Improving routes of a repair company

IEM Bachelor Thesis

written by: Julian van Engelen

Studentnumber: s2386496

School: University of Twente

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Supervisors UT:

1. Alessio Trivella
2. Dennis Prak

Supervisor Hamer:

1. Wilfred Ensing

UNIVERSITY OF TWENTE.

Hamer

Preface

Dear reader,

You are about to read my thesis, which is the last component of the University of Twente's Industrial Engineering and Management (IEM) Bachelor's degree and was carried out at Hamer. Before you begin reading my thesis, allow me to express my gratitude to a few individuals who were crucial to the process of producing this thesis.

I want to express my gratitude to Alessio Trivella, my first university supervisor, for his time, advice, and thorough feedback. He assisted me in finishing my bachelor's thesis. I also like to thank Dennis Prak, my second supervisor, for his time and dedication. I also want to thank Hamer for making it feasible for me to finish my bachelor's degree with a rewarding and difficult challenge. The organization was enjoyable to work with, and I appreciate them taking the time to assist me with my thesis.

Julian van Engelen, July 2022

Management summary

Hamer is a technical installation company, which provides services and installations in the utility, industry, automotive and fuel sectors. Numerous Hamer departments are located throughout the Netherlands and Belgium, with the headquarters being located in Apeldoorn. The core activity of Hamer consists of the installation of technical machinery and the maintenance of these devices. This research focuses on the fuel department, which mainly repairs malfunctions spread throughout the Netherlands. Hamer is constantly seeking for higher efficiency, but currently, a mechanic can handle 20 malfunctions in a week on average, while their norm is 21. After the current situation had been investigated, it was decided that the routes of the mechanics could provide the necessary improvements. Thereafter, in-depth observation and literature research has been conducted to learn more about the problem. The problem is a Vehicle Routing Problem (VRP) and after research it is classified as an adapted Multi-Depot Vehicle Routing Problem with Time Windows (MDVRPTW).

Currently, the routes are made manually a day prior without any software assistance. Hamer has to handle various malfunctions per day, but they are limited by the current capacity of employees. Next to that, malfunctions have a difference in priority due to the Service Level Agreements (SLAs) Hamer has with their clients. Therefore the routes need to be based on the distance and priority of jobs. The VRP is an NP-hard problem (nondeterministic polynomial time), meaning that computing the optimal solution could take non-affordable time. Therefore certain heuristic algorithms were chosen, which gave a sufficient solution in reasonable time. The heuristics take into account the distance and priority of associated jobs. For creating an initial solution, an algorithm is made using an adapted Push Forward Insertion Heuristic (PFIH). In order to optimize the initial solution, the following improvement heuristics were used: an adapted 2-interchange as inter-route operator, and 2-opt as intra-route operator.

The Route Planning Software (RPS) decision support tool for Hamer was made using Python and Excel. A single-day approach is utilized to determine the routes for the following day. This was done because of additional malfunctions that often occur throughout the week, thus making it difficult to plan far ahead of time. The software produces routes for Hamer in relatively short computational time, allowing Hamer to use it to find efficient routes quickly.

Using the self-made RPS decision support tool with the explained heuristics, various experiments were conducted. The priority of locations can be set to Hamer's desires, so that Hamer can improve certain Key Performance Indicators (KPIs). There are different experiments conducted to evaluate the algorithms and parameters. In addition, an experiment was carried out to compare the outcomes of the real situation with the results recommended by the RPS. The outcomes were attained at a time when there were, on average, 5.6 mechanics available. The results showed a predicted change in the average distance traveled from 53.0 km per failure to 48.1 km. Additionally, the findings demonstrated that 1.25 more jobs could be performed on average by each mechanic in a week while requiring them to work 13.4 hours less overall. In total the distance driven weekly was reduced from 6044 km to 5821, while handling 121 jobs instead of 114.

The primary proposal for Hamer after this research is to conduct further research concerning RPS. Hamer has many additional departments where the implementation of RPS could increase productivity. Due to time constraints, the problem could not be fully resolved and implemented into Hamer's departments. For further implementation, Hamer could adapt the software to attain their wishes. Firstly, the provided

solution is still a single-period approach, whereas Hamer faces a multi-period problem. Additionally, the distance and driving time are now based on the orthodromic distance and average driving speeds, which could be modified using Add-ins. Finally, the emphasis was solely on mechanics, which are capable of resolving any malfunctions in the fuel department. However, there is a minor amount of mechanics that do not possess the required skill set to solve a certain problem. Certain adaptations to the RPS could ensure that all mechanics are included with their personalized skills taken into account. Thus, excluding certain mechanics from malfunctions they are unable to resolve. Further research in these areas would result in a better reflection of reality and thus more accurate route optimization.

1. Introduction

1.1. About Hamer

Hamer is the organization in which this bachelor thesis has been completed. The company was founded in 1938 and since then has grown into a medium-sized company with more than 450 employees (Hamer, 2021). Hamer is a significant provider in the utility, industry, automotive, fuel supply and chemical and food industries. This includes taking care of the design, construction, and maintenance of many clients. As described, Hamer specializes in several categories. Their core activity is technology. If there is a technical problem, regardless of the context, Hamer will be able to resolve the issue.

Hamer has several branches in the Netherlands and Belgium. These branches are divided into various departments. For this thesis the main department is the fuel department. The fuel department makes sure that gas stations are maintained and fixed when needed.

1.2. Background information

Hamer is a major provider for gas stations; this thesis will primarily focus on their fuel department. The fuel department primarily focuses on fuel flaws of gas stations, such as broken fuel nozzles. Besided the department is also able to resolve alternative problems that occur at gas stations, for example electrical issues. To maximize customer satisfaction, Hamer acts in one of two strategies: corrective and preventive. Corrective actions are used as a reaction after something is noticeably broken. Preventive actions are precautionary measures which are held after a certain time period to forestall problems, e.g. status check-ups of parts to ensure all segments are still reliable and safe. Currently, Hamer has a surplus of clients. Hence, additional employees are sought after. However, difficulties persist regarding obtaining new employees. Therefore, it is impossible to handle all malfunctions in a week with the current capacity Hamer has. This results in due dates that cannot be reached as well as unnecessary kilometers. Since the company is focused on serving as many clients as possible while guaranteeing the quality of work that Hamer aims to provide, an increase in efficiency is needed whilst keeping the employee count constant.

1.3. Identification of the problem

Hamer has several objectives, but mainly focuses on efficiency, environment and customer service. This is no different for the fuel department. While focus thus lays primarily on efficiency, the company is confident that efficiency can be increased even further and consequently handle more clients. This presents the action problem of this research:

The amount of malfunctions handled by the current mechanics is too low.

This paper is solely focused on the fuel department due to the fact that most mechanics of Hamer are active in this area and is therefore most suitable for in-depth research into efficiency in the limited time span of ten weeks.

1.3.1. Problem cluster

Based on observations and semi-structured interviews with employees of Hamer, a list of problems was created. These problems are concentrated in the fuel department and are mapped in a problem cluster, where different types of problems are plotted in relation to each other. A problem cluster is used because it provides a graphical explanation for causes and effect relations of problems in firms (Heerkens & van Winden, 2021). With the help of Figure 1, potential core problems can be found. These potential core problems do not have a cause but can be the foundation for other problems. By solving these potential core problems, it is easier to solve general problems.

