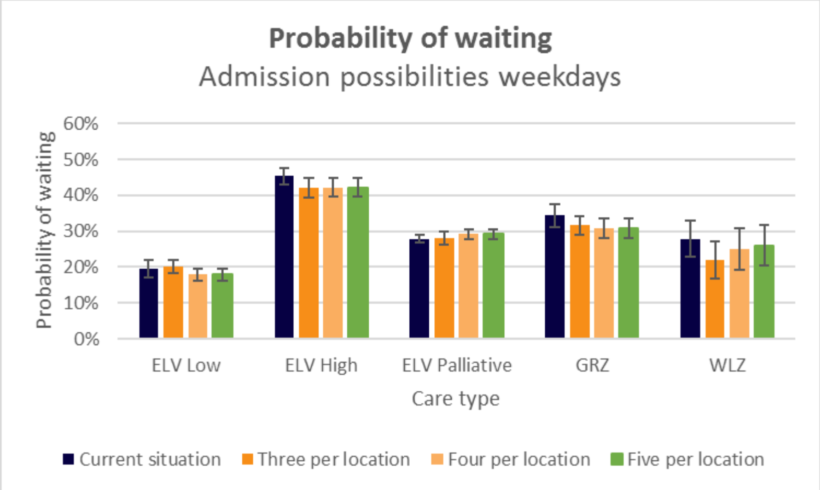

Figure 37: Probability of waiting for admission possibilities on weekdays with a 95% confidence interval

We observe that if there is one more admission possibility on weekdays, there is a decrease in the average waiting time and the probability of waiting for ELV high. For the other types of care, the difference is not significant. Therefore, we can conclude that only adding one admission possibility for ELV high on weekdays makes sense.

5.4.3 No admission restrictions

In this section, we experiment with the situation when there are no admission restrictions at all. Figure 38 and Figure 39 show the average waiting time and probability of waiting per type of care when there are no admission restrictions.

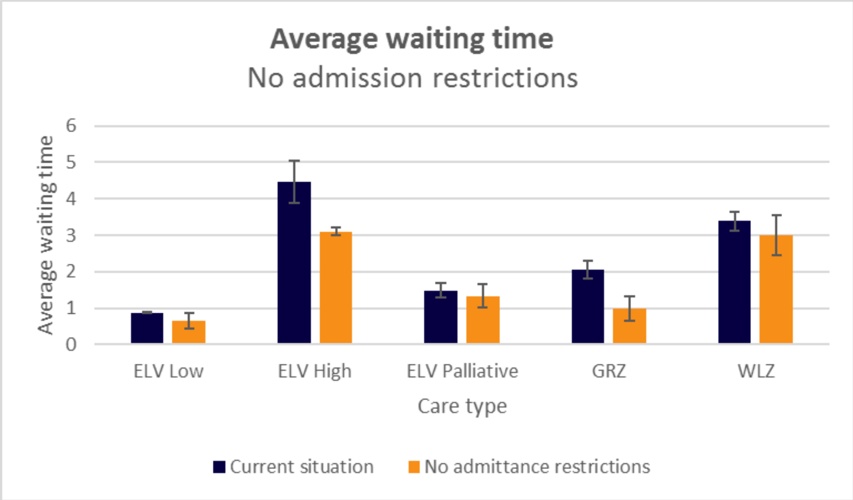

Figure 38: Average waiting time with no admission restrictions on weekdays with a 95% confidence interval

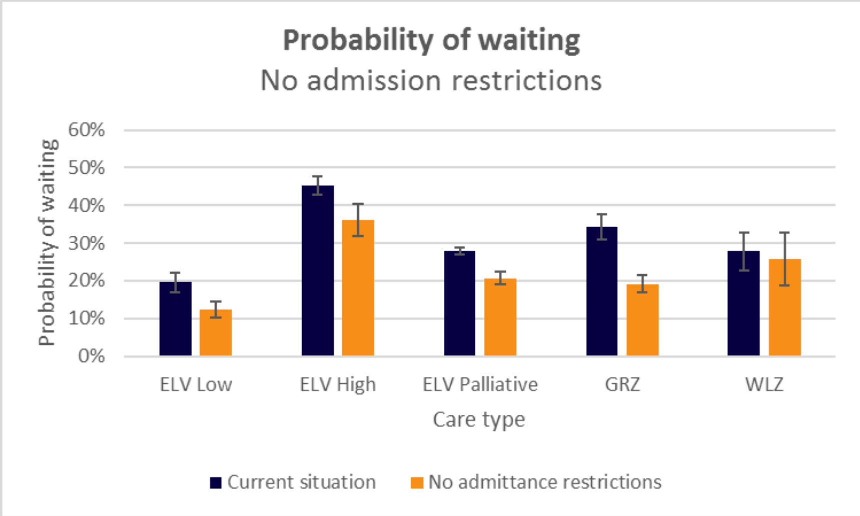

Figure 39: Probability of waiting with no admission restrictions on weekdays with a 95% confidence interval

We observe that when there are no admission restrictions, the average waiting time decreases for ELV Low, ELV high and GRZ. The probability of waiting decreases for these types of care, but also for ELV Palliative. For ELV high for example, the average waiting time decreases with 1.4 days without admission restrictions. For the GRZ, the average waiting time decreases with 1 day.

5.4.4 Conclusion of experiment

We experimented with adding more admission possibilities. With one admission possibility on the weekend per location, the average waiting time decreases for all types of care, except for the WLZ. With two admission possibilities, there is no improvement anymore relative to one admission possibility. Therefore we can conclude that one admission possibility per location on the weekend would satisfy. Adding more admission possibilities on weekdays only gives an improvement at ELV high. Also in this case, one additional admission possibility would satisfy. When there are no admission restrictions at all, the average waiting time for ELV high decreases from 4.5 to 3.1. This result is in line with the expectations. A positive results for the managers is that only one admission possibility per location in the weekend would satisfy.

5.5 Estimation of discharge dates

In this section, we show the results of the effects of the estimation of the discharge date. We experimented with a better estimation of the discharge date and with an earlier estimation of the discharge date. In section 5.5.1 we perform the experiments in the current situation. In section 5.5.2 we perform the experiment in the situation where there is five percent more capacity.

5.5.1 Current situation

We performed three experiments. In the first experiment called "perfect estimation", the discharge date is always perfectly estimated, which means that there is no difference between the first estimated discharge date, which is used to prioritize, and the final discharge date. In the second experiment called "Early estimation", the discharge date is already estimated on the first day of the hospital treatment, instead of on average 3 days. The last experiment, called "Perfect and early estimation", is a combination of the two experiments where the estimation is perfect and at the start of the hospital treatment. Figure 40 and Figure 41 show the average waiting time and probability of waiting for these experiments.

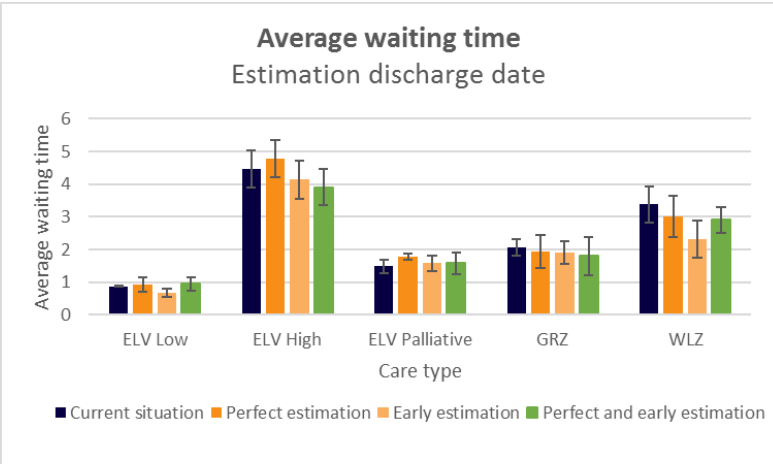

Figure 40: Average waiting time for experiments with discharge date with a 95% confidence interval

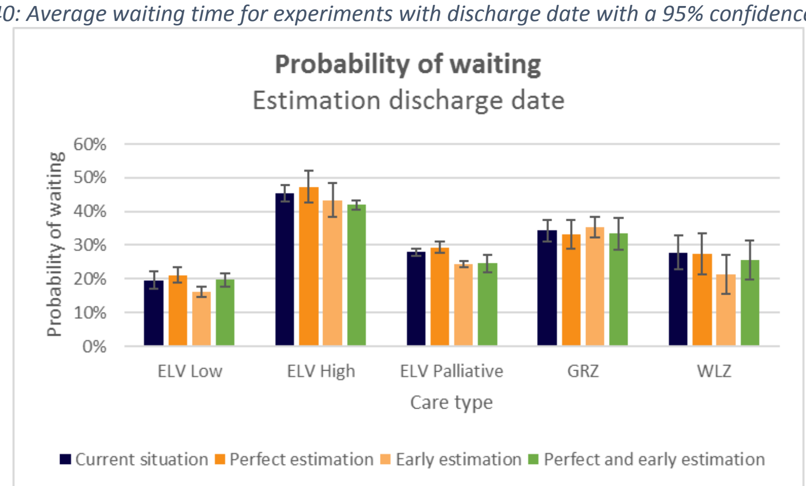

Figure 41: Probability of waiting for experiments with discharge date with a 95% confidence interval

In the average waiting time, we see no significant difference between the current situation and the experiments. For the probability of waiting, we only see a significant difference for ELV palliative for "early estimation" and "perfect and early estimation". So, in the current situation, it is not very important to make a perfect and early estimation of the discharge date. It could also be said that the estimation is currently on time and good enough. For ELV Palliative, making an early estimation is most important.

5.5.2 Situation with 5% more capacity

We perform the same experiments in the situation when there is 5% more capacity. In this situation, capacity is less of a problem and therefore it could be more important to make a good and on-time estimation. Figure 42 and Figure 43 show the average waiting time and probability of waiting for these experiments.

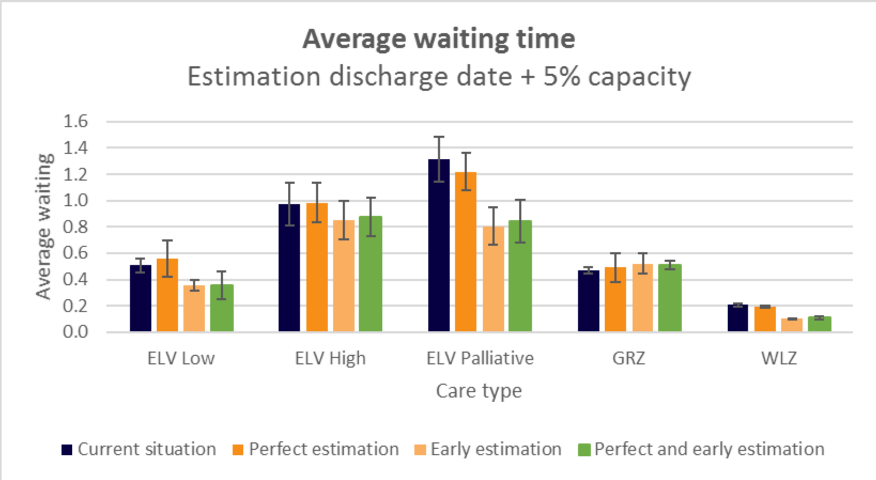

Figure 42: Average waiting time for experiments with discharge date with a 95% confidence interval

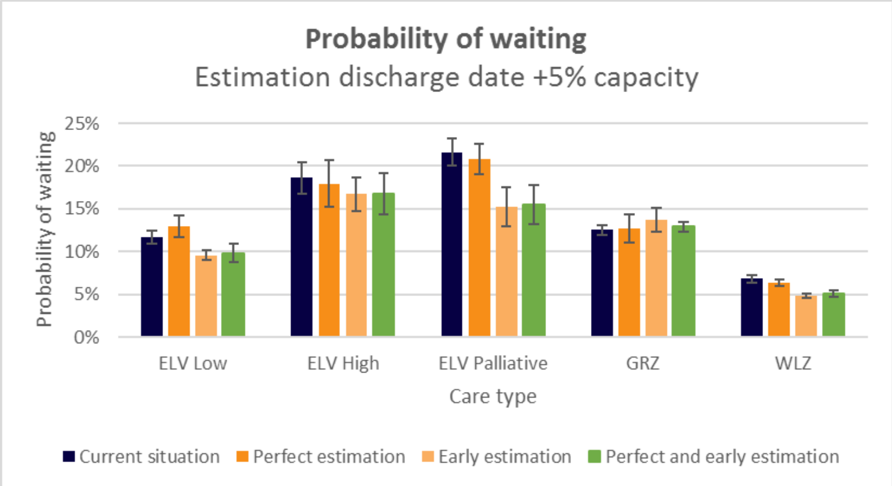

Figure 43: Probability of waiting for experiments with discharge date with a 95% confidence interval

As expected, we observe that when there is more capacity, it is more important to make an early estimation of the discharge date. We see the greatest effect at ELV Palliative. Also at ELV High and ELV Low, we see a decrease in the average waiting time.

