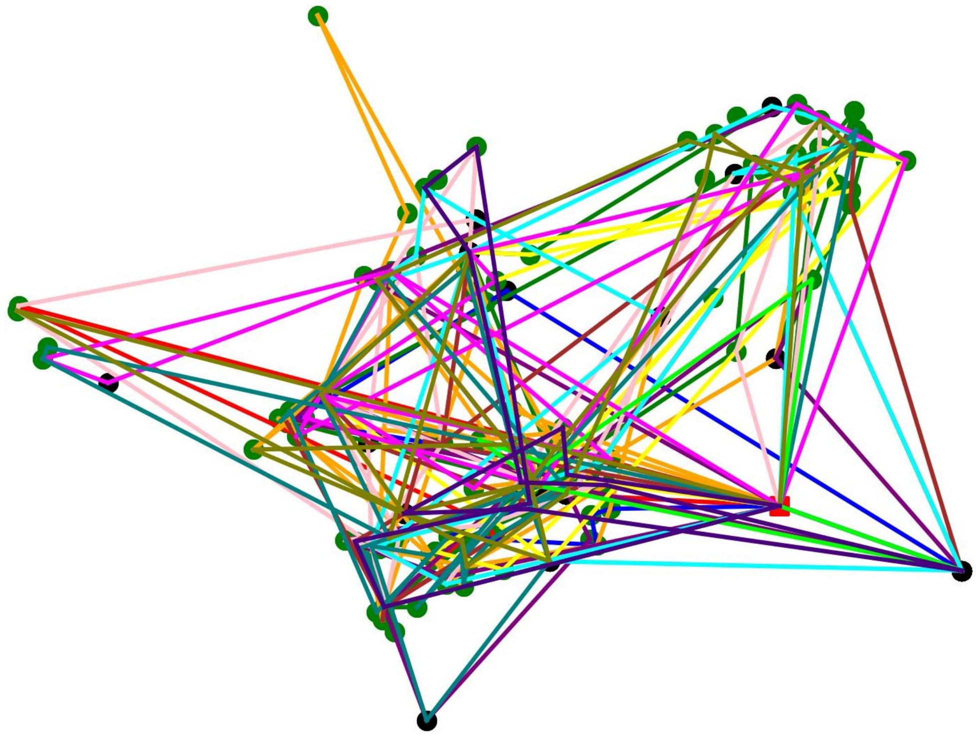
Optimizing transportation of clients for social care services

Feike Weijzen



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Preface

This is the final version of my thesis entitled ”Optimizing Transportation of Clients for Social Care Services”. This thesis emerged from a study I conducted on behalf of PPRC for the Gooi and Vechtstreek region. With this thesis, I am concluding my studies in beautiful Twente. I am very grateful for the knowledge I have gained during my studies in the Bachelor of Technical Medicine, the Master of Health Sciences, and ultimately the Master of Industrial Engineering & Management.

I want to thank my supervisor from PPRC, Niels Uenk. His company, PPRC, does not typically conduct research in the direction I wanted to take my thesis. Thanks to Niels his enthusiasm and flexibility, I could shape the thesis to my liking at PPRC. I also want to thank Erwin Hans, firstly for his role in the courses that made me a fan of Industrial Engineering & Management, and secondly, along with Daniela Guericke, for guiding this project.

Furthermore, I would like to express my gratitude to my friends, family, and girlfriend for their support, occasional advice, and the joy they brought me during this period. In particular, Sjon, Paul, and Lars made my graduation time a little celebration every day at the Langezijds. Thank you for that!

Feike Weijzen
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Management summary

Motivation of this research: The Gooi en Vechtstreek region (RGV) and its care providers face high costs in social care services. One of the reasons for these costs is the inefficient transportation of clients for social care services. A solution could be to reorganize this transportation. This thesis examines the impact of a potential new strategy.

Research objective and questions: The objective of this study is to develop a decision-making algorithm to prospectively assess the impact of various strategies on key performance indicators related to transportation services for clients of social care services in the RGV. To complete this objective the following research questions are formulated:

- What is the current strategy regarding the transportation of clients for social care services in the RGV?
- What methods are known to solve VRPs?
- How should the transportation planning algorithm be constructed?
- What is the performance of various strategies regarding Key Performance Indicators (KPIs) in the model?
- Are there recommendations that can be suggested to the RGV for improving the current situation regarding the transportation of clients for social care services?

Approach: Because there is no available data on the outcomes of KPIs for the current strategy validation of the model is difficult. The current strategy is modelled. Additionally, two strategies are tested. First is the horizontal cooperation strategy, in which clients remain with their current care provider, but the transportation is coordinated from a central vehicle depot. Second is the client allocation strategy, where, in addition to the central vehicle depot, clients can also be allocated to other care providers if this is beneficial for the transportation routes.

For every strategy, an Integer Linear Programming (ILP) model is formulated. Due to the complexity of the problem, the ILP models were not suitable. Therefore a meta-heuristic is employed. A random greedy heuristic feeds an initial solution to an Adaptive Large Neighbourhood Search (ALNS) algorithm, which optimizes the solution. The ALNS algorithm works by destroying the current solution and then repairing it to create a new solution. A simulated annealing framework determines whether this new solution is accepted. After a certain number of iterations, the best-found solution is returned.

Results and conclusions: Various experiments are performed to tune the parameters that are present in the ALNS algorithm. With the tuned parameters, the various strategies are tested on the total distance driven during a week of transporting clients to their social care services. The following results were found:

Current strategy:	7618 ($\pm$160) kilometres,	53.2 ($\pm$1) vehicles needed
Horizontal cooperation strategy:	7047 ($\pm$120) kilometres,	16.4 ($\pm$1) vehicles needed
Client allocation strategy:	6387 ($\pm$79) kilometres,	14 ($\pm$1) vehicles needed

We conclude that the new strategies have a positive impact on the current situation based on the distance driven and vehicles needed. The average driving time per transport request was similar for the current strategy and the horizontal cooperation strategy with 27.0 ($\pm$0.3) and 27.3 ($\pm$0.3) minutes, respectively. The client allocation strategy presented a small decrease with 25.3 ($\pm$0.3) minutes. The LP models were not able to generate a lower bound. The solution consists of multiple routes. To check that the routes are logical, they are verified visually. This thesis helps the RGV to make a more informed decision about strategies for the transportation of clients of social care services. Additionally, the thesis makes a scientific contribution; no articles with the same characteristics as those in the RGV situation were found in the literature. We demonstrate that an ALNS algorithm provides solutions to a problem with the specific characteristics of the RGV.

Where to from here?: The ALNS algorithm can easily be expanded to incorporate more KPIs for making a better-informed decision. For example, costs or the quality of the ride can be considered in the objective function. Finding a balance between the various KPIs enables a decision which balances the interests of all stakeholders. Other strategies can also be tested. Examples include positioning the vehicle depot more central in the region or adopting a multi-depot approach. If the RGV decides to implement a new strategy, it would be beneficial to conduct more research on the impact a new strategy would have on the clients. During the data collection, several care providers indicated that a change in transportation or care provider has a significant impact on these clients. A gradual transition to a different strategy could be a solution.

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Abbreviations

Abbreviation	Explanation
AWBZ	Algemene Wet Bijzondere Ziektekosten (Exceptional Medical Expenses Act)
PGB	Persoonsgebonden Budget (Personalized Budget)
WMO	Wet Maatschappelijke Ondersteuning (Social Support Act)
RGV	Region of Gooi and Vechtstreek, a region in the Netherlands
KPI	Key Performance Indicator
VRP	Vehicle Routing Problem
ILP	Integer Linear Programming
CVRP	Capacitated Vehicle Routing Problem
VRPTW	Vehicle Routing Problem with Time Windows
MDVRP	Multi-Depot Vehicle Routing Problem
MCVRP	Multiple Commodities Vehicle Routing Problem
VRPPD	Vehicle Routing Problem with Pick-up and Delivery
DARP	Dial-A-Ride Problem
LNS	Large Neighbourhood Search
VNS	Variable Neighbourhood Search
ALNS	Adaptive Large Neighbourhood Search

Contents

1 Introduction

This chapter describes the context of this research, including the motivation for conducting this study. Section 1.1 describes the context of this research. Section 1.2 defines the problem context, including the core problem. Last, Section 1.3 states the research objective and questions.

1.1 Context description

This thesis focuses on an issue related to the transportation of clients for social care services. To understand the current situation and its origins, this section describes the context regarding social care services, including the development of the law that regulates this matter.

The Netherlands is widely regarded as a welfare state. In 1901 the first social insurance scheme was introduced, a law to compensate for work-related injuries. Over time, additional national plans were implemented [6]. The central government became responsible for the provision of social care, which was regulated by the *Algemene Wet Bijzondere Ziektekosten* (Exceptional Medical Expenses Act) or AWBZ. This law was introduced by, at the time, Minister Veldkamp in 1968 [7]. To illustrate the magnitude of the AWBZ, its total budget in 2004 was approximately 20.5 billion euros. The AWBZ consisted of a mandatory insurance scheme for the whole population. This resulting fund paid for care not included in health insurance or private insurance policies. The AWBZ covered the following aspects:

- Treatment from a medical specialist, behavioural science, or specialized paramedical care.
- Support with activities to prevent mental issues or help cope with medical conditions.
- Support with promoting or maintaining self-reliance.
- Nursing, aimed at recovering or preventing medical conditions and disabilities.
- Personal care aimed at maintaining or promoting self-reliance.
- Domestic care provided in case of limitations/dysfunction in performing household tasks.

The Dutch social care system had several strengths and weaknesses under the AWBZ regulation. The main positives from the AWBZ were that every citizen was insured and the right to receive social care if needed was recognized by law [8]. Additionally, clients could choose which caregiver suits them most through a *Persoonsgebonden Budget* (personalized budget) or PGB. This PGB could be requested from the municipality to arrange care yourself. However, some limitations also occurred in the way social care was handled in the Netherlands under the AWBZ. Client needs and desires were not sufficiently taken into account. There was little incentive to increase the efficiency and quality of care. According to the minister of Health, Welfare and Sport, the natural tendency to look after another was lost [9]. Furthermore, costs and quality were difficult to monitor under this regulation, and costs were increasing [10] [11] [8].

Because of the rising costs, the government decided to decentralize how social care was managed, and in 2015, the Social Support Act, in Dutch the *Wet Maatschappelijke Ondersteuning* (WMO), was introduced to regulate social care in a different way [12] [13]. In the new law, the responsibility to provide care was shifted from the central government to local governments in the hope that better efficiency and higher quality could be achieved. It was assumed that local governments were in closer contact with their citizens and could therefore better determine what care citizens should receive and how that care should be arranged [14].

Hortulanus identifies the importance of the WMO [15]. He states that the introduction of the WMO creates a safety net for vulnerable people, while also giving the possibility to link vulnerable people to healthy people. In the new WMO, local initiatives of collective solidarity and the tendency to rely on your own social environment are encouraged. However, the introduction of the new WMO received criticism as well. Houten argues that the WMO is merely a cost-cutting policy [16].

Under the new WMO, municipalities were made responsible for supporting people who are not self-reliant [12]. This meant that municipalities were accountable for arranging personal guidance, day care or arranging support to relieve the family caregiver temporarily. Another task of the municipalities under the WMO was to arrange a safe living environment for citizens with mental disorders. These were largely the tasks previously included in the AWBZ.

According to a report about the WMO in practice, municipalities were struggling to find the best way to implement the WMO [17]. The most important aspect for municipalities was continuity of care. Citizens were to experience as little inconvenience as possible from the transition. For caregivers, the transition meant the administrative burden increased as a lot had to be reported to the local governments.

When the new WMO was introduced, local governments could choose what kind of care contracting policy they would like to adopt. The ideology behind this approach was that municipalities are more familiar with the needs of citizens and therefore better able to determine how to tailor care to those needs [14]. Since citizens' needs differ from one municipality to another, different municipalities have adopted various models of contracting care. One of the models that local governments use is the so-called "Zeeuws model" or "open house model" [4] [5]. In the setting of this thesis, the open house model is adopted. Therefore, this model is further explained here.

In the open house model, every caregiver is contracted if they are compliant with certain quality requirements and are willing to provide care at a fixed price. In theory, this means that an unlimited amount of caregivers could be contracted. Citizens can choose for themselves which provider to get care from. Table 1.1 displays the advantages and disadvantages of the open house model.

Table 1.1: The advantages & disadvantages of the open house model [4] [5].

Aspect	Advantages	Disadvantages
Client has the freedom to select their own care provider	The most suitable care provider is selected by the client themselves. Which improves their empowerment and engagement in their own care.	The open house model requires a high amount of care providers. Otherwise, clients do not have enough options to find a suitable care provider.
Quality of care	The freedom of client to choose their own care provider, creates a natural incentive for care provider to deliver high-quality care. This competition motivates care providers to keep improving.	The municipality has little contact with the end user, making it difficult to check for quality of care.
Costs & administrative burden	While the initial contracting phase may involve higher administrative burden, the administrative burden of other phases in the open house model is low compared to other models.	Control over costs is established by restricting the provision of care (there is no "open access"). However, with a high number of care providers, implementing such limitations is complicated.

The open house model faced some criticism from State Secretary Van Ooijen (Ministry of Health, Welfare and Sport) and Minister Weerwind (Legal affairs) [18]. According to their letter, the model creates an influx of new care providers, some of whom make high profits. The influx of new care providers makes it difficult for municipalities to keep in control. Therefore, they proposed a new law making it more difficult for municipalities to apply the open house model as a procurement method. However, the article of Hoogenraad et al. [19] showed that the open house procurement method was not related to higher cost increases. This study also shows that changing the procurement method from an open house procurement method to another on average does not reduce costs.

Municipalities often procure WMO care together with other municipalities [20]. This is done to share knowledge and have more power over care providers. Contrary, the process of buying care becomes more complex. In the region of "Het Gooi en Vechtstreek" (RGV), the municipalities of Blaricum, Gooise Meren, Eemnes Hilversum, Huizen, Laren and Wijdemeren collaborate. These municipalities purchase WMO support and youth care together.

In the Netherlands, more than one million people received some form of care from the WMO during the first half year of 2022 [21]. In the RGV nearly 14.000 people make use of the WMO facilities. The total expenses of the WMO in 2020 were around 5.6 billion euros, of which around 44.3 million from the RGV [1]. Figure 1.1 illustrates a significant increase in o costs in the RGV since 2018. The total expenses in the Netherlands have grown since 2017 from 4.5 billion euros to more than 5.6 billion euros in 2020.

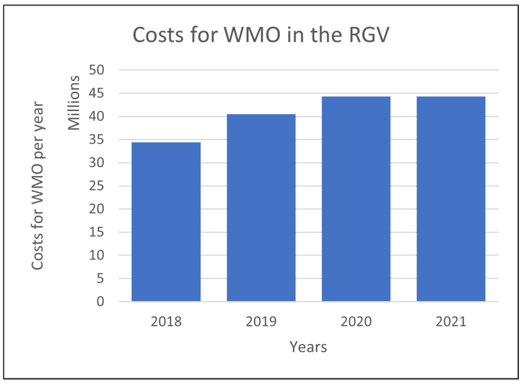


Figure 1.1: Total expenses WMO in RGV, 2022 [1]

Since 2015, the social care services of clients have been part of the WMO, which includes both adults and juveniles [13]. Social care services aim to help clients have a meaningful purpose for the day. Clients are guided in various activities, such as assistance with administration, education, outdoor activities, or leisure activities. The goal is to increase clients' self-reliance and reduce their social exclusion. The article by Law et al. [22] shows that having a daytime occupation leads to improved well-being and health benefits. Social care services in the Netherlands are provided to clients at a designated location. Transportation to this location is arranged by either the clients themselves, the municipality, or the care provider.

The open-house method offers clients in the region of the RGV the option to select which care provider will deliver the social care services. Clients should select care providers who can handle their condition. Conversely, care providers are specialised in certain conditions and only attract and accept clients with such conditions. Approximately 1000 clients receive social care services in the RGV, and out of those, 439 clients also receive transportation. A high amount of kilometres is travelled to ensure access to care for these clients. This poses challenges that make the current approach unsustainable in the long term. Therefore, the RGV aims to look at new strategies and assess whether they could offer potential solutions to the issues at hand. An example of such a strategy is linking clients to specific caregivers. This could potentially create efficiencies that keep costs manageable. To understand the possible benefits of various strategies, a model is created that includes the following aspects.

- Type of clients
- Caregivers, including location, type of care they can deliver and capacity
- Distance from caregiver to client
- Amount of transport movements
- Constraints for clients (for example, a client needs special treatment)

Part of the project involves assessing the model's feasibility of accurately simulating new transportation strategies. If the model is deemed sufficiently realistic, we will examine the potential outcomes of various strategies and make recommendations based on those calculated strategies.

1.2 Problem context

The problem context in this situation is complex. Various stakeholders have interests regarding the situation. Examples of stakeholders are care providers, clients and municipalities. To get a better grasp of the problem, conversations with policy-makers, contract managers and data analysts from the RGV are held. Through these conversations, several problems were identified. This thesis focuses on one aspect of these problems, namely the problems surrounding the transportation of clients. The following sub-problems are identified within the context of the transportation of clients.

1.2.1 Allocation of clients

By default, clients are responsible for arranging their own transportation to the social care services. However, if a client is unable to do so, the RGV can assign the responsibility for the transportation of the client to the care provider. The assessment of whether a client is capable of arranging their own transport is not strict. Consequently, many clients are relying on the care providers for transportation, even when they could have made their own arrangements.

When care providers are responsible for the transportation of clients to the facilities, they have several options at their disposal. They can utilize volunteers, hire a transportation company, or use their own staff members to pick up the clients. Typically, a van is used to transport the clients. One of the challenges faced is accommodating clients who require wheelchairs or extra assistance during transit, as they take up more space than clients with no additional needs.

Clients have the freedom to choose their preferred care provider, provided they can arrange suitable care for their specific condition. Clients do not always choose the nearest care provider. As a result, large distances are covered to transport all clients to their respective care providers.

1.2.2 Transportation prices

The price of the transportation of clients has increased. Various world events, such as the COVID-19 pandemic and the war in Ukraine have led to the increase of fuel prices in the Netherlands [23]. Not only fuel prices but also maintenance costs have gone up. Transportation is a big part of the total costs for social care services, therefore an increase in the price of transportation affects the total costs as well.

The care providers get paid a fixed price per client they pick up, this means clients that are closer to the facility are more economical to pick up than clients who live far away from the social care services. Although the prices of transportation have increased, the fixed compensation has stayed the same. Consequently, care providers have additional expenses, without receiving additional compensation.

1.2.3 Lack of providers

Some care providers quit their services in the RGV. This meant the network of providers became less dense. Consequently, clients have fewer care providers to choose from, leading to longer travel distances. Because of the fixed prices per client per transport regardless of the distance or travel time, the rising costs of transportation are amplified. The pressure on the remaining care providers increased because some providers quit.

1.2.4 High absenteeism

The care providers are struggling with high absenteeism due to the aftermath of the COVID-19 pandemic [24]. Two problems occur due to the high absenteeism in the population. The employees of the care providers call in sick more often, which means that expensive staff is needed as a substitute. This harms the profitability of the care providers, which consequently causes more care providers to stop their services.

The other problem is occurring due to clients not showing up to their scheduled appointments. The care providers are compensated based on the actual time clients spent at the facility, rather than fixed blocks of 4 hours. The revenues are budgeted according to the expected duration of the clients (the 4-hour blocks). Consequently, when a client is not attending during the planned time, the care providers incur a loss in revenue, while still having to cover costs for employees and facility maintenance. This situation means the profitability is at risk, which again causes more care providers to stop their business.

1.2.5 Lack of central planning and optimization

The care providers are solely responsible for the transportation of their own clients who are unable to arrange transportation themselves. This strategy lacks centralized planning and collaboration among care providers regarding the transportation of clients, which hampers the possibility of optimizing efficiency. Additionally, routes for transporting patients to and from the social care services are not optimized. In combination with the lack of collaboration, this leads to a high amount of kilometres travelled. Which results in higher costs for care providers.

The combination of challenges results in an unsustainable strategy for the long term. If an excessive number of providers discontinue their services, the RGV has to arrange alternatives to group-based social care services. The alternatives to group social care services are often more individually organized, which means that the costs are higher. Therefore, the RGV aims to prevent this scenario. A part of the solution is to improve the efficiency of the transportation of clients. Figure 1.2 depicts the problem bundle from the problems regarding the transportation of clients, including the core problem that this project focuses on. Note that there are more challenges regarding social care services; however, they are not the main focus of this thesis.

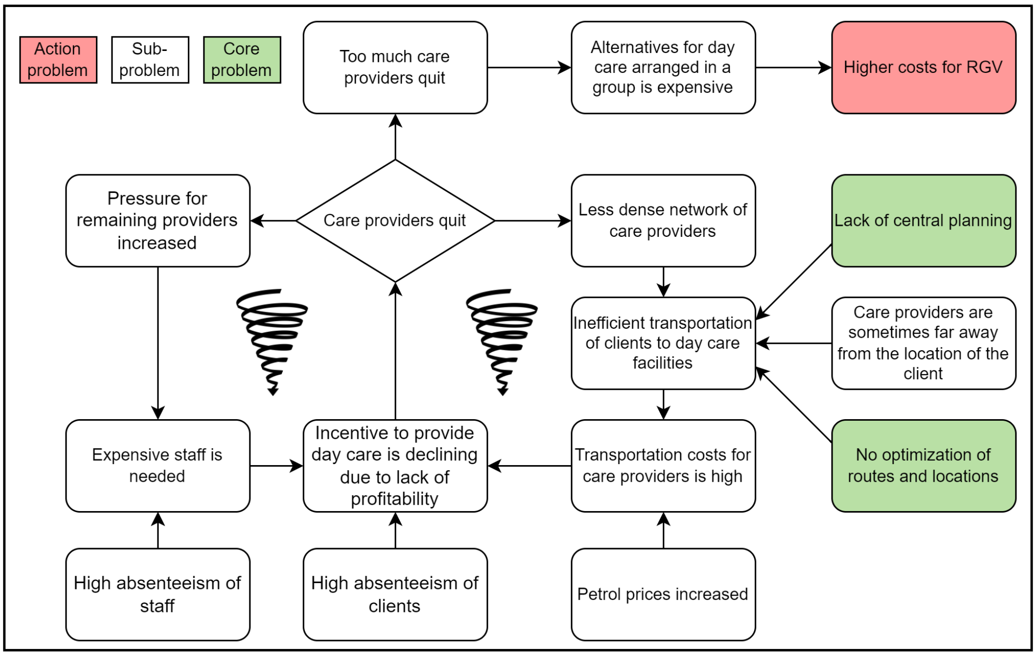


Figure 1.2: Problem bundle: Social care services for the RGV

Implementing a new strategy could be part of the solution for the RGV. Examples of new strategies could be assigning clients to care providers, contracting more care providers or refusing clients. These strategies may allow the RGV to regain control of the problems it faces and may provide the opportunity to influence the number of kilometres travelled, which is a major factor in the incurred costs. While various strategies are promising, their effectiveness is yet to be determined. This leads to the core problem at hand in this project. There is no information available on how new strategies, including optimization of routes, perform. Therefore, implementing a new strategy is risky due to the unknown consequences associated with the change. A knowledge gap is present on whether it is advantageous to switch to a different strategy. Part of this knowledge gap is the problems surrounding the transportation of clients. This project develops a transportation planning algorithm to provide insight into the impact that various strategies have on the key performance indicators for the RGV.