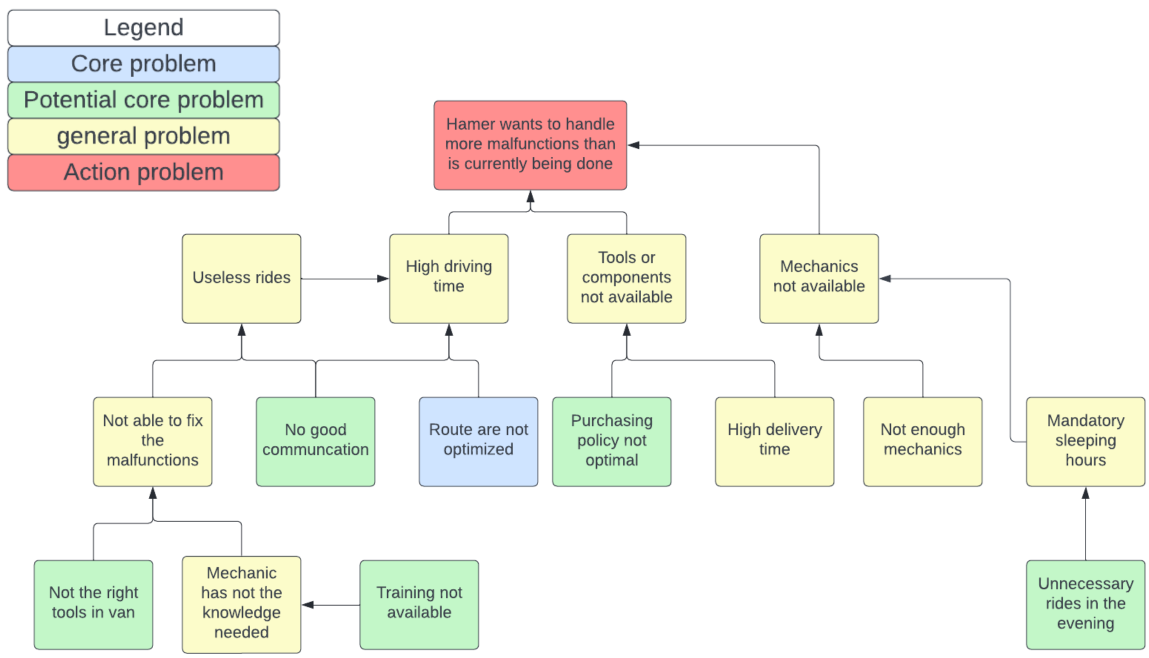

Figure 1. Problem cluster, based on the action problem of Hamer

1.3.2. Potential core problems

The potential core problems, found in the graphical analysis above, are discussed shortly below.

Poor communication

The first potential core problem regarding communication is broad. Lack of good communication is a problem which results in many adverse effects, not only for Hamer but almost in all companies. In Hamer for example, it sometimes occurs that a malfunction reported at a location is canceled, which means that the location does not have to be visited anymore. In some situations, desk-based employees or employees on site were aware of this yet failed to communicate properly with a mechanic, resulting in unnecessary visits to certain locations. These cases could have been prevented if proper, clear communication was present.

Lack of proper tools

Every mechanic has responsibility for their own tools. Sometimes, this results in mechanics arriving at a destination without having the right equipment to solve the malfunction. This accounts for a significant amount of wasted time and is therefore seen as a potential core problem, which could be fixed if a checklist of tools for the mechanics is made.

Training not available

Working for Hamer as a mechanic is a complicated job, especially if you are active at the fuel department. There are many different kinds of malfunctions the fuel department faces. There are many different types of pumps, varying from old to new with different ways of fixing. This difference requires significant knowledge where newer employees might not have seen older types of pumps or vice versa. To solve this, companies could be contacted to give the training. This is already done in small batches but often employees do not know how to solve a malfunction, this could be analyzed and new possible solutions for this could be investigated.

Unnecessary rides in the evening
In the evening, a malfunction can occur that still has to be solved in several hours. Two mechanics therefore have breakdown service in the evening. If they attend a malfunction in the evening, the two mechanics have mandatory sleeping hours, eight hours for the first consecutive days and eleven for the days after. This means that there are fewer mechanics available during the day due to evening shifts and this results in less construction and maintenance. From recent experience, it is found that some breakdowns fixed in the evening are unnecessary and could be postponed. To solve this, a stricter policy could be developed in order to avoid unnecessary rides and increase efficiency.

Purchasing policy not optimal
Hamer has a warehouse in which all kinds of products are stored. Hamer has thousands of products which makes it difficult to keep track of their purchasing policy. According to many employees, certain products are used more often than others and require more resupply. If the purchasing policy is not adjusted for individual products, which are more demanded by the mechanics, certain malfunctions cannot be solved. Hence, if the tools or products are not available and certain locations cannot be visited due to this, it is a potential core problem.

Routes are not efficient enough
The last potential core problem that could be tackled is the route efficiency. At the moment, the routes are made by planners without any kind of assistance. Since it is almost impossible for a human to determine the routes for multiple mechanics spread throughout the Netherlands in an efficient way, implementing time and cost reducing measures is relatively easy. This is a potential core problem because improving it can ensure that more malfunctions can be handled and mechanics can increase efficiency.

1.3.3. Core problem

In consultation with various employees amongst most of the hierarchy levels within the company, indication was given that the lack of efficiency in route planning was identified as the most important issue within the company.

1.4. Norm and reality

1.4.1. Reality

The current reality is that the mechanics can handle around 20 malfunctions a week per mechanic for the fuel department; this number is obtained using a given dataset of Hamer. Hamer is convinced they should be able to tackle more malfunctions per week. In addition, Hamer also wants to reduce the average number of kilometers driven per location, so they spend less time on the road and work more.

1.4.2. Norm

The norm is defined as the situation Hamer thinks is possible. They want to increase the number of malfunctions handled per mechanic, and strive to increase the amount with one malfunction a week to a total of 21 malfunctions. Hamer believes route planning is not optimized yet due to the fact that route-planning is solely done by employees without additional assistance by planning-software tools, therefore leaving room for efficiency improvement . Of course, the more malfunctions fixed the better, however there is a certain limit to the amount of malfunctions the mechanics can fix within a week with the current capacity of employees. For this thesis, the norm is an increase of one more malfunction per mechanic per week for the fuel department. This thesis looks at the possibility of making the routes more efficient so that more malfunctions can be tackled and less driving is required on average so that more time can be spent on fixing problems.

1.5. Key Performance Indicators

Hamer has several important key performance indicators (KPIs) that must be taken into account when planning the routes. To examine if Hamer's route could be more efficient, these KPIs must be taken into consideration. The KPIs are shown below:

- Amount of malfunctions visited
- Average distance traveled
- Working percentage (= work time at jobs / total work time)
- Total working hours
- Due dates not fulfilled

The major goal for Hamer is to tackle more malfunctions with the same employees, while also improving the other KPIs. To achieve this, it must be examined whether the routes can be made more efficient. On the other hand, the routes cannot be based only on the shortest distance since Hamer also has to deal with due dates, which are based on Service Level Agreements (SLA) Hamer has with their clients. The resolution time can vary from 4 hours to more than a month, sometimes it is decided not to meet a due date in order to keep the travel costs low. Therefore there is a trade-off that must be taken into account in this research. To check if the KPIs could be improved, an experiment is done later in this research with a dataset based on a real scenario.

1.6. Research questions

In order to solve the core problem, different research questions should be investigated and answered.

How can Hamer routes be more efficient?

All sub-research questions are derived from the main question and are discussed below.

1. What does Hamer's current route planning look like?

The current situation is of big importance and must be analyzed in order to conclude whether it is possible to handle more malfunctions given the current number of employees, this is done in Chapter 2. This results in more insight into the current planning strategy of Hamer, which is needed to compare the results of efficiency after this research.

2. *What can literature tell about the following research questions?*
   In Chapter 3 a literature review was conducted to answer the following sub-research questions.

2.1. What are various forms of vehicle routing problems and what are the characteristics of Hamer's?

To be able to make improvements to the current situation at Hamer, possible strategies of route development should be investigated. Simple route optimization is based on the idea of traveling the shortest distance, but in the situation of Hamer there are other factors that could affect the definition of the optimal route . Therefore multiple variants will be discussed to gain more knowledge about the routing problem.

2.2. What are possible solving methods for the vehicle routing problem Hamer faces?

There are many different possible ways to improve the routes, broadly classified into exact and heuristic methods. Most strategies are not suitable for the situations of Hamer, therefore the selection of right strategies should be done.

2.3. How to perform the solving methods and conduct experiments?

When the data is collected an experiment should be done as proof, to show whether it is possible to achieve the goal. Knowledge of how to create an experiment is of big importance for this research. Literature study is conducted to obtain this information.

3. Which data should be taken into account in the experiments?

To perform an experiment certain data is needed, in Chapter 4 it is determined which data needs to be taken into account. To make the experiments as valid and reliable as possible, the data and results should not deviate too much from reality.

4. Which constraints should be taken into account in the experiments?

To perform an experiment certain constraints are needed, such as work time or capacity. To make the experiment as reliable as possible, so that practice and results do not deviate too much. The problems Hamer faces in real life should be constrained in the experiment, so the results are valid and not favorable for the researcher. The research to answer this sub-research question is conducted in Chapter 4.

5. How to show and interpret the results?

When the results are obtained, they must be visualized, using graphs, tables and figures to show stakeholders a clear overview of the outcomes. Certain KPIs must be identified and investigated to compare the model with the current situation. The KPIs chosen for this research are discussed in Section 1.5. Based on the desires of Hamer, it must be decided what and how the results should be displayed; this subject is discussed in Chapter 5.

6. What conclusions and recommendations may be drawn from the research done at Hamer?

Finally, conclusions can be drawn and suggestions for additional research will be given after the study has been completed and the solution to the research question has been evaluated. Chapter 6 answers the last sub-research question using the research on the other sub-research questions.