5.5.3 Conclusion of experiment

In the current situation, it is not very important to focus on a better and early estimation of the discharge date. The current estimation is already quite good and on time. However, when capacity is less of a problem in the transfer chain, we showed that a good and early estimation of the discharge date becomes more important, especially for the ELV. For ELV palliative, it is most important to focus on a good and early estimation of the hospital discharge date.

6. Sensitivity analysis and financial impacts

In this chapter, we look deeper into the benefits of the various interventions. We look into the reduction of ALC days on a yearly basis and what the financial savings can be. Also, we look at the consequences of the interventions on the bed occupation and days of stay on a yearly basis for aftercare institutions. Further, we used serval input parameters in the simulation model. In this chapter, we show the impact of some of these input parameters on some of the results of the experiments.

6.1 Financial impacts

6.1.1 Bed occupation

In section 5.1, we experimented with different options to lower the bed occupation in aftercare institutions, such that the waiting time in the hospital decreases. In section 2.4.3 we explained that each ALC day for ELV and GRZ costs the hospital by estimation 100 Euro, and for the WLZ 200 Euro. Having a lower bed occupation, will cost aftercare institutions money. In this section, we show on a yearly basis how much money the hospital can save by the reduction in ALC days and what the difference in days of stay on a yearly basis is for aftercare institutions. We calculated the savings for ZGT by multiplying the reduction in ALC days on a yearly basis, due to the reduction in waiting time, by 100 Euro for ELV and GRZ and by 200 Euro for WLZ. It is important to note that this is a rough estimation and the savings are rounded to multiples of 100. We calculated the change in days of stay for aftercare by multiplying the change in bed occupation by the total number of beds and the number of days in a year. This overview can be used for discussion between the hospital and aftercare institutions. Appendix I shows the full overview of the reduction in ALC days, the savings for the hospital and the reduction in bed occupation and thereby the reduction in days of stay for aftercare institutions. Table 18 shows for ELV High the savings for ZGT when the length of stay, capacity or demand changes by 1, 3, 5 or 10%. This means a reduction in length of stay and demand and an increase in capacity. Table 19 shows how much the days of stay decrease at aftercare institutions on a yearly basis.

Table 18: Estimation of savings for ZGT with a change of 1,3,5 and 10% in LOS (decrease), capacity (increase) or demand (decrease) for ELV High

	1%	3%	5%	10%
Length of stay	€ 19,400	€ 62,900	€ 80,000	€ 94,800
Capacity	€ 24,100	€ 55,200	€ 85,900	€ 96,900
Demand	€ 38,500	€ 48,300	€ 54,300	€ 62,000

Table 19: Estimation of change in days of stay for aftercare with a change of 1,3,5 and 10% in LOS (decrease), capacity (increase) or demand (decrease) for ELV High

	1%	3%	5%	10%
Length of stay	-250	-660	-1010	-1880
Capacity	-300	-620	-1190	-1930
Demand	-320	-430	-470	-680

For example, we see that a decrease in the length of stay of 3% results in a reduction of 629 ALC days for ELV High, which corresponds to a saving of € 62,900 for ZGT. The bed occupation in aftercare decreases from 93.0% to 90.5%, which results in 660 fewer days of stay on a yearly basis.

6.1.2 Capacity pooling

In section 5.2 we showed that capacity pooling in aftercare can reduce the waiting time in the hospital. In this section, we show how much ZGT can save by reducing the ALC days and what changes in the bed occupation and days of stay in aftercare institutions. Table 20 shows the savings for ZGT with 10% and 20% flexible ELV beds in aftercare. Table 21 shows the change in days of stay and bed occupation in aftercare. Table 22 and Table 23 show the same for the situation where 5% and 10% of the ELV and GRZ beds are flexible

Table 20: Estimation of savings for ZGT with 10% and 20% flexible ELV beds

	10% flexible ELV beds	**20% flexible ELV beds**
ELV Low	€ 5,400	€ 6,600
ELV High	€ 79,400	€ 91,300
ELV Palliative	€ 4,400	€ 5,600
Total	€ 89,200	€ 103,500

Table 21: Estimation of change in days of stay and bed occupation for aftercare with 10% and 20% flexible ELV Beds

	0%	**10%**	**20%**
Total bed occupation	88%	89%	90%
Difference in days of stay	0	20	510

Table 22: Estimation of savings for ZGT with %5 and 10% flexible ELV and GRZ beds

	5% flexible ELV and GRZ beds	**10% flexible ELV and GRZ beds**
ELV Low	€ 2,800	€ 8,100
ELV High	€ 98,100	€ 101,700
ELV Palliative	€ 3,500	€ 5,800
GRZ	€ 80,100	€ 138,000
Total	€ 184,500	€ 253,600

Table 23: Estimation of change in days of stay and bed occupation for aftercare with 10% and 20% flexible ELV Beds

		5%	**10%**
Total bed occupation	90.6%	91.0%	91.4%
Difference in days of stay		400	440

A percentage of flexible ELV beds of 10% can already save € 89,200 for ZGT. In Table 21 we observe that the bed occupation in aftercare increases a bit with more flexible beds. However, there is no large difference in bed occupation and therefore in days of stay. At least, the days of stay do not increase for aftercare, so this has not a negative influence. This result is as expected, as a flexible bed can be taken more often than a labeled bed. Therefore, we expect fewer empty beds. For 5% flexible ELV and GRZ beds, the savings for ZGT can already be around € 184,500. Also in this situation, we see a small increase in the days of stay in aftercare.

6.1.3 Admission restrictions

In section 5.4 we showed that when there are fewer admission restrictions, the average waiting time in the hospital decreases. In this section, we show how much ZGT can save when there are no admission restrictions at all and what changes in the bed occupation and days of stay in aftercare institutions. Table 24 shows the savings for ZGT and the change in days of stay in aftercare with no admission restrictions.

Table 24: Estimation of savings for ZGT and change in days of stay in aftercare with no admission restrictions

	Savings ZGT	Change in days of stay
ELV Low	€ 3,000	130
ELV High	€ 29,400	0
ELV Palliative	€ 1,200	70
GRZ	€ 90,700	160
WLZ	€ 26,300	320
Total	€ 150,600	680

When there are no admission restrictions at all, we estimate that ZGT can save €150,600. When there are no admission restrictions, the bed occupation in aftercare increases a bit, and therefore the days of stay increase on a yearly basis. This result is as expected as when there is a free place, this place will always be filled up when there is demand.

6.2 Impact of length of stay

Unfortunately, we did not have data about the length of stay in aftercare institutions in Twente. Therefore, we used data from Actiz (2018) and Vektis (2020). In section 5.1.2, we show results when the length of stay decreases. Here we already saw that the length of stay has a great influence on the average waiting time in the hospital. In this section, we show for two experiments what the difference in outcome is when the length of stay is increased or decreased by 3%. First, we look at the results of the experiment when there are 5% flexible ELV and GRZ beds. Figure 44 shows these results, which we discuss below.

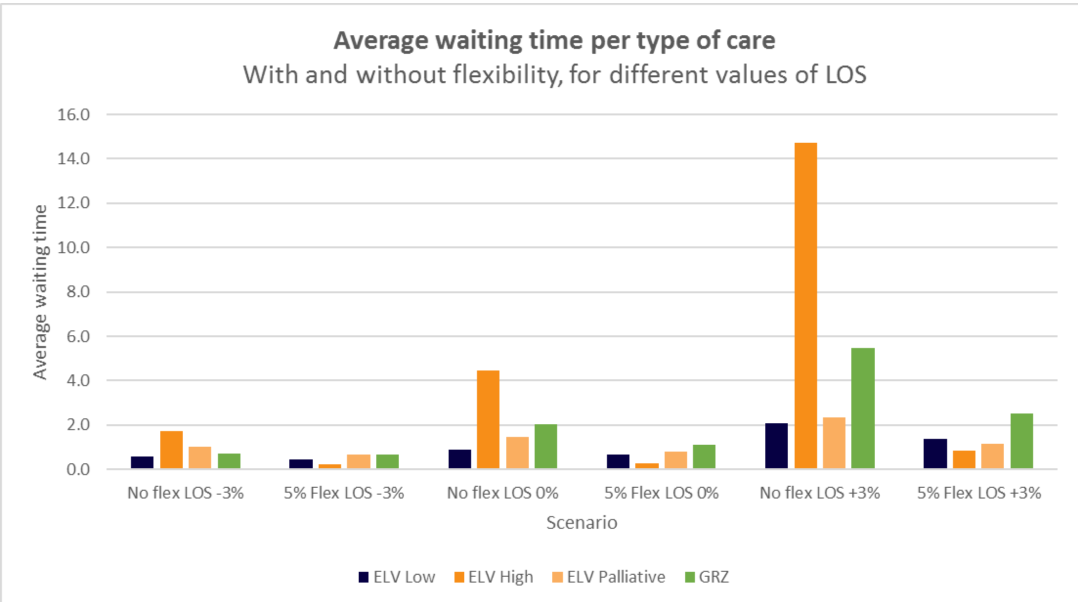

Figure 44: Average waiting time per type of care, with and without flexibility for different values of LOS

We observe that the average waiting time always decreases when there are 5% flexible ELV and GRZ beds. The differences are larger when the length of stay increases. In section 6.1.2, we show that the estimated savings for ZGT with 5% flexible ELV and GRZ beds are € 184,500. When the length of stay is 3% less, these savings are € 49,800. When the length of stay is 3% more, these savings are € 231,800.

Second, we look at the results with and without admission restrictions. Figure 45 shows these results, which we discuss below.

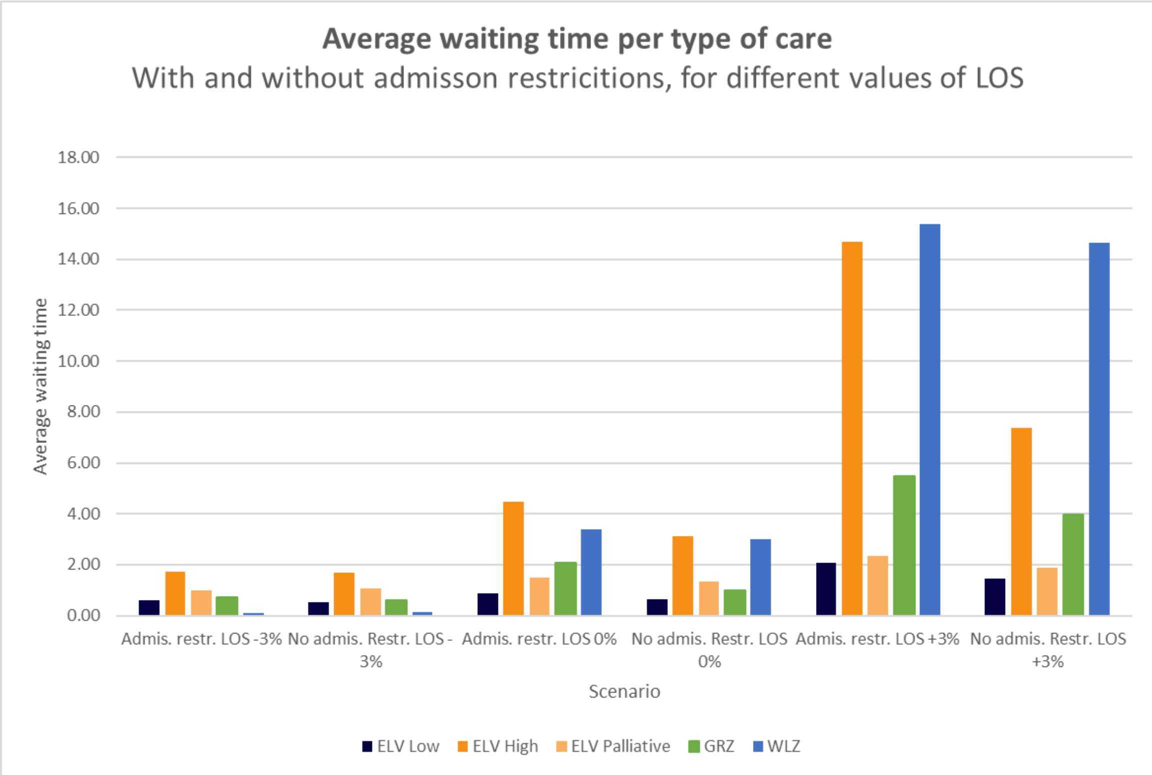

Figure 45: Average waiting time per type of care, with and without admission restrictions for different values of LOS

We observe that the average waiting time always decreases when there are no admission restrictions. The differences are larger when the length of stay increases. For the WLZ, we still see only a small decrease, also with a longer length of stay. In section 6.1.3, we show that the estimated savings for ZGT without admission restrictions are € 150,600. When the length of stay is 3% less, these savings are € 13,900. When the length of stay is 3% more, these savings are €359,200.