1.3 Goal and research questions

This project aims to give insights into outcomes regarding various strategies for the transportation of clients of social care services in the RGV. The various components that could be changed in the current situation are the following:

- Restricting patients' choices
- Amount of patients
- Capacity of transport
- Capacity of care providers
- Location of care providers
- Combining of specialisations of clients to certain care providers

A change in some of these components could be part of the solution to the problem at hand.
Part of this project is to identify whether the constructed model sufficiently reflects reality in a way that useful information could be gathered through the model. Key performance indicators (KPIs) are determined to distinguish the best strategy.

The following research objective is formulated:

> The objective of this study is to develop a decision-making algorithm to prospectively assess the impact of various strategies on key performance indicators related to transportation services for clients of social care services in the Gooi en Vechtstreek region (RGV).

To reach this objective, the following research questions are defined:

1. *What is the current strategy regarding the transportation of clients for social care services in the RGV? (Chapter 2)*

   The current situation is studied, including the limitations and challenges that occur. This question is answered by analyzing the available data on the current situation and having interviews with employees of the RGV.

   1.1. *What are characteristics of the current strategy in the RGV?*

   1.2. *What stakeholders are involved in the transportation of clients for social care services in the RGV?*

   1.3. *What are limitations of the current strategy of transportation of clients in the RGV?*

   1.4. *What are the KPIs for the transportation of clients in the RGV?*

2. *What methods are known to solve VRPs?(Chapter 3)*

   A literature review regarding the methods and theories on VRPs is performed. To answer this question a literature search on the following questions is performed in Scopus and Google Scholar.

   2.1. *What types of VRPs are associated with the situation in the RGV and what methods are used to solve them?*

   2.2. *Are there cases known in the literature similar to the situation in the RGV?*

3. *How should the transportation planning algorithm be constructed? (Chapter 4)*

   A solution approach is constructed using knowledge from the literature. The solution approach preferably adds to existing literature. A mathematical model is constructed and implemented in software using Python.

   3.1. *What are possible strategies that could be implemented in the current situation in the RGV?*

   The various rules and regulations of the situation are described or approximated using assumptions/literature or the knowledge of the employees of the RGV.

   3.2. *What are the rules and regulations that the solution should fulfil?*

   3.3. *What assumptions need to be made for the model to be constructed?*

   3.4. *Can we solve the problem exactly?*

   First, we try an Integer Linear Programming (ILP) approach to model the various strategies.

   3.5. *What data is available to solve the VRP at hand?*

   The problems turned out to be too complex for an ILP approach, as described in Section 5.3. Therefore, a metaheuristic is applied.

   3.6. *How can a constructive heuristic be formulated for this problem?*

   3.7. *How can a metaheuristic be formulated for this problem?*

4. *What is the performance of various strategies regarding KPIs in the model? (Chapter 5)*

   The metaheuristic needs tuning of various parameters.

   4.1. *What experiments are conducted to tune the various parameters in the model and what are the results of these experiments?*

   Various strategies are implemented in the model and compared based on their respective KPIs.

   4.1. *How do various strategies perform regarding KPIs?*

   A strategy can only be accepted if it outperforms the current strategy, therefore the various strategies are compared to the current strategy. This leads to the final sub-question in this thesis.

5. *Are there recommendations for the RGV to improve the transportation of clients for social care services? (Chapter 6)*

2 Current strategy

This chapter discusses the current strategy for arranging transportation of clients to and from social care services in the RGV. Information about this strategy is gathered through interviews with employees of the RGV. Section 2.1 examines the stakeholders involved and their respective roles in the transportation process. Section 2.2 explains the characteristics of the current strategy. Section 2.3 determines the key performance indicators of the stakeholders. The gained insights from this chapter are input for the literature study in chapter 3 and the model construction in chapter 4.

2.1 Stakeholders

Three key stakeholders with various interests are involved in this project. The relation between these stakeholders is shown in Figure 2.1.

2.1.1 Region of Gooi and Vechtstreek

The most influential stakeholder is the RGV. The RGV is responsible for purchasing social care services in seven municipalities. The municipalities together decided to give the RGV these responsibilities. Additionally, the RGV handles the payment to care providers. It is the RGV's responsibility to ensure the quality and accessibility of care for those in need. The RGV builds a strong relationship with the care provider to achieve these goals. The RGV is not in power to make policies, however, can advise the municipalities regarding policies. The main interest of the RGV is ensuring care is accessible, of high quality, and that costs are maintained reasonable.

2.1.2 Care providers

The care providers deliver the social care services to the clients. According to the Ministry of Health, Welfare and Sports, social care services refer to delivering useful and structured activities during the day [12]. This can be in the form of activities, such as making art or doing sports. The social care services provided by the care providers can also have an educational character or a labour-oriented character. An example is animal care or working in a restaurant or supermarket. In these examples, clients are not judged on performance but the social care service is such that something is produced.

The social care services are categorized into youth and adult care. These categories have arisen because there are two separate laws governing juvenile (Youth Act) and adult (WMO) social care services. The conditions that clients have are the following:

- Dementia: Only adults
- Acquired brain injury
- Mild intellectual disability
- Intellectual disability
- Mental disorders
- Autism
- ADHD
- Physical disability

Several care providers have separate locations for these specializations. The interest of the care providers is mainly to focus on delivering the best care possible. Additionally, care providers are interested in being compensated fairly for the services they provide.

2.1.3 Clients

Clients who utilize the social care services are highly diverse, ranging from young to old and from mild to severe disabilities. When referring to a client, not only the individual themselves but also the parents, caregivers, and decision-makers who are closely involved in their care and well-being are referred to. In the open house model, the clients have the opportunity to choose their care provider, allowing them to influence the type of care they receive. The primary concern of clients is to receive the best possible care that aligns with their individual needs.

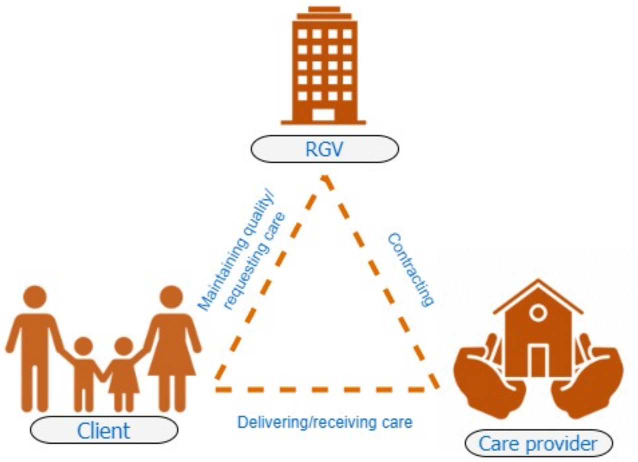


Figure 2.1: Relation between stakeholders

2.2 Characteristics

This section discusses the current transportation strategy of the RGV for clients requiring transport to social care services.

There are 26 care providers in the RGV for clients who require transportation to access the social care service. Care providers are responsible for the transportation of 439 clients to and from social care services, while more than 1000 clients receive social care services. The social care services are categorized into youth and adult care. These categories have arisen because there are two different laws governing juvenile and adult social care services. In total 216 assignments are given for youth transport for social care services, while 223 citizens have an assignment for adult transport.

In the transportation of clients, a distinction is made between the severity of the condition. Clients are divided into two groups: those requiring light transport and those needing medium transport. Light transport refers to standard transportation provided to clients who can be transported under normal circumstances. Contrary, medium transport is provided for clients who require extra supervision while travelling or have specific impairments that prevent them from being transported under normal conditions. An example in this category is clients who need to be transported in a wheelchair.

Apart from the various types of transportation, clients also differ in terms of the types of conditions they have. Similarly, care providers differ in their capability to offer social care services for various conditions. A good match of client and provider is needed to ensure that the right social care service is given.

Care providers are compensated for the transportation per client. There are two standard fees: one for light transport and one for medium transport. These fees do not take into account travelling distance. Therefore, if a client is located far away from the social care services facility, this is disadvantageous for the care provider. Clients are in power to choose their preferred care provider, resulting in clients of one provider being scattered throughout the region as is shown in Figure 2.2. The figure illustrates the location of clients associated with certain care providers, locations are shown based on their postal codes. To ensure the clarity of the figure, not all care providers and associated clients are shown.

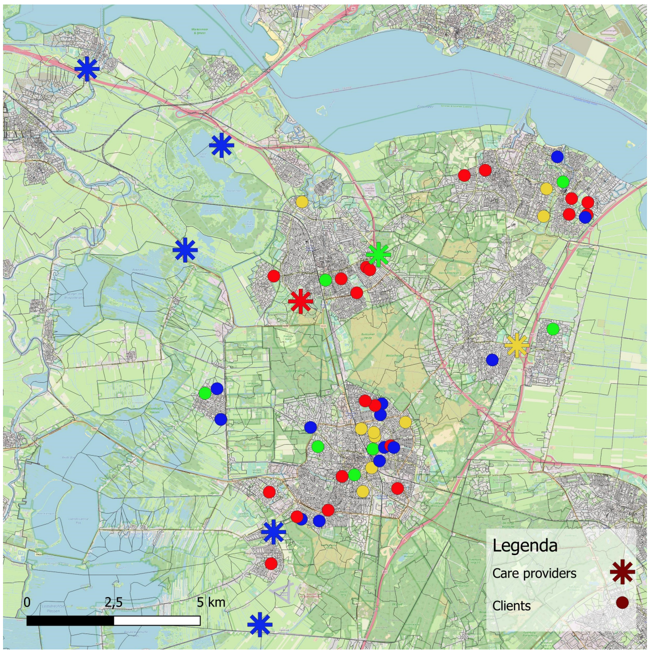


Figure 2.2: Locations of clients and care providers

In 2023, the total expenses for transportation of clients were €553,884. This is distributed over the various care providers based on the number of transport movements they need to perform to pick up and deliver their clients. The total distance that is covered by transportation in the current situation is not known. However, this will be estimated using the model presented in Chapter 4.

2.3 Key performance indicators

A key performance indicator (KPI) is selected to provide a clear comparison between the current strategy and the possible new strategies.

Examples of useful KPIs are the following:

- **The total/average amount of kilometres travelled:**
  This KPI provides information about the total distance that is covered during the transportation of clients during a week.
- **The total/average time a client spends in the vehicle:**
  This KPI represents the total or average time spent by clients in transit.
- **The total costs of transporting clients:**
  This KPI measures the overall costs incurred by care providers for transporting clients to the social care services facilities in terms of fuel consumption, maintenance, salary etc.
- **Number of vehicles:**
  This KPI indicates how many vehicles are needed for the transportation of clients during a week

The stakeholders share a common objective, which is to ensure the best care for the clients, including the best possible transportation. However, the RGV and the care providers have an additional aim of achieving this while maintaining manageable costs. From the client's perspective, the right transportation means not spending too long in the vehicle, not having to wait for the vehicle and being on time at the social care services.

The KPIs are intertwined. If a client is spending longer in the vehicle, most likely the distance will be longer. A longer distance usually results in higher transportation costs for the care providers. Due to the intertwined nature of the KPIs, the total distance travelled in a week is chosen as the main KPI. The number of vehicles and the average time a client spends in the vehicle per ride are also computed.

A challenge resulting from the context of the RGV is that the total amount of kilometres travelled and the total transportation costs in the current situation are unknown. The care providers arrange the transport themselves and are not able to deliver reliable data on this topic. As a result, the validation of the model could be based on the current budget that the RGV pays care providers for arranging transport. This budget is based on the number of clients rather than the actual distance or costs incurred when transporting clients.

2.4 Conclusion

In this chapter, the current situation at the RGV is explained. The stakeholders in the context of the region are the RGV, the care providers and the clients that need social care in the region. Care providers have several options to fulfil their responsibility of transporting clients to and from the care providers. Compensation for this transport is based on a per-client basis. Clients are categorized based on the type of transportation they need and the type of care they need to receive. The current allocation of clients to care providers is scattered throughout the region, which means an optimization of allocating the clients could be helpful. The main KPI to compare strategies is the weekly distance travelled in transporting clients to and from their care providers. The next chapter describes the literature on how the current strategy and potential new strategies can be modelled.

3 Literature review

The literature is reviewed to study methods and characteristics that are present. The advantages and disadvantages of certain methods are reviewed, this way the best-fitting method is chosen. To ensure this study contributes to existing literature, a literature gap is found. Literature about VRPs is searched through the databases of Google Scholar and Scopus. Sections (3.1-3.7) discuss the literature about the characteristics of VRPs and the variations in models and constraints associated with them. Section 3.8 considers the literature on solving VRPs. Section 3.10 describes problems similar to the context of social care services that are found in the literature.

3.1 Vehicle routing problems

A VRP can be defined as a problem where the solution tries to minimize a certain objective by selecting routes through customer locations. The routes have to comply with certain constraints that need to be satisfied [25]. A VRP is often an NP-hard problem, so there is no guarantee that an optimal solution can be found in reasonable time [26]. This is why heuristics and meta-heuristics are often used to solve VRPs. The first mention of VRPs in the literature was by Danzig et al. [27], who presented a large-scale travelling salesman problem. Since then, numerous VRP variants have been introduced and explored in the literature as Figure 3.1 showcases.

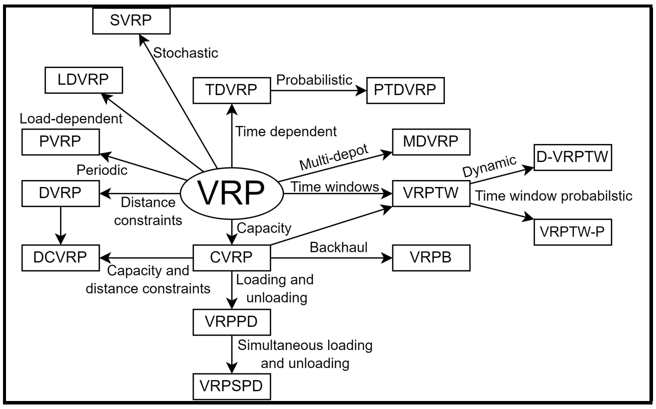


Figure 3.1: Known variants of the Vehicle Routing Problem [2]

The problem that the RGV faces is a VRP, which is related to the following VRP variants. When picking up clients the capacity of the vehicle should be considered. Section 3.2 discusses a capacitated VRP (CVRP), this is also considered as the base model. The social care services have certain opening hours for the groups that the clients are in, therefore Section 3.3 assesses a VRP with time windows (VRPTW). In the context of the RGV multiple locations are present, where clients can go or vehicles can be driven from. This can be approached as a multi-depot VRP (MDVRP). Section 3.4 considers the formulation of the multi-depot problem. The problem of the social care services in the RGV gets even more complex because there are constraints which ensure that clients go to the correct facility. Not every client can go to every facility and can be transported in the same way. Section 3.5 describes a VRP with multiple commodities (MCVRP). The social care services require clients to be brought to their destination and afterwards brought back home. This means a pick-up and delivery VRP (VRPPD), which is formulated in Section 3.6. A variant of the VRPPD is the dial-a-ride problem (DARP). Section 3.7 discusses the DARP. The difference is that DARP focuses on the transportation of people and therefore concerns about the quality of services are present [28].

3.2 Capacitated VRP

There is not one standard VRP model. However, the basis for more complex variants is often the CVRP. The model of this variant considers the capacity of vehicles as a constraint. A variety of integer linear programming models (ILPs) have been proposed to solve this problem [29].

- Two-index vehicle-flow formulations
  Where a binary variable indicates whether a route is travelled.
- Three-index vehicle-flow formulations
  Where a binary variable for every vehicle indicates whether the vehicle travels a certain route.

- Set-partitioning formulations
  Formulation with a binary variable for every potential vehicle route.

The article of Rieck et al. [29] showed that the computational time of a three-index vehicle-flow model is significantly higher than the two-index vehicle-flow model. However, the three-index vehicle-flow formulations are easier when implementing additional constraints. The set-partitioning formulation considers all potential candidates for an optimal solution and is therefore impractical for complex problems.

3.2.1 Two-index Capacitated Vehicle Routing Problem

The CVRP is modelled according to the two-index vehicle-flow as follows [30]:

Parameters:

Set of Customers, indexed by i an j	$\mathcal{C} = \{1, ..., n\}$
Set of locations, where 0 and $n+1$ is the depot	$\mathcal{N} = \mathcal{C} \cup \{0, n+1\}$
Number of vehicles in fleet	K
Capacity of vehicle	Q
Cost of driving from i to j	c_{ij}
Demand of customer i	q_i

Decision variables:

$$x_{ij} = \begin{cases} 1, & \text{Route exist directly between customer } i \text{ and } j, \\ 0, & \text{No route is made.} \end{cases}$$

$$y_j = \text{Cumulative demand on route at place } j$$

Constraints:

$$\text{minimize} \quad \sum_{i=0}^{n+1} \sum_{j=0}^{n+1} c_{ij} x_{ij} \tag{3.1}$$

$$\text{subject to} \quad \sum_{\substack{j=1 \\ j \neq i}}^{n+1} x_{ij} = 1 \qquad i = 1, ..., n, \tag{3.2}$$

$$\sum_{\substack{i=0 \\ i \neq h}}^{n} x_{ih} - \sum_{\substack{j=1 \\ j \neq h}}^{n+1} x_{hj} = 0, \qquad h = 1, \ldots, n, \tag{3.3}$$

$$\sum_{j=1}^{n} x_{0j} \leq K, \tag{3.4}$$

$$y_j \geq y_i + q_j x_{ij} - Q\left(1 - x_{ij}\right), \qquad i, j = 0, \ldots, n+1, \tag{3.5}$$

$$q_i \leq y_i \leq Q, \qquad i = 0, \ldots, n+1, \tag{3.6}$$

$$x_{ij} \in \{0, 1\}, \qquad i, j = 0, \ldots, n+1. \tag{3.7}$$

The objective function of the CVRP is given by (3.1). This function aims to minimize the sum of the total costs to travel between locations. Note that in this variant of the model, only the costs to travel are taken into account, whereas a multi-objective function provides additional possibilities for defining and solving problems [31]. Constraints (3.2) make sure that every customer is visited exactly once. The next constraints (3.3) guarantee that once a vehicle arrives at a certain node h, the vehicle also leaves the node again. This way a correct flow of the vehicles is achieved. Constraints (3.4) limit the number of routes that are constructed to the number of vehicles that are in the fleet. Because this model takes into account vehicle capacity, the following two constraints are needed. Constraints (3.5 and 3.6) ensure that capacity is not exceeded. Additionally, constraints (3.5) guarantee that no sub-tours, routes that do not pass the depot, exist. There are other ways to model this, however, this variant of the model makes sure that computation time is kept at a minimum with a high number of locations [32]. The last constraints (3.7) define the variables.

3.2.2 Three-index capacitated vehicle routing problem

The three-index vehicle-flow formulation is the basis for the other models described in this chapter. The model is as follows [33]:

Parameters:

Number of vehicles	$\mathcal{K} = 1, \dots, K$
Number of location, where 0 is the central depot	$\mathcal{N} = \{0, \dots, n\}$
Capacity of vehicle k	b_k
Demand of customer i	q_i
Cost of driving from i to j	c_{ij}

Decision variables:

$$y_{ik} = \begin{cases} 1, & \text{if order from customer } i \text{ is delivered by vehicle } k, \\ 0, & \text{otherwise.} \end{cases}$$

$$x_{ijk} = \begin{cases} 1, & \text{if vehicle } k \text{ drives directly from customer } i \text{ to customer } j, \\ 0, & \text{otherwise.} \end{cases}$$

Constraints:

$$\text{minimize} \quad \sum_{ijk} c_{ij} x_{ijk} \tag{3.8}$$

$$\text{subject to} \quad \sum_{i} q_i y_{ik} \leq b_k, \qquad k = 1, \dots, K \tag{3.9}$$

$$\sum_{k} y_{ik} = \begin{cases} K, & \text{if, } i = 0 \\ 1, & \text{if, } i = 1, \dots, n \end{cases} \tag{3.10}$$

$$\sum_{i} x_{ijk} = y_{jk}, \qquad \begin{array}{l} j = 0, \dots, n \\ k = 1, \dots, K \end{array} \tag{3.11}$$

$$\sum_{j} x_{ijk} = y_{ik}, \qquad \begin{array}{l} i = 0, \dots, n \\ k = 1, \dots, K \end{array} \tag{3.12}$$

$$\sum_{ij \in SxS} x_{ijk} \leq |S| - 1, \qquad \begin{array}{l} S \subseteq \{1, \dots, n\} \\ 2 \leq |S| \leq n-1 \\ k = 1, \dots, K \end{array} \tag{3.13}$$

$$y_{ik}, x_{ijk} \in \{0, 1\}, \qquad \begin{array}{l} i = 0, \dots, n \\ j = 0, \dots, n \\ k = 1, \dots, K. \end{array} \tag{3.14}$$

In this model composed by Fisher & Jaikumar in 1981, the main decision variable takes into account which vehicle is travelling the route [33]. Note that in this model the vehicle fleet can be heterogeneous, which means vehicles can have different capacities. In this formulation the objective function is the same as before, namely to minimize the cost of driving the computed routes. Constraints (3.9)&(3.10) ensure that every vehicle starts and ends at the depot, that all customers are visited exactly once and that the capacity constraint is not exceeded. The constraints from (3.11)-(3.14) are constraints from a travelling salesman problem for all customers that are visited by vehicle k.

3.3 VRP with time windows

A VRPTW is used when customers have to be visited at certain times. Time windows are categorized as either hard or soft. A hard constraint indicates that the solution is infeasible if the time window is not met. Contrary, a soft time constraint means that the time window is not needed for feasibility, but is desirable if possible. An example of a problem including time windows is the delivery of drugs to patients for use at home as shown in the article of Lui et al. [34]. The two-index vehicle-flow model shown at the beginning of Section 3.2 can easily be extended to be a model that includes time windows. The same holds for the second model in Section 3.2.2, only the decision variables differ. The following lines have to be added to the models:

Parameters:

Earliest time that service is allowed to start at location i	w_i^a
Latest time that service is allowed to start at location i	w_i^b
Time that service starts at location i	w_i
Service time at location i	s_i
Travel time from location i to j	t_{ij}

Constraints:

$$w_j \geq w_i + (s_i + t_{ij})\,x_{ij} - M_{ij}\,(1 - x_{ij}), \qquad i = 0,\dots,n; \quad j = 1,\dots,n+1, \tag{3.15}$$

$$w_i^a \leq w_i \leq w_i^b, \qquad i = 0,\dots,n+1, \tag{3.16}$$

M_{ij} is a large value, which is defined as $M_{ij} = max\{w_i^b - w_j^a, 0\}$.