1.7. Deliverables

The deliverables of this thesis consist of three parts. First a report is made, which consists of a clear description regarding the problem-analysis, a literature study, current situation and, a data analysis used to determine if Hamer could operate more efficiently. The end of the report consists of a clear recommendation combined with a conclusion of the main findings of this research.

Besides, verbal presentations regarding the content of this research and findings will be discussed. This presentation has possible solutions and recommendations as the center of attention, so that the message of this paper is distinct for the company.

Finally, a route planning decision support tool is made to see whether routes could be more efficient. At the moment Hamer does not use any kind of route planning system for the corrective fuel department, therefore the tool can be highly valuable for the company. This program is based on the analysis and literature found in this research and could be used as a foundation for further development of the program for in-house development of efficiency and other contributing research.

2. Current situation

To improve the fuel department's routes, a comprehensive picture of how the routes are now planned in Hamer is required; the next chapter will go over this in detail. The entire process must be clear in order to comprehend it adequately. To accomplish this, data must be acquired, interviews must be conducted, and field experience must be gained.

In this chapter the first sub-research question is answered: ‘What do Hamer's current situational variables look like?’.

2.1 Current situation

As previously indicated, Hamer is subjected to a variety of problems; nevertheless, the focus of this report is on the fuel department, where reports are classified into two categories: corrective and preventive. The focus of this thesis is mainly on corrective notifications. If a problem occurs at a location, the failure coordinators are notified through email or phone, and the notification is entered into the system Hamer uses. If there is any missing information, they ask the client to complete it or to back up their claim with evidence such as photographs. The malfunctions are assigned to the appropriate department with a deadline based on their judgment. This due date is set by an arrangement Hamer has with a few companies; these agreements are referred to as service level agreements (SLA). An agreement like this establishes the quality of service that a company can anticipate from Hamer (Overby, 2017). If Hamer fails to meet these SLAs, they are penalized or bonuses are not awarded. The day before, the corrective fuel malfunctions are primarily planned. When it comes to planning, the due dates and distance are the most important considerations. The system Hamer uses shows the postcode and due dates. In conjunction with these variables and the capability of each mechanic, malfunctions are assigned to employees. The locations and malfunctions are sent to a certain mechanic, and they plan their own routes, which are based on their preferences or priority. Because of new problems, the routes can still be altered during the day. Communication is crucial in this process, and due to the planners' experience, a reasonable estimate of how long something will take is made.

As malfunctions are given to mechanics during the day, it is impossible for them to plan the routes optimally, since they are not aware of everything.

2.2. Hamer’s data

Data must be evaluated in order to gain a better understanding of the circumstances Hamer is facing. The data used is from prior years; the reason for this is that Hamer converted to a new IT system, in April 2022. In order to minimize overlap errors and other incorrect data, the old system is chosen for data collection. The information acquired is used to describe the scenario and provide insight into the thesis's purpose. This data is transferred to an Excel file, which allows for the creation of charts. The raw data must first be cleaned before it can be evaluated, such as internal notifications, for example mechanic training and faults that were not addressed by Hamer or completed during the night shift are removed. The remaining data displays the fuel department's malfunctions. The data can now be displayed, without giving a distorted image.

Locations

A heat map is constructed to gain a sense of the scenario that the fuel department is in, illustrating the locations of the malfunctions across the Netherlands. The heatmap can be found in Figure 2 and is made with PowerBI.

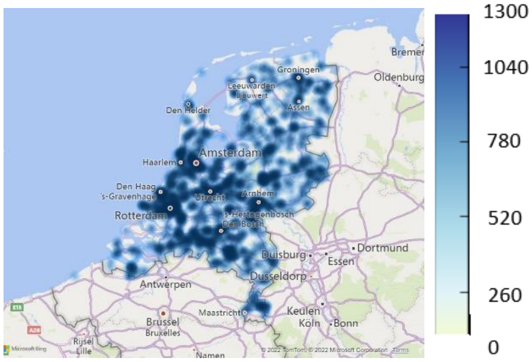

Figure 2: Heatmap of malfunctions, year overview

From the heat map it can be concluded that the disturbances are not evenly distributed over all the areas. It becomes clear that in the west of the Netherlands the most malfunctions occur and there seems to be a correlation between population density and the number of outages that occur.

Mechanics

There are approximately 14 mechanics active at the corrective fuel department, the majority of them keep their van at home, but there are also mechanics who live near a depot and have their van stored there. For the corrective fuel department, mechanics start and end their route at the same location. This guarantees that mechanics start and end their route in different places compared to each other.

Malfunctions

Because the number of malfunction notifications for the fuel department is not always consistent, a table graph is created to show the average number of malfunctions Hamer gets for the fuel department. Figure 4 demonstrates that there are more malfunctions occuring at the beginning of the week, this is due to failures occurring on weekends but being processed on working days. Figure 5 shows a yearly overview of the number of malfunctions occurring per week and the number of visits per week. It can be seen that the number is around a trend but there are fluctuations during the year.

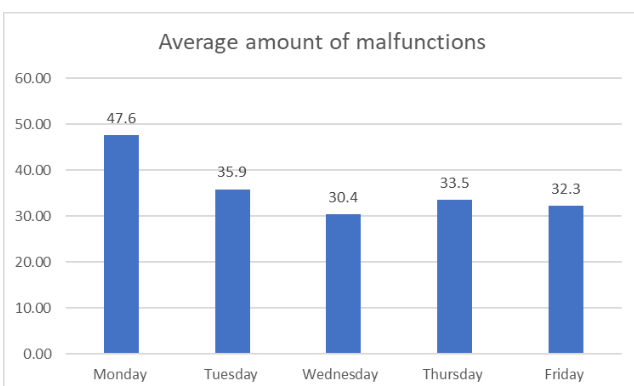

Figure 4. Average incoming malfunctions a day

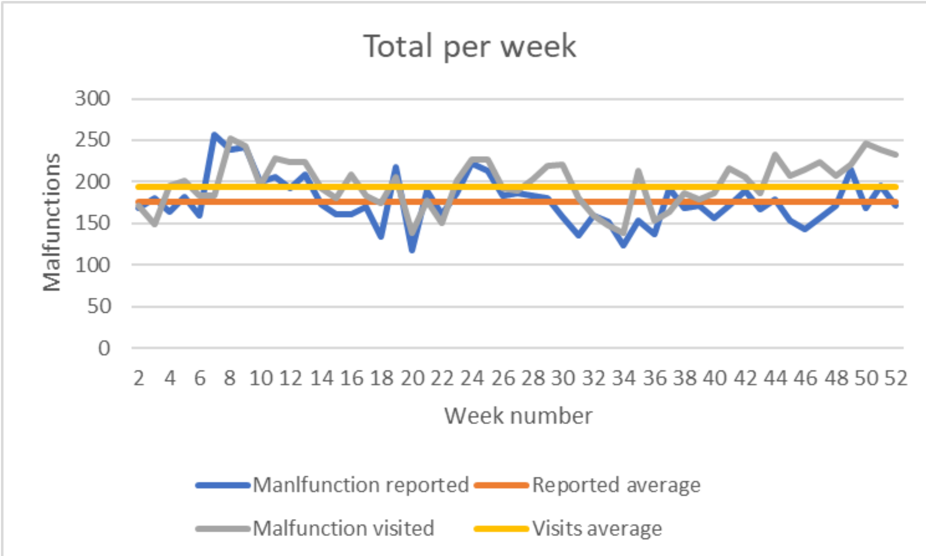

Figure 5. Year overview total malfunctions reported and visited

Figure 5 shows that on average there are more malfunctions visited than occurs. A variety of reasons persists, one of them is that locations are visited more than once as explained in the fix rate part later in this section. By utilizing the information provided in the Figures and taking into account the number of mechanics who were active at that moment, the conclusion can be made that on average, 20 malfunctions per mechanic are handled in a week.

Due dates

The permitted reaction time is defined by the SLA Hamer has with its clients; not all malfunctions are of the same importance. The bigger the relative damage caused by the issue, the sooner Hamer must get to the station.

According to the data, the distribution of the allowed response time is shown in Figure 6. The data must be slightly modified for this to convert it into an actual display of the situation. After this is done only a few mistakes, such as duplicates, need to be filtered out to be able to convert the data into a visual chart.