Although the impact of the interventions differs with different length of stays, the interventions still have a positive impact.

6.3 Impact of arrival rates

An input parameter that we used is the number of arrivals per day. For ZGT, we had data about the number of arrivals, but for the other parties, we have estimated them based on the waiting time for ZGT patients (section 4.2.2). In this section, we show the impact of the arrival rates of ZGT and other parties on the waiting time and probability of waiting.

6.3.1 Arrival rates ZGT

In this section, we show the impact of an increase in demand. Due to the aging population, it is likely that the demand will increase. We looked at an increase in demand of 1, 3, 5 and 10%. Figure 46 and Figure 47 show the average waiting time per type of care with increasing demand. The figures also indicate the probability of waiting.

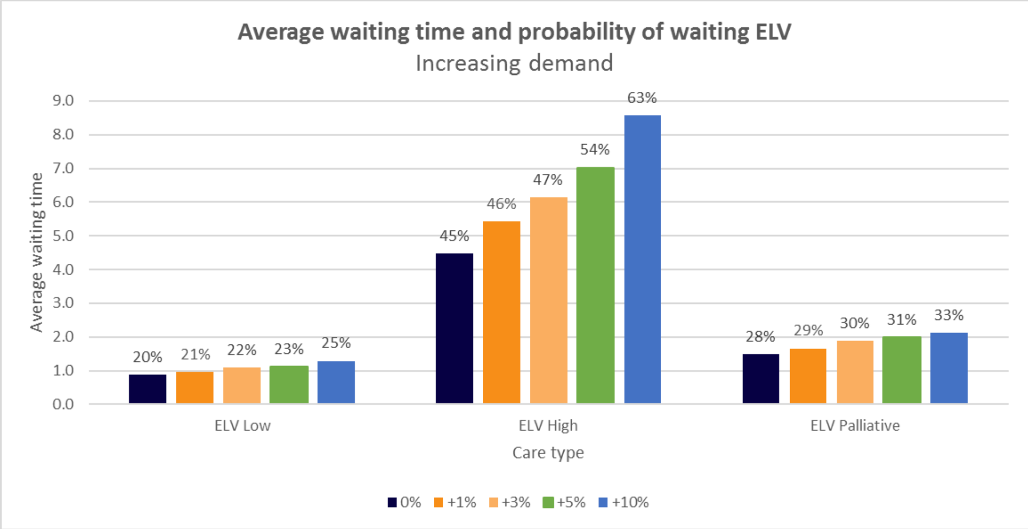

Figure 46: Average waiting time and probability of waiting (label) for ELV for increasing demand

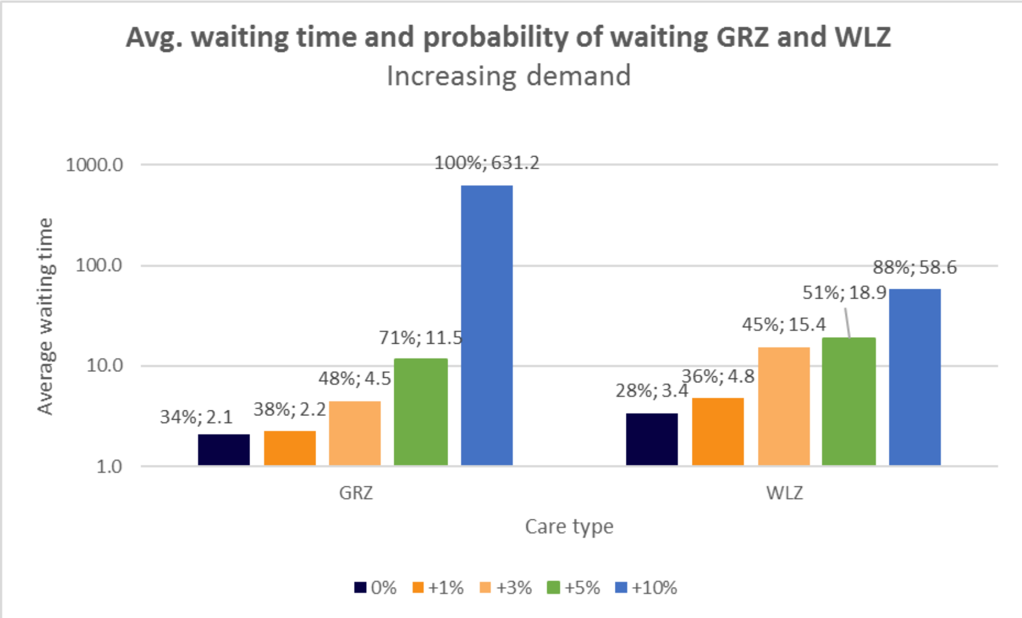

Figure 47: Average waiting time and probability of waiting (label) for GRZ and WLZ for increasing demand

We observe that the waiting time for ELV low and ELV Palliative increases slowly when the demand increases. There is no exponential growth, which indicates that there is room for a slight increase in demand. For ELV high, we see faster growth in waiting time. With an increase in demand of 10%, the probability that a patient has to wait is already 63%. For GRZ, we see a large increase in waiting time with an increase in demand of 10%. The probability that a patient has to wait is 100%. This indicates that the demand for GRZ cannot grow much without significant issues in the transfer chain. Also, the waiting time for WLZ becomes large when the demand grows by 10% and the probability of waiting would be 88%.

6.3.2 Arrival rates other parties

In section 4.2.2 we explained the arrivals rate we used for patients coming from other parties, e.g. other hospitals and general practitioners. We experimented with an arrival rate that is 3% higher and 3% lower and compared this to the used arrival rate in the simulation model (basis scenario).

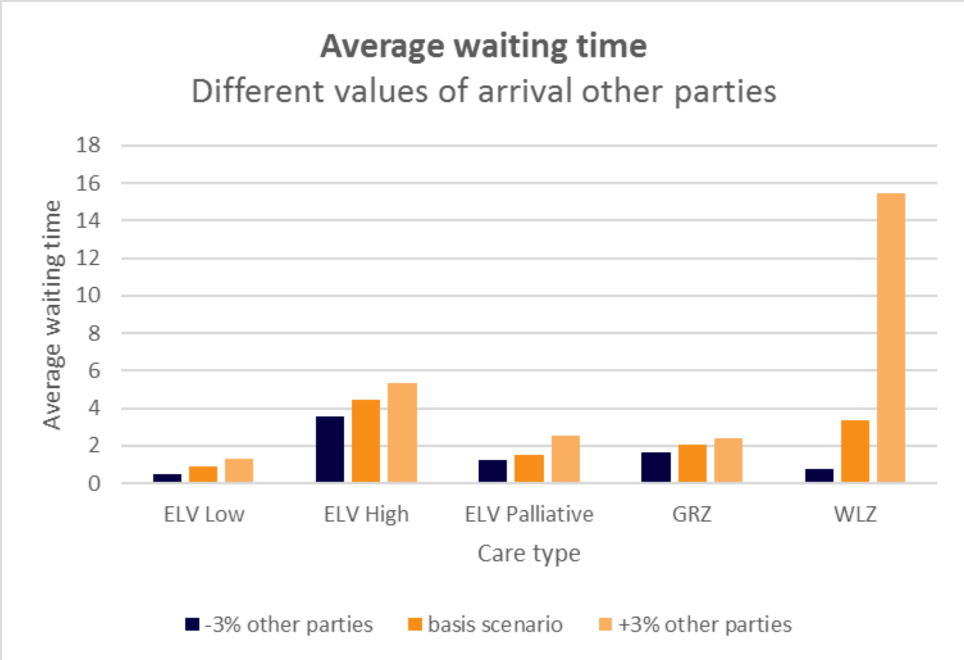

Figure 48: Average waiting time per type of care for different values of the arrival rate for other parties

As expected, we observe that the waiting time increases when there are more patients from other parties. For the WLZ, the largest proportion of patients comes from other parties. Therefore, if the demand increases by 3%, the waiting time increases drastically.

6.4 Conclusion

We investigated the reduction of ALC days on a yearly basis and what the financial savings can be. Also, we examined the consequences of the interventions on the bed occupation and days of stay on a yearly basis for aftercare institutions. For example, we see that a decrease in the length of stay of 3% results in a reduction of 629 ALC days for ELV High, which corresponds to a saving of € 62,900 for ZGT. The bed occupation in aftercare decreases from 93.0% to 90.5%, which results in 660 fewer days of stay on a yearly basis. Further, a percentage of flexible ELV beds of 10% can already save € 89,200 for ZGT and 5% flexible ELV and GRZ beds can save € 184,500. Having flexible beds results in a small increase in the bed occupation in aftercare. Next, when there are no admission restrictions at all, we estimate that ZGT can save €150,600. When there are no admission restrictions, the bed occupation in aftercare increases a bit, and therefore the days of stay increase on a yearly basis. Further, the actual length of stay has an impact on the results of the experiments. However, the interventions still have a positive impact with a longer or shorter length of stay. At last, we explored the effects of an increasing demand. We observe that the waiting time for ELV low and ELV Palliative increases slowly when the demand increases. There is no exponential growth, which indicates that there is room for a slight increase in demand. For ELV high, we see faster growth in waiting time. For GRZ, the waiting time increases exponentially at an increasing demand, this indicates that the demand for GRZ cannot grow much without significant issues in the transfer chain.

7. Conclusion, discussion and recommendations

In this chapter, we describe the conclusion of our study. Further, we discuss the limitations and make recommendations for further research. At last, we describe a roadmap to perfect collaboration between the hospital and aftercare institutions.

7.1 Conclusion

This study focused on the care that patients need after being in the hospital. From the hospital's point of view, it is important that the care for a patient can be transferred to an aftercare institution as soon as possible after a patient has finished medical treatment. The number of days that a patient is in the hospital after the patient has finished the medical treatment, is labeled as ALC days. ALC days cost the hospital time and money, the estimated loss for the hospital is 200 euro per day for WLZ patients and 100 euro for other ALC patients. From the aftercare point of view, it is important to have a high bed occupation, as empty beds may lead to financial difficulties. The core problem we address in this study is: *The healthcare providers in the transfer chain of Twente do not know how much capacity is needed when and where in the system and how the demand should be optimally allocated between them.* We chose to use Discrete Event Simulation. The object of our simulation model is to analyze the effects of interventions and scenarios on the system performance.