The constraints (3.15 and 3.16) make sure that the service at the location of the customer is taking place within a certain time window.

3.4 VRP with multiple depots

There are often multiple depots present from which a service is delivered. If multiple depots are present in the VRP, it is considered a MDVRP. The complexity of the model becomes larger if multiple depots are present. The MDVRP can be divided into two stages [35]. The first stage is assigning clients to the depots, and then the optimal routes with this configuration are constructed. The assignment of clients is partially chosen as the closest depot to the client, the clients that are around the same distance away from two depots are assigned in the algorithm to solve the VRP. The article of Lim and Wang shows that ideally these two stages are solved simultaneously, this way a close-to-optimal solution is obtained with less computation time [36]. Articles are proposed where the possibilities are discussed to use the depots as intermediate depots, where vehicles are replenished while being on a route [37]. An example where the MDVRP is applied is given in the article of Tohidifard et al. [38]. In this study, a home care routing problem is presented. Along with the multi-depot characteristic, other complexities such as time windows are also present in this problem.

Golden et al. [39] describes the classical MDVRP. This model is slightly modified in the article of Ramos et al. [40]. The model is very similar to the 3-index CVRP, the changes and extra constraints are given below. Some parameters are given different letters for the sake of consistency in this thesis.

Parameters

Set of nodes from customers	$\mathcal{V}_c = \{1,\dots,n\}$
Set of nodes from depots	$\mathcal{V}_d = \{n+1,\dots,n+w\}$
Subset of vehicles belonging to depot d	$\mathcal{K}_i$

Constraints:

Minimize
$$\sum_{ijk} x_{ijk} c_{ijk} \tag{3.17}$$

Subject to
$$\sum_{j \in V_c} x_{ijk} \leq 1 \qquad \forall k \in \mathcal{K}_i, \quad \forall i \in \mathcal{V}_d \tag{3.18}$$

$$\sum_{i \in \mathcal{V}_c} x_{ijk} \leq 1 \qquad \forall k \in \mathcal{K}_j, \quad \forall j \in \mathcal{V}_d \tag{3.19}$$

$$\sum_{i \in \mathcal{V}_c} x_{ijk} = 0 \qquad \forall j \in \mathcal{V}_d, \quad \forall k \notin \mathcal{K}_j \tag{3.20}$$

$$\sum_{j \in \mathcal{V}_c} x_{ijk} = 0 \qquad \forall i \in \mathcal{V}_d, \quad \forall k \notin \mathcal{K}_i \tag{3.21}$$

(3.22)

The constraints (3.18-3.19) guarantee that each vehicle leaves and returns to its home depot at most once. The constraints (3.20-3.21) make sure a vehicle can not leave its home depot and return to a different depot, preventing vehicles from crossing to other depots.

3.5 VRP with multiple commodities

It is not always the case that only one type of demand is transported. A VRP can cover a wide range of issues, including a problem with multiple commodities. Sometimes these commodities are not compatible, which means the commodities can not be transported in the same vehicle. There are often multiple compartments in vehicles that carry different goods at the same time. An example is cooled and heated compartments with frozen food and regular food. This type of VRP is called a multi-compartment VRP (MCVRP) [41]. When vehicles can transport different commodities simultaneously, the customer's demands of all commodities can be aggregated into a single demand. The demands of the various commodities can be normalized into vehicle capacity units. Consequently, the remaining VRP is a single-commodity VRP [42]. If this is not the case, a MCVRP is used.

Extra constraints are added to the base model given in Section 3.2.2 to account for the MCVRP [41].

Parameters:

Set of nodes, where 0 is the depot	$\mathcal{N}$
Set of customers	$\mathcal{C}$
Set of products	$\mathcal{M} = 1, \dots, m$
Capacity for product m	Q_m
Demand for product m by customer i	q_{im}

Decision variables

$$y_{jkm} = \begin{cases} 1, & \text{if customer } j \text{ receives product } m \text{ from vehicle } k, \\ 0, & \text{otherwise.} \end{cases}$$

Constraints:

$$\text{Minimize} \quad \sum_{ijk} x_{ijk} c_{ijk} \tag{3.23}$$

$$\text{Subject to} \quad y_{jkp} \leq \sum_{i \in \mathcal{N}} x_{ijk} \qquad \forall j \in \mathcal{C}, \quad \forall k \in \mathcal{K}, \quad \forall m \in \mathcal{M}, \tag{3.24}$$

$$\sum_{k \in \mathcal{K}} y_{jkm} = 1 \qquad \forall j \in \mathcal{C}, \quad \forall m \in \mathcal{M}, \tag{3.25}$$

$$\sum_{j \in \mathcal{C}} y_{jkm} q_{jm} \leq Q_m \qquad \forall k \in \mathcal{K}, \quad \forall m \in \mathcal{M}, \tag{3.26}$$

$$y_{jkm} \in \{0, 1\} \qquad \forall j \in \mathcal{C}, \quad \forall k \in \mathcal{K}, \quad \forall m \in \mathcal{M}, \quad q_{jm} \neq 0. \tag{3.27}$$

In this model, a new decision variable is introduced, y_{jkm} is one if the customer receives a certain product from vehicle k and is zero otherwise. Constraints 3.24 set y_{jkm} to zero for every product if a vehicle does not visit the customer. Constraints 3.25 make sure that a product ordered by a customer is brought by a single vehicle. Constraints 3.26 are capacity constraints for the compartments in vehicles. Last, constraints 3.27 define the binary variables y_{jkm}.

3.6 VRP with pickup and delivery

Another instance representing a real-life issue is the VRP with pickup and delivery (VRPPD). In this case, there is a pickup point and a different delivery location [43]. A certain demand should be transported between these two points, this demand can be goods, but also persons. In the case of the transportation of persons, the VRPPD is often referred to as a DARP. In literature, three kinds of VRPPD are differentiated [44].

- VRP with backhauls (VRPB) [45]
  All deliveries must be completed before the pickup services can be started.
- VRP with mixed delivery (VRPMDP)
  A node can be either a delivery or a pickup node, but not both.
- VRP with simultaneous pickup and delivery (VRPSDP)
  Both delivery and pickup services can be performed at the same node.

An example of a VRPPD is encountered in the soft drink industry [46]. Full bottles have to be transported to supermarkets. While empty bottles should be transported in the other direction, from supermarket to depots.

The extra constraints that need to be added to the VRPTW from Section 3.3 are the following [43]:

Parameters:

Set of pickup nodes	$\mathcal{P} = \{1, \ldots, n\}$
Set of delivery nodes	$\mathcal{D} = \{n+1, \ldots, 2n\}$
Set of pickup & delivery nodes	$\mathcal{N} = \mathcal{P} \cup \mathcal{D}$
Origin depot of vehicle k	$o(k)$
Destination depot of vehicle k	$d(k)$

Constraints:

$$\text{Minimize} \quad \sum_{ijk} x_{ijk} c_{ijk} \tag{3.28}$$

$$\text{Subject to} \quad \sum_{k \in K} \sum_{j \in \mathcal{N}_k \cup \{d(k)\}} x_{ijk} = 1 \qquad \forall i \in \mathcal{P}, \tag{3.29}$$

$$\sum_{j \in \mathcal{N}_k} x_{ijk} - \sum_{j \in \mathcal{N}_k} x_{j,n+i,k} = 0 \qquad \forall k \in \mathcal{K}, \quad i \in \mathcal{P}_k, \tag{3.30}$$

$$\sum_{j \in \mathcal{P}_k \cup \{d(k)\}} x_{o(k),j,k} = 1 \qquad \forall k \in \mathcal{K}, \tag{3.31}$$

$$\sum_{i \in \mathcal{N}_k \cup \{o(k)\}} x_{ijk} - \sum_{i \in \mathcal{N}_k \cup \{d(k)\}} x_{j,i,k} = 0 \qquad \forall k \in \mathcal{K}, \quad j \in \mathcal{N}_k, \tag{3.32}$$

$$\sum_{i \in \mathcal{D}_k \cup \{o(k)\}} x_{i,d(k),k} = 1 \qquad \forall k \in \mathcal{K}, \tag{3.33}$$

$$w_{ik} + t_{i,n+i,k} \leq w_{n+i,k} \qquad \forall k \in K, \quad i \in P_k. \tag{3.34}$$

Constraints (3.29&3.30) ensure that every request is served exactly once and by the same vehicle. Constraints (3.31-3.33) guarantee that every vehicle starts at its origin depot and ends its route at its destination depot. The pickup node should be visited before the delivery node, therefore the final constraints (3.34) are constructed.

3.7 DARP

As mentioned in Section 3.6, the DARP is a special case of a vehicle routing problem, where persons are transported as opposed to goods. The literature review of Ho et al. [47] shows the extensive amount of papers that are published regarding DARPs. DARPs often arise in the management of transportation systems for elderly and disabled people. Due to the ageing of the population, it is expected that these services will gain importance in the coming years [48]. The DARP represents a generalisation of other vehicle-routing problems, such as the VRPPD and the VRPTW, the main difference being the human perspective in the DARP. In the DARP user inconvenience is often taken into consideration [49]. The user experience is balanced against the minimization of operating costs. Additionally, capacity constraints are usually stricter in the DARP whereas often redundant in VRPPD. For instance, the delivery of letters is an example where capacity constraints are not applicable.

DARPs are distinguished into two categories the static and dynamic variants. In the static case, the requests for transportation are known beforehand, whereas in contrast in the dynamic case, the requests are revealed during the day. In the dynamic case, the routes can be adjusted in real-time to meet the demand that is occurring. In the case of the RGV, the requests are known beforehand, so a static DARP is present. The model formulation is given below [50]:

Parameters:

Set of pickup nodes	$\mathcal{P} = \{1, \ldots, n\}$

Set of delivery nodes	$\mathcal{D} = \{n+1, \ldots, 2n\}$
Total set of nodes, where 0 & $2n+1$ are the origin & destination depots respectively	$\mathcal{N} = \mathcal{P} \cup \mathcal{D} \cup \{0, 2n+1\}$
Load of a vehicle k	l_k
Ride time of a client i with vehicle k	r_{ik}
Maximum time vehicle k can be on one route	T_k
Maximum time a client can be on a route	L

Constraints:

$$\text{Minimize} \quad \sum_{ijk} x_{ijk} c_{ijk} \tag{3.35}$$

$$\text{Subject to} \quad \sum_{k \in \mathcal{K}} \sum_{j \in \mathcal{N}} x_{ijk} = 1 \qquad \forall i \in \mathcal{P}, \tag{3.36}$$

$$\sum_{i \in \mathcal{N}} x_{0ik} = \sum_{i \in \mathcal{N}} x_{i,2n+1,k} = 1 \qquad \forall k \in \mathcal{K}, \tag{3.37}$$

$$\sum_{j \in \mathcal{N}} x_{ijk} - \sum_{j \in \mathcal{N}} x_{n+i,j,k} = 0 \qquad \forall i \in \mathcal{P}, \quad \forall k \in \mathcal{K}, \tag{3.38}$$

$$\sum_{j \in \mathcal{N}} x_{jik} - \sum_{j \in \mathcal{N}} x_{i,j,k} = 0 \qquad \forall i \in \mathcal{P} \cup \mathcal{D}, \quad \forall k \in \mathcal{K}, \tag{3.39}$$

$$w_{jk} \geq (w_{ik} + s_i + t_{ij}) x_{ijk} \qquad \forall i, j \in \mathcal{N}, k \in \mathcal{K}, \tag{3.40}$$

$$l_{jk} \geq (l_{ik} + q_j) x_{ijk} \qquad \forall i, j \in \mathcal{N}, k \in \mathcal{K}, \tag{3.41}$$

$$r_{ik} \geq w_{n+i,k} - (w_{ik} + s_i) \qquad \forall i \in \mathcal{P}, \quad \forall k \in \mathcal{K}, \tag{3.42}$$

$$w_{2n+1,k} - w_{0k} \leq T_k \qquad \forall k \in \mathcal{K}, \tag{3.43}$$

$$w_i^a \leq w_{ik} \leq w_i^b \qquad \forall i \in \mathcal{N}, \quad \forall k \in \mathcal{K}, \tag{3.44}$$

$$t_{i,n+i} \leq r_{ik} \leq L \qquad \forall i \in \mathcal{P}, \quad \forall k \in \mathcal{K}, \tag{3.45}$$

$$max\{0, q_i\} \leq l_{ik} \leq min\{Q_k, Q_k + q_i\} \qquad \forall i \in \mathcal{N}, \quad \forall k \in \mathcal{K}, \tag{3.46}$$

$$x_{ijk} \in \{0, 1\} \qquad \forall i, j \in \mathcal{N}, \quad \forall k \in \mathcal{K}. \tag{3.47}$$

The objective function minimizes the total routing costs. Constraints (3.37&3.39) make sure that each request is served once and by the same vehicle, while constraints (3.38&3.40 ensure that the vehicle starts and ends at the depot. Next, constraints (3.41-3.43) set the service times, the load of the vehicle and the ride times of clients, respectively. Last, constraints (3.44-3.47) guarantee that these constraints will be feasible.

3.8 Solving VRPs

This section discusses the literature regarding the various methods to solve VRPs. Exact methods are examined in Section 3.8.1. Section 3.8.2 analyzes the use of constructive heuristics, and Section 3.8.3 discusses improvement heuristics.

3.8.1 Exact methods

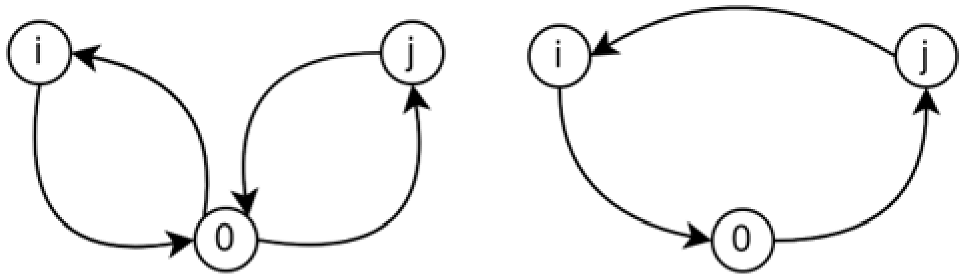
When trying to solve VRPs, the size of the solution space determines if a problem can be optimally solved. Only small instances of the DARP are solvable in polynomial time [49]. According to the book of Laporte et al., [51] problems with around a hundred customers or less can be solved exactly. An example of an exact method to solve a VRP is given in the article of Ibramhim et al. [52]. The branch-and-cut method is the most common exact-solving method in the literature.

The branch-and-cut method is a combination of a branch and bound method and the cutting plane method. The concept of this method is to find the relaxation of the ILP and set that value as a global lower bound. If the resulting solution is not an integer solution, a branching procedure is started around one of the fractional variables of the relaxed outcome. Two branches are created by adding additional constraints ensuring that the variable is either larger or smaller than its fractional value. By branching the problem is divided into smaller problems. The branches that are constructed are again solved by relaxing the ILP. If a lower bound found by relaxing the ILP of a sub-problem is higher than the best integer solution thus far, the branch is pruned. By repeating this process eventually an optimal solution is found.

3.8.2 Constructive heuristic

Real-life problems are often bigger and higher in complexity, therefore heuristics are used to construct solutions that are close to optimal. Heuristics are composed of construction and improvement procedures [51]. A constructive heuristic is used to provide a starting position for improvement heuristics. Most metaheuristics can be initialized from any feasible solution, therefore constructive heuristics are falling into disuse.

One constructive heuristic is the Clarke and Wright savings heuristic [53]. This heuristic is a very simple method to establish a starting solution. The heuristic starts by constructing routes from the depot to a customer and back, this is done for every customer. From 0 (depot) to i and back to the depot, $(0, i, 0)$. These routes are then merged, $(0, i, 0)$ and $(0, j, 0)$ become $(0, i, j, 0)$. This procedure is illustrated in Figure 3.2. The savings of this route are determined by the following formula where $c =$ costs of the route and $s =$ saving of merging routes, $s_{ij} = c_{0i} + c_{j0} - c_{ij}$. A list is made where the highest amount of savings is the top value and the lowest amount of savings is the lowest value. Then from the top combination of the list, every possible value is merged if possible with the constraints. This gives a fast and easy method to establish an initial solution.



(a) Initial state **(b)** Merged state

Figure 3.2: Clark & Wright savings heuristic concept

3.8.3 Improvement heuristics

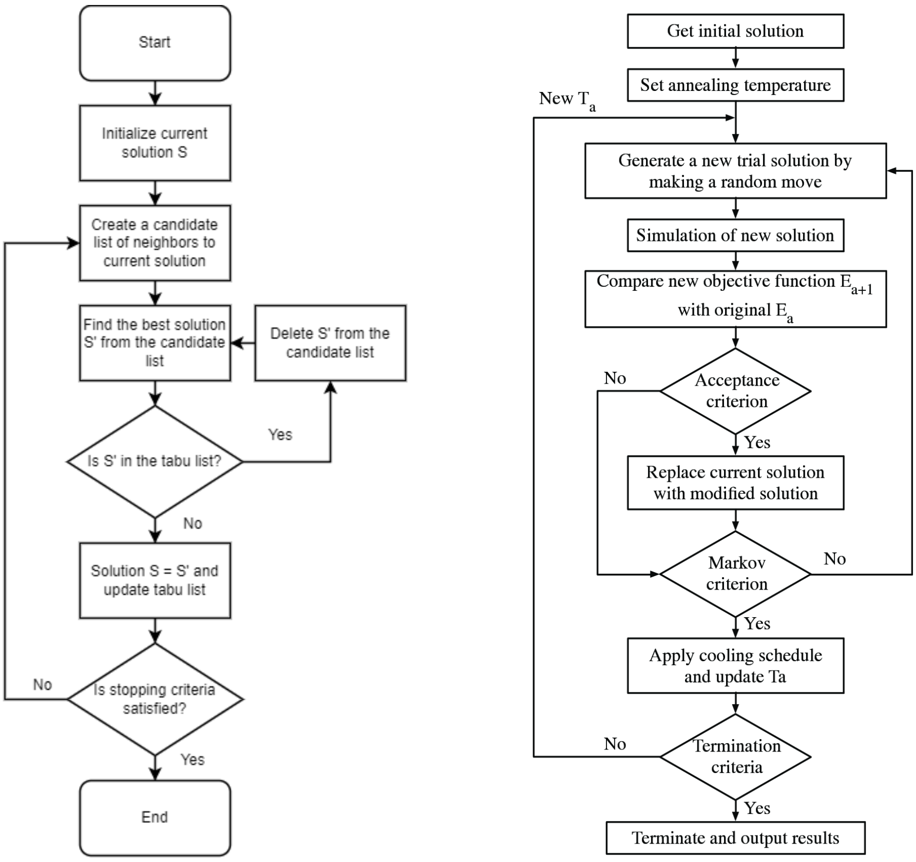
Once an initial starting solution is found, improvement heuristics can be used to find better solutions. Ho et al. [47] present various metaheuristics for DARPs. As Tabu search, Simulated annealing and Large neighbourhood search are the most common single-solution-based methods, a short description of these methods is given in this section [54].

Tabu Search

Tabu search is a metaheuristic that starts with a solution and explores a subset of the neighbour solutions. The best solution from that subset is taken as the next solution to search from. A list of recent solutions is recorded, this way revisiting recent solutions is avoided. Tabu search can escape local optima by allowing the acceptance of non-improving solutions. This characteristic enables the algorithm to explore a larger search space and potentially discover better solutions. The flowchart of this algorithm can be found in Figure 3.3a.

Simulated annealing

Simulated annealing is a stochastic local search metaheuristic. It is inspired by the physical process of annealing. A neighbor solution is selected and checked if it is better than the best solution. To avoid local optima the algorithm accepts worse solutions with a certain probability. This probability is decreasing over the time of the run. At the end of the run, the best-found solution is returned. Figure 3.3b illustrates the flowchart of the algorithm of simulated annealing.

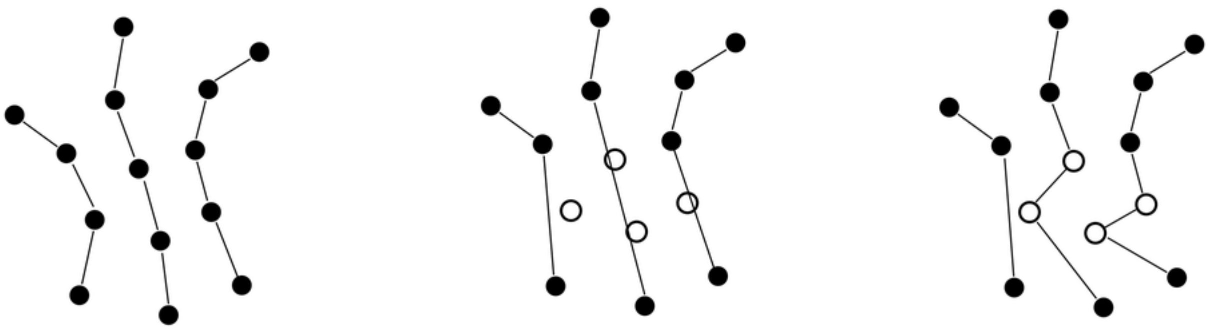


(a) Tabu search algorithm [55] **(b)** Simulated annealing algorithm [56]

Figure 3.3: Metaheuristics

Large neighbourhood search

In a large neighbourhood search, part of the solution is destroyed and then repaired again by insertion heuristics. Whether the created solution is chosen or not, is determined by implementing the principles of simulated annealing. The changes that are made to the current solution are larger than with typical neighbourhood operators. The large neighbourhood search allows for larger parts of the solution space to be explored more easily. Figure 3.4 illustrates the concept of the large neighbourhood search.



(a) Initial state **(b)** Destroyed state **(c)** Repaired state

Figure 3.4: Concept of a large neighbourhood search

3.9 Context of RGV

The number of publications regarding VRPs has increased significantly in the last years [57]. VRPs can differ a lot in characteristics. Because the literature on VRPs is so extensive and diverse, many taxonomy reviews are written [58] [57] [59] [60] [3] [61]. In these taxonomies, various characteristics are made to classify certain articles. The article of Eksioglu et al. [57] is the starting point of a very well-defined taxonomy overview. In 2015, the article of Lahyani et al. [3] expanded this overview into a taxonomy where researchers could search for the characteristics of their problem and could analyze the literature accordingly. We use the taxonomy of Lahyani et al. [3] to place the context of the RGV in the current literature. Figure 3.5 illustrates the various characteristics of the taxonomy. The characteristics of the context of this project are given in red.