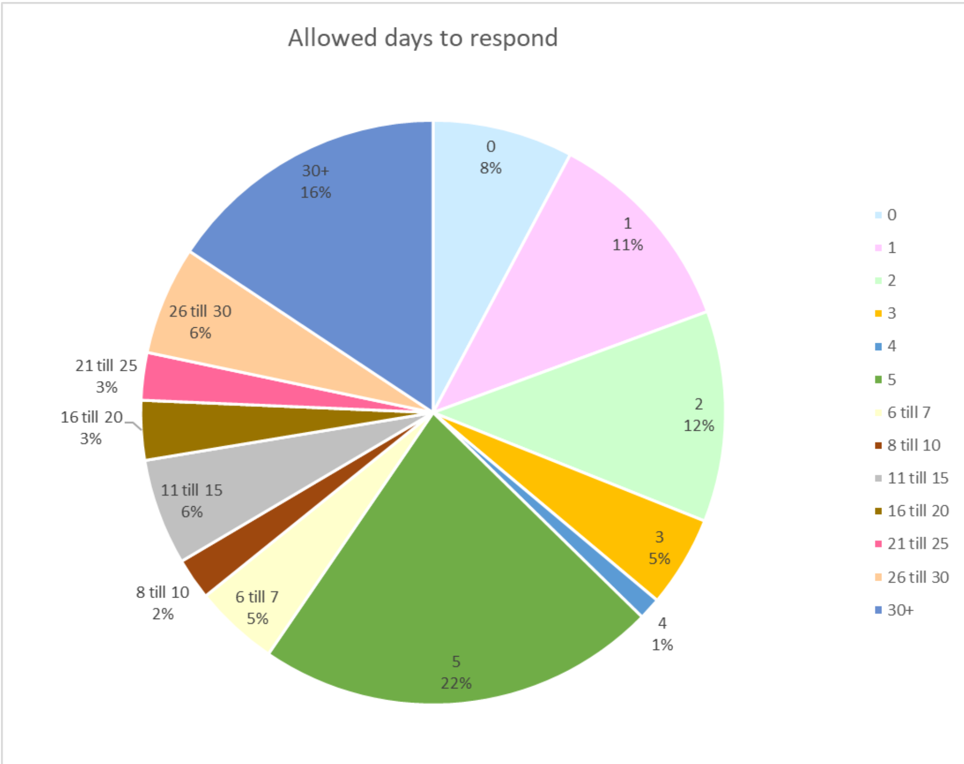

Figure 6. Allowed response time based on SLA

Since only 8% of the malfunctions have to be scheduled on the same day, on which they are reported, the routes can generally be planned in advance. After the fieldwork, it can be concluded that this is not done enough. It often occurs that a mechanic is already done at his malfunctions and thereafter a malfunction is added to his route, this generates inefficiency.

Fix rate

Not every malfunction can be solved with just one visit, if a mechanic fails to fix it at least one extra visit is needed to solve. Possible reasons could be that the mechanic does not have the skills or tools needed. This research mainly focuses on the response time and not the resolution time, but in the planning also malfunctions with more visits needed are scheduled. In Figure 7, the average number of visits needed to fix a malfunction is shown in percentages.

Figure 7. Visits needed to fix, year overview

Other relevant data

Different data is relevant for this study, but it is not readily available in the system, such as service time or working hours and must therefore be gathered. A time period of two weeks in the old system's age has been chosen to conduct experiments and gather data. The data is gathered in Section 5.1, so that exactly is known how and which data needs to be collected.

2.3 KPI score

A selected dataset of the old system is given by Hamer to check whether this research can lead to improvements, in this dataset there were on average 5.6 mechanics available per day. The scores of the KPIs (Section 1.5) are shown in Table 2 and are obtained using measuring methods explained in Section 5.1. In the first column of Table 2, the day and available mechanics of that day are given. Hamer wants to improve these scores and believes that the required number of locations should be increased while the distance and failed due dates are now too high.

	Distance	Locations	Failed due dates	Working percentage	Hours worked
Day 1	990	24	18	67.4	43.21
Day 2	865	21	20	68.6	38.90
Day 3	1219	28	20	65.6	49.92
Day 4	1673	24	18	58.3	56.56
Day 5	1297	17	17	59.5	45.02
Average	1208.8	22.8	18.6	63.88	46.7
Total	6044	114			233.61

Table 2. KPIs of the real situation

2.4. Conclusion

Currently, routes are defined by a planner manually; mechanics are given locations and allowed to choose their own routes in general. As a result, Hamer generally scores worse on KPIs than would be possible with an optimization approach for determining the routes.

Besides, we now have all the information to answer the first sub-research question: ‘What does Hamer's current route planning look like?’

The number of malfunctions seems to follow the population density, while the mechanics are not spread out corresponding to the population density, which results in a worse KPI score. In addition, certain situational variables of Hamer become clear. For example, an average of 36 failures are received and a mechanic handles on average 20 malfunctions a week. The requirements of Hamer’s clients are displayed and it could be noted that in general it is possible to schedule in advance because only a small percentage has to be solved the same day.

3. Literature review

With a clear picture of the existing scenario, it is time to look into how the issues of Hamer are addressed in literature. The problem Hamer is facing can be classified as a Vehicle Routing Problem (VRP); this chapter first gains more knowledge about the VRP in order to learn how to improve the routes of Hamer. In this chapter, we strive to answer research question 2 (2.1, 2.2 and 2.3).

3.1. Vehicle routing problems

There are many different variants of the VRP. Firstly, the classic VRP will be discussed and then the important features of Hamer's situation will be described.

3.1.1. Classic vehicle routing problems

The vehicle routing problem (VRP) is a problem which has been known and researched for decades. It is a variant of the traveling salesman problem (TSP), which was first formulated in 1930 by Karl Menger (Menger, 1930). The TSP is an algorithmic problem tasked with finding the shortest route of a set of locations that must be visited. The vehicle routing problem appeared almost two decades later in 1959, in a research article of Dantzig & Ramser (Dantzig & Ramser, 1959). The classical VRP model has one depot, a fixed number of vehicles available and fixed customers located in different places. The goal for a VRP is to find efficient feasible routes to visit the customers. The older the problem got, the more difficult and advanced the problems and constraints became. One of the most famous VRP is the Capacitated Vehicle Routing Problem (CVRP). This model searches for a solution which contains the cheapest routes without taking up too much capacity per vehicle or depot. The customers have a certain demand and the routes are made based on these constraints (Longo et al., 2006).

Figure 8 displays an example of a CVRP, the black circle is the depot and the blue circles are the locations that need to be visited without violating the capacity rules. The capacity in this example is 15 per vehicle and customer demand can be found in Figure 8 addressed in red (OR-tools, 2021).

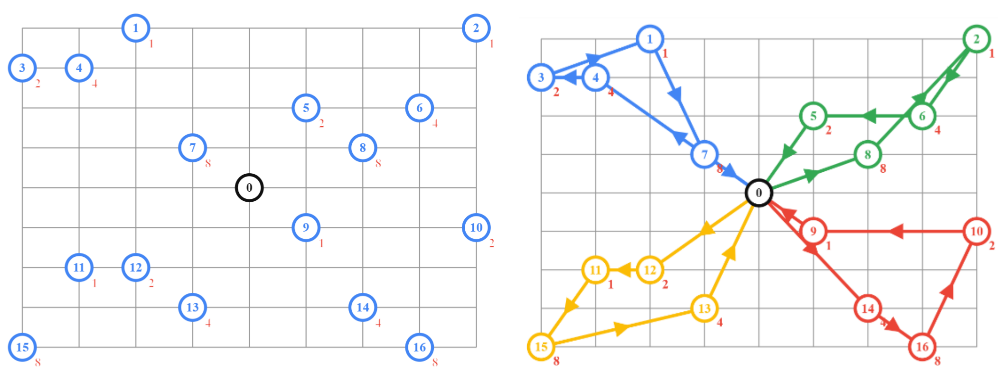

Figure 8. Left: locations and their demand, right: route constructed using solving method (OR-tools, 2021)

In the example of Figure 8, there are only 16 customers, four vehicles and one depot, and already finding a close to optimal solution manually is difficult. For a more complex problem, like these Hamer faces on a daily basis, it becomes more and more difficult for a human without any kind of assistance tools.

There are many different VRPs, based on the classical VRP, with different parameters, objectives and constraints. In Figure 9 an overview can be found of the VRP and some variants, for sake of brevity not all VRPs are presented. Figure 9 will be useful in determining which VRP Hamer faces.