7.1.1 Effect of bed occupation in aftercare on waiting time in hospital

As expected, the average waiting time in the hospital is lower with a lower bed occupation in aftercare institutions. Options to lower the bed occupation are increasing the capacity, decreasing the length of stay or decreasing the demand. The results show how much the bed occupation and waiting time decrease with each intervention. To halve the waiting time for each type of care, the capacity of ELV Low should be increased by 5% or the LOS decreased by 5%. For ELV High and GRZ, an increase in capacity or decrease in LOS of 3% is enough for halving the waiting time. Looking at ELV Palliative, an increase of 1 bed would already be enough to halve the waiting time. At last, for the WLZ an increase in capacity of 1% or a decrease in LOS of 1% would already be enough. Further, we observe that even with an increase in capacity or decrease in length of stay of 10%, the probability of waiting in the simulation model is still around 10%. In the real situation, the probability of waiting was even higher. So, getting a waiting probability of less than 10% is quite hard and should not be the aim in our opinion. It differs per type of care how high the bed occupation in aftercare can be for a certain waiting time. For WLZ, the bed occupation can be around 95% to have a very low waiting time, while for ELV Palliative, the waiting time is low with an average bed occupation of 70%.

7.1.2 Capacity pooling

Using the simulation model we showed that some flexibility in who can be admitted to which bed has a large impact on the average waiting time and the probability of waiting. When only ELV beds are flexible, such that each type of ELV can be admitted to the flexible beds, 20% or 29 flexible beds are enough as we do not see improvement when more beds are flexible. The average waiting time for ELV decreases with 29 flexible beds from 3.1 to 0.5 days. We estimate the savings for ZGT on a yearly basis to be €103,500. When also GRZ patients can be admitted to flexible beds, 10% or 30 flexible beds are enough. The average waiting time for ELV and GRZ decreases with 30 flexible beds from 2.4 to 0.4 days. We estimate the savings for ZGT on a yearly basis to be €253,600.

7.1.3 Redistribute beds between the care types

Using the simulation model, we tried three new distributions of beds between the types of ELV and GRZ. We kept the total number of beds the same in this experiment. With one option, we see a slight improvement in the total average waiting time. However, this causes a large increase in the waiting time for ELV low and ELV palliative, which is especially for the latter not desirable. Therefore, we cannot immediately conclude that the tested bed distributions are better than the current distribution.

7.1.4 Admission restrictions

Using the simulation model, we experimented with adding more admission possibilities. With one admission possibility on the weekend per location, the average waiting time decreases for all types of care, except for the WLZ. With two admission possibilities, there is no improvement anymore relative to one admission possibility. Therefore, we can conclude that one admission possibility per location on the weekend would satisfy. Adding more admission possibilities on weekdays only gives an improvement at ELV high. Also in this case, one additional admission possibility would suffice. When there are no admission restrictions at all, the average waiting time for ELV high decreases from 4.5 to 3.1. We estimate the total savings for ZGT on a yearly basis when there are no admission restrictions at all at 150,600 Euro.

7.1.5 Estimation of discharge dates

In the current situation, it is not very important to focus on a better and early estimation of the discharge date. The current estimation is already quite good and on time. However, when capacity is less of a problem in the transfer chain, we showed that a good and early estimation of the discharge date becomes more important, especially for the ELV. For ELV palliative, it is most important to focus on a good and early estimation of the hospital discharge date.

7.2 Discussion

7.2.1 Theoretical contribution

Modeling in healthcare is an emerging field, but most of the current work focuses on the optimization of a specific healthcare provider (e.g. a hospital) or even a specific department (e.g. the operating theatre). Little work is performed on how to integrate the care need between different healthcare providers.

By analyzing the effects of bed occupation in aftercare on ALC days in the hospital, this study provides a nuanced understanding of the relationship between bed occupation in the aftercare and waiting times and ALC days in the hospital. Further, our study provides insights into which factors influence the bed occupation in aftercare institutions.

Next, by evaluating the effects of pooling capacity between different types of aftercare, our study addresses the issue of fragmentation in capacity and its impact on system performance. Our study offers insight into the potential improvement in performance that can be achieved by using a more flexible approach to bed allocation.

By exploring the effects of transferring patients on weekends, increasing admission capacity and improving the estimation of discharges date, the study provides guidelines for decision-makers on the potential benefits of relaxing these restrictions and optimizing discharge planning processes.

Overall, the theoretical contribution of this research lies in the exploration of various interventions in a detailed discrete event simulation, which is able to handle more details and stochasticity than an explicit mathematical model formulation as used in other studies. The insights gained from this research can also be applied to other regions or countries facing similar challenges. Also, the conceptual model can be used to set up a similar simulation model.

7.2.2 Practical contribution

The results of this research align with the expectations of the managers of the aftercare institutions and the capacity manager of ZGT. Specifically, they acknowledge the lack of admission possibilities during weekends, which leads to unnecessary prolonged hospital stays and ALC days. A positive result for the managers is that only one admission possibility during weekends per location would satisfy.

Moreover, they found it to be a common experience that a shorter length of stay for the ELV and GRZ contributes to better patient outcomes and a decrease in ALC days. In this research, we used national data, as there was no specific data available for this region. However, recent findings revealed that the length of stay in aftercare in Twente is longer than national. This indicates that there is even greater potential for improvement and underscores the importance of optimizing the length of stay.

For the hospital, it is a valuable finding that the current estimation of the discharge date is quite good, so it is not necessary to put a lot of effort into improving this.

Increasing capacity in the aftercare leads to a lower bed occupation, vacancy and financial difficulties for the aftercare, although the hospital benefits from it. Therefore, the managers suggest that it may be better to explore alternative solutions than increase capacity. Furthermore, they mentioned that an increase in capacity for ELV Palliative might not be necessary, as there is, for example, only a high waiting time for ELV Palliative in Almelo and not in Hengelo. Therefore, shifting capacity may be a solution. We did not include a preference for locations in our research. However, a valuable lesson learned from this research is the significance of placing patients based on capacity rather than preferred location.

Finally, the managers acknowledge that the concept of flexible capacity, allowing for easy scalability, is a great solution. However, implementing this solution is complex in terms of personnel planning and financing, but it is worth further investigation.

7.2.3 Limitations

In this study, we used some assumptions and simplifications that might affect our results. First, we did not have all the needed data available. Therefore, we made assumptions about the length of stay in aftercare per type of care and the demand for places in aftercare institutions not coming from ZGT. In the sensitivity analysis, we saw that the impact of an intervention is influenced by the length of stay. If the length of stay is shorter, the impact of capacity pooling and adding admission restrictions are less positive. However, we still see an improvement. Also, the demand from other parties affects the simulation model results. For example, if ZGT uses a larger proportion of the beds in aftercare than we estimated, the effects of a good and early estimation of the discharge date might be larger.

Another limitation of this study is that we do not know all reasons why a patient has to wait in the hospital. In our simulation model, a patient is solely rejected at an aftercare institution when there is no free capacity or when there is no admission capacity. We also saw that in our simulation model, the probability that a patient has to wait is lower than in the real situation. We expect that this is caused by the fact that there are more reasons why a patient is rejected from admission on a certain day.

A simplification we used in our simulation model is that patients do not switch locations when they are in aftercare. We used this simplification, as there is no data available about it. However, this can affect our results as if patients for example often switch from ELV low to ELV high, we overestimate the demand for ELV low places and underestimate the demand for ELV high. Also, we did make a distinction between patients who leave the hospital and go to an aftercare institution for the first time and patients who already had a place in an aftercare institution. When there is a case of a readmission, the transfer process goes quicker.

Another assumption we made is that the length of stay in aftercare is not influenced by the length of stay in the hospital. So, if a patient waits in the hospital, these days are not (partly) subtracted from the length of stay in aftercare. This might be the case, but there is no data available about this. If this is the case, the negative consequences of ALC days are overestimated. It could even be the case that when a patient receives more care at the hospital, the recovery goes quicker.

7.3 Recommendations and further research

To improve the validity of the results and give a more complete view, further research can be performed. We have some recommendations for further research:

At first, we recommend also performing research from aftercare institutions' perspective. In our research, we focused on lowering the ALC days in the hospital. Doing research from the aftercare institutions' point of view would give other insights which are valuable for the transfer chain. From the aftercare institutions' point of view, it would e.g. be interesting to study the allocation and priority rules used.

Second, we recommend broadening this study by also including smaller aftercare institutions and care at home. Although there are currently only a few ALC days for patients that need home care, the expectations are that this will increase. When incorporating home care into the study, the focus of analysis expands beyond physical locations in aftercare. In addition to considering the allocation and capacity planning of physical spaces in aftercare institutions, personnel planning becomes an aspect to be taken into account. Home care services involve healthcare professionals visiting patients in their own residences to provide necessary medical and support services. Including all aftercare institutions and home care will give a more complete view of the transfer chain in Twente. The collaboration with the three large aftercare institutions is already quite improved due to the project group "The transfer chain of Twente". It is advisable to also include the smaller institutions by making better agreements and collaborations.

Third, we recommend using the developed simulation model for testing other situations and options than explored in this study. For example, we only focused on exclusively increasing capacity or decreasing the length of stay or demand, while also a combination of these options can be tested.

Further, when there is reliable data, the foundation of the model assumptions can be explored. It would, among others, be important to explore the behavior of the patient's length of stay and recovery in aftercare. It is important to know how the ALC days influence the recovery of a patient. Therefore, close cooperation between the hospital and aftercare is necessary.

Next, we did a rough estimation of the savings ZGT can make when there are fewer ALC days and which consequences this has for the days of stay in an aftercare institution. We could not estimate which financial consequences it has for aftercare institutions. It should be further investigated how aftercare institutions, insurers and the hospital can collaborate to share the financial burden properly in order to keep the care for the elderly affordable, also in the future.

Due to time limitations, data availability and stakeholders' preferences, we did not include the preference of a patient for a certain location. For example, they want a place close to their home location and family. An interesting experiment for further research is to analyze the effect on the system performance when giving patients a place of their preference. Hereby, it is possible to give guidelines for defining norms on how long a patient can wait on a place of their preference.

7.4 Roadmap to perfect collaboration

This research is meant to be a starting point for better collaboration in terms of capacity planning between ZGT and aftercare providers. We showed the bottlenecks, where the most profit can be made and how this can be done. Achieving a perfect collaboration is challenging due to the complexity of the healthcare system. This roadmap aims to provide a path to a successful collaboration between the hospital and aftercare institutions. The goal is to optimize resource utilization, reduce waiting times, and provide better patient care.

1. Create a foundation for collaboration

The first step is to create a foundation for a strong collaboration. Before a good collaboration can be established, it is important to have a shared vision. This is important because it ensures that all parties are involved and working towards the same goals. The project group "The Transfer Chain of Twente" defined this vision already as: "There is insight and joint coordination over the transfer chain, ensuring that there are no delays in the flow, so that the patient always receives appropriate care at the right time and place." The next step is to incorporate norms in this vision, for example about the waiting time and number of patients that have to wait. Next to a shared vision, a communication plan should be developed. This communication plan should outline the number of meetings that need to be organized, who should attend each meeting, and what topics will be discussed at each meeting. The proposal is to meet at least four times a year.

2. Conduct joint capacity planning

A large and important step in a perfect collaboration is to conduct joint capacity planning and demand allocation. At present, this is not being implemented. However, this research serves as a starting point for it. This will be a process of continuously improving and learning. The developed simulation model can be used in this process.

Before the start of a year, there should be a year plan regarding the capacity. To conduct joint capacity planning, it is important to analyze demand patterns and forecasts, and length of stay developments. Expected changes in demand and length of stay can be changed in the input parameters of the simulation model. The simulation model can be used to assess the capacity needs to reach the waiting time norms. In this way, bottlenecks and capacity shortages can be recognized on the forehand, also when the situation changes. A proposal is to perform this analysis twice a year, before the start of a year, there should be a year plan which for example can be evaluated and adjusted halfway through the year.

As we showed that flexible beds can reduce waiting times enormously, it is advisable to implement a pilot with for example 10 to 15 flexible beds. It is important to assess and track the impacts of the flexible beds and bed occupation rates. This enables us to adjust the number of flexible beds as needed to optimize capacity planning. The same holds for the admission restrictions. We showed that one admission possibility on the weekend per location can reduce waiting times, especially for ELV High. It is advisable to implement a pilot and evaluate and monitor the effects and usage of this admission possibility.