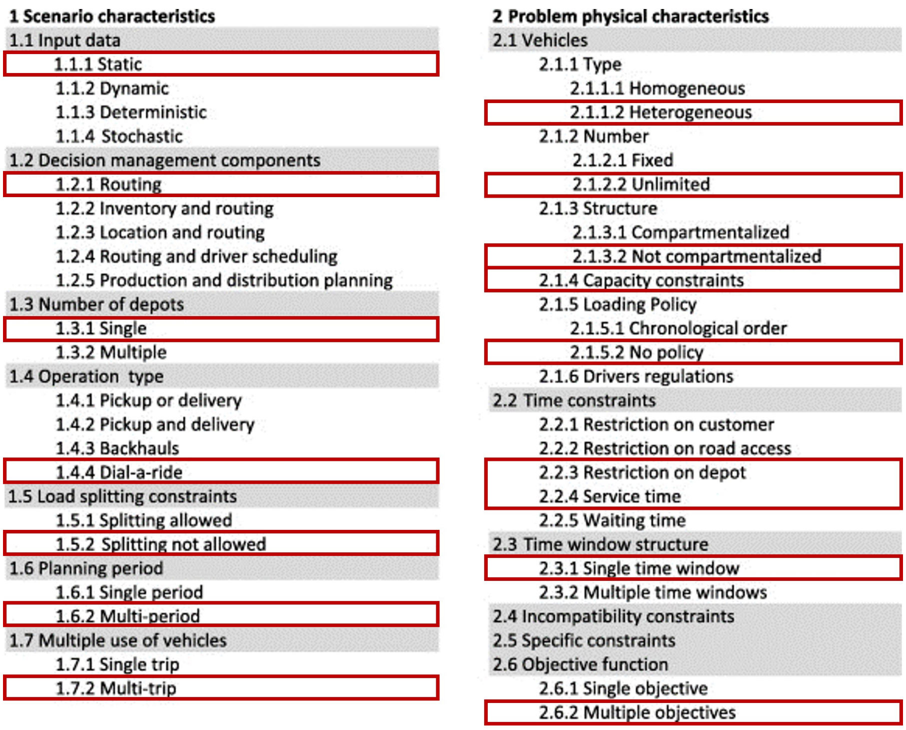


Figure 3.5: The taxonomy used in the article of Lahyani et al. with the characteristics of the context of this project [3].

In the format made by Lahyani et al. [3] the characteristics of the situation are filled in to examine if there is literature about similar situations. When doing so for the context of the RGV, no articles are shown, so no literature exists for situations with the same characteristics.

3.10 Similar problems to context of social care services

The situation in the RGV is considered a DARP problem because the transportation is based on persons. Real-life problems are nearly always a combination of various types of VRPs. This section will focus on examining literature that is similar to the context of the RGV. Table 3.1 displays articles with similar problems to the situation in this thesis.

Articles are found using the taxonomy of Lahyani et al. [3]. Additionally, articles are found using Google Scholar and Scopus with a combination of the following search terms: *VRP, Dial-a-ride-problem, Pickup-and-delivery, Time-windows, Capacity, Multi-trip, and heterogeneous users/vehicles.*

Gaul et al. [62] presents a DARP with a static format. The context of the RGV is also a static one. Predetermined requests of origin-destination transport are assigned to a heterogeneous fleet of vehicles. In this instance, all requests have fixed time windows, which can be denied if they can not be met in a reasonable time or at reasonable costs. In the context of the RGV, it is not possible to deny requests. Their case study was based on a public transportation service in a German city. Their solution approach was solved using a standard IP-solver.

In DARPs, there is a trade-off between minimizing costs and maximizing service quality [63]. Multiple attributes contribute to the service quality of clients. The most commonly used is the waiting time between expected arrival and real arrival. Paquette et al. [48] showed a DARP with a common depot. This problem aims to plan a set of minimum-cost vehicle routes and maintain a high level of service quality. While satisfying all/as many requests as possible and being compliant with additional constraints. In the article, a general model is given, which is solved using tabu search. The main difference with the context of the RGV is that not all requests are completely known. Clients receive care at certain locations, however, determining the most convenient location is an allocation problem itself.

The article of Feillet et al. [64] presents another similar problem. Rather than focusing on the allocation of clients, time consistency is deemed important in this article. People with disabilities are transported almost daily to social care services centres. Because of their disabilities, the clients benefit from having a consistent service. Although the social care services are not necessarily daily in the RGV, the context of the article is similar to the problem the RGV is facing with a VRP for disabled people who need transport to and from social care services facilities. A large neighbourhood search heuristic was used to address this issue.

Instead of individual care providers creating routes, horizontal cooperation could bring benefits to dial-a-ride services. Horizontal cooperation means that care providers can share rides, making centralized planning possible. The article of Molenbruch et al. [65] explains a large neighbourhood search to solve a DARP that incorporates horizontal cooperation.

An extensive amount of articles is written on DARPs, including some specifically for disabled people who need to transfer to social care services facilities. However, in all static DARP articles, the origin of the request is determined and the destination of the request is known. No articles were found, with multiple possible destinations for one customer. This is the case in the context of the RGV as clients could potentially receive care from various care providers. The decision of which care provider to allocate the client to is integrated into the model in Chapter 4.

3.11 Conclusion

An extensive amount of literature is present on the VRP. Various formulations for different versions of the problem are known and described in the literature. The version of the VRP that is most similar to the context of the RGV is a DARP, a version that includes the transportation of persons. The situation in the RGV contains a combination of CVRP, VRPTW, MCVRP and VRPPD. The assignment of clients to care providers can be compared to the assignment of clients to depots in the MDVRP. So the theory on MDVRP is considered as well. As most DARPS and VRPs are NP-hard there is no guarantee that an exact solution is found in a reasonable time, therefor the use of heuristics is widely considered in the literature. Large neighbourhood search, tabu search and simulated annealing all provided suitable solutions for a wide variety of problems and could be used in the context of the RGV.

Table 3.1: Overview of the characteristics found in Darp literature compared to the situation of the RGV

Authors	Subject	Solving method	Problem characteristics									
			Time windows	Data type	Problem Size	Type of requests	Depots	Planning period	Capacity constraints	Type of fleet	Users	Objective function
Gaul et al. (2022) [62]	Ride-pooling case study in a German city	Standard IP solver	On pickup and delivery	Real	40	Static (can be denied)	Single	Single	On vehicles	Homogeneous	Homogeneous	Distance and user experience (waiting time)
Paquette et al. (2013) [48]	Dial a ride services for people with reduced mobility in Montreal	Tabu search	On origin for inbound and on destination for outbound. Including driver breaks	Real and fictional	900	Static	Single	Single	On vehicles	Heterogeneous	Homogeneous	Distance and quality of service (ride time/waiting time)
Malheiros et al. (2021) [66]	Uses a combination of Meta-heuristic and exact methods to solve a fictional DARP	Local search with set partitioning approach	On pickup and delivery	Fictional	192	Static	Multi	Single	On vehicles	Heterogeneous	Homogeneous	Minimizing travel costs
Detti et al. (2017) [67]	Italian non-emergency hospital patients transport,	Tabu search and VNS	On pickup and delivery	Real	200	Static	Multi	Single	On vehicles (Some users need specific vehicles)	Heterogeneous	Heterogeneous	Travel costs, ride time and waiting time
Feillet et al. (2014) [64]	This article proposes a way to incorporate time-consistency for each day	LNS	On pickup and delivery, with consistency for each day	Modified real instances	65	Static	Single	Multi	On vehicles	Homogeneous	Homogeneous	Travel costs, Variability of routes between periods
Molenbruch et al. (2017) [65]	Horizontal cooperation of routes is incorporated in this DARP	LNS	On origin for inbound and on destination for outbound	Fictional	200	Static	Single and Multi	Single	On vehicles	Heterogeneous	Homogeneous	Minimizing travel costs
Molenbruch et al. (2017) [68]	Patient transportation	Local search	On pickup and delivery	Real	1300	Static	Single	Single	On vehicles	Homogeneous	Heterogeneous (Some users cannot be transported together)	Travel costs, demand satisfaction and service level
Melachrinoudis et al. (2007) [69]	Client transport for healthcare organizations	Branch and Bound	Soft time windows	Real	4	Static	Multi	Multi	On vehicles	Homogeneous	Homogeneous	Travel costs, customer inconvenience time
Gschwind et al. (2015) [70]	No direct practical implication	Branch-and-cut-and-price	Dynamic time windows	Fictional	96	Static	Single	Single	On vehicles	Homogeneous	Homogeneous	Travel costs
Zhang et al. (2015) [71]	Patient transportation for a hospital in Hong Kong	Memetic algorithm with extra variables for multi-trip	Time windows	Real	185	Static	Single	Single	On vehicles	Homogeneous	Homogeneous	Travel costs and number of unserved requests
Seixas et al. (2012) [72]	No direct practical implication	Column generation with four index variable for multi-trip	Time windows	Fictional	50	Static	Single	Single	On vehicles	Heterogeneous	Homogeneous	Travel costs
This thesis	Day care service transportation in the Netherlands	ILP solver and ALNS	On origin for inbound and on destination for outbound	Real	439	Static	Single	Multi	On vehicles (Some users need specific vehicles) and destinations	Heterogeneous	Heterogeneous	Multi

4 Model description

This chapter explains the construction of the models for the strategies that are investigated. Section 4.1 shows the investigated strategies. Section 4.2 describes the parameters and rules that are consistent for every strategy. Section 4.3 explains how the clients are distributed throughout the week. Section 4.4 is about the construction of various ILPs. Section 4.5 explains the constructive heuristic, where-after section 4.6 describes the adaptive large neighbourhood search (ALNS) algorithm.

4.1 Strategies

This section explains the three strategies that are investigated. The first strategy is the current strategy implemented in the RGV, which is explained in detail in Chapter 2. The other two strategies are strategies that the RGV could potentially implement. These strategies, named the horizontal cooperation strategy and the client allocation strategy, were formulated based on interviews with RGV employees.

4.1.1 Current strategy

The current strategy is explained in detail in Chapter 2. A summary of the strategy is given in this section.

Clients can choose their preferred care provider. Subsequently, the care providers are responsible for arranging the transportation of clients. Vehicles depart from the care provider, pick up/deliver the clients of that care provider, and then return to the care provider. Figure 4.1 illustrates a simplistic view of the strategy.

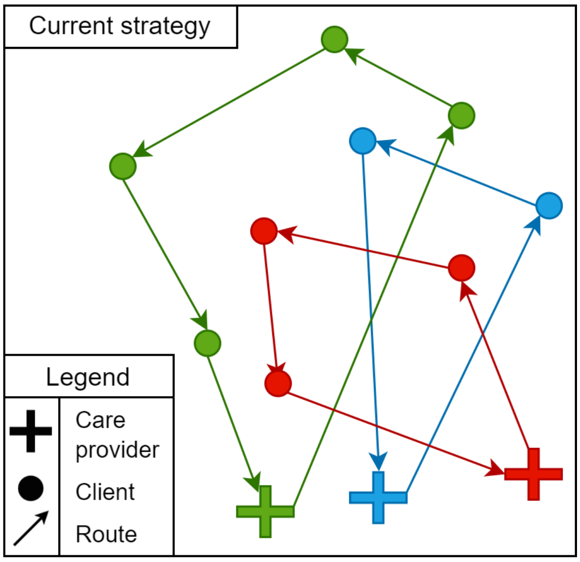


Figure 4.1: Current strategy of the transportation of clients to care providers.

4.1.2 Horizontal cooperation strategy

One of the strategies that the RGV is considering implementing is the strategy of ”horizontal cooperation”. This strategy involves care providers collaborating in the transportation of clients. This means a central vehicle depot is established, from which all routes will start. In this strategy, clients from different care providers can share a vehicle if this results in a more cost-effective route. From the client’s perspective, one aspect of the social care services changes; the transportation to the social care services is no longer managed by their care provider but will be arranged by a central vehicle depot. Figure 4.2 depicts what this strategy may look like compared to the current strategy.

In this strategy, routes from various healthcare providers can be combined, potentially offering optimization compared to the current strategy. This strategy could be particularly advantageous when care providers are located near each other, and the clients they serve also reside next to each other. In such a scenario, it may be possible to achieve the same pickups of clients with only one bus instead of two, potentially having a positive effect on the number of vehicles needed.

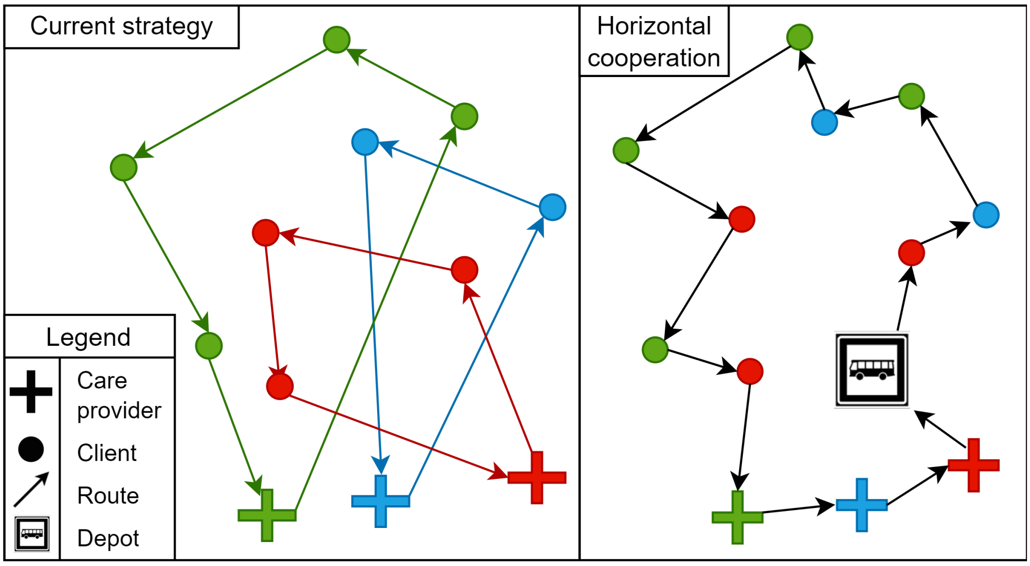


Figure 4.2: Strategy of horizontal cooperation for transportation of clients for daycare versus the current strategy.

4.1.3 Client allocation strategy

From the client's perspective, the strategy that imposes the most change to the current strategy is the strategy of client allocation. This strategy involves establishing a central vehicle depot and allows clients to be reassigned to another care provider. The care provider to which a client is allocated should have the capability to deliver the required type of care. Additionally, the care providers have a maximum number of clients that can be assigned to them due to their capacity. A potential advantage of this strategy is that clients can be assigned to a care provider that is located closer to their home. This would mean less distance travelled to transport a client to their care provider, potentially decreasing the average time clients spend in transit. However, this strategy comes with the drawback of limiting clients' freedom of choice. From the client's perspective, this strategy implies a substantial change, as not only will transportation change, but also the care provider delivering their care might change. Figure 4.3 illustrates what this strategy entails in comparison to the horizontal cooperation strategy.

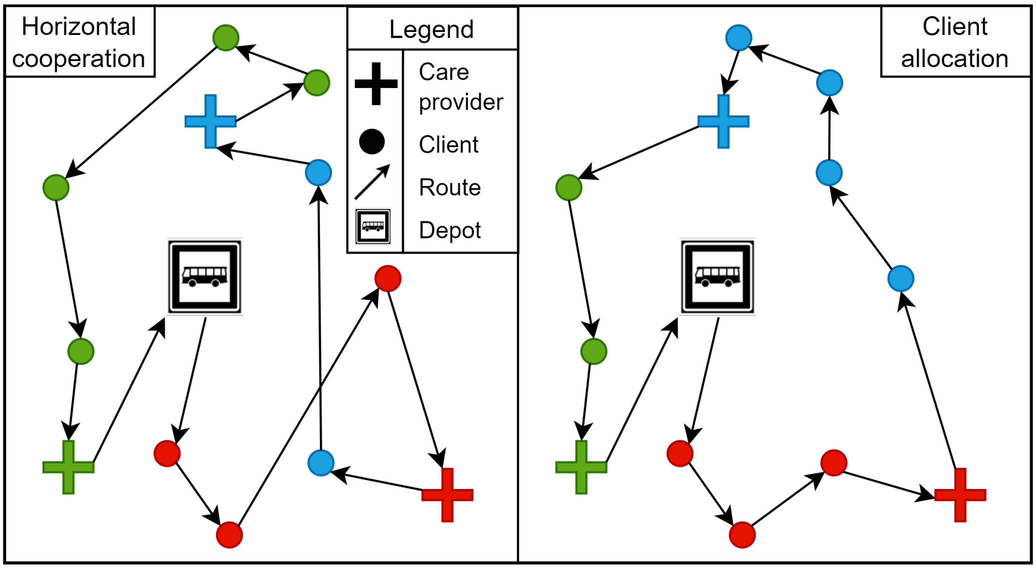


Figure 4.3: Strategy of horizontal cooperation compared to the strategy of client allocation.

4.2 Rules and regulations

This section discusses the rules and regulations to establish the models for every strategy. While most regulations are consistent across the strategies, some regulations vary in the strategies.

The following rules/assumptions apply to all strategies:

Client related rules

- Clients have a fixed residential address from which they need to be picked up and returned after the social care service.
- Each client has two transportation requests: one request from their residential address to their care provider and a second request from their care provider back to their residential address once the social care service is finished.

Every client is connected to four locations; A location for pickup at home, a location for delivery at the care provider, a location for pickup at the care provider and a location for delivery at home.

Care provider related rules

- Care providers have a fixed address from where they deliver the social care service.
- The opening times of care providers are fixed.

Vehicle related rules

- It is assumed that there is an unlimited amount of vehicles available.
- Each vehicle has a fixed capacity for seating clients.
- Each vehicle has a fixed capacity for wheelchair-bound clients.
- Each client occupies a fixed number of seats in the vehicle, depending on whether they are wheelchair-bound.
- Each client has a fixed boarding and disembarking time, depending on whether they are wheelchair-bound.
- There is a maximum duration that clients are allowed to spend in a vehicle during a single transport request.

Route related rules

- The possible arcs between locations are constant, which means the distances between these locations are also constant
- The travel speed is assumed to be constant, which means the travel time is directly linked to the distances between locations.

The most significant difference in rules between the strategies is the start location of the vehicles. In the current strategy, the vehicle depot is at the care providers, while in the horizontal cooperation and client allocation strategies, the vehicles come from a central depot. In current and horizontal cooperation strategies, clients have a fixed care provider. In the third strategy, the client is allocated to the care provider which results in the least total direct distance between clients and their care provider.

4.3 Allocating clients throughout the week

A client receives the social care service a fixed number of times per week. From the available data, it is not possible to determine the exact days a client receives the social care service. This section explains the choices made to address this issue.

Algorithm 1 describes how clients are assigned to the opening days of their care provider. A client can require multiple social care services per week. For each service, a day is randomly selected from the days their care provider is open. If the capacity of that day is exceeded or the client is already assigned to that day, an alternative day is chosen. This process is done for every client so that ultimately, each client is assigned a day for every instance they require the social care service.

Algorithm 1 Assign clients to a random day

```
for All clients do
    D ← Days that client is already assigned
    Empty D
    for Amount of days client goes to social care service do
        A ← Create a list of available days a client can go to social care service
        Empty A
        for Days that care provider is open do
            if Capacity of care provider is not exceeded then
                if Day is not in D then
                    Add day to A
                end if
            end if
        end for
        Assign client to random day from A
        Add assigned day to D
        Update the capacity of the care provider for the assigned day
    end for
end for
```

4.4 ILPs

This section describes the ILPs that are formulated for the various strategies. ILPs are formulated in an attempt to compute the optimal solution for the issue at hand.

4.4.1 Current strategy

The current strategy assumes that the vehicles depart from the care providers. Each care provider serves as a vehicle depot, creating a multi-depot VRP. However, since the care providers only pick up their clients, each care provider can be handled like a sub-problem. This results in the current strategy becoming a single-depot VRP.

The ILP for the current strategy is as follows:

Sets:

$i, j \in V$	Set of locations
$V^{Ph} = \{1, ..., n\} \subseteq V$	Locations where clients are picked up from home
$V^{Dcp} = \{n+1, ..., 2n\} \subseteq V$	Locations where clients are delivered to care provider
$V^{Pcp} = \{2n+1, ..., 3n\} \subseteq V$	Locations where clients are picked up from care provider
$V^{Dh} = \{3n+1, ..., 4n\} \subseteq V$	Locations where clients are delivered home
$V^{Dep} = \{4n+1\} \subseteq V$	Location of vehicles of care provider
$V^{Rest} = \{4n+2\} \subseteq V$	Location were vehicles can wait
$V^{P} = V^{Ph} \cup V^{Pcp}$	Set of pickup locations
$V^{D} = V^{Dh} \cup V^{Dcp}$	Set of delivery locations
$R_i = \{V_i^{Ph}, V_i^{Dcp}\} \cup \{V_i^{Pcp}, V_i^{Dh}\}$	Combination of pickup and delivery locations for every client i
$A = \{(i, j) : i, j \in V\}$	Arcs
$k \in K$	Set of vehicles
$r \in TR$	Set of transportation requests

Parameters:

n	Number of clients
S_i	Number of seats occupied by client i
SW_i	Number of wheelchair spaces occupied by client i
BT_i	Boarding/embarking time for client i

F	Maximum time a clients may spend in a vehicle
Q_k	Seating capacity of Vehicle k
QW_k	Wheelchair capacity of Vehicle k
$C_{i,j}$	Travel distance between location i and location j
$T_{i,j}$	Travel time between location i and location j
$[E_i, L_i]$	Time window at location i
M_{Load}	Big number for load constraint
M_{Time}	Big number for time constraint

For modelling purposes, separate parameters are used for V^{Pcp}, V^{Dcp}, V^{Dep} and V^{Rest}. However, in reality, these locations are all the location of the care provider.