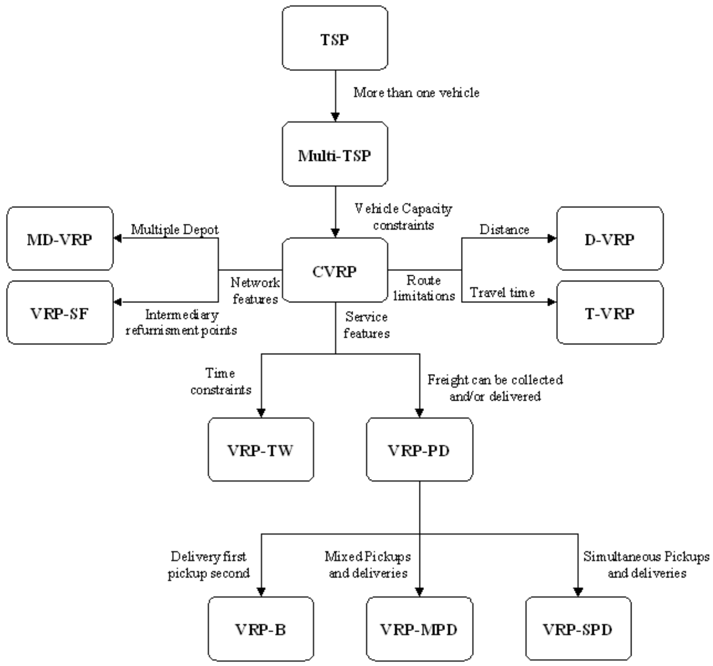

Figure 9. Overview of VRP variants (Créput & Koukam, 2008)

In Table 3, a taxonomy is given to define the input data for the VRP of Hamer. The input data is defined using two categories: information quality and information evolution. Information evolution indicates whether the information can change while the routes are being executed. Dynamic means that for example new customer requests could arrive during the day, which is the case for Hamer. The opposite of dynamic is static, in which everything is known in advance and remains the same during the work period.

The information quality indicates the possibility of variability in the input data. This can relate to different parts of a route planning, such as service time, travel time and service demand. If a VRP is deterministic this data does not change but often in real life a VRP is stochastic. This is most often the travel or service time, in real life this can suddenly change. The situation of Hamer can be classified as a stochastic and dynamic problem.

		Information quality	
		Deterministic input	Stochastic input
Information evolution	Input known beforehand	Static and deterministic	Static and stochastic
	Input changes over time	Dynamic and deterministic	Dynamic and stochastic

Table 3. Taxonomy of vehicle routing problems by information quality and evaluation (Pillac et al., 2013)

3.2. VRP of the department

Over the years, different VRP variants have been developed with all kinds of different goals and constraints. This section describes several characteristics, to find out what kind of situation Hamer encounters.

3.2.1. Depots

A depot in the VRP is a location, which a vehicle leaves to go to the network and returns to after the route is completed (Chen et al., 2017). In the classical VRP there is only one depot, but in Hamer's case there are multiple depots, because mechanics take their van home and are replenished at their home. This makes the VRP a Multi-Depot Vehicle Routing Problem (MDVRP). Depots can be characterized by vehicles, capacity, associated cost etc. (Chen et al., 2017). In some VRP the locations are already linked to a certain depot or mechanic. In Hamer's case there are situations where a location is already linked to a mechanic, but this is rare and therefore not discussed in depth. Solving a multi-depot problem is different compared to a single-depot problem, often other approaches are used to find better or faster solutions. In the paper of Salhi and Sari (1997) a method was proposed to solve the MDVRP consisting of three different levels, the first constructed the route and the second and third improved it using heuristics.

3.2.2. Time constraints

Time is an important factor in many VRPs in different ways. This section discusses examples of time constraints and explains how this is reflected in Hamer. The most known VRP with time constraints is the Vehicle Routing Problem with Time Windows (VRPTW). These VRP have a constraint, which indicates when a client's problem needs to be fixed or between which times a job can be visited, for example. There are two types of time windows, hard and soft. Soft time windows can be exceeded, but there are costs associated if this happens, while hard time windows are strict and cannot be exceeded (Balakrishnan, 1993). Another VRP which is of use for the situation of Hamer is the Vehicle Routing Problem with release and Due dates (VRPD). In this case there are certain moments when a job is released and the company should visit the job before the associated due time (Shelbourne et al., 2017). This is reflected in the problem of Hamer because of the SLAs the company has with their clients as stated in Section 2.2. If the SLAs cannot be met, Hamer will receive penalties. The third time constraint discussed in this sector is the Vehicle Routing Problem with Service Time (VRPST). Service times are defined as what time a vehicle service takes to complete a certain job (SPE BoK, 2018). In Hamer's case, all the above time constraints are present. In the paper of Funes et al. (2017), an approach can be found to tackle VRP with these types of time constraints.

3.2.3. Vehicle features

In a VRP, different types of vehicles could be present; these problems are defined as Heterogeneous Vehicle Routing Problems (HVRP). This feature is most known in CVRP; a certain vehicle has in this case more capacity than others. The situation Hamer faces could be seen as HVRP; not every mechanic has, for example, the same level of skills or the same amount of work hours available. Certain technicians cannot solve certain malfunctions because they do not have the knowledge or experience. To be able to research the VRP of Hamer only the mechanics who can do everything are considered, since there are thousands of different malfunctions and the mechanics do sometimes not even know themselves if they are able to solve it in advance. Because of the different working hours, the problem still has characteristics of an HVRP and therefore solutions found in literature must be explored. In the paper of

Seixas & Mendes (2013) a solving method is proposed, in which they use various heuristics to keep costs as low as possible.

Using the literature research and in consultation with Hamer, it was decided that an adapted Multi-Depot Vehicle Routing Problem with Time Windows (MDVRPTW) will be tackled in this research.

3.3. Solving methods

A VRP can be solved in three ways, manually, with self-developed software or using commercial route optimization software. This study focuses on the second option, because calculating by hand is inefficient and more subject to human mistakes. Besides, the last option often is expensive and may be unable to incorporate specific constraints that Hamer faces. Hamer does not know yet if more efficiency could be achieved using one, and is therefore not suitable for this research.

Despite the fact that the situation of Hamer is dynamic and stochastic, the company is satisfied with a static and deterministic study. A static approach still provides useful insights since only a small percentage of the malfunctions occuring should be scheduled the same day. Besides, the planners are currently decisive in the routes, but RPS gives recommendations, which could result in better KPI scores. Lastly, although the situation of Hamer is stochastic, with the use of data sufficient estimations could be made for the model to work.

3.3.1 Solution approach

The first step in developing software for a VRP is composing a mathematical formulation that could be used to solve the VRP to optimality with an optimization solver (Meyers, 2001). In a mathematical formulation, a situation is transferred into variables and there are often binary decision variables which are either 1 or 0, which indicate a yes or no decision. Besides, there is an objective function which needs to be optimized without violating the constraints (Meyers, 2001).

Secondly, the method needs to be determined to be able to solve the VRP of Hamer. There are many different algorithms to solve a VRP, and new ways are always being devised to find better and faster solutions to new situations. In Figure 10, an overview can be found of some algorithms for solving a VRP. The three main categories will be discussed in the next sections, exact method, heuristics and metaheuristics. In Section 3.3.5 is decided which category is most suitable for this research and in Section 4.2 is researched which algorithms are used to solve the VRP of Hamer.

Lastly, the algorithms have to be implemented into a computer program, so experiments and calculations on the VRP of Hamer can be performed. In Section 3.4 the computer program is determined, which will be used in the model of Hamer. The selected program is used in Chapter 4 to transfer the algorithms into the programming language and a working algorithm.