3. Continuously monitor and evaluate performance

Having a set of KPIs with established norms is essential for monitoring and evaluating the process and results of initiatives. The Twente Transfer Chain project has taken the first steps by organizing a midterm evaluation of the project, for example. The next steps involve further integration, establishing KPIs, and ensuring their periodic assessment. Examples of KPIs to monitor are the average waiting time, the percentage of patients that have to wait, the number of ALC days and bed occupation in the aftercare. These KPIs are important to evaluate the performance of joint capacity planning. Next to these KPIs, it is also advisable to monitor more operational KPIs, the throughput time of process steps and the estimation of the discharge dates in the hospital, for example. By monitoring these KPIs, bottlenecks in the process can be captured to speed up the process.

4. Develop a perfect information system

There should be an information system that perfectly fits the needs and enables seamless data exchange. At present, an information system called POINT is already available. This provides a solid foundation to initiate joint capacity planning. However, there are still certain aspects that do not meet the desired criteria, leaving room for further enhancements. This includes a dashboard that is available for each party to monitor the KPIs. Next to that, there should be perfect insight into the availability of beds, not only including the current availability, but also anticipated discharges. The number of patients waiting for care should be visible, including those referred by external parties. By implementing the other steps of the roadmap, it will become clear what the perfect information system would look like.

5. Create a culture of collaboration in Twente

The project group 'The Twente Transfer Chain' is an initiative by ZGT and three large aftercare institutions. Once the foundation is well-established, it is important to include smaller institutions and other hospitals in this initiative as well. The culture of collaboration involves effective communication and encouraging knowledge and data sharing on a day-to-day basis. Further, best practices and success stories should be shared to inspire collaboration and continuous learning.

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Appendix

A: Literature search method

The search method we used for the theoretical framework is snowballing. Table 25 shows how the papers are located, namely through citation or reference tracking and via which paper. We found the references not mentioned in Table 25 by using a specific search string.

Table 25: Literature search method (snowballing)

Article	Citation / reference tracking	Source article
Van Zyl-Cillié et al. (2022)	Source article	
Bidhandi et al. (2019)	Citation tracking	Van Zyl-Cillié et al. (2022)
Patrick (2011)	Citation tracking	Bidhandi et al. (2019)
Intravado et al. (2015)	Citation tracking	Bidhandi et al. (2019)
Cardoso et al. (2015)	Citation tracking	Intravado et al. (2015)
Bretthauer et al. (2011)	Citation tracking	Van Zyl-Cillié et al. (2022)
Weiss and Mcclain (1987)	Citation tracking	Bidhandi et al. (2019)
Avkiran and Mccrystal (2014)	Citation tracking	Intravado et al. (2015)
Cardoso et al. (2012)	Citation tracking	Bidhandi et al. (2019)
Cardoso et al. (2015)	Cited by tracking	Cardoso et al. (2012)
Cardoso et al. (2016)	Cited by tracking	Cardoso et al. (2012)
Zhang et al. (2012)	Citation tracking	Bidhandi et al. (2019)
Zhang et al. (2013)	Citation tracking	Bidhandi et al. (2019)
Xie et al. (2015)	Citation tracking	Zhang et al. (2016)
Zychlinski et al. (2019)	Cited by tracking	Xie et al. (2015)
Bae et al. (2017)	Cited by tracking	Xie et al. (2015)
Koizumi et al. (2004)	Citation tracking	Van Brakel (2010)
Benson et al. (2006)	Citation tracking	Van Brakel (2010)
Travers et al. (2008)	Citation tracking	Van Brakel (2010)
Dilip Chhajed, & Lowe, T. J. (2010)	Citation tracking	Xie et al. (2015)
Haraden, C., & Resar, R. (2004)	Citation tracking	Harper, P. R., & Shahani, A. K. (2002).
Intravado et al. (2018)	Cited by tracking	Intravado et al. (2015)
Lin et al. (2011)	Citation tracking	Koizumi et al. (2004)
Harper, P. R., & Shahani, A. K. (2002).	Cited by tracking	Xie et al. (2015)

B: Input distribution

Discharge rates

We need to determine a probability distribution for the discharge rate, to use as input for the simulation model. As the discharge rate can be seen as an arrival process, it is most likely that it will follow a Poisson distribution. Therefore, we first calculate the mean number of discharges per day. On weekdays 5.3 patients are discharged with aftercare on average. Therefore, we fit a Poisson distribution with a mean of 5.3 onto a histogram of the data, see Figure 49.

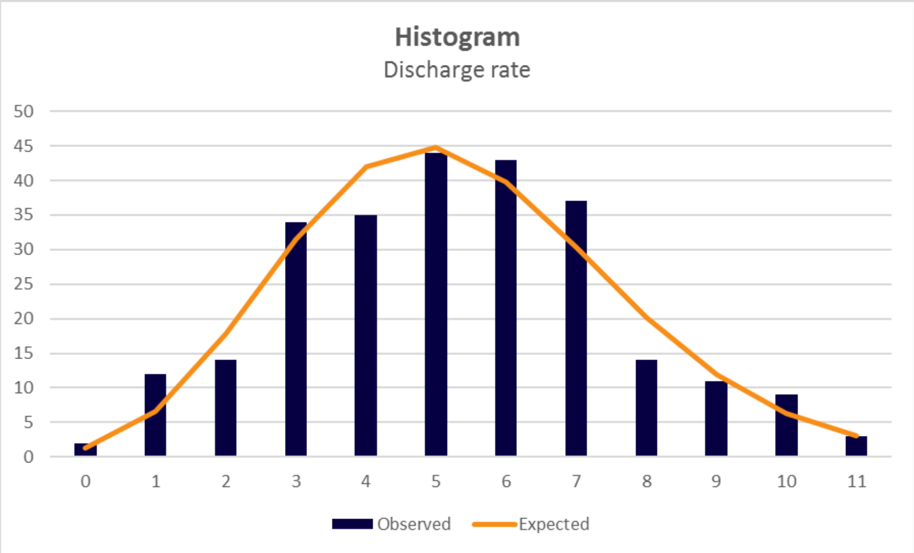

Figure 49: Histogram of discharge rate

It looks like a Poisson distribution fits the data well. Therefore, we tested this hypothesis using a chi-square test, see Table 7. With a significance level of 5%, we could not reject the hypotheses that the discharge rates are Poisson distributed. So, we use the Poisson distribution in our model.

Table 26: CHI-SQUARE test discharge rate

#	Observed	Expected	Error	Chi-square
0	2	1.3	0.7	0.4
1	12	6.7	5.3	4.3
2	14	1.8	3.8	0.8
3	34	31.5	2.5	0.2
4	35	42.0	7.0	1.2
5	44	44.8	0.8	0.0
6	43	39.8	3.2	0.3
7	37	30.3	6.7	1.5
8	14	20.2	6.2	1.9
9	11	12.0	1.0	0.1
10	9	6.4	2.6	1.1
11	3	3.1	0.1	0.0
Total				11.7
Chi-square value				18.3
Because 11.7 < 18.3 we do not reject H0!				

Days between register and initial discharge date

By looking into the shape of the histogram, we expected the data of the days between registering and initial discharge date to be gamma distributed. Therefore, we fit the gamma distribution onto the histogram, see Figure 50

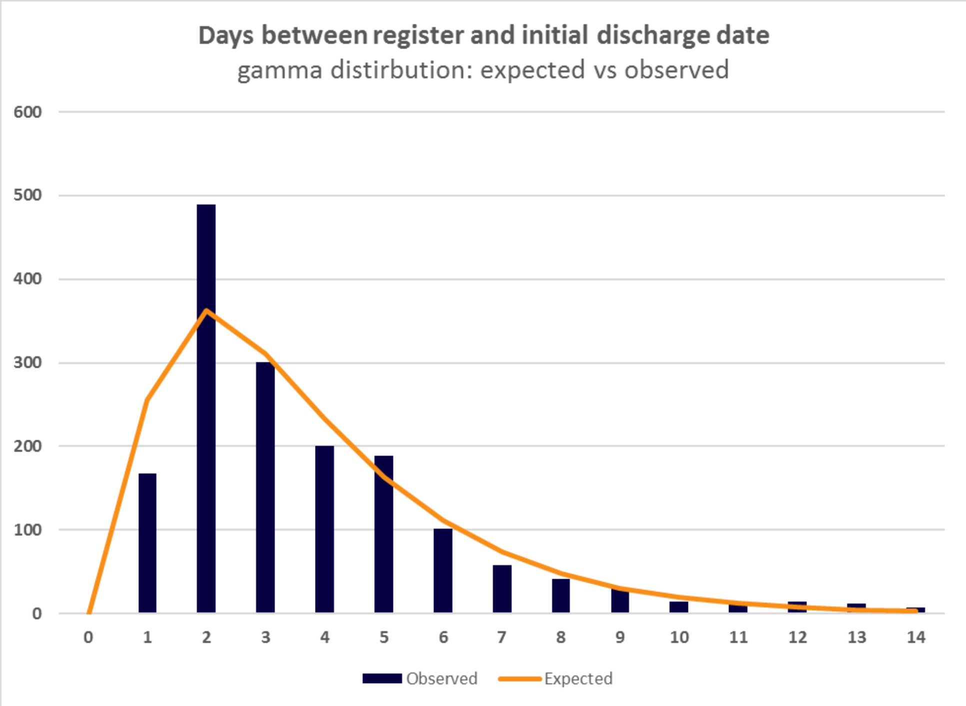

Figure 50: Histogram of days between register and IDD

The gamma distribution has the best fit with the data, so therefore we use this distribution.

C: Starting point arrival rate and capacity

ELV Low

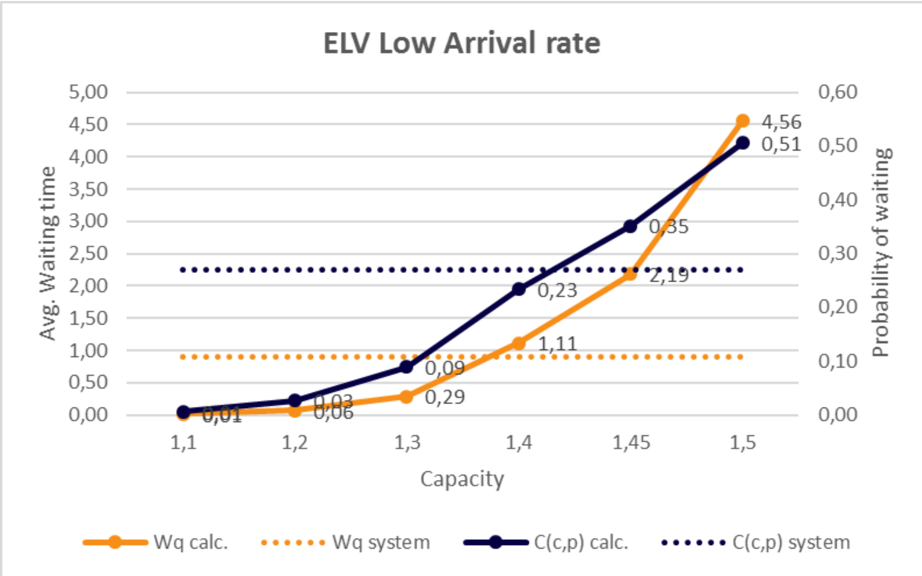

Figure 51: Avg. waiting time and prob. of waiting for different arrival rates ELV Low

For ELV low, we choose a total starting arrival rate of 1.40, as this is the best match with the average waiting time and probability of waiting measured in the real system.