Variables:

$q_i^k =$	Number of seating spaces occupied in vehicle k after location i
$qw_i^k =$	Number of clients in wheelchairs in vehicle k after location i
$u_i^k =$	Time vehicle k is at location i
$ur_r =$	Time a request r takes to complete
$wt^k =$	Waiting time at location V^{Rest} for vehicle k

Decision variables:

$$x_{i,j}^k = \begin{cases} 1, & \text{if vehicle k travels arc (i,j)} \\ 0, & \text{otherwise} \end{cases}$$

Objective function:

The objective function is to minimize the total distance travelled.

$$\text{Min} \quad \sum_{i,j \in A} \sum_{k \in K} C_{i,j} x_{i,j}^k$$

Restrictions:

Every pickup node should be visited exactly once

$$\sum_{k \in K} \sum_{j \in V} x_{i,j}^k = 1 \quad \forall i \in V^P \tag{4.1}$$

Every pickup and corresponding delivery should be visited by the same vehicle

$$\sum_{j \in V} x_{i,j}^k - \sum_{j \in V} x_{j,i+n}^k = 0 \quad \forall i \in V^P, \quad k \in K \tag{4.2}$$

Flow conservation, if a vehicle arrives at a location it should also leave that location

$$\sum_{i \in V} x_{i,j}^k - \sum_{i \in V} x_{j,i}^k = 0 \quad \forall j \in V, \quad k \in K \tag{4.3}$$

A vehicle can only start a maximum of one route from the depot

$$\sum_{j \in V} x_{i,j}^k \leq 1 \quad \forall i \in V^{Dep}, \quad k \in K \tag{4.4}$$

The load of a vehicle k at location j is equal to the load of last location i plus the demand of seats of last location i for seating and wheelchair-bound clients

$$q_j^k \geq q_i^k + S_i - M_{Load} * (1 - x_{i,j}^k) \quad \forall i,j \in A \quad k \in K \tag{4.5}$$

$$q_j^k \leq q_i^k + S_i + M_{Load} * (1 - x_{i,j}^k) \quad \forall i,j \in A \quad k \in K \tag{4.6}$$

$$qw_j^k \geq qw_i^k + SW_i - M_{Load} * (1 - x_{i,j}^k) \quad \forall i,j \in A \quad k \in K \tag{4.7}$$

$$qw_j^k \leq qw_i^k + SW_i + M_{Load} * (1 - x_{i,j}^k) \quad \forall i,j \in A \quad k \in K \tag{4.8}$$

The capacities of vehicles is not exceeded

$$0 \leq q_i^k \leq Q_k \quad \forall i \in V, \quad k \in K \tag{4.9}$$

$$0 \leq qw_i^k \leq QW_k \quad \forall i \in V, \quad k \in K \tag{4.10}$$

Vehicle loads at depots are zero

$$q_0^k = 0 \quad \forall k \in K \tag{4.11}$$

$$qw_0^k = 0 \quad \forall k \in K \tag{4.12}$$

Time at node i is equal to the last node plus driving time and service time plus a waiting time for arriving to the waiting location

$$u_j^k \geq u_i^k + T_{i,j} + BT_i - (M_{Time} * (1 - x_{i,j}^k)) \quad \forall i \in V^P \cup V^D \cup V^{Rest}, \quad j \in V^P \cup V^D, \quad k \in K \tag{4.13}$$

$$u_j^k \leq u_i^k + T_{i,j} + BT_i + (M_{Time} * (1 - x_{i,j}^k)) \quad \forall i \in V^P \cup V^D \cup V^{Rest}, \quad j \in V^P \cup V^D, \quad k \in K \tag{4.14}$$

$$u_j^k \geq u_i^k + T_{i,j} + BT_i + wt_{j,k} - (M_{Time} * (1 - x_{i,j}^k)) \quad \forall i \in V^P \cup V^D, j \in V^{Rest}, \quad k \in K \tag{4.15}$$

$$u_j^k \leq u_i^k + T_{i,j} + BT_i + wt_{j,k} + (M_{Time} * (1 - x_{i,j}^k)) \quad \forall i \in V^P \cup V^D, j \in V^{Rest}, \quad k \in K \tag{4.16}$$

Pickup of a client should happen before the delivery of the client

$$u_i^k \leq u_{i+n}^k \quad \forall i \in V^P, \quad k \in K \tag{4.17}$$

Time at care providers should be before the starting time of the social care service

$$E_i \leq u_i^k \leq L_i \quad \forall i \in V^{Dcp} + V^{Pcp}, \quad k \in K \tag{4.18}$$

Total time a transport request takes should be less than F

$$ur_i \geq u_i^k - u_{i+n}^k \quad \forall \quad i \in V^P \tag{4.19}$$

$$ur_i \leq F \quad \forall i \in V^P \tag{4.20}$$

Binary constraints

$$x_{i,j}^k \in \{0,1\} \quad \forall i,j \in A \quad k \in K \tag{4.21}$$

4.4.2 Horizontal cooperation

In the strategy of horizontal cooperation, a central vehicle depot is established from which all vehicles depart to transport the clients. This means the various care providers can no longer be treated as sub-problems. Thus, the complexity of this problem is greater than the current strategy. The ILP for horizontal cooperation shares many similarities with the ILP for the current strategy. In the current strategy, vehicles are constrained to wait at the location of the care provider. This modelling choice aligns with reality. In the horizontal cooperation strategy vehicles are able to wait at any location, provided there are no clients in the vehicle. If the waiting of vehicles was not modelled differently, both strategies could have been solved with the same model but with different input data.

The ILP for the horizontal cooperation strategy is as follows:

Sets:

$i,j \in V$	Set of locations
$V^{Ph} = \{1,...,n\} \subseteq V$	Locations where clients are picked up from home
$V^{Dcp} = \{n+1,...,2n\} \subseteq V$	Locations where clients are delivered to care providers
$V^{Pcp} = \{2n+1,...,3n\} \subseteq V$	Locations where clients are picked up from care providers
$V^{Dh} = \{3n+1,...,4n\} \subseteq V$	Locations where clients are delivered home
$V^{Dep} = \{4n+1\} \subseteq V$	Location of vehicles of care provider
$V^P = V^{Ph} \cup V^{Pcp}$	Set of pickup locations

$V^D = V^{Dh} \cup V^{Dcp}$	Set of delivery locations
$R_i = \{V_i^{Ph}, V_i^{Dcp}\} \cup \{V_i^{Pcp}, V_i^{Dh}\}$	Combination of pickup and delivery locations for every client i
$A = \{(i,j) : i,j \in V\}$	Arcs
$k \in K$	Set of vehicles
$r \in TR$	Set of transportation requests

Parameters:

n	Number of clients
S_i	Number of seats occupied by client i
SW_i	Number of wheelchair spaces occupied by client i
BT_i	Boarding/embarking time for client i
F	Maximum time a clients may spend in a vehicle
Q_k	Seating capacity of Vehicle k
QW_k	Wheelchair capacity of Vehicle k
$C_{i,j}$	Travel distance between location i and location j
$T_{i,j}$	Travel time between location i and location j
$[E_i, L_i]$	Time window at location i
M_{Load}	Big number for load constraint
M_{Time}	Big number for time constraint

Variables:

$q_i^k =$	Number of seating spaces occupied in vehicle k after location i
$qw_i^k =$	Number of clients in wheelchairs in vehicle k after location i
$u_i^k =$	Time vehicle k is at location i
$ur_r =$	Time a request r takes to complete
$wt_i^k =$	Waiting time at location i for vehicle k

$$y_i^k = \begin{cases} 1, & \text{if load of vehicle k at location i is bigger than zero} \\ 0, & \text{otherwise} \end{cases}$$

Decision variables:

$$x_{i,j}^k = \begin{cases} 1, & \text{if vehicle k travels arc (i,j)} \\ 0, & \text{otherwise} \end{cases}$$

Objective function:

The objective function is to minimize the total distance travelled.

$$\text{Min} \quad \sum_{i,j \in A} \sum_{k \in K} C_{i,j} x_{i,j}^k$$

Restrictions:

Every pickup node should be visited exactly once

$$\sum_{k \in K} \sum_{j \in V} x_{i,j}^k = 1 \quad \forall i \in V^P \tag{4.22}$$

Every pickup and corresponding delivery should be done by the same vehicle

$$\sum_{j \in V} x_{i,j}^k - \sum_{j \in V} x_{j,n+i}^k = 0 \quad \forall i \in V^P, \quad k \in K \tag{4.23}$$

Flow conservation if a vehicle arrives at a destination it should also leave that destination

$$\sum_{i\in V} x_{i,j}^k - \sum_{i\in V} x_{j,i}^k = 0 \quad \forall j \in V, \quad k \in K \tag{4.24}$$

A vehicle can start a maximum of one route from the depot

$$\sum_{j\in P} x_{i,j}^k \leq 1 \quad \forall i \in V^{Dep}, \quad k \in K \tag{4.25}$$

Load of a vehicle is equal to last node plus load at node j for both seating clients as wheelchair clients

$$q_j^k \geq q_i^k + S_i - M_{Load} * (1 - x_{i,j}^k) \quad \forall i,j \in A \quad k \in K \tag{4.26}$$
$$q_j^k \leq q_i^k + S_i + M_{Load} * (1 - x_{i,j}^k) \quad \forall i,j \in A \quad k \in K \tag{4.27}$$
$$qw_j^k \geq qw_i^k + SW_i - M_{Load} * (1 - x_{i,j}^k) \quad \forall i,j \in A \quad k \in K \tag{4.28}$$
$$qw_j^k \leq qw_i^k + SW_i + M_{Load} * (1 - x_{i,j}^k) \quad \forall i,j \in A \quad k \in K \tag{4.29}$$

Capacities of vehicles at Depot is zero

$$q_0^k = 0 \quad \forall k \in K \tag{4.30}$$

Capacities of vehicles is not exceeded

$$0 \leq q_i^k \leq Q_k \quad \forall i \in V, \quad k \in K \tag{4.31}$$
$$0 \leq qw_i^k \leq QW_k \quad \forall i \in V, \quad k \in K \tag{4.32}$$

Time at node i is equal to the last node plus driving time and service time plus a possible waiting time

$$u_j^k \geq u_i^k + T_{i,j} + BT_i + wt_i^k - (M_{Time} * (1 - x_{i,j}^k)) \quad \forall i \in V^P \cup V^D, j \in V, \quad k \in K \tag{4.33}$$
$$u_j^k \leq u_i^k + T_{i,j} + BT_i + wt_i^k + (M_{Time} * (1 - x_{i,j}^k)) \quad \forall i \in V^P \cup V^D, j \in V, \quad k \in K \tag{4.34}$$

The waiting time is zero if the load of the vehicle is not zero

$$y_i^k \leq q_i^k \quad \forall i \in V, \quad k \in K \tag{4.35}$$
$$y_i^k \geq q_i^k / Q_k \quad \forall i \in V, \quad k \in K \tag{4.36}$$
$$wt_i^k \leq M_{Time} * (1 - y_i^k) \quad \forall i \in V, \quad k \in K \tag{4.37}$$

Pickup of a client should happen before the delivery of the client

$$u_i^k \leq u_{n+i}^k \quad \forall i \in V^P, \quad k \in K \tag{4.38}$$

Time at care providers should be before starting time group

$$E_i \leq u_i^k \leq L_i \quad \forall i \in V^{Dcp} + V^{Pcp}, \quad k \in K \tag{4.39}$$

Total time a request r takes should be less than F

$$ur_i \geq u_{n+i}^k - u_i^k \quad \forall i \in V^P \tag{4.40}$$
$$ur_i \leq F \quad \forall i \in V^P \tag{4.41}$$

Binary constraints

$$x_{i,j}^k \in \{0,1\} \quad \forall i,j \in A \quad k \in K \tag{4.42}$$
$$y_i^k \in \{0,1\} \quad \forall i \in V \quad k \in K \tag{4.43}$$

4.4.3 Client allocation

The ILP described in Section 4.4.2 on the horizontal cooperation strategy is also used for the client allocation strategy. The difference between these two strategies is the input of clients. In the client allocation strategy, clients can be assigned to a different care provider, while complying with some constraints. These constraints include the capacity of the care provider and the type of care that should match between the client and the care provider. This allocation of clients to care providers is optimized before optimizing the routes using the

ILP of the horizontal cooperation strategy.

The following ILP minimizes the total distance between the clients and their respective care providers.

Sets:

$i \in I$	Set of clients
$j \in J$	Set of care providers

Parameters:

D_i	Number of days a client i receives care
O_j	Number of days a care provider j is open per week
T_i	Type of care a client i receives
T_j	Type of care a care provider j delivers
L_i	Type of law that client i falls under
L_j	Type of law that care provider j falls under
Q_j	Capacity of care provider j
$C_{i,j}$	Distance between client i and care provider j

$$y_{i,j} = \begin{cases} 1, & \text{if client i type of care matches care providers j type of care} \\ 0, & \text{otherwise} \end{cases}$$

$$z_{i,j} = \begin{cases} 1, & \text{if client i type of law matches care providers j type of law} \\ 0, & \text{otherwise} \end{cases}$$

Decision variables:

$$x_{i,j} = \begin{cases} 1, & \text{if client i is placed at care provider j} \\ 0, & \text{otherwise} \end{cases}$$

Objective function:

The objective is to minimize the total distance between care providers and clients, taking into account the number of times a client receives social care service per week.

$$\text{Min} \quad \sum_{i \in I} \sum_{j \in J} C_{i,j} * x_{i,j} * D_i$$

Restrictions:

Every client should be allocated to one care provider

$$\sum_{j \in J} x_{i,j} = 1 \quad \forall i \in I \tag{4.44}$$

If a client is allocated to a care provider, they receive and provide the same type of care

$$y_{i,j} \geq x_{i,j} \quad \forall i \in I, \quad j \in J \tag{4.45}$$

If a client is allocated to a care provider, they are categorized under the same law type

$$z_{i,j} \geq x_{i,j} \quad \forall i \in I, \quad j \in J \tag{4.46}$$

Number of days per week a client receives care should not exceed the number of opening days of the care provider

$$D_i * x_{i,j} \leq O_j \quad \forall i \in I, \quad j \in J \tag{4.47}$$

The capacity of care providers should not be exceeded

$$\sum_{i \in I} x_{i,j} * D_i \leq Q_j \quad \forall j \in J \tag{4.48}$$

4.4.4 Feasibility of using the ILPs

Due to the complexity of the strategies, it is not feasible to attain an exact solution for the optimization of the routes through the ILPs. Section 5.3 shows that the ILP for route optimization is not able to find a feasible solution within a reasonable time. Considering this problem is not suitable for solving using an ILP, we develop a meta-heuristic. The client allocation ILP is still applied before the optimization of the routes using the meta-heuristic for the client allocation strategy.

4.5 Constructive heuristic

To apply a meta-heuristic, an initial solution is constructed. This section explains how an initial solution is found for this problem.

Algorithm 2 Constructive heuristic to find an initial solution

$Request \leftarrow$ A list of all transport requests is constructed
Randomly shuffle $Requests$
$Routes \leftarrow$ Initialize an empty list for the routes
for each $Request$ **do**
    $BestDistance \leftarrow \infty$ ▷ Initiate the best-found distance as infinity
    $BestRoutes \leftarrow$ empty
    for each insertion place in $Routes$ **do** ▷ Creating a new route is also an insertion place
        Insert $Request$ in $Routes$
        if $Routes$ is a valid solution **then** ▷ Verify that ILP constraints are not violated
            $Distance \leftarrow$ Calculate the distance of the created route
            if $Distance < BestDistance$ **then**
                $BestDistance \leftarrow Distance$
                $BestRoutes \leftarrow$ Save the route
            end if
        end if
        Remove $Request$ from $Routes$
    end for
    $Routes \leftarrow BestRoutes$
end for

A random greedy heuristic is used to construct the initial routes. Algorithm 2 shows the pseudo-code of how the routes are constructed. A transport request consists of two locations; A pickup location and a delivery location. A list containing all transport requests from the clients is created and shuffled randomly. This randomization facilitates generating alternative initial solutions by choosing different random seeds. Each request is inserted into the routes one by one. For each request, all possible insertion points of the existing routes are checked for validity. The test to determine if the routes are valid uses the constraints of the strategy's ILP in Section 4.4. If one of the constraints is violated the route is deemed invalid and the request can not be inserted at those points in the route. The request is inserted at the insertion points which create a valid solution and add the least distance to the total routes. Once every request is inserted, a complete route is built, and an initial solution is ready to be used as input for an optimization heuristic. Figure 4.4 illustrates a simplified overview of the constructive heuristic.

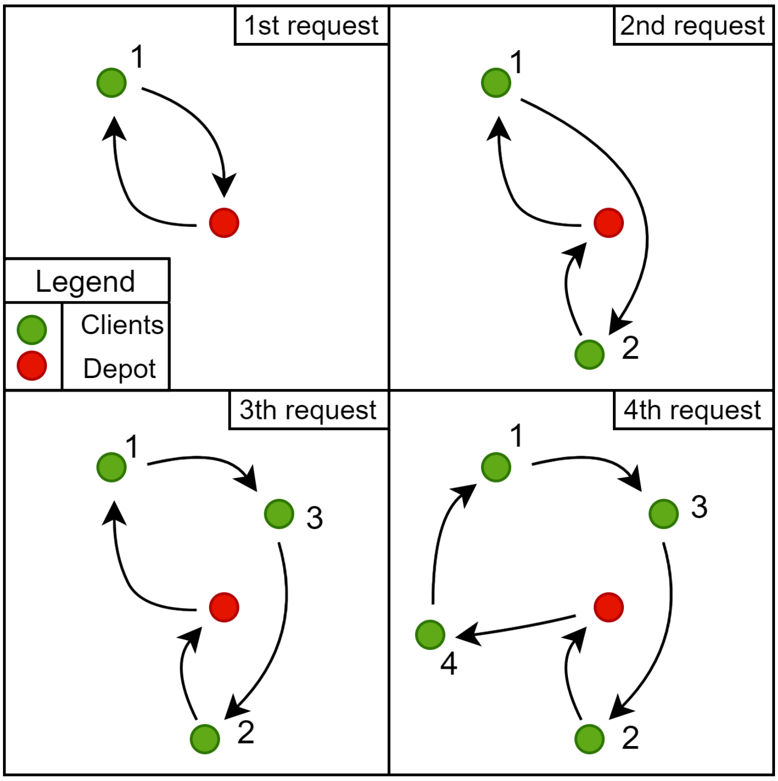


Figure 4.4: Overview of the Constructive heuristic

4.6 Meta-heuristic: adaptive large neighborhood search

This section explains how the initial solution is improved using an adaptive large neighbourhood search (ALNS). Subsection 4.6.1 gives an overview of the algorithm. Subsection 4.6.2 explains the destroy and repair operators. Subsection 4.6.3 describes the various parameters and the adaptability of the method.

The ALNS algorithm is an extension of the large neighbourhood search algorithm described in Section 3.8.3. For problems with high complexity and many constraints, a large neighbourhood search is a useful method [73]. Due to the numerous constraints, it is challenging to find a valid solution among the direct neighbours of the current solution. The large neighbourhood search circumvents this by partially destroying the current solution and then repairing it. The adaptive version of the large neighbourhood search changes the way of destroying and repairing during the search process, which leads to a more frequent selection of successful ways to alter the solution.

4.6.1 Outline of the ALNS algorithm

The ALNS algorithm uses the principles of simulated annealing to diversify and intensify the search. Figure 4.5 shows a flowchart of the ALNS algorithm.

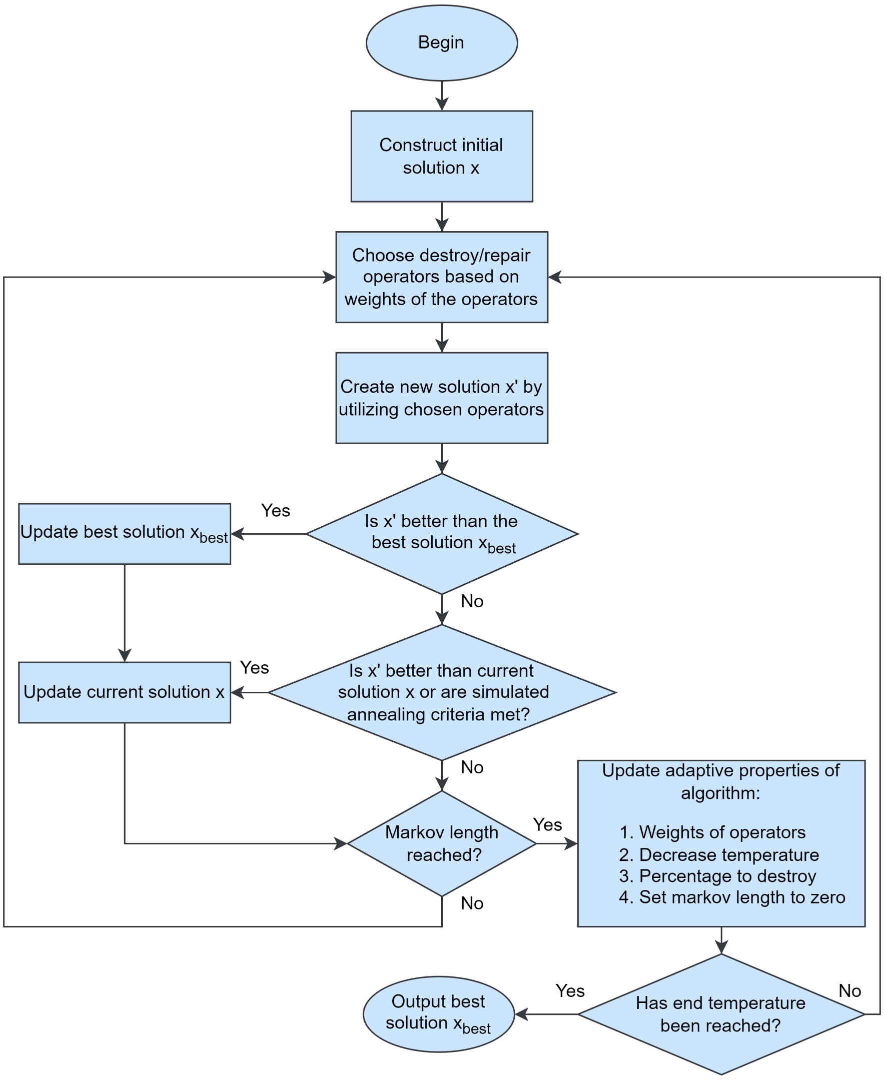


Figure 4.5: Flowchart of the ALNS algorithm

During the search, a temperature parameter is gradually decreased. This temperature influences the likelihood of accepting a worse solution. At the start of the search, with a high temperature, there's a greater chance of accepting a worse solution. This diversifies the search. As the search progresses, after each Markov length of iterations, the temperature decreases. Consequently, the probability of accepting a worse solution also decreases, leading to intensification of the search.

The algorithm starts with an initial solution constructed using the constructive heuristic. Destroy and repair operators are chosen based on their performance during the run. Using the selected destroy and repair operators, the current solution is transformed into a new solution. Section 4.6.2 outlines how the destroy and repair operators are selected and operated to generate a new solution. Once the operators have created a new solution, the algorithm evaluates whether this solution is better than the best solution found so far. If this is the case, the new solution is adopted as the current solution for the next iteration, and it becomes the new best solution. If the new solution is not better than the best solution so far but is still an improvement to the current solution, it is also accepted as the new current solution. If the new solution is worse than the current solution, Formula 4.49 calculates the probability of still accepting the solution. In the formula, the current temperature influences the probability of accepting a worse solution.

$$AcceptanceProbability = e^{-\left(\frac{NewSolution - CurrentSolution}{Temperature}\right)} \tag{4.49}$$

Once the Markov length number of iterations is completed the parameters that influence the algorithm are updated. The parameters that make the algorithm adaptable during the run are also modified here. These parameters are discussed in Section 4.6.3. The temperature is also decreased, if the end temperature is reached, the best solution is returned. Otherwise, a new iteration starts. Algorithm 3 presents the pseudocode of the algorithm.