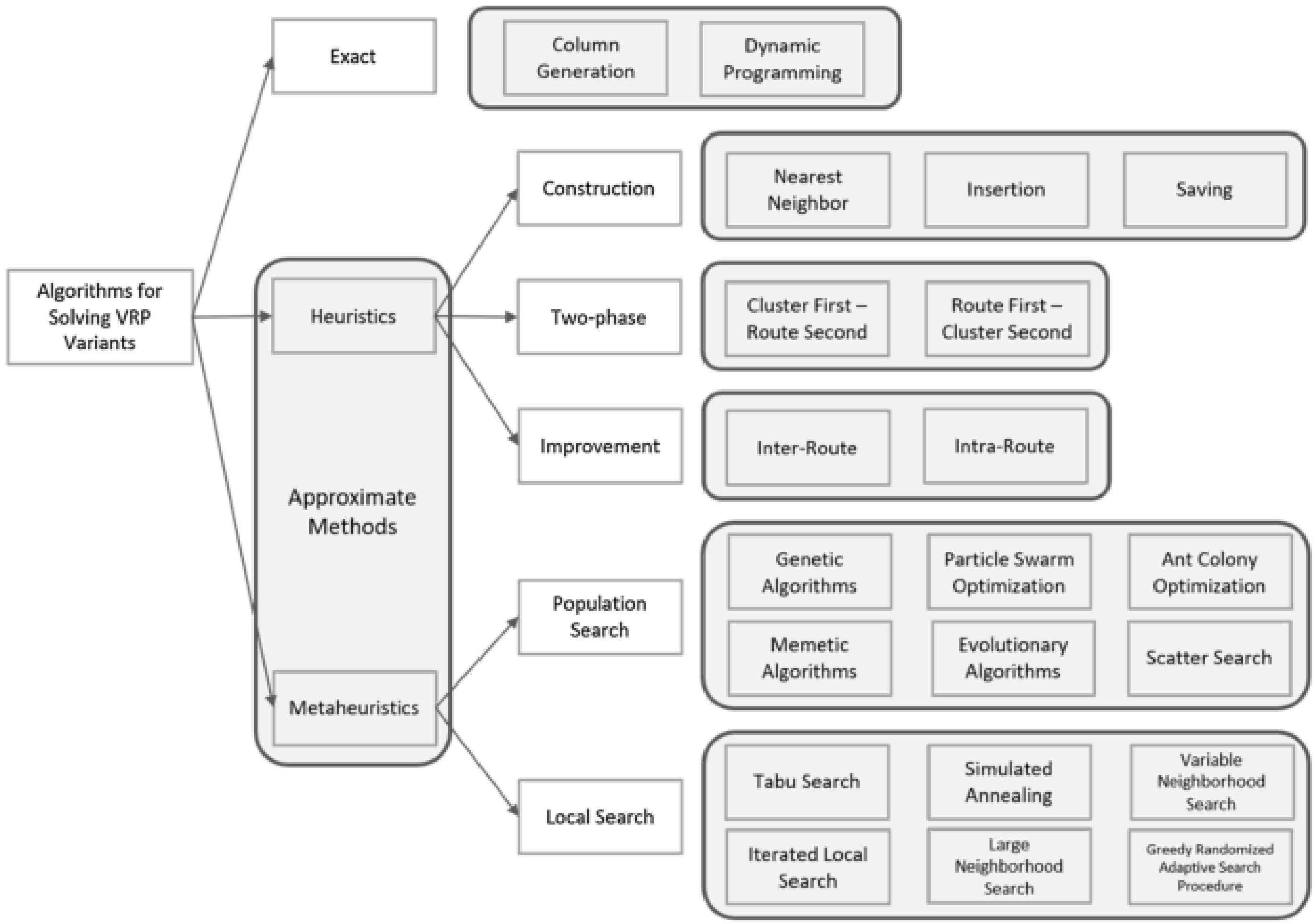

Figure 10. Taxonomy of solving methods and algorithms (Konstantakopoulos et al., 2020)

3.3.2. Methods

Exact methods

Exact methods find the optimal solution between all possibilities. The VRP model is an NP-hard problem (nondeterministic polynomial time); this means that the required solution time for the optimal solution increases exponentially with the size (Hochba, 1997). Exact methods are not often used for complex VRP unless the amount of decision variables is small (Yilmaz & Tüfekçí, 2017). Otherwise the time needed to solve the problem increases and it could become too large for a computer to handle (Oxford, 2008). Because the waiting time for these solutions is so long, other approaches are made, some of which will be discussed in this thesis.

The problem Hamer is facing has multiple depots and more than 100 jobs, thus using exact methods for these circumstances will take more time than Hamer prefers. Therefore only using exact methods is not suitable.

Heuristics

If a complex VRP needs to be solved fast and efficiently, using heuristics is ideal. Heuristic algorithms solve a VRP using various shortcuts; the solution may not be optimal but is often sufficient and given in a short amount of time (Laporte et al., 2014). Heuristics are almost as old as the classical VRP and are problem dependent. Because continuous research into VRP problems is conducted, heuristics are still being designed and adapted. Heuristics can solve problems with a large number of nodes, malfunctions in the case of Hamer, and decision variables in a short amount of time, making it suitable for Hamer's problem.

The heuristics discussed in this research are classified into constructive and improvement.
The purpose for constructive heuristics is to make an initial solution, the first solution. This solution serves as a basis, so it can later be adapted by the improvement heuristic. While constructive heuristics attempt to develop a workable solution while keeping cost in mind, they lack an improvement phase. The solutions obtained by the constructive heuristic are often far from optimal and are therefore improved by the improvement heuristic (Rodrigues, 2021). Every improvement heuristic is based on the idea of adapting the initial solution in a variety of ways and evaluating whether or not this adaptation is a feasible improvement. The improvement heuristics can be divided into two categories for a VRP with multiple routes, intra- and inter- heuristics. Intra-route operators check whether improvements could be made within a route and Inter-route operators search for improvements between different routes (Layeb et al., 2013). Intra- and inter- heuristics can be combined together and used sequentially.

Metaheuristics
The last category discussed is metaheuristics. Metaheuristics are a higher-level form of heuristics and are problem-independent. They are designed to find a sufficient solution within the time available. Metaheuristics were first discussed by Glover (1986), which combines meta- (beyond the sense of high level) and heuristics. There are many different metaheuristics and just like with heuristics, new methods are constantly being discovered and designed. Metaheuristics are divided into two groups as shown in Figure 10, population search and local search. Local searches make it possible to find a good solution locally. In contrast, population-based algorithms draw on a pool of potential answers (Grigorios et al., 2020).

3.3.3. Method choice
To conclude, algorithms are needed to get a (near-)optimal solution for the VRP of Hamer. An exact approach provides the best possible solution, however due to the computational time preferences, it would not be suitable. Therefore, heuristics are used in this research. Further in this research, the focus is no longer on metaheuristics because there are problem-specific methods used to solve the VRP Hamer faces. The solutions obtained will not be optimal but sufficient and will be obtained in a relatively short time.

Hamer is not able to visit every client in a day due to the capacity and time available. The clients which are visited must be based on two categories; their distance and priority. In the paper of Ghoseiri and Ghannadpour (2010) an approach for constructing routes can be found, which takes into account multiple factors and is therefore chosen as the constructive method. In Section 4.2 the heuristics used in this research are further discussed.

3.4. Programming language
To make a model and conduct experiments a code is needed, this code has to perform certain algorithms. These algorithms are written in a programming language used to write computer instructions. It allows the programmer to express data processing in a symbolic way without having to worry about machine details (PCMag, 2020). There are many different program languages, all with different pros and cons. The

most used programming language at the moment of writing is JavaScript, followed by Python (Ijeert, 2017). In this research Python will be used because of the possibilities Python offers and the experience the researcher has with the program.

3.5. Conclusion

After the literature study has been conducted, the research question mentioned in the introduction of this chapter could be answered.

This chapter starts by explaining the VRP and some variables and extensions, which are relevant for Hamer's situation. The Multi-Depot Vehicle Routing Problem with Time Windows (MDVRPTW) is the VRP which needs to be modeled and adapted in this research for solving Hamer's VRP.

Section 3.3 describes how a VRP should be solved, starting by explaining the concept of a mathematical formulation. For a mathematical formulation an objective value is tried to be optimized without violating the constraints. A mathematical formulation for the situation of Hamer is given and explained in Section 4.1 and is needed to solve the VRP of Hamer. For solving the mathematical formulation, different methods could be used. The literature research showed that exact methods will give the optimal solution but are very time consuming and therefore not preferable for Hamer's situation. Therefore, approximate methods are preferred and are chosen based on the literature research. PFIH will be used as the constructive heuristic, because PFIH can take into account the priority and distance of jobs while constructing the routes.

To solve the VRP of Hamer and conduct experiments, a computer program must be developed. This computer program executes heuristic algorithms. In this program the algorithms must be translated into a computer language, which is done in Chapter 4 using Python.

4. Solution design

With the knowledge obtained in the previous chapters, a mathematical programming formulation can be provided and optimized. To do this certain heuristics are needed. In this chapter it becomes clear which heuristics are preferred and the constraints of the model are described. This is needed to answer the following research questions clearly: 'Which constraints should be taken into account in the experiments?' and 'Which data should be taken into account in the experiments?'.

The model consists of multiple phases, first the initial solution is formulated using a constructive algorithm, which cannot violate constraints explained in this chapter. Thereafter this initial solution is improved using different improvement algorithms, which decreases the distance traveled while taking constraints into account. Because of this there could be more time available and therefore all the algorithms are repeated to replenish and improve the solution. This sequence is repeated until no more nodes can be added.

4.1. Model description

In this section the model is further described. In Section 4.1.1 the symbols of the model are given and discussed. In Section 4.1.2, the mathematical formulation of the model is shown and discussed. The mathematical formulation should consist of an objective value and constraints, displaying the situation of Hamer.