ELV High

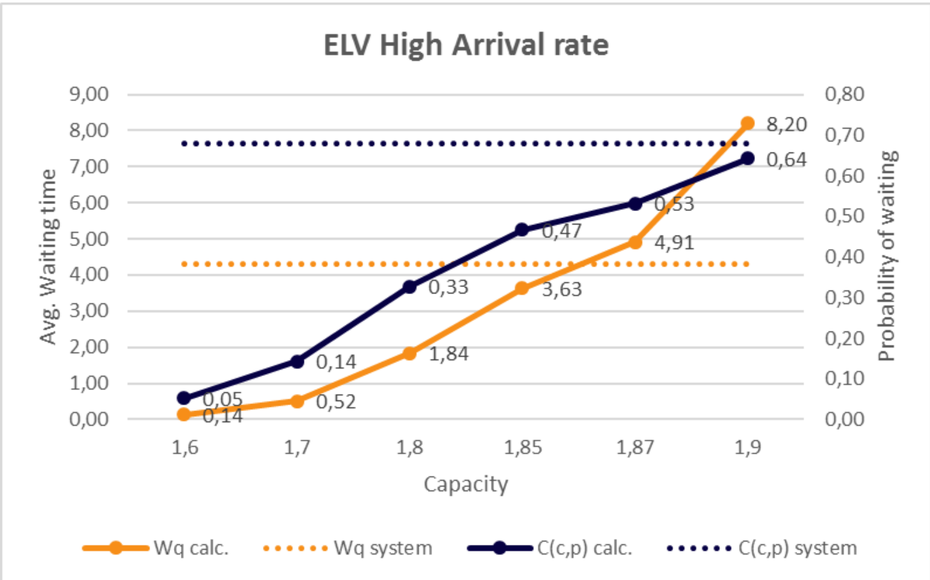

Figure 52: avg. waiting time and prob. of waiting for different capacity values ELV High

For ELV High, we choose a total starting arrival rate of 1.85, as this is the best match with the average waiting measured in the real system.

ELV Palliative

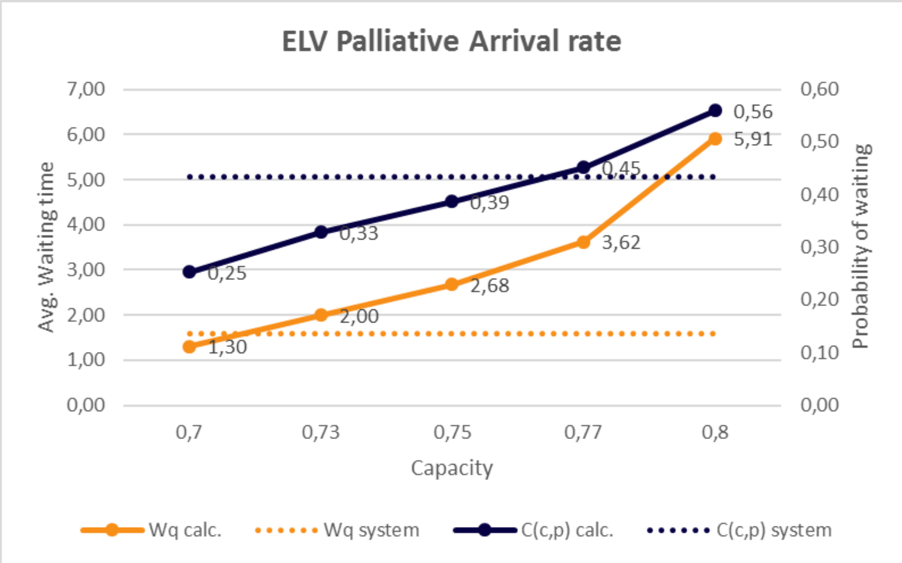

Figure 53: avg. waiting time and prob. of waiting for different capacity values ELV Palliative

For ELV Palliative, we choose a total starting arrival rate of 0.73, as this is the best match with the average waiting measured in the real system.

Capacity per municipality, per organization

Table 27: Number of beds per municipality per care type

Municipality	Organization	GRZ	ELV Low	ELV High	ELV Palliative	WLZ
Twenterand	Carintreggeland	0	0	0	0	0
	TMZ	0	1	0	0	134
	Zorgaccent	0	5	0	0	82
Rijssen-Holten	Carintreggeland	0	0	0	0	129
	TMZ	0	0	0	0	0
	Zorgaccent	0	0	0	0	41
Hof van Twente	Carintreggeland	24	16	7	0	286
	TMZ	0	0	0	0	0
	Zorgaccent	0	0	0	0	0
Wierden	Carintreggeland	0	0	0	0	125
	TMZ	0	0	0	0	0
	Zorgaccent	0	0	0	0	24
Almelo	Carintreggeland	25	6	6	2	326
	TMZ	38	1	17	4	218
	Zorgaccent	0	7	10	0	64
Borne	Carintreggeland	0	0	0	0	0
	TMZ	0	0	0	0	111
	Zorgaccent	0	0	0	0	0
Hengelo	Carintreggeland	0	12	9	0	377
	TMZ	48	0	24	7	212
	Zorgaccent	0	0	0	0	0
Dinkelland	Carintreggeland	0	0	0	0	32
	TMZ	0	0	0	0	0
	Zorgaccent	0	0	0	0	0
Tubbergen	Carintreggeland	0	0	0	0	0
	TMZ	0	0	0	0	103
	Zorgaccent	0	0	0	0	0
Hellendoorn	Carintreggeland	0	0	0	0	0
	TMZ	0	0	0	0	0
	Zorgaccent	20	5	0	4	398
Total		**155**	**53**	**73**	**17**	**2667**

D: Warm-up period and run characteristics

Warm-up period

To calculate the warm-up period, we use Welch's graphical procedure (Law, 2015), which we apply to the following KPIs:

- Average waiting time for ELV-Low, ELV-High, ELV-Palliative, GRZ and WLZ
- Total average occupation of ELV-Low, ELV-High, ELV-Palliative, GRZ and WLZ

To determine the warm-up period, we run five replications of the simulation, with a run length of 10 years. Figure 54 to Figure 63 show the moving averages of the results of these experiments. The simulation model was run with the initial arrival rates, therefore the waiting times are not representative. The used window of the moving average depends on the KPI. The description of the figures show the used window. If a window is for example 10, this means that the moving average of 10 patients is used in case of the waiting time KPIs and 10 days in case of the occupation KPIs.

For the average waiting time, Table 28 shows from which patient we see a stable waiting time, and to which day number this patients corresponds.

Table 28: warm-up period based on waiting time

Care type	Patient number	Day number
ELV Low	210	1088
ELV Palliative	348	1641
ELV High	109	173
GRZ	517	214
WLZ	939	1699

It takes the longest before the WLZ has a stable waiting time, namely after 1699 days. For the average occupation, Table 29 shows from which day we see a stable occupation.

Table 29: warm-up period based on occupation

Care type	Day number
ELV Low	84
ELV Palliative	254
ELV High	67
GRZ	217
WLZ	1400

It takes the longest before the WLZ has a stable occupation, namely after 1400 days. In this simulation model, a year is a natural run length. After 1699 days, all KPIs show a stable result, so the warm-up period should be at least 1699 days, which is 4.7 years. Therefore, we take a warm-up period of five years.