Algorithm 3 Adaptive large neighborhood search

```
Initiate parameters: EndTemperature, Amount, Counter, ScoresOperator, MarkovLength, CoolingRate
Routes ← Initial solution from constructive heuristic
Weights ← equal divided among operators
BestRoutes ← empty
BestDistance ← ∞
while Temperature > EndTemperature do
    for MarkovLength do
        BackupRoutes ← Make a backup of the current Routes
        Choose Destroy and Repair operators based on Weights
        Routes ← Destroy Amount of Routes with Destroy operator
        Routes ← Repair Routes with Repair operator
        NewDistance ← Calculate distance of Routes
        CurrentDistance ← Calculate distance of CurrentRoutes
        AcceptanceProbability ← Determine the acceptance probability of the NewDistance
        if NewDistance < CurrentDistance or Random[0, 1] < AcceptanceProbability then
            if Newdistance < BestDistance then
                BestRoutes ← Save the current Routes
                Add scores to ScoresOperator                    ▷ Scores for finding BestRoutes
            else
                if NewDistance < CurrentDistance then
                    Add scores to ScoresOperator     ▷ Scores for better Routes than BackupRoutes
                else
                    Add scores to ScoresOperator           ▷ Scores for getting an accepted Routes
                end if
            end if
        else
            Routes ← BackupRoutes Do not make a change to the route
        end if
        Update Counter
    end for
    Amount ← Decrease proportionally with Temperature
    Weights ← Update based on ScoresOperator
    Temperature ← Decrease with CoolingRate factor
end while
Return BestRoutes
```

4.6.2 Operators

This subsection discusses the selection mechanism of destroy/repair operators at the start of an iteration. This subsection also explains how the various operators work.

There are various ways to destroy and repair the current solution. The ALNS algorithm utilizes four destroy operators and three repair operators. In each iteration, each operator has a certain weight depending on how much it has contributed to the current solution. This weight adapts throughout the search process, as further explained in Section 4.6.3. The destroy and repair operators are selected separately. A roulette wheel selection first chooses the destroy operator and then the repair operator. The probability that operator j is chosen is determined by formula 4.50 using the weight of operator j. In this formula, n represents the number of operators of the same type.

$$P_j = \left(\frac{Weight_j}{\sum_{i=1}^{n} Weight_i} \right) \tag{4.50}$$

A specific number of requests from the current solution is destroyed using the selected destroy operators. The adaptability of the number of requests that is destroyed during the search process is further explained in 4.6.3. The output of the destroy operator consists of the remaining route along with a set of transportation requests that need to be inserted into the routes by the selected repair operator. The output of the repair operator is the new solution.

The operations of the destroy and repair operators are explained here:

Destroy random locations

From the list of transport requests, a random selection is chosen. The corresponding locations are removed from the routes. Figure 4.6a illustrates the random destroy operator.

Destroy routes

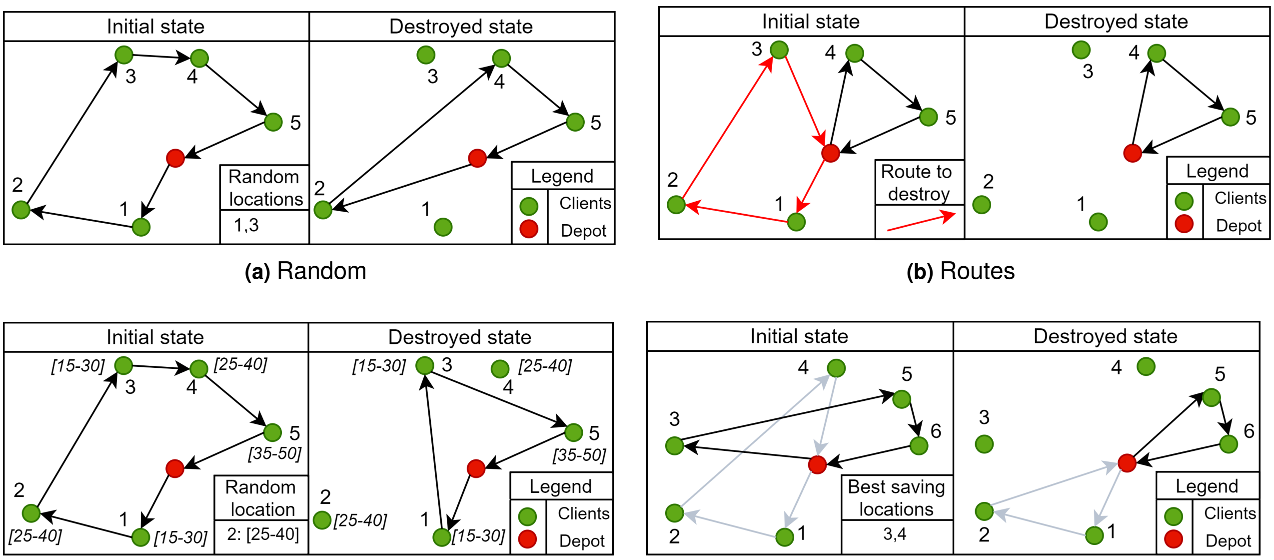
A solution consists of multiple routes. In this operator, one or more routes are destroyed in their entirety. Random routes are selected from the list of available routes. These selected routes are then removed. Allowing the locations of the removed routes to be inserted into different routes. Figure 4.6b illustrates how the destroy routes operator works.

Destroy locations based on time

To maximize the likelihood of a successful alteration of the solution, locations with a similar time window can be removed together. This increases the probability that these locations can be inserted in one route during the repair process. A random location is chosen. Then random locations with a similar time window as the first location are removed. Figure 4.6c shows the working of this operator.

Destroy locations with high potential savings

For each location, the theoretically shortest possible distance required to reach and get away from that location is calculated. If the current travel distance is significantly longer than this minimum distance, the location has a good potential to be inserted into a more efficient route. This operator sorts locations based on their potential savings and subsequently removes those at the top of the list. Figure 4.6d illustrates the operator for destroying locations with high potential savings.



(a) Random

(b) Routes

(c) Time

(d) High savings

Figure 4.6: The four destroy operators that are used in the ALNS algorithm

Repair random

From the list of all removed transport requests a random request is selected and inserted at the best possible place in the solution. The request is then extracted from the list of removed transport requests. This process is repeated until all removed transport requests are inserted back into the solution.

Repair greedy

For every request that needs to be inserted back into the solution, the best possible place for insertion is determined. The distance added by inserting each request is evaluated. The request that adds the least additional distance upon insertion is inserted first. Subsequently, the second best request is inserted, and so on, until all requests are inserted into the solution.

Repair regret-2

The regret operator attempts to take into account future insertions when deciding which request to re-insert first into the solution. The operator determines the difference in added distance between the best possible insertion place and the second-best insertion place. This is called the regret distance. Requests with a high regret distance are prioritized over requests with a low distance and are inserted into the solution first.

4.6.3 Adaptability

This subsection describes the adaptability of the ALNS algorithm during the search process. Two main components in the algorithm are adaptable: The weights that determine the probability of selecting the operators, and the number of requests that are destroyed from the solution.

The weights of the operators are influenced by how well they perform during the search process ($Score$). These weights of operator i are updated at the end of each Markov segment j using formula 4.51.

$$Weight_i^{j+1} = Weight_i^j * (1 - \rho) + \rho * \left(\frac{Score_i}{N_i}\right) \tag{4.51}$$

In this formula, j represents the current Markov segment, while $j+1$ represents the next segment. N denotes the number of times the operator was chosen in the current segment. Parameter ρ influences how much the current segment contributes to the weight adjustment. When $\rho = 1$, the weights are solely based on the scores from the current Markov segment. If $\rho = 0$, the values are not updated, and the current Markov segment's weights are the same for the next segment. The parameter $Score$ reflects the operator's performance in the current Markov segment.

The $Score$ of the operators is adjusted when they are selected to generate a new solution. The $Score$ is adjusted based on the quality of the new solution. There are four possible scenarios for assigning a score to the operator based on the new solution. The values that are assigned to each scenario are based on the article of Pisinger and Ropke [73]. Table 4.1 describes the various scenarios including their corresponding $Score$.

Table 4.1: Scores of the scenarios for a new solution

Parameter	Scenario	Value
σ_1	The new solution is better than the best solution.	33
σ_2	The new solution is worse than the best solution, but better than the current solution.	9
σ_3	The new solution is worse than the current solution, but accepted as the new current solution by the simulated annealing criteria.	13
σ_4	The new solution is not accepted as the new current solution.	0

The number of requests that are removed (ω) is proportional to the temperature during the run. Formulas 4.52 and 4.53 are utilized to update the number of requests to remove corresponding with the current temperature. First, the percentage of the current temperature compared to the total temperature change is determined, and then this percentage is used to calculate the number of requests to be removed. ω_{Start} is the number of requests that are removed at the start of the run, while ω_{End} represents the number of requests that are removed at the end of the run.

$$PercentageTemperature = \left(\frac{StartTempertare - Temperature}{StartTemperature - EndTemperature}\right) \tag{4.52}$$

$$\omega = \omega_{Start} - PercentageTemperature * (\omega_{Start} - \omega_{End}) \tag{4.53}$$

4.7 Conclusion

In addition to the current strategy employed by the RGV, two new strategies are assessed in this thesis. The first is the horizontal cooperation strategy, where clients keep their current care provider, but their transportation to that care provider is arranged by a central vehicle depot. The second strategy is the client allocation strategy, where, in addition to the central vehicle depot managing the transportation, clients can also be allocated to a care provider with a more convenient location compared to their current care provider. Data on the outcomes of the current strategy is unavailable, and thus, this strategy is also modelled.

Various rules and regulations are assumed for constructing the models. ILPs are formulated for the various strategies. The difference in ILPs between the current strategy and the horizontal cooperation strategy is in the way the waiting time of vehicles is modelled. For the client allocation strategy, the ILP of the horizontal cooperation strategy is used. However, the input is modified with an ILP model that optimizes the allocations of clients, ensuring they are placed with a care provider that minimizes the total distance between clients and their care providers.

Due to the complexity of the problems, ILPs are found to be unsuitable for these problems. Therefore, a meta-heuristic is employed to approximate the exact solution. A random greedy algorithm provides an initial solution to an Adaptive Large Neighbourhood Search algorithm (ALNS). In each iteration, the algorithm destroys the current solution using one of four destroy operators. Subsequently, the destroyed solution is repaired using one of the three repair operators. The acceptance of the newly created solution is determined based on simulated annealing criteria. Throughout the algorithm's run, the probability of selecting operators adapts to their performance. Additionally, the extent to which the solution is destroyed is also adaptive.

5 Results

This chapter describes the computational experiments that were performed. Section 5.1 presents the data instances that were used in the various experiments. Section 5.2 presents the values of the fixed parameters that the model uses. Section 5.3 explains the experiments and results of the ILP method. Section 5.4 showcases how the various parameters are tuned in the ALNS algorithm. Section 5.5 presents an illustrated verification of the routes. Section 5.6 describes the results of the various strategies that are tested using the ALNS algorithm.

5.1 Data instances

The data on which the experiments are performed consists of clients distributed across different days. An instance represents a day when clients need to be transported to care providers. The size of this instance depends on the number of care providers that are open that day. Because clients are randomly distributed over the days, as described in Section 4.3, data instances are generated for five random seeds per day. This results in a total of 30 instances. Table 5.1 illustrates the number of clients to be transported per day on average over the five random seeds. On Saturday, only a few care providers are open, resulting in fewer clients being transported. Furthermore, the maximum distance from a client to their care provider is shorter on Saturday than on other days. The mean and median distance between clients and their respective care providers is similar for all the instances.

Table 5.1: Averages of data instances over the random seeds for distributing clients to days

Day	Number of clients	Max distance (km)
Monday	$113.2(\pm 14.8)$	$15.4(\pm 1.3)$
Tuesday	$110.8(\pm 13.1)$	$15.8(\pm 1.4)$
Wednesday	$108.2(\pm 3.6)$	$17.6(\pm 4.4)$
Thursday	$119.6(\pm 9.5)$	$17.0(\pm 3.3)$
Friday	$96.6(\pm 6.0)$	$18.2(\pm 4.1)$
Saturday	$9.6(\pm 1.9)$	$9.1(\pm 0.4)$

5.2 Fixed parameters

In the various strategies, some parameter values are tailored to the RGV. This section showcases these values. Clients are categorized into two types: wheelchair-bounded clients and clients occupying a regular seat in the vehicles. For some parameters different values apply for the different types of client. The fixed parameters are the following:

$S = [Seating : 1, Wheelchair : 2]$	Number of seats occupied by a client
$SW = [Seating : 0, Wheelchair : 1]$	Number of wheelchair spaces occupied by a client
$BT = [Seating : 3, Wheelchair : 6]$	Boarding/embarking time (in minutes) for a client
$F = 60$ minutes	Maximum time a client may spend during a transport request
$Q = 6$	Capacity of a vehicle
$QW = 2$	Wheelchair capacity of a vehicle
$TravelSpeed = 40\ km/h$	Constant travel speed of a vehicle

5.3 Results of ILP

The ILP tries to compute the exact solution to the problem at hand. Due to the complexity of the model, it is challenging to arrive at a solution within a reasonable amount of time. Figure 5.1 shows the time it takes to reach a solution as the number of clients increases. In this experiment, the time is measured to reach an optimality gap of less than 40%.

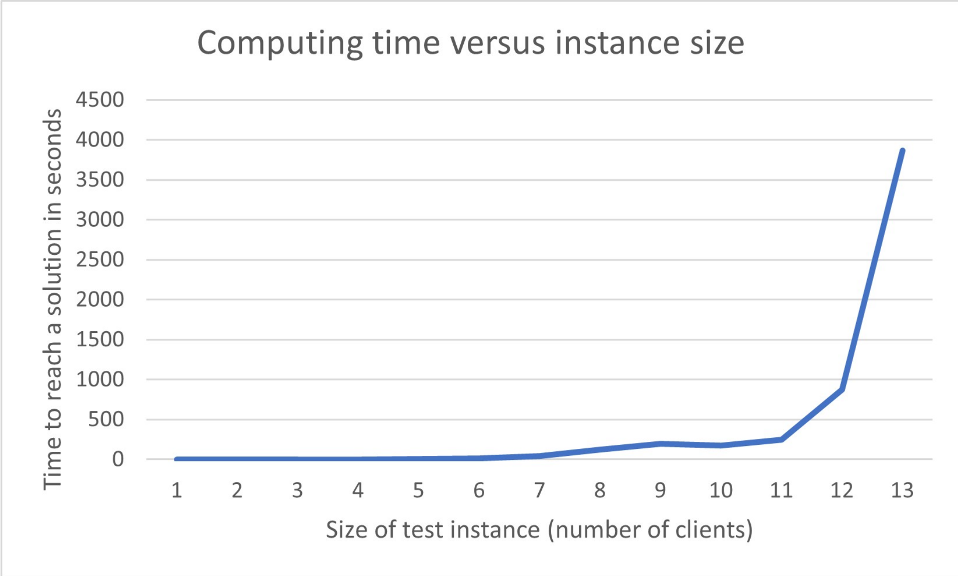


Figure 5.1: Time it takes to reach a solution with an optimality gap less than 40% for various instance sizes

For small instances, the ILP finds solutions in a reasonable time, however, if the number of clients increases the complexity of the model increases rapidly. As a result, the time required to reach a solution also increases significantly. For the size of the instances that need to be tested, using an ILP is not feasible due to computational constraints.

5.4 Parameter tuning

Several parameters in the ALNS algorithm require tuning to find the best configuration of the algorithm. This subsection describes these parameters and the experiments that we conducted to tune them.

5.4.1 Start temperature

The temperature influences the likelihood of accepting worse solutions. At the beginning of the run, worse solutions have a good chance of being accepted. Formula 5.1, an adapted version of Formula 4.49, is used to determine the precise starting temperature. The starting temperature depends on both the value of μ and the value of the initial solution. The $StartTemperature$ is set such that a solution which is μ percentage worse than the current solution is accepted with a probability of 50%.

$$StartTemperature = -\left(\frac{(CurrentSolution * \mu) - CurrentSolution}{Ln(0.5)}\right) \tag{5.1}$$

The assumption is made that a solution which is 50% worse should have a 50% probability of being accepted at the start of the run. This means μ becomes 1.5. To verify that the acceptance probability is sufficiently high at the beginning of the run, the algorithm is initiated without allowing the temperature to decrease. This experiment is conducted with an instance size of 50 clients. After one thousand iterations, the average acceptance probability is found to be 0.991. This indicates that these settings are effective in ensuring a high likelihood of accepting worse solutions at the start of the run.

5.4.2 End temperature

The value of the $EndTemperature$ determines how long the algorithm can search before it is terminated. When the temperature is low, the likelihood of accepting a worse solution is also low. This transforms the algorithm into a greedy one. To determine a suitable value for the end temperature, the behaviour of the objective value (distance) during the run is looked at. The goal is to choose a value at which the objective value at the end of the run remains unchanged or changes negligibly, which means likely a (local) optimum is reached. Figure 5.2 showcases a run with an instance size of 120 clients and an $EndTemperature$ of 0.5. In this figure, each step represents an iteration. The objective value does not decrease significantly at the end of the run, indicating a good end temperature is chosen.

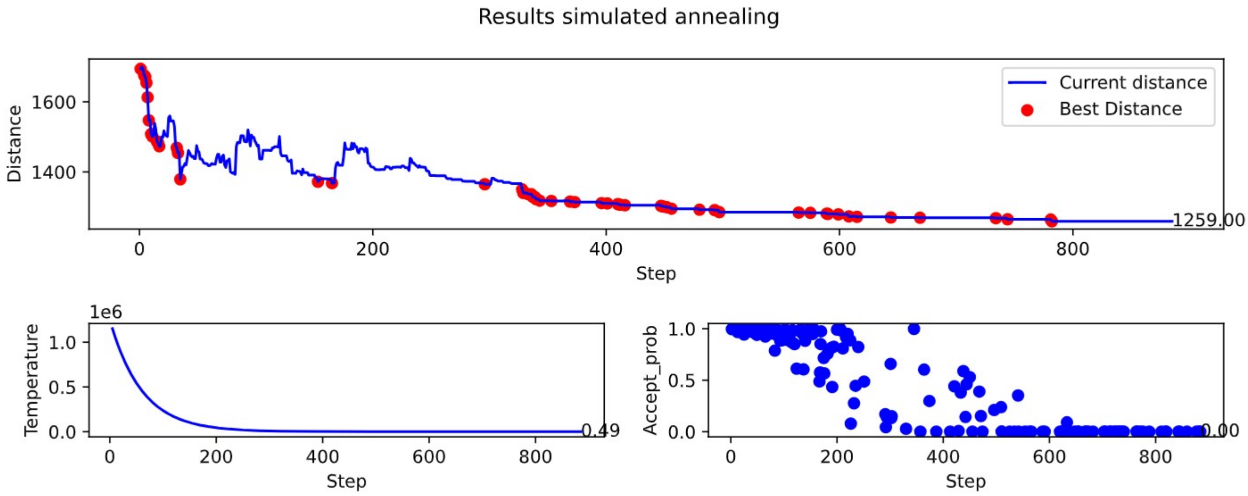


Figure 5.2: ALNS algorithm run results: Objective value development (top), temperature (bottom left), and acceptance probability (bottom right) during the run.

5.4.3 Number of requests to remove with destroy operators

The destroy operators destroy a certain number of requests (ω). At the start of the run, a high ω_{start} is removed to make sure diversification is possible, at the end of the run only small portions of the solution are removed to intensify the search. The parameter that requires tuning is the start value of ω_{start}. An experiment is run, where ω_{start} is varied. In the tests, instance sizes of 50 clients are used with a temperature cooling rate (C) of 0.8 and the influence of the scores (ρ) set to 0.1. Table 5.2 presents the outcomes of these tests.

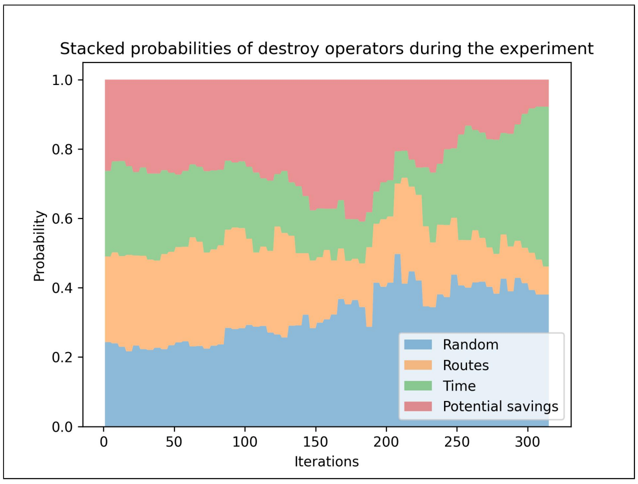
Table 5.2: Results of experiment: percentage to remove at the start of a run

ω_{start}	**Best solution (in kilometres)**	**Percentage of run where best solution is found**	**Number of times best solution is found**
80%	608	79%	16
60%	601	92%	21
40%	629	82%	13
20%	595	100%	27

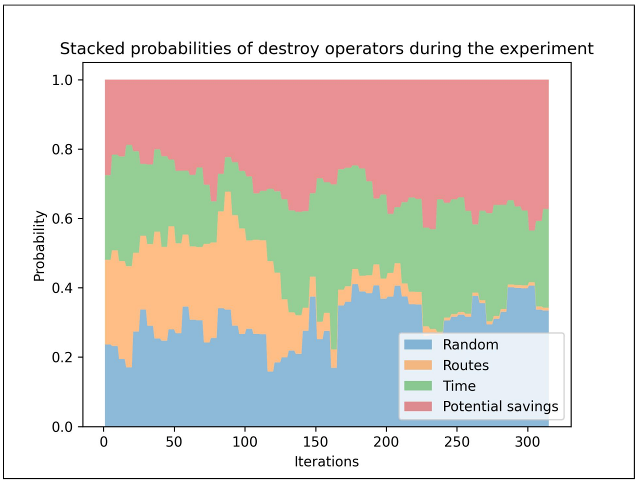
An ω_{start} of 20% results in the best outcomes. The ω at the end of the run is set to 5 for all operators except the destroy routes operator. Due to the nature of the operator, it is not possible to remove a fixed number of clients. Experiments show that selecting a minimum of 2 routes to be destroyed yields the best outcomes. Appendix A displays the detailed results of these experiments.