4.1.1. Notation used in the model

In table 4 a list of all parameters and decision variables is given, which are essential for Hamer's model. These values will be used in Section 4.1.2 to define the objective function and constraints in the mathematical formulation.

Sets	
D	The depot set
C	The customer set
V	The vertex set
A	The arc set
K	The vehicle set
K_d	The set of vehicles at depot d
Parameters	
S_i	Service time of location i
r_i	Release time of location i
L_i	End time-window of location i
B_{ij}	Travel time from i to j
Q_{ij}	Distance from i to j
C_{ij}	Cost to travel from i to j
P_i	Penalty if location i is not visited
$\|K_d\|$	The number of vehicles in K_d set
z (around 9)	Number of vehicles
n (around 120)	Number of malfunctions
d (around 7)	Number of depots
W_k (available work hours)	Available work hours of vehicle k
Decision variables	
Binary variable	
X_{ijk}	Decision variable, X_{ijk} = 1 if vehicle k travels directly form node i to j, otherwise X_{ijk} = 0
Continuous variables	
T_{ik}	Arrival time at node i of vehicle k
Y_{ik}	Departure time at node i of vehicle k
WD_k	The working duration of vehicle k

Table 4. Overview model parameters

4.1.2. Mathematical formulation

A literature review earlier in this report showed that one of the first steps to visualize and improve a VRP, is to translate the real situation into mathematical formulas. These formulas should include an objective function and constraints. As stated earlier, the situation of Hamer is approached as an MDVRPTW. The selected model utilized in this research is inspired by Li et al. (2014). In the model of Hamer, not every job can be visited. Besides, the penalties and release times are added to the formulation and the depot constraints are adapted since vehicles return only to their own depot in this research. The mathematical formulation is formulated, so algorithms can try to minimize the distance and cost, therefore allowing more nodes to be visited.

To make a model, everything has to be transformed into the measurable variables and parameters, shown in Table 4. Firstly the vertex set is transformed and is defined as followed, $V = \{v_0, v_1, \dots v_m, \dots v_n\}$. $D = \{v_0, v_1, \dots v_m\}$ represents m depots and $C = \{v_{m+1}, v_{m+2}, \dots v_n\}$ represent n-m malfunctions. Every vertex, $v_i \in C$, is connected to a nonnegative service time, S_i a nonnegative penalty, P_i and time constraints, $[r_i, L_i]$. The nodes have hard time windows and release times. A mechanic is not able to travel to a location before r_i or visit after L_j. Besides there are no service time connected to $v_i \in D$. The arc set is defined as follows, $A = (v_i, v_j) | v_i, v_j \in V$, and denotes the connection between the depots and malfunctions. The arc set is connected to a non-negative cost C_{ij} and non-negative value B_{ij}, which indicates the travel time from *i* to *j*. Finally, $K = \{k_1, k_2, ..., k_z\}$ represents the vehicles set, z is the number of vehicles and since not all vehicles are homogeneous, each vehicle is connected to W_k; which indicates the maximum work hours per vehicle and cannot be violated in the model.

The definition of a standard MDVRPTW is described in the preceding chapter. However the comprehensive explanation of a specific vehicle routing problem varies by situation. As a result, the following limitations have been created to meet all of Hamers' criteria and desires for the model:

- Maximum working hours cannot be violated
- Every malfunction can only be served by one vehicle
- Malfunctions cannot be traveled to before release time
- Malfunctions cannot be visited after end time
- The start depot for a vehicle is the end location of a vehicle

The routes are currently based on the penalties and distance; this should also be reflected in the objective function. Besides, certain constraints should be formulated in order to let the model work for Hamer's situation. The formulation, which matches Hamer desires, is given as follows:

$$\text{Min} \sum_{k=1}^{m}\sum_{i=1}^{n}\sum_{j=1}^{n} C_{ij}X_{ijk} + \sum_{j\in C} P_j\left(1 - \sum_{i=1}^{n}\sum_{k=1}^{m} X_{ijk}\right) \qquad (1)$$

S.T.

$$\sum_{k\in K}\sum_{j\in C} X_{ijk} \le |K_d| \qquad \forall i \in D \qquad (2)$$

$$\sum_{k\in K}\sum_{j\in V} X_{ijk} = \sum_{k\in K}\sum_{j\in V} X_{jik} \le 1 \qquad \forall i \in C \qquad (3)$$

$$\sum_{j\in V} X_{ijk} = \sum_{j\in V} X_{jik} \le 1 \qquad \forall i \in D, k \in K \qquad (4)$$

$$\sum_{i\in R}\sum_{j\in R} X_{ijk} \le |R| - 1 \qquad \forall R \subseteq C, k \in K \qquad (5)$$

$$Y_{ik} = 0 \qquad \forall i \in D, k \in K \qquad (6)$$

$$X_{ijk}(S_i + T_{ik} - Y_{ik}) = 0 \qquad \forall i, j \in C, k \in K \qquad (7)$$

$$X_{ijk}\left(Y_{ik} + B_{ij}\right) = T_{jk} \qquad \forall i, j \in V, k \in K \qquad (8)$$

$$WD_k = \sum_{i\in V}\sum_{j\in V} X_{ijk}(B_{ij} + S_j) \le W_k \qquad \forall k \in K \qquad (9)$$

$$\sum_{k\in K}\sum_{i\in V} X_{ijk}\left(Y_i\right) \le r_j \qquad \forall j \in V \qquad (10)$$

$$L_i \ge T_{ik} \ge 0 \qquad \forall i, j \in C, k \in K \qquad (11)$$

$$X_{ijk} \in \{0, 1\} \qquad \forall i, j \in V, k \in K \qquad (12)$$

$$T_{ik}, Y_{ik}, WD_k \ge 0 \qquad \forall i \in V, k \in K \qquad (13)$$

The objective functions consist of two parts, the first part indicates the travel cost.

$$\sum_{k=1}^{m}\sum_{i=1}^{n}\sum_{j=1}^{n} C_{ij}X_{ijk}$$

The second part refers to the penalty if a location is not visited on the current day.

$$\sum_{j\in C} P_j\left(1 - \sum_{i=1}^{n}\sum_{k=1}^{m} X_{ijk}\right)$$

Constraints (2) ensure that not more vehicles leave a depot than available. Constraints (3) ensure that each malfunction is at most tackled by one mechanic; this prevents multiple mechanics going to the same malfunction. Constraints (4) ensure that each mechanic leaving from a depot ends their route at the same depot. Constraints (5) is the subtour eliminator and ensures the solution is connected. Constraints (6) represent that each depot is left at the start of the day and it indicates that every vehicle leaves their depot at the same time. Constraints (7) ensure that the departure time of *i* is equal to the arrival time plus the service time of *i*. Constraints (8) imply the visit order of nodes. Constraints (9) ensure that vehicles cannot work longer than their available work hours. Constraints (10) indicate that a location cannot be traveled to before it is released. This is necessary to ensure that the results are more realistic and in this way the actual history can be compared with the routes suggested by the model. Constraints (11) represent the end time window and make sure that a location is not visited after its end time window.

4.2. Solution method

Since all input is clear, it becomes possible to solve the model. In this section all steps are explained to find a heuristic solution. This needed to investigate whether Hamer could handle more malfunctions using a planning tool and score better on their other KPIs (Section 1.5).

4.2.1. Constructive heuristic

Initial solution

Firstly, an initial solution has to be generated, which can later be improved by the improvement heuristics. The initial solution stores different jobs into a route for a vehicle; during this process the constraints cannot be violated. Mechanics are only available for a certain amount of hours and cannot visit every malfunction due to this. The jobs which are visited must be based on their priority and distance; the constructive heuristic should take these factors into account. The literature review showed that in the paper of Ghoseiri and Ghannadpour (2010) a suitable approach was used. The constructive heuristic used in this research is the Push Forward Insertion Heuristic (PFIH) and will be adapted in the research to meet the requirement needed for Hamer's circumstances.

The PFIH is used to develop initial routes for the mechanics and was first introduced by Solomon (1987). The procedure adds malfunction between locations based on their insertion cost and the time windows, release times and work hours constraints cannot be violated during this process. The routes are made based on vehicle order, so vehicle 1's route is made first, then vehicle 2 etc. In Figure 11 a PFIH example is displayed.

The PFIH algorithm is described below. For a more detailed explanation, see Appendix B, where the corresponding code and flowchart can be found.

Step 1. Initialize k to 0.

Step 2. Set k=k+1. Compute the route initialization costs according to (1) for each unrouted customer u. Select customer u that minimizes this cost and uses it as a seed customer for route k. If clients can be added, go to Step 3, otherwise STOP.*

Step 3. For each unrouted customer u, find its best feasible insertion place in route k according to (2).