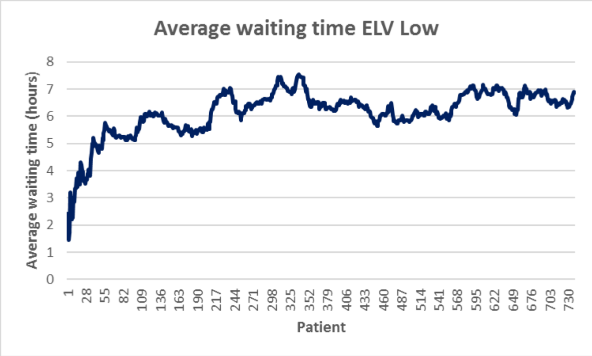

Figure 54: Moving average waiting time ELV Low, window = 25

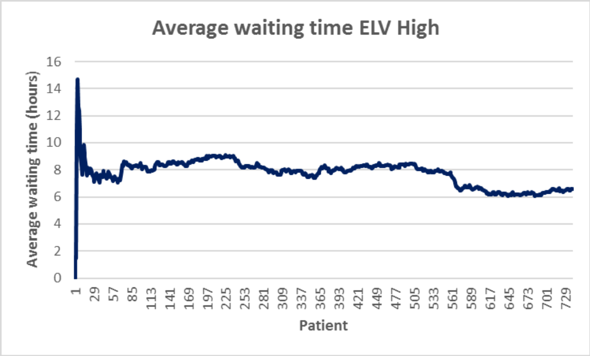

Figure 55: Moving average waiting time ELV High, window=100

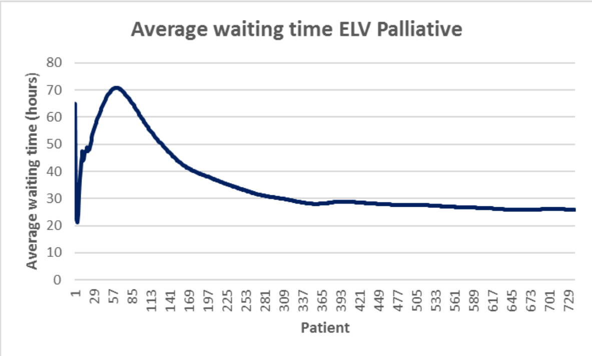

Figure 56: Moving average waiting time ELV palliative, window = 20

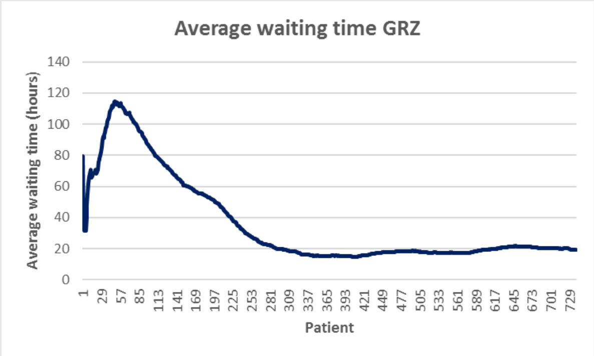

Figure 57: Moving average waiting time GRZ, window = 100

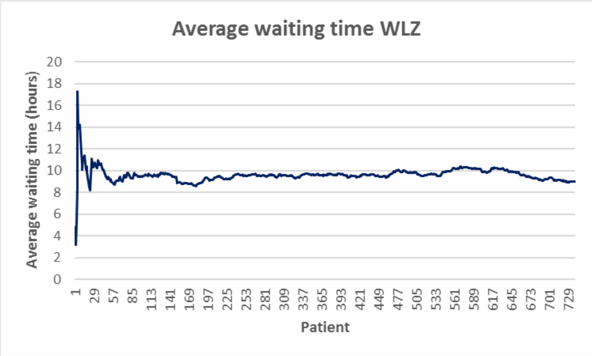

Figure 58: Moving average waiting time WLZ, window = 100

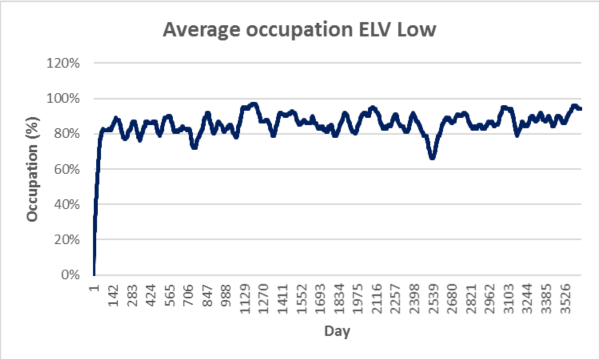

Figure 59: Moving average occupation ELV Low, window = 20

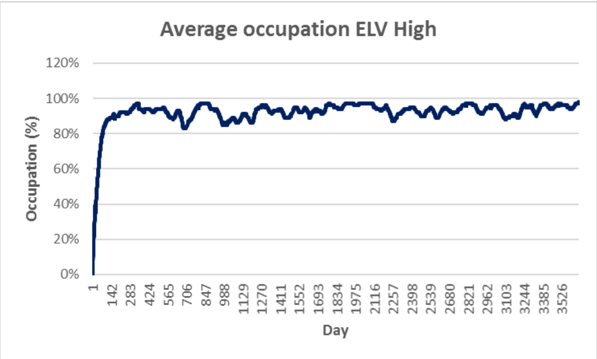

Figure 60: Moving average occupation ELV High, window = 20

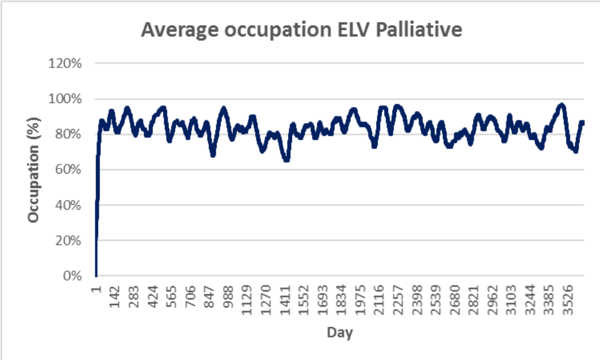

Figure 61: Moving average occupation ELV Palliative, window = 20

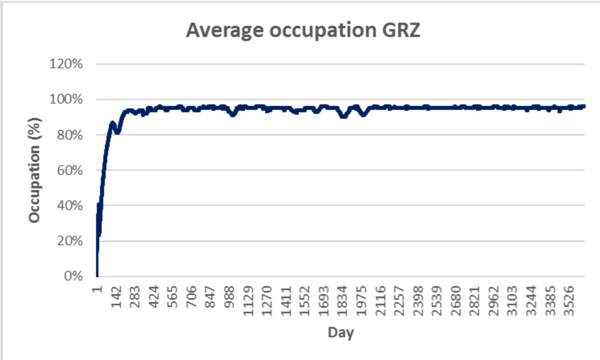

Figure 62: Moving average occupation GRZ, window = 20

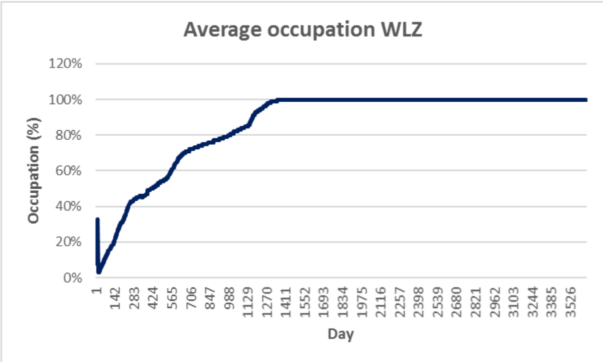

Figure 63: Moving average occupation WLZ, window = 20

Run characteristics

As also indicated for the warm-up period, we want to run the model over the period of a whole year. We want to do this, as in the hospital they also look quite often to the data of one year, and we have seasonal patterns over a year. We use as rule of thumb that the run length is ten times as large as the warm-up period, which gives us a run length of fifty years. To determine how many replications we should do, we run the model with the initial arrival rates. We apply confidence intervals to the simulation output per replication and look when the interval becomes sufficiently narrow, where we choose a significance level (α) of five percent. As KPI, we chose the average waiting time of all types of care. Figure 64 shows the confidence interval half width divided by the mean per number of replications per KPI. The confidence interval is small enough is this number is smaller than the threshold of 0.025. With five replications, the confidence interval is small enough for all KPI's.

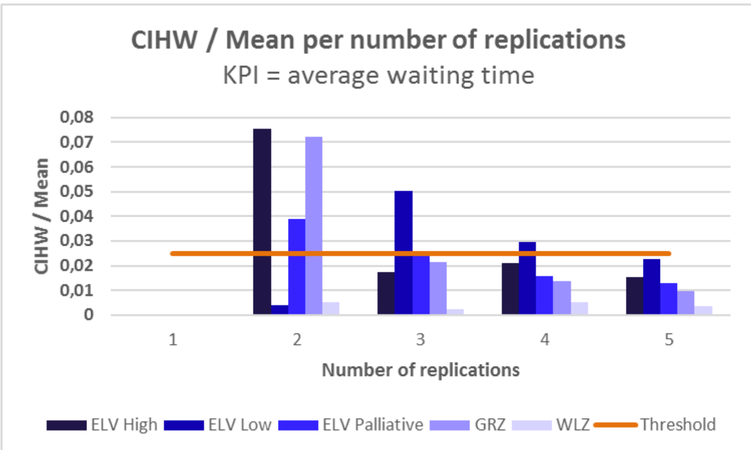

Figure 64: Confidence interval half width / mean per number of replications

According to Robinson (2014), ensuring that enough output data have been obtained from the simulation, can be addressed in two ways. The first is to perform a single long run with the model. As we have a non-terminating simulation, this is an option for us. We have a warm-up period of five years, therefore we chose to do a single long run, to avoid having many warm-up periods. The run length should be the warm-up period plus five times fifty years, which corresponds to $5 + (5 * 50) = 255$ years.

E: Flowchart of the simulation model logic

Figure 65 shows the flowchart of the simulation logic. There are two events that triggers a process, namely the start of a new day and when a patient ends treatment at aftercare.

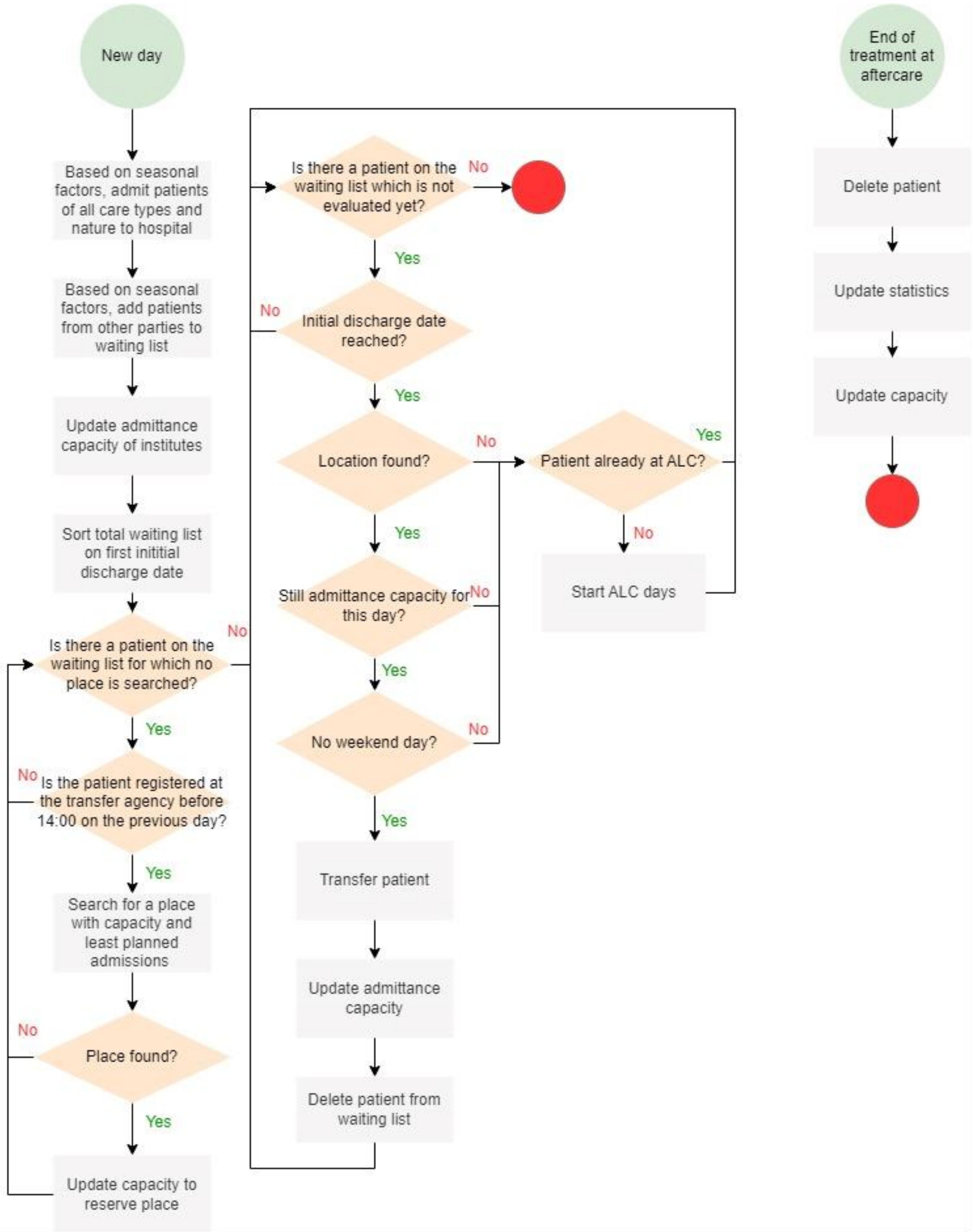

Figure 65: Flow chart of the simulation logic

F: Screenshot of the simulation model interface

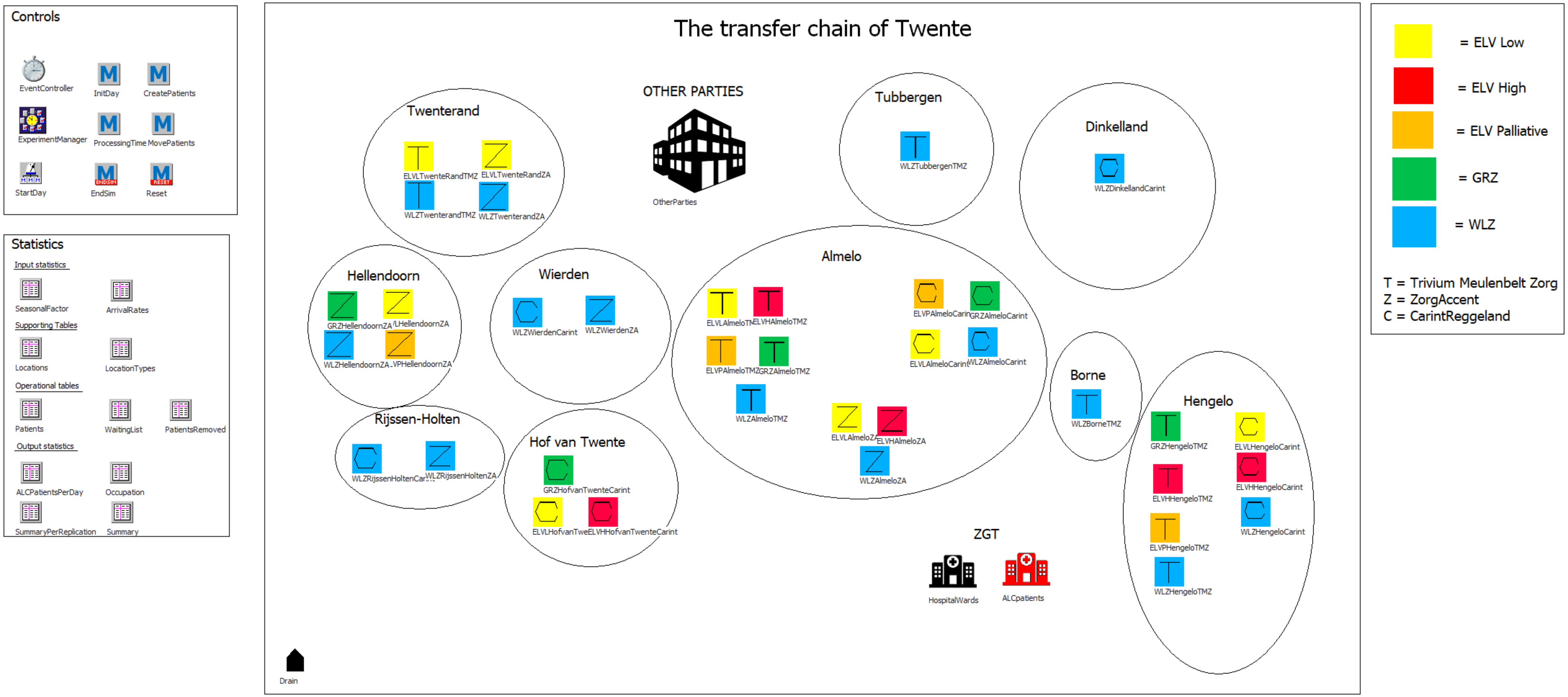

Figure 66: Screenshot of the simulation model interface

G: Validation of simulation model

Table 30 to Table 34 show the waiting time per type of care for different values of the arrival rate from other parties and the target value. The marked cells show the chosen values.