5.4.4 Influence of last Markov segment on weights

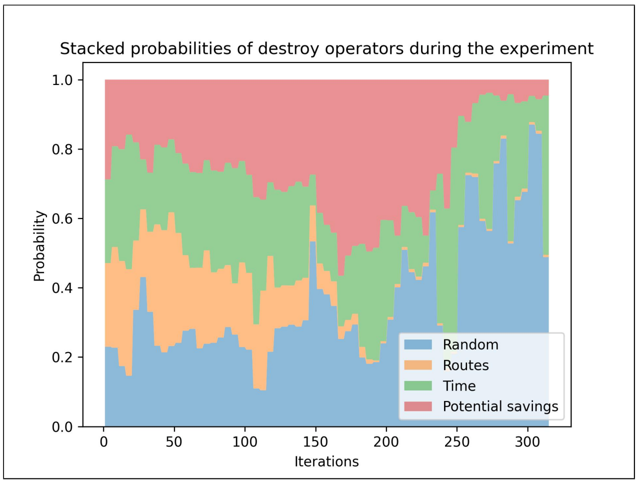
The weights that determine the probability of selecting certain operators are updated during the run. The influence of the last Markov segment on the weights of the operators (ρ) is a parameter that needs tuning. Tests were performed on various settings of ρ with 50 clients as instance size. The test was done with a cooling rate ($C = 0.8$) and start $\omega_{start} = 20\%$. Figure 5.3 shows the probability that a certain operator is chosen during the run for various settings of ρ. The ALNS algorithm adapts the most in the experiment with setting $\rho = 0.8$. This setting also yields the best objective value and performance indicators. Appendix A presents the detailed results of various performance indicators of the experiments.



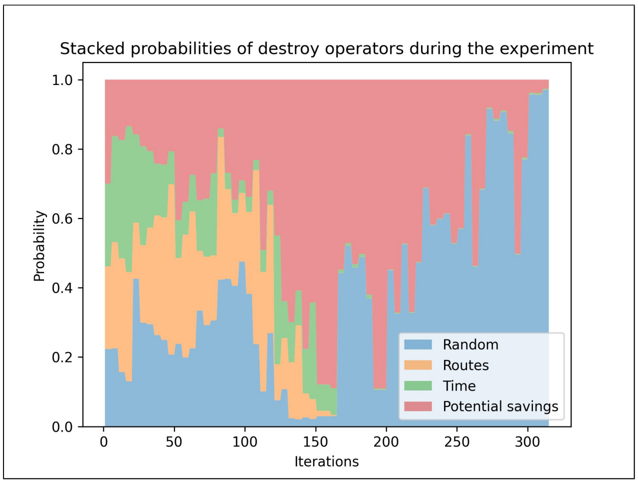
(a) $\rho = 0.2$



(b) $\rho = 0.4$



(c) $\rho = 0.6$



(d) $\rho = 0.8$

Figure 5.3: Outcomes of probabilities of selecting destroy operators with various settings for ρ

5.4.5 Multi-start and cooling rate

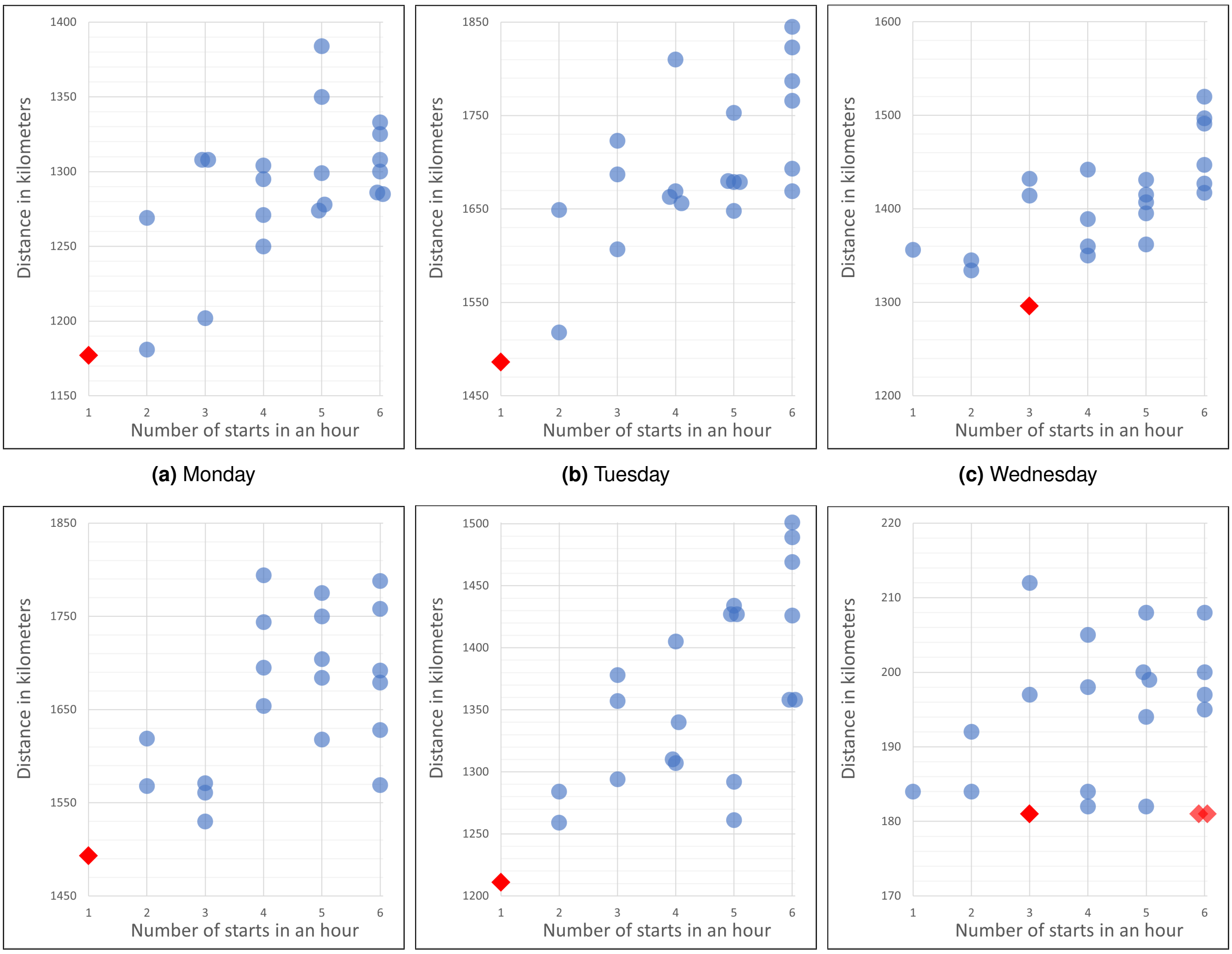
The cooling rate (C) determines the rate at which the temperature decreases, thereby affecting the time it takes for the algorithm to finish. Two shorter runs with different initial solutions may lead to a better result than a single, longer run. The following experiments explore the impact of the initial solution and cooling rate on the final solution. For this experiment, the starting point is a total run-time of one hour. Various numbers of starts within an hour are tested, with each start utilizing a different initial solution. The cooling rate for these experiments is calculated using Formula 5.2. Here, M represents the number of Markov segments that should be completed to achieve a certain run time. This can be calculated by multiplying the average time for an iteration by the number of iterations in a Markov segment. In this algorithm, the average Markov segment takes approximately 20 seconds. So for a run of one hour and one initial solution, 180 Markov segments can be completed. Tests are run for various numbers of runs within an hour with a max of 6 different initial solutions within an hour.

$$C = \sqrt[M]{\frac{EndTemperature}{StartTemperature}} \tag{5.2}$$

The experiments use the tuned parameters:

- $\omega_{start} = 0.2$
- $\rho = 0.8$
- $\mu = 1.5$
- $EndTemperature = 0.5$
- Number of routes for destroy routes operator at end run = 2

The experiment is conducted for each day of the week when care providers are open. Figure 5.4 presents the result of the experiments. The x-axis displays the number of starts conducted within an hour. Each dot in the figure represents the result of an individual run. For instance, if six starts are performed in an hour, there will be six dots on the figure.



(a) Monday **(b)** Tuesday **(c)** Wednesday

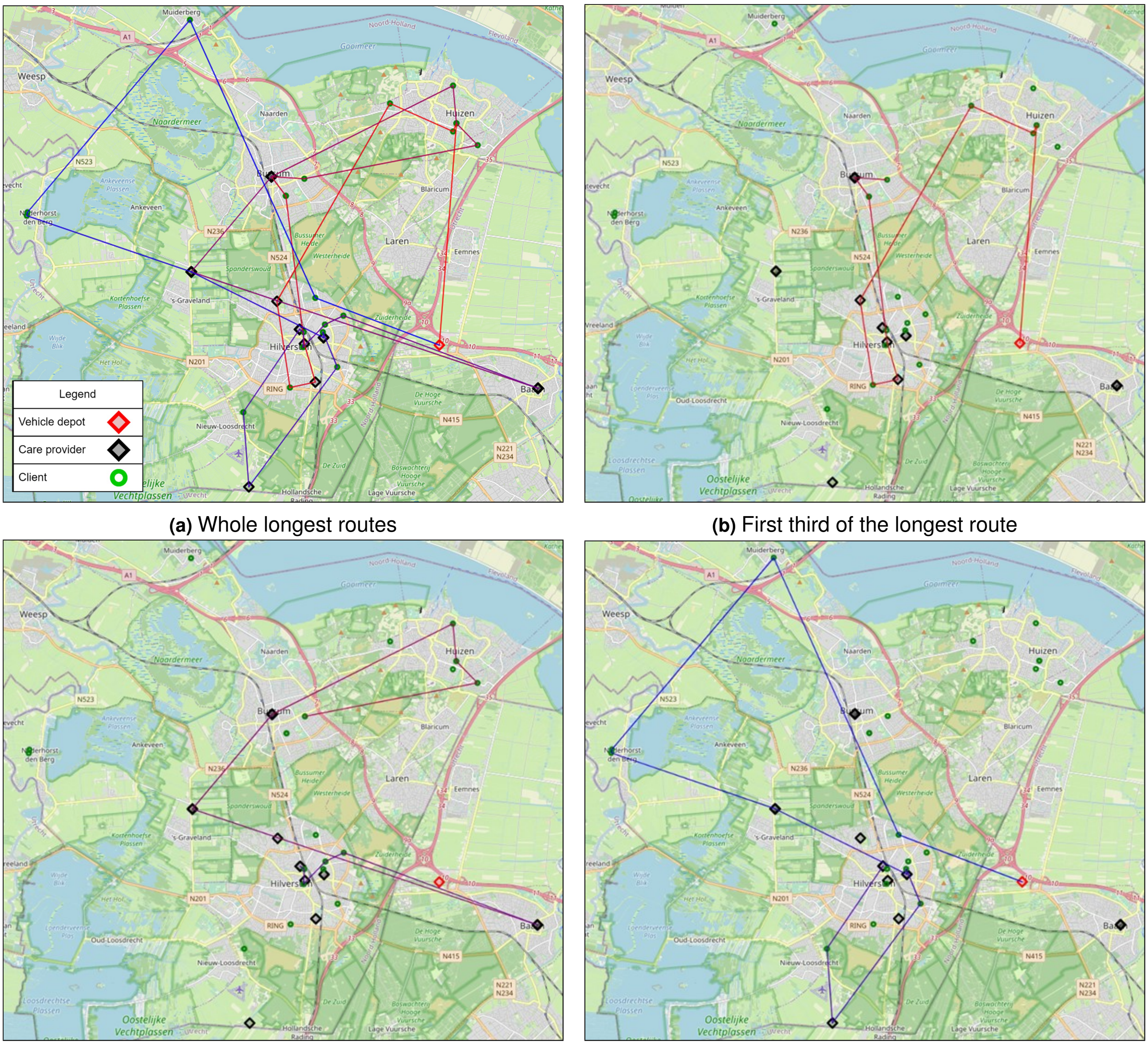
(d) Thursday **(e)** Friday **(f)** Saturday

Figure 5.4: Results of the experiment on using multi-start for various days of the week. The red diamond indicates the best-found distance for that day

The longer runs with one initial solution and a C of 0.92 result in the best solution on four of the six days. Appendix A shows the detailed results of this experiment. The differences in the outcomes from runs with a multi-start are on average 8.24%. This indicates that the impact of the initial solution on the outcome is limited in the ALNS algorithm.

5.5 Verification of the routes

Once a solution is found, the routes are checked on whether they are correct and logical. The solution should fulfil all constraints formulated in the ILP of the strategy. If all these constraints are satisfied the solution is considered a feasible solution. A feasible solution however does not imply a solution of high quality. Because the ILP is not able to identify a lower bound, the quality of the routes is visually confirmed. The longest route in the solution is plotted to assess its logic. Figure 5.5 shows the longest route divided into sections. The route appears logical considering clients who are located close together are picked after each other, taking into account the various constraints. Appendix B displays the shortest route from this solution.



(a) Whole longest routes

(b) First third of the longest route

(c) Second third of the longest route

(d) Last third of the longest route

Figure 5.5: Longest route of a best-found solution. The route is colour-coded, with the start marked red, the end in blue and a gradient to represent the middle portion.

5.6 Outcomes of strategies

This section depicts the outcomes of the various strategies that are tested for the transportation of clients for social care services in the RGV. The ALNS model with the parameters described in Section 5.4 tests the strategies.

For the client allocation strategy, the distance between clients and their care providers is reduced by choosing a more efficient allocation of clients. The distance between clients and their care providers, when considered as a direct route, is 3541 kilometres in the current strategy and the horizontal cooperation strategy. The client allocation strategy reduces this distance to 3122 kilometres. A total of 113 clients are allocated to a different care provider compared to the current strategy.

Because there is randomness involved in the allocation of clients, the model is run five times with clients distributed differently over the days for every strategy. This results in a confidence interval of the mean distance travelled during the week. In the current strategy, the total number of clients is distributed among the various care providers. Therefore, the ALNS algorithm runs faster because the instance sizes are smaller. The total run time for the current strategy is approximately two hours. For the horizontal cooperation and client allocation strategy, a single day takes, on average, one hour to complete, resulting in a total run time for one of the strategies of approximately 30 hours. Figure 5.6 shows the results of these tests.

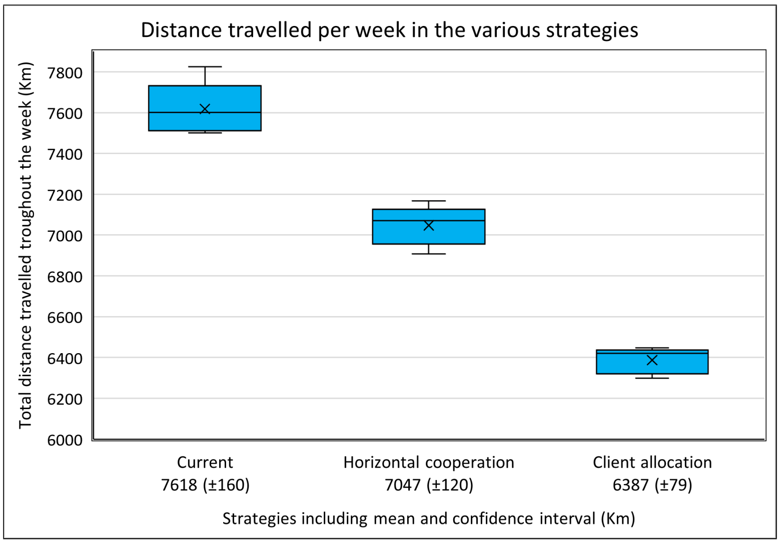
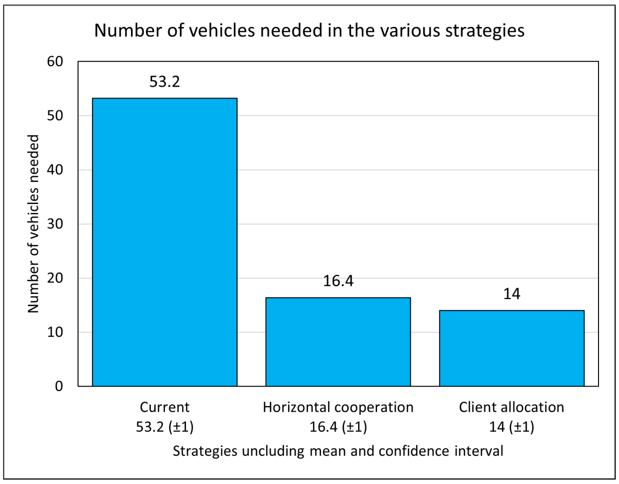


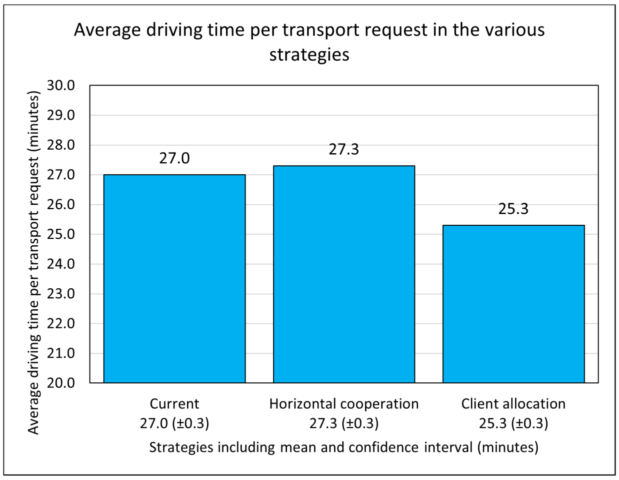
Figure 5.6: Outcome of distance for the various strategies

Compared to the current strategy, both the horizontal cooperation and client allocation strategies are improvements. The horizontal cooperation gives a 7.5% decrease in the number of kilometres travelled, while the client allocation strategy gives a 16.2% decrease. This corresponds to a decrease of 571 km and 1231 km per week, respectively. If we extrapolate these outcomes for an entire year, the savings are approximately 29,700 kilometres for the horizontal cooperation strategy and approximately 64,000 kilometres for the client allocation strategy.

Figure 5.7 presents the average time clients spend in the vehicle during a transport request and the number of vehicles needed in the strategy. Appendix C shows the detailed results of the conducted tests.



(a) Number of vehicles needed



(b) Average time a client spends in the vehicle per transport request

Figure 5.7: Number of vehicles needed and average driving time per transport request in the various strategies

The number of vehicles required to transport clients throughout the week is lower in the horizontal cooperation and client allocation strategy compared to the current strategy. The horizontal cooperation strategy results in a savings of approximately 37 vehicles, and the client allocation strategy yields a savings of about 39 vehicles. The horizontal cooperation and client allocation strategies do not have a big impact on the average driving time per transport request. The client allocation strategy shows a small decrease of approximately two minutes.

5.7 Conclusion

The number of clients is evenly distributed over the days Monday to Friday. On Saturdays, fewer clients need transportation to the care provider. Furthermore, the maximum distance to the care provider on that day is also smaller.

The time it takes for the ILP to reach a feasible solution with an optimality gap of at least 40% increases significantly if the instance size is larger than 12 clients. As a result, the ILP is not a suitable method for this problem.

The ALNS algorithm has several parameters that require tuning. The $StartTemperature$ depends on the value of μ, which determines how much worse the solution may be at the beginning of the run to still have a 50% chance of being accepted. The $EndTemperature$ is chosen based on the graph of a run. The number of requests to remove at the start of the run (ω_{start}), is determined by running several tests with different values for ω_{start}. The same is done for the influence of the last Markov segment on the weights of operators (ρ), to determine the most appropriate cooling rate (C), and to see whether using a multi-start is beneficial or not.

The best-found values for these parameters are the following:

- $\mu = 1.5$
- $EndTemperature = 0.5$
- $\omega_{start} = 0.2$
- $\rho = 0.8$
- $C = 0.92$
- Not beneficial to use a multi-start

Routes are verified when the constraints from the ILP are satisfied and the route is visually logical.

The strategies of horizontal cooperation and client allocation were tested versus the current strategy. Both strategies outperformed the distance of the current strategy. The distance of the current strategy was 7618 ($\pm$160) kilometres, while the distance of the horizontal cooperation and client allocation strategies was 7047 ($\pm$120) and 6387 ($\pm$79) respectively. The number of vehicles needed in the current strategy was 53.2 ($\pm$1). The horizontal cooperation and client allocation strategies resulted in 16.4 ($\pm$1) and 14 ($\pm$1) vehicles needed respectively. The average driving time per transport request for the current strategy and the horizontal cooperation strategies was similar with 27.0 ($\pm$0.3) and 27.3 ($\pm$0.3) respectively. The client allocation strategy resulted in a small decrease with 25.3 ($\pm$0.3) minutes for the average driving time per transport request.

6 Conclusion

This thesis investigates the impact of various strategies on the transport of clients for social care services in the RGV. The motivation for this research is that the current strategy does not seem sustainable. If the transportation of clients cannot be arranged more efficiently, the costs will rise. This creates a lack of profitability, which causes care providers to quit. Fewer care providers means less efficient transportation due to a less dense network of care providers. A different strategy could bring benefits.

In the literature, several examples of similar situations are present. However, the combination of characteristics specific to the RGV is not seen in the literature. To assess whether alternative strategies can have a positive impact on the RGV's situation, a transportation planning algorithm is developed. An ILP model proved unsuitable due to the complexity and scale of the problem. Therefore, a meta-heuristic was employed to approximate the exact solution. A random greedy heuristic is used for the initial solution, followed by an ALNS algorithm that optimizes the solution.

In each iteration, the ALNS algorithm destroys the solution using one of four destroy operators. Subsequently, one of the three repair operators repairs the solution. The principles of simulated annealing are employed to determine whether this new solution is accepted as the new solution. The ALNS algorithm is adaptable during the run. After each Markov segment, the probability of choosing the operators and the percentage of the route that is destroyed is adjusted. After a number of iterations, the best solution is returned as the final solution.

The ALNS algorithm contains several parameters that need tuning. This was done through various experiments with different settings. The tested parameters that performed the best were the following:

- Percentage above current solution that is accepted with 50% probability, $\mu = 1.5$
- $EndTemperature = 0.5$
- Percentage of the solution that is destroyed at the start of the search process, $\omega_{start} = 0.2$
- Influence of the last segment on the weights to choose the operators, $\rho = 0.8$
- Cooling rate, $C = 0.92$
- Not beneficial to use a multi-start

In the current strategy, clients are located to care providers who are responsible for the transportation of these clients. Vehicles depart from the care providers and can only pick up and deliver clients from that care provider. Performance outcomes on the current strategy are not available therefore this strategy was also modelled with the ALNS algorithm. Two new strategies are tested with the algorithm. The first new strategy is the horizontal cooperation strategy. In this approach, clients remain with their original care provider, but the transportation is not organized by that care provider. Instead, it is managed from a central vehicle depot. The second strategy is the client allocation strategy, where clients are allocated to a care provider that allows for a more efficient route. In this strategy, a central vehicle depot is also used to arrange the transportation. Clients are allocated to a care provider using an ILP model that minimizes the distance between the clients and their care provider.