ELV Low

Table 30: Waiting time ELV Low per arrival rate from other parties

Arrival rate	Waiting time	Target value
1.15	0.21	0.9
1.49	0.51	0.9
1.50	0.80	0.9
1.51	0.95	0.9
1.52	1.15	0.9

ELV High

Table 31: Waiting time ELV High per arrival rate from other parties

Arrival rate	Waiting time	Target value
1.24	0.27	4.30
1.58	2.98	4.30
1.59	3.79	4.30
1.60	4.00	4.30
1.61	5.32	4.30

ELV Palliative

Table 32: Waiting time ELV Palliative per arrival rate from other parties

Arrival rate	Waiting time	Target value
0.53	0.49	1.60
0.70	1.27	1.60
0.71	1.60	1.60
0.72	1.84	1.60
0.73	2.52	1.60

GRZ

Table 33: Waiting time GRZ per arrival rate from other parties

Arrival rate	Waiting time	Target value
0.90	0.28	1.90
1.36	1.83	1.90
1.37	2.45	1.90
1.38	2.33	1.90
1.39	2.37	1.90

WLZ

Table 34: Waiting time WLZ per arrival rate from other parties

Arrival rate	Waiting time	Target value
2.87	0.19	3.50
3.00	0.81	3.50
3.02	3.53	3.50
3.05	3.61	3.50
3.06	7.88	3.50

H: Results experiments

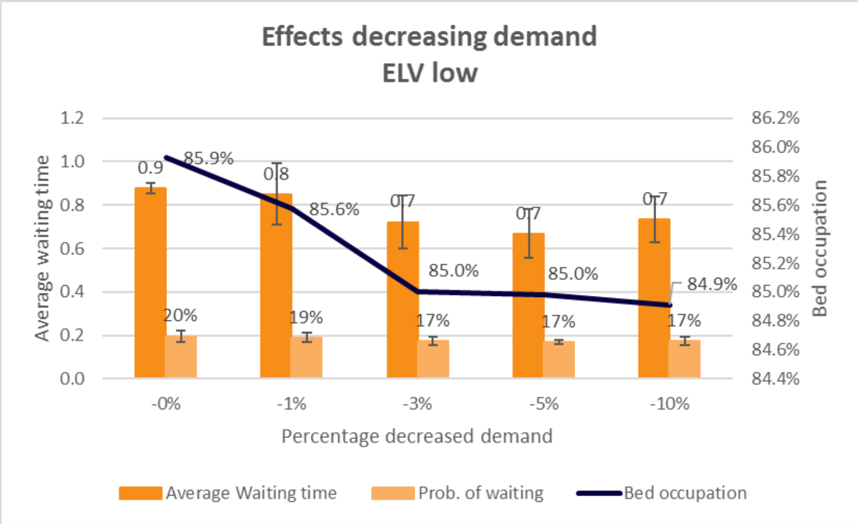

Figure 67: Effects of decreasing demand for ELV Low with a 95% confidence interval

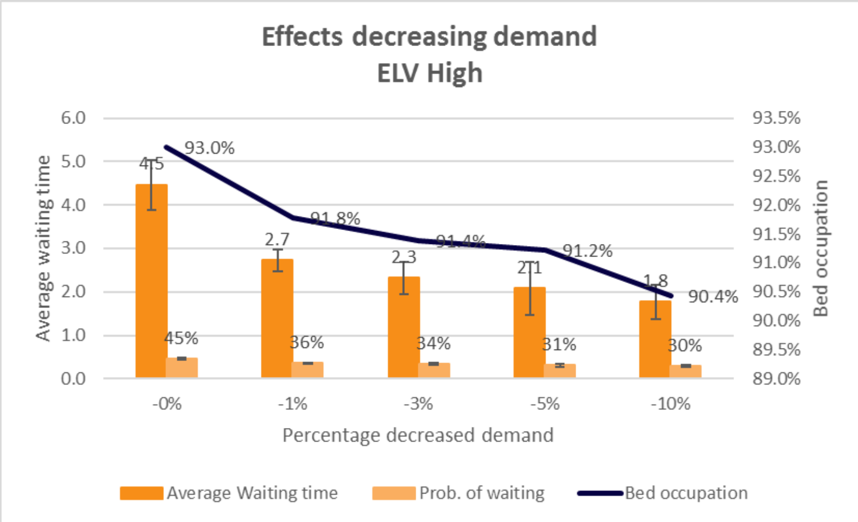

Figure 68: Effects of decreasing demand for ELV High with a 95% confidence interval

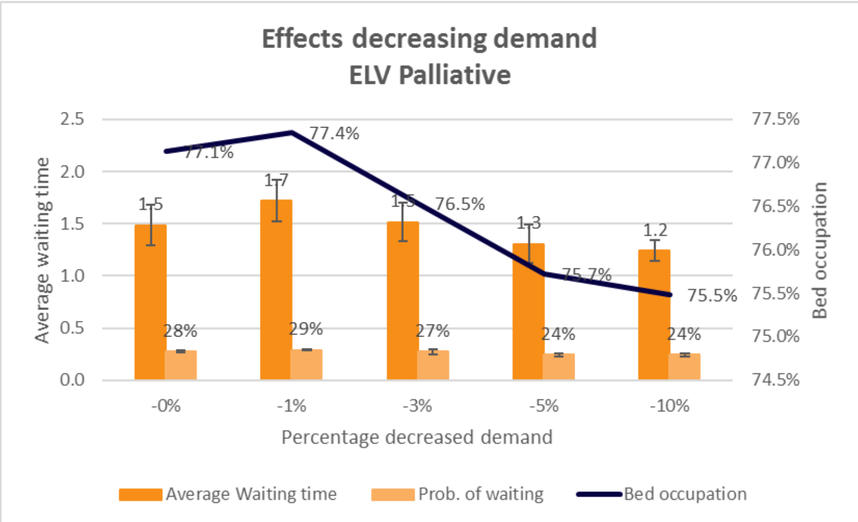

Figure 69: Effects of decreasing demand for ELV Palliative with a 95% confidence interval

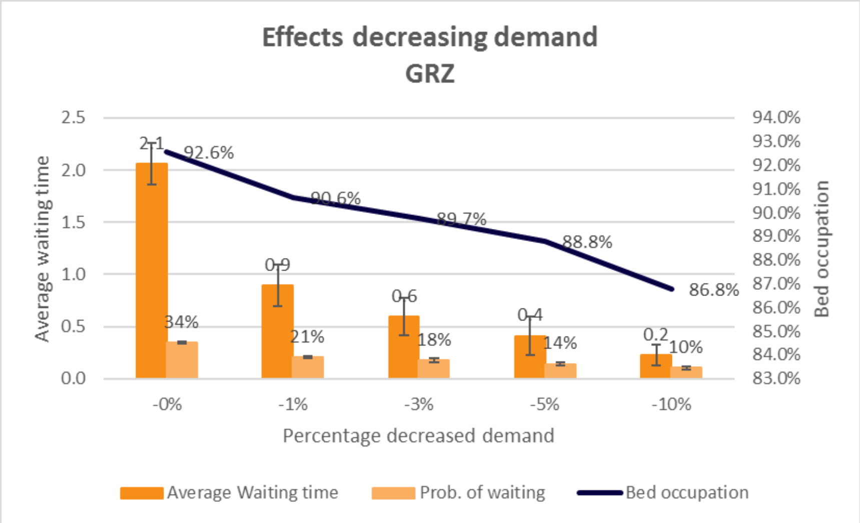

Figure 70: Effects of decreasing demand for GRZ with a 95% confidence interval

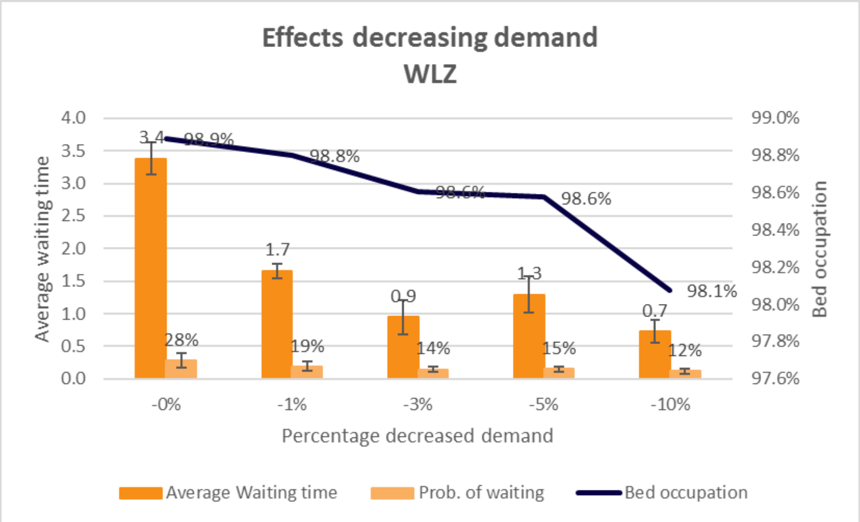

Figure 71: Effects of decreasing demand for WLZ with a 95% confidence interval

I: Financial impacts

Table 35: Yearly savings for ZGT due to a decrease in waiting time

	Length of stay			
	-1%	-3%	-5%	-10%
ELV Low	€ 1,300	€ 3,900	€ 6,700	€ 7,900
ELV High	€ 19,400	€ 62,900	€ 80,000	€ 94,800
ELV Palliative				
GRZ	€ 45,800	€ 118,600	€ 143,900	€ 172,300
WLZ	€ 65,500	€ 88,000	€ 88,600	€ 88,600
Total	€ 132,000	€ 273,400	€ 319,200	€ 363,700
	Capacity			
	1%	3%	5%	10%
ELV Low	€ 3,900	€ 6,100	€ 7,000	€ 8,100
ELV High	€ 24,100	€ 55,200	€ 85,900	€ 96,900
ELV Palliative			€ 3,400	€ 5,100
GRZ	€ 67,900	€ 109,300	€ 151,000	€ 178,000
WLZ	€ 67,600	€ 88,400	€ 88,600	€ 88,600
Total	€ 163,500	€ 259,000	€ 335,900	€ 376,600
	Demand			
	-1%	-3%	-5%	-10%
ELV Low	€ 600	€ 2,200	€ 2,900	€ 2,100
ELV High	€ 38,500	€ 48,300	€ 54,300	€ 62,000
ELV Palliative		€ 400	€ 1,300	€ 1,600
GRZ	€ 100,800	€ 130,500	€ 149,000	€ 167,200
WLZ	€ 47,700	€ 66,200	€ 57,200	€ 71,900
Total	€ 187,100	€ 247,600	€ 264,700	€ 304,800

Table 35 gives an overview of the estimated savings ZGT can make on a yearly basis for a reduction of 1, 3, 5 or 10% in the length of stay or demand or an increase in capacity of 1, 3, 5 or 10%. A reduction of one ALC day for WLZ saves approximately 200 euro and a reduction of one ALC day for the other types of care 100 euro.

Table 36: Yearly decrease in days of stay due to a decrease in bed occupation

	Length of stay			
	-1%	-3%	-5%	-10%
ELV Low	-90	-330	-610	-1130
ELV High	-250	-660	-1010	-1880
ELV Palliative	-4790	-4790	-4790	-4790
GRZ	-480	-1180	-2120	-4110
WLZ	-3050	-11210	-18990	-40580
Total	-8660	-18170	-27520	-52490
	Capacity			
	1%	3%	5%	10%
ELV Low	-230	-410	-650	-1150
ELV High	-300	-620	-1190	-1930
ELV Palliative			-230	-500
GRZ	-420	-1230	-2100	-4510
WLZ	-4230	-12840	-21730	-42230
Total	-5180	-15100	-25900	-50320
	Demand			
	-1%	-3%	-5%	-10%
ELV Low	-70	-180	-180	-200
ELV High	-320	-430	-470	-680
ELV Palliative		-40	-90	-100
GRZ	-1090	-1600	-2130	-3270
WLZ	-850	-2790	-3080	-7950
Total	-2330	-5040	-5950	-12200

Table 36 gives an overview of the estimated reduction in days of stay in aftercare on a yearly basis for a reduction of 1, 3, 5 or 10% in the length of stay or demand or an increase in capacity of 1, 3, 5 or 10%. This reduction is calculated by multiplying the reduction in bed occupation by the number of beds and the number of days in a year.