The strategies were tested on the total distance driven in a week to transport the clients to their care providers. The current strategy had an outcome of 7618 ($\pm$160) kilometres. The horizontal cooperation strategy had a total distance driven in a week of 7047 ($\pm$120). The client allocation strategy resulted in a distance of 6387 (± 79). This means the horizontal cooperation strategy resulted in a 7.5% decrease, while the client allocation strategy resulted in a 16.2% decrease in distance driven per week. The number of vehicles needed in the current strategy is 53.2 ($\pm$1). The horizontal cooperation strategy resulted in 16.4 ($\pm$1) vehicles needed, while the client allocation strategy resulted in 14 ($\pm$1) vehicles needed. This corresponds to a decrease of approximately 37 vehicles for the horizontal cooperation strategy and 39 vehicles for the client allocation strategy. The average driving time per transport request for the current and the horizontal cooperation strategies are similar with 27.0 ($\pm$0.3) and 27.3 ($\pm$0.3) respectively. The client allocation strategy resulted in an average of 25.3 ($\pm$0.3) minutes driving per transport request.

6.1 Managerial recommendations

This section outlines the managerial recommendations. It discusses the potential to expand the model and some further research the RGV should take before implementing the strategies.

The current model is aimed at minimizing the total distance travelled, which serves as a good baseline KPI. However, more KPIs may be of interest. Section 2.3 outlines some additional KPIs that could be relevant. It would be beneficial to have a more holistic approach to check all the stakeholders' interests.

Clients want the quality of their trip to be as high as possible, which means minimizing the time they spend in the vehicle. Additionally, they want to be picked up at a certain time and delivered at a certain time. In the model, this could be implemented by giving a penalty if a vehicle is late or early. For clients, driver consistency could be a factor to implement in the model. Having the same driver every time could have a large impact on the quality of a trip for the client.

The driver's perspective can also be taken into account by adding constraints to ensure a driver gets enough breaks and can be limited to certain working hours.

Costs could be an important KPI to the RGV and the care providers. From the current objective of minimizing the distance, a reasonable estimation can be made regarding the costs associated with a strategy. However, a more accurate estimation can be made by expanding the model to take into consideration the costs of different vehicles, including the purchasing and maintenance costs. This way a more accurate representation of the total annual costs is made.

These examples of KPIs can be incorporated into the model by altering the objective function. A balance between these KPIs should then be found to come to the best configuration for the model.

The horizontal cooperation and client allocation strategies demonstrate that by reorganizing the transportation of clients, potential savings can be achieved. By checking the models' outcomes, some potential improvements come to mind.

The depot that is used for the horizontal cooperation and client allocation strategies is located outside of the main area where the addresses of clients and care providers are. A strategy with a vehicle depot that is more central than the current location could provide improved outcomes.

A potential addition to the strategies could be to add a second depot. The distance between the depot included in the current model and the farthest clients exceeded 20 kilometres. Utilizing an ILP model to minimize the total distance between one of the two depots and the clients could provide valuable information for identifying an optimal location for the depots.

The investigated strategies show a clear potential for savings. However, some considerations need to be taken into account before implementing any of these strategies. Table 6.1 displays the positive and negative impact of each strategy on the various stakeholders.

Table 6.1: Impact of the strategies on the various stakeholders

Strategy:		**Current strategy**	**Horizontal cooperation strategy**	**Client allocation strategy**
Clients:	**+**	Freedom of choice for the preferred care provider	Freedom of choice for the preferred care provider	• Care provider is closer to home • Reduced average driving time of $\pm$ 2 minutes
	-	-	Adapting needed to change in transportation	Adapting needed to change in transportation
Care providers:	**+**	Easy way of connecting with the caregiver of the client	Transportation is outsourced to the RGV	Transportation is outsourced to the RGV
	-	High costs for arranging the transportation	Easy way of connecting with the caregiver of the client is lost	• Easy way of connecting with the caregiver of the client is lost • Less influence on client acquisition
RGV:	**+**	No responsibility for the transportation of clients	• Savings in number of kilometres ($\pm$29,700 km per year) • Saving in number of vehicles ($\pm$37)	• Savings in number of kilometres ($\pm$64,000 km per year) • Saving in number of vehicles ($\pm$39)
	-	• High costs from care providers are passed on to the RGV • Have to deal with unhappy care providers	The transportation service of the RGV must be able to handle and organize the transportation	• The transportation service of the RGV must be able to handle and organize the transportation • Additional research is needed on the impact of the strategy on clients

The group of clients is a vulnerable one, and any changes can have a significant impact on them. Switching transportation providers, let alone changing care providers, constitutes a major change. Therefore, it should be evaluated whether such changes are wise for these clients.

During the data collection process, multiple care providers indicated that the transportation of clients is also considered a moment where information of the day could be handed over to the caregiver/parent of the client. The importance of this moment for the quality of care should not be underestimated. If this moment is carefully considered, the majority of care providers would be willing to have the transportation arranged by the RGV.

If the RGV decides to implement the client allocation strategy a big impact is made on the clients. Further research could provide more insights into this impact. If the RGV wishes to implement the client allocation strategy, it could be wise to do it gradually, possibly starting with the horizontal cooperation strategy. And allocating only new clients to a more ideal-located care provider.

6.2 Discussion

In this thesis, an overview of the issues that arise in the transportation of clients to social care services in the RGV is given. An ALNS algorithm investigates the impact of various strategies on the current situation. This section discusses the used methodology and its assumptions. The strengths and limitations of this research are identified and the contribution to the existing literature is explained.

The RGV has limited information available on how client transportation is organized in the current strategies. This lack of detailed data makes it unclear how many kilometres are covered in the current strategy. For this reason, not only the horizontal cooperation and the client allocation strategy but also the current strategy was modelled with the ALNS algorithm. As a result, the model may optimize the current strategy more than it is in reality because it is unknown whether care providers themselves use optimization to plan client routes. However, modelling all strategies with the same algorithm allows for a more fair comparison between them.

An attempt was made to compute an exact solution for the various strategies, however, the problem proved to be too complex for exact resolution. The obtained results are an approximation of the exact solution. Given the complexity of the problems, it is unclear how close this solution is to the exact one, as it was not possible to compute a lower bound using the ILP model.

In the model, several assumptions are made with various degrees of impact. These assumptions are presented here and an approximation of the impact of all the assumptions on the outcomes can be found in Appendix D.

The analyses did not use the exact addresses of clients due to confidentially rules, instead, the postal codes of the clients and care providers were used. This has a minor impact on the accuracy of the locations. For some routes, this will mean that they are slightly longer, while for others, they may be slightly shorter in reality.

The distance between all locations is calculated using QGIS's ArcMap 10.8. Via a road network, the shortest route is computed between every possible location that is needed for this analysis. In reality, the shortest route is not always the fastest route. When comparing certain distances between locations obtained from the road network to the distances provided by Google Maps, the road network sometimes finds slightly shorter routes. As a result, the total distance computed for a week of transporting clients is shorter than the real distance that is needed to transport all the clients during that week. For a fair comparison between the strategies, the impact of computing the distances between locations in this manner is minimal since the same road network is used for all strategies.

The day on which clients go to the care providers is an important assumption in the model. This data was not available, so in the model, clients were randomly assigned to a day. In reality, it is possible that the scheduling of the days that clients go to the care providers already takes into account route optimization, or that clients have a preference for a particular day, resulting in an uneven distribution between the days. This effect is not considered in the model but could mean that the various strategies may yield slightly higher distances as a result compared to reality.

The parameters in the model are modelled in a deterministic way. Most parameters were estimated with the knowledge of the RGV, such as the embarking time of clients and the number of seats a wheelchair occupies. Some of these parameters have a stochastic nature, but it is assumed in the model that these values are constant. This assumption may have a minor impact on the results.

Another deterministic parameter is the travel speed. A driving speed of a constant 40 km/hour is assumed between each location, which also determines the travel time between different locations. This is a significant assumption, as different routes may have varying speed limits and traffic density. However, the impact on the final results on the distance travelled will not be substantial, as speed primarily affects travel time and not the actual distance travelled.

The exact condition of a client is not known to the RGV; only the conditions treated by their care providers are known. In the client allocation strategy, clients are allocated to a care provider that treats the exact same conditions as their current care provider. In reality, a more optimal allocation of clients is likely possible if the exact condition of clients is known. This would result in a decreased distance outcome for the client allocation strategy.

This thesis provides insight into how the strategies of horizontal cooperation and client allocation can impact the current situation. Despite the assumptions made in the model, this project shows how a change in strategy can affect the number of kilometres travelled per week for clients attending social care services or the number of vehicles needed. No articles with the same characteristics as the RGV were found in the literature. We demonstrate that an ILP is not suitable for solving a problem of this magnitude with this many constraints. However, we conclude that an ALNS algorithm provides a good feasible solution. Thereby the thesis adds to the existing literature.

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A Detailed results of parameter tuning

Number of requests to remove at start of the run

Experiment	Results experiments			
Percentage to remove at start run (ω_{start})	Best solution	Percentage of run to find best solution	Number of improvements	Percentage of end solution above best solution
0.8	608	79%	16	0
0.6	601	92%	21	0
0.4	629	82%	13	0
0.2	595	100%	27	0

Number of routes to remove at end of the run with destroy routes operator

Experiment	Results experiment			
Minimum routes to be removed	Best solution	Percentage of run to find best solution	Number of improvements	Percentage of end solution above best solution
3	657	97%	20	0
2	622	97%	22	0
1	661	64%	15	0

Influence of last Markov segment on weights of operators

Experiment	Results experiment			
Influence of last Markov segment during run (ρ)	Best solution	Percentage of run to find best solution	Number of improvements	Percentage of end solution above best solution
0.8	604	91%	32	0
0.7	664	83%	22	0
0.6	674	96%	20	0
0.5	657	87%	26	0
0.4	633	91%	29	0
0.3	650	84%	25	0
0.2	606	94%	23	0
0.1	631	91%	20	0

Multi-start & Cooling rate

Experiment for determining multi-start and cooling rate: Monday

Experiment				Results experiment				
Approximate runtime (min)	Amount of markov iterations	Cooling rate (C)	Multi-starts	Best solution	Percentage of run to find best solution	Number of improvements	Percentage improvements	Percentage of end solution above best solution
60	180	0.92	1	1177	89%	80	9%	0
30	90	0.85	2	1269	89%	46	10%	0
30	90	0.85	2	1181	89%	51	11%	0
20	60	0.78	3	1308	100%	65	22%	0
20	60	0.78	3	1308	83%	27	9%	0
20	60	0.78	3	1202	100%	55	18%	0
15	45	0.72	4	1271	98%	49	22%	0
15	45	0.72	4	1295	93%	34	15%	0
15	45	0.72	4	1250	100%	42	19%	0
15	45	0.72	4	1304	65%	39	17%	0
12	36	0.67	5	1299	98%	44	24%	0
12	36	0.67	5	1350	98%	36	20%	0
12	36	0.67	5	1274	89%	28	16%	2.22045E-16
12	36	0.67	5	1384	89%	31	17%	0
12	36	0.67	5	1278	97%	35	19%	2.22045E-16
10	30	0.62	6	1325	99%	48	32%	0
10	30	0.62	6	1300	94%	31	21%	0
10	30	0.62	6	1333	97%	29	19%	0
10	30	0.62	6	1286	97%	33	22%	0
10	30	0.62	6	1285	99%	33	22%	0
10	30	0.62	6	1308	99%	41	27%	0

Experiment for determining multi-start and cooling rate: Tuesday

Experiment				Results experiment				
Approximate runtime (min)	Amount of markov iterations	Cooling rate (C)	Multi-starts	Best solution	Percentage of run to find best solution	Number of improvements	Percentage improvements	Percentage of end solution above best solution
60	180	0.92	1	1486	99%	74	8%	0
30	90	0.85	2	1649	100%	53	12%	0
30	90	0.85	2	1518	100%	56	12%	0
20	60	0.78	3	1607	98%	59	20%	0
20	60	0.78	3	1723	100%	40	13%	0
20	60	0.78	3	1687	82%	51	17%	0
15	45	0.72	4	1810	94%	27	12%	0
15	45	0.72	4	1663	100%	45	20%	0
15	45	0.72	4	1669	97%	49	22%	0
15	45	0.72	4	1656	99%	50	22%	0
12	36	0.67	5	1680	94%	52	29%	0
12	36	0.67	5	1679	96%	38	21%	0
12	36	0.67	5	1679	98%	45	25%	0
12	36	0.67	5	1753	99%	49	27%	0
12	36	0.67	5	1648	99%	28	16%	0
10	30	0.62	6	1766	93%	26	17%	0
10	30	0.62	6	1693	95%	40	27%	0
10	30	0.62	6	1823	95%	30	20%	0
10	30	0.62	6	1845	86%	31	21%	0
10	30	0.62	6	1669	96%	48	32%	0
10	30	0.62	6	1787	100%	34	23%	0

Experiment for determining multi-start and cooling rate: Wednesday

Experiment				Results experiment				
Approximate runtime (min)	Amount of markov iterations	Cooling rate (C)	Multi-starts	Best solution	Percentage of run to find best solution	Number of improvements	Percentage improvements	Percentage of end solution above best solution
60	180	0.92	1	1356	100%	64	7%	0
30	90	0.85	2	1345	98%	54	12%	0
30	90	0.85	2	1334	90%	43	10%	0
20	60	0.78	3	1414	99%	52	17%	0
20	60	0.78	3	1432	90%	25	8%	0
20	60	0.78	3	1296	99%	72	24%	0
15	45	0.72	4	1442	96%	53	24%	0
15	45	0.72	4	1360	100%	56	25%	0
15	45	0.72	4	1350	94%	58	26%	0
15	45	0.72	4	1389	99%	40	18%	0
12	36	0.67	5	1407	98%	67	37%	0
12	36	0.67	5	1415	97%	33	18%	0
12	36	0.67	5	1362	96%	55	31%	0
12	36	0.67	5	1395	99%	43	24%	0
12	36	0.67	5	1431	97%	44	24%	0
10	30	0.62	6	1491	89%	42	28%	0
10	30	0.62	6	1447	99%	53	35%	0
10	30	0.62	6	1520	96%	43	29%	0
10	30	0.62	6	1497	99%	31	21%	0
10	30	0.62	6	1427	99%	46	31%	0
10	30	0.62	6	1417	99%	35	23%	0

Experiment for determining multi-start and cooling rate: Thursday

Experiment				**Results experiment**				
Approximate runtime (min)	Amount of markov iterations	Cooling rate (C)	Multi-starts	Best solution	Percentage of run to find best solution	Number of improvements	Percentage improvements	Percentage of end solution above best solution
60	180	0.92	1	1493	100%	92	10%	0
30	90	0.85	2	1568	100%	57	13%	0
30	90	0.85	2	1619	94%	36	8%	0
20	60	0.78	3	1530	98%	71	24%	0
20	60	0.78	3	1571	97%	40	13%	0
20	60	0.78	3	1561	100%	79	26%	0
15	45	0.72	4	1654	99%	52	23%	0
15	45	0.72	4	1794	96%	37	16%	0
15	45	0.72	4	1744	100%	31	14%	0
15	45	0.72	4	1695	100%	33	15%	0
12	36	0.67	5	1684	95%	29	16%	0
12	36	0.67	5	1704	97%	29	16%	0
12	36	0.67	5	1750	93%	33	18%	0
12	36	0.67	5	1775	99%	28	16%	0
12	36	0.67	5	1618	96%	41	23%	0
10	30	0.62	6	1679	99%	41	27%	0
10	30	0.62	6	1758	88%	33	22%	0
10	30	0.62	6	1628	95%	48	32%	0
10	30	0.62	6	1692	98%	29	19%	0
10	30	0.62	6	1788	100%	28	19%	0
10	30	0.62	6	1569	95%	41	27%	0

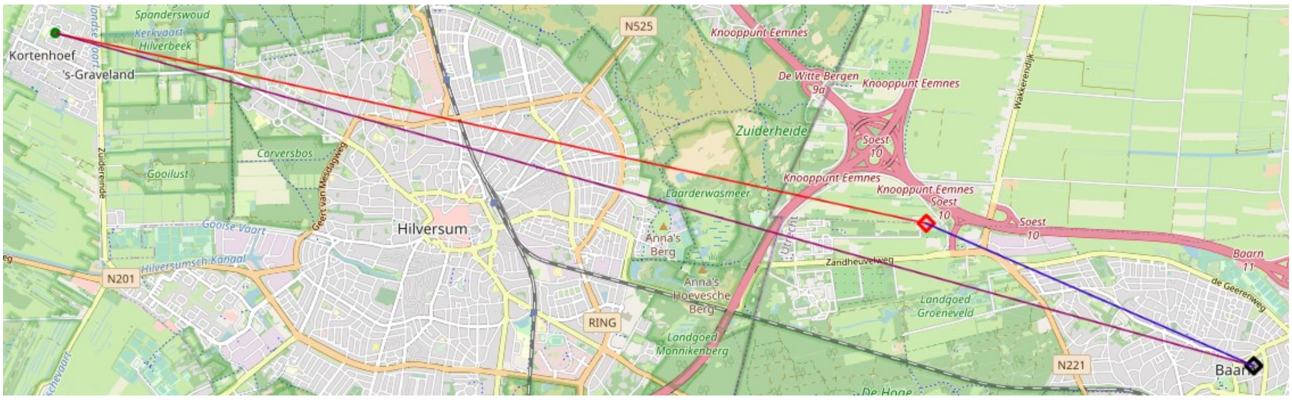
Experiment for determining multi-start and cooling rate: Friday

Experiment				**Results experiment**				
Approximate runtime (min)	Amount of markov iterations	Cooling rate (C)	Multi-starts	Best solution	Percentage of run to find best solution	Number of improvements	Percentage improvements	Percentage of end solution above best solution
60	180	0.92	1	1211	99%	78	9%	0
30	90	0.85	2	1284	81%	64	14%	0
30	90	0.85	2	1259	98%	64	14%	0
20	60	0.78	3	1378	96%	43	14%	0
20	60	0.78	3	1294	97%	42	14%	0
20	60	0.78	3	1357	100%	40	13%	0
15	45	0.72	4	1310	98%	44	20%	0
15	45	0.72	4	1340	100%	43	19%	0
15	45	0.72	4	1405	100%	35	16%	0
15	45	0.72	4	1307	95%	53	24%	0
12	36	0.67	5	1427	98%	42	23%	0
12	36	0.67	5	1261	92%	33	18%	0
12	36	0.67	5	1434	98%	35	19%	0
12	36	0.67	5	1292	99%	41	23%	0
12	36	0.67	5	1427	97%	42	23%	0
10	30	0.62	6	1358	92%	38	25%	0
10	30	0.62	6	1489	17%	10	7%	0.022
10	30	0.62	6	1358	98%	35	23%	0
10	30	0.62	6	1501	95%	19	13%	0
10	30	0.62	6	1469	97%	38	25%	0
10	30	0.62	6	1426	99%	36	24%	0

Experiment for determining multi-start and cooling rate: Saturday

Experiment				Results experiment				
Approximate runtime (min)	Amount of markov iterations	Cooling rate (C)	Multi-starts	Best solution	Percentage of run to find best solution	Number of improvements	Percentage improvements	Percentage of end solution above best solution
60	180	0.92	1	184	58%	12	1%	0
30	90	0.85	2	192	67%	10	2%	0
30	90	0.85	2	184	37%	6	1%	2.22045E-16
20	60	0.78	3	197	25%	12	4%	0
20	60	0.78	3	181	30%	9	3%	0.064355244
20	60	0.78	3	212	18%	4	1%	0.004679573
15	45	0.72	4	198	29%	9	4%	0
15	45	0.72	4	184	17%	8	4%	0.074830283
15	45	0.72	4	205	63%	8	4%	0
15	45	0.72	4	182	5%	5	2%	0.123766543
12	36	0.67	5	194	89%	12	7%	0
12	36	0.67	5	200	12%	5	3%	0.010473479
12	36	0.67	5	199	44%	5	3%	0
12	36	0.67	5	182	6%	5	3%	0.09338248
12	36	0.67	5	208	29%	4	2%	0
10	30	0.62	6	197	19%	11	7%	0.045694975
10	30	0.62	6	200	14%	5	3%	0.014802294
10	30	0.62	6	195	75%	6	4%	0
10	30	0.62	6	181	36%	6	4%	0
10	30	0.62	6	208	37%	5	3%	0
10	30	0.62	6	181	47%	10	7%	0

B Verification of routes: Shortest route



C Detailed outcomes of strategies

Current strategy

Detailed results of the current strategy

Random seed number	Total distance travelled througout a week (kilometres)	Number of vehicles needed	Average driving time per transport request (minutes)
0	7639	52	27.3
1	7523	53	26.8
2	7601	54	26.8
3	7825	54	27.0
4	7500	53	27.2

Horizontal cooperation strategy

Detailed results of the horizontal cooperation strategy

Random seed number	Total distance travelled througout a week (kilometres)	Number of vehicles needed	Average driving time per transport request (minutes)
0	7167	17	27.3
1	7007	15	27.5
2	6907	17	27.4
3	7085	17	27.2
4	7071	16	26.9

Client allocation strategy

Detailed results of the client allocation strategy

Random seed number	Total distance travelled througout a week (kilometres)	Number of vehicles needed	Average driving time per transport request (minutes)
0	6427	14	25.0
1	6447	14	25.5
2	6342	15	25.6
3	6420	14	25.3
4	6299	13	25.2

D Assumptions in the model

Assumption	Explanation	Degree of impact and explanation	Impact of assumption to the modelled solution
Locations are based on postal codes	Due to conifidentiality the precise adresses were unavailable.	Minimal impact as locations that are chosen are very close to the real locations.	Effect cancels out
The distance between locations	Distances are determined by QGIS's ArcMap road network, which produces the shortest route.	The total distance of the solution is likely higher in reality, as a lot of the routes are longer in reality than in the model.	Model underestimates total distance
Allocation of clients to random days	Data on which day clients have day care was unavailable, therefore they are randomly assigned.	The more clients in one day, the more optimization is possible, therefore an even distribution makes the solution worse than reality.	Model overestimates total distance
Deterministic parameters	To simplify the model, deterministic parameters were chosen. Such as a fixed boarding/embarking time.	Minimal impact as these parameters do not have a great influence on the outcome of distance.	Effect cancels out
Fixed travel speed	The driving time between locations is approximated using a constant travel speed.	The driving time partially determines how many clients can be transported in a single vehicle. The impact of the fixed travel speed is minimal as it does not influence the distance.	Effect cancels out
Unlimited vehicles	An unlimited number of wheelchair busses is available in the model.	In reality, the number of vehicles might be a restriction. A homogeneous fleet creates a better solution than in reality possible.	Model underestimates total distance
Exact match on conditions needed in client allocation strategy	The exact condition of a client is not known, therefore an exact match between the conditions of the current care provider and allocated care provider needs to be present.	Only for the client allocation strategy: the solution is likely lower in reality. A better allocation of clients is possible as an exact match between current and allocated care providers is not needed in reality.	For client allocation strategy only: Model overestimate total distance
Approximate total impact of assumptions:		**Current strategy:** **Horizontal cooperation strategy:** **Client allocation strategy:**	Model underestimates the total distance Model underestimates the total distance Model overestimates the total distance