Step 4. If there are no feasible insertion places in route k for any unrouted customer, go to Step 2.

Step 5. Select customer u with the minimum feasible insertion cost, and insert this customer at its best feasible insertion place in route k. Update the route k. If clients can be added, go to Step 3, otherwise STOP.*

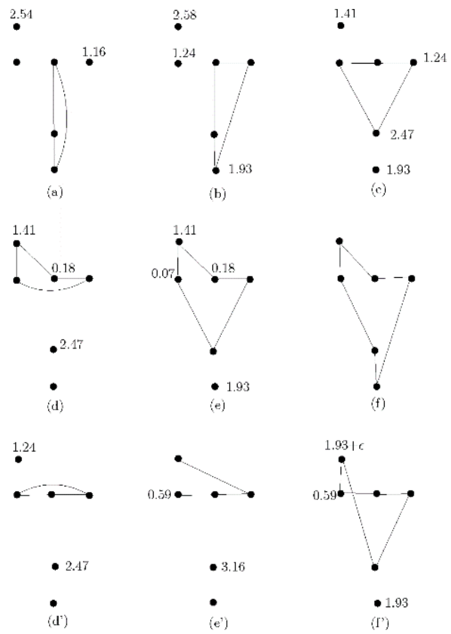

Figure 11: Visualization of basic PFIH-operator (Hassin & Keinan, 2008)

4.2.2. Improvement heuristics

The improvement heuristics are used to improve the initial solution. The driven routes cannot be adapted after a malfunction is visited which occurs during the same day, to make the results as realistic as possible for the experiments in Chapter 5. For more detail see Appendix E.

The initial routes have different work hours constraints compared to the improvement heuristics in this research. There are more work hours available in the improvement algorithm, which makes it easier to switch nodes between routes. The difference between the work hours is set to one hour on wishes of the company, so the mechanics can work overtime maximal to an hour according to the model.

λ-Interchange

The first improvement heuristic used in the model is called λ-interchange. The λ-interchange method was first introduced by Osman and Christofides (1989) and was chosen in this research due to the literature support of the combination with the PFIH (Tam & Ma, 2004). The λ-interchange method is an inter-route method, Inter-route heuristics try to find better solutions due to changing nodes between different routes. For this research an adapted 2-interchange is used, which indicates the following options (0,1), (1,0), (1,1), (0,2), (2,0), (1,2), (2,1) and (2,2). The operator (0,1) indicates for R_1 and R_2 that 0 customers from R_1 are shifted toward R_2 and one customer is shifted from R_2 to R_1. Every possible insertion place is checked with λ-interchange, and it selects the cheapest feasible insertion place.

Cross-Exchange

The interchange operators (1,2), (2,1) and (2,2) have many iterations and will therefore take a relatively long time. Therefore these operators will be replaced by another inter-route operator called Cross-Exchange. The big difference between cross-exchange and λ-interchange is that cross-exchange only switches certain nodes and will not check all possible insertion combinations. If, for example, the interchange operator (2,1) is runned, and the first route has n nodes and the second one has m nodes. There will be n*(n-1)*m iterations using the interchange operator, this could take a lot of time. Using cross-exchange there will be (n-1)*m iterations, which saves a lot of time but the improvements will be in rare scenarios worse compared to the interchange operator. After experimenting it is worth the trade-off because of the computational time saving. In Figure 12, an example of the cross-exchange operator (2,2) is displayed.

The sequence of the routes chosen to apply the inter-route algorithms to are specific. Suppose there are K drivers available, where K is more than three. This means that there are K routes $\{R_1, R_2, R_3, \ldots, R_K\}$, the sequence is then defined as follows:

$$(R1\ ,\ R2\ ),(R1\ ,\ R3\ ),\ldots,\ (R1\ ,\ RK),\ (R2\ ,\ R3\ ),\ldots,(R2\ ,\ RK),\ldots,(RK\text{-}1\ ,\ RK) \qquad (14)$$

The operators are performed in the mentioned order, the route combinations are chosen in ascending order (14) and the customers are chosen sequentially. In literature, there are two strategies when it comes to λ-interchange: The First-Improvement (FI) and the Best-Improvement (BI) strategy, FI strategy selects the first solution that decreases cost compared to the current situation and BI strategy first generates all possible solutions and selects the cheapest solution.

Both strategies have their pros and cons compared to each other and not one of the two strategies generates better solutions (Thangiah et al., 1996). For this research, the first improvement strategy is preferred, because the computational time is less in general.

The adapted interchange algorithm is described below. For a more detailed explanation, see Appendix B, where the corresponding code and flowchart can be found.

Step 1. Start with a feasible solution S obtained with the PFIH.

step 2. initialize rc to 0.

Step 3. Set rc = rc + 1. generate solutions, S', using the operators.

Step 4. If the cost of S' is lower than S then S = S'. If no more improvement can be made and there are still route combinations available, go to Step 3, otherwise STOP.

Step 5. Go to Step 2.

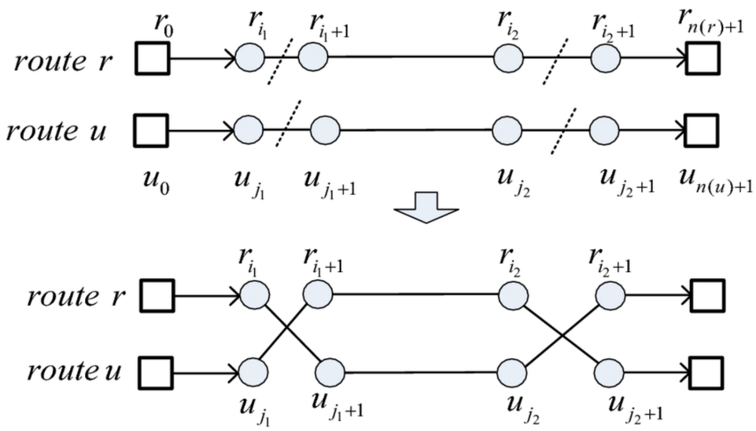

Figure 12. Visualization of Cross-exchange operator (Liu & Jiang, 2018)

2-Opt

The last heuristic applied to the situation is the 2-opt operator, which was first introduced by Croes (1958). 2-Opt is an intra-route method; intra-route operators focus only on improving a route without changing nodes with other routes (Tavares et al., 2009). The strategy is straightforward, two edges are broken and replaced by other edges as shown in Figure 13. This is done at every route at every possibility, to check whether improvements are possible without violating any constraint (Diniz, 2017).

The 2-opt algorithm is described below. For a more detailed explanation, see Appendix B, where the corresponding code and flowchart can be found.

step 1. start with a feasible solution S obtained with PFIH and λ-interchange.

Step 2. initialize r to 0. If all routes are investigated, then STOP.

Step 3. r = r + 1 appy 2-opt to obtain S', if S' is cheaper than S without violating constraints S = S'. Go to Step 2 if no more improvements can be made, otherwise STOP.

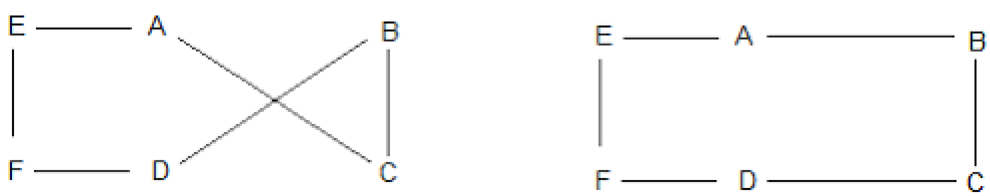

Figure 13. Visualization 2-opt operator (Diniz, 2017)

4.3. Conclusion

To conclude, a list with constraints is made, shown below, this list is made to meet the requirements of Hamer and are taken into account in the model.

- Maximum working hours cannot be violated (with one hour extra for the improvement heuristics)
- Every customer can only be served by one vehicle
- Malfunctions cannot be traveled to before release time
- Malfunctions cannot be visited after end time
- The start depot for a vehicle is the end location of a vehicle

Besides, the chosen heuristics for the model are determined. For creating the initial solution an adapted PFIH is used, because it can take into account the distances and penalties. The initial solution is improved by inter- and intra-route heuristics. The inter-route heuristic is an adapted 2-interchange operator, which was chosen because literature support the combination of PFIH and λ-interchange. 2-Opt is used as an intra-route operator in the model and is well explained in Section 5.2.1.2.

5. Numerical experiments

After the planning tool is made, experiments can be conducted. The planning tool can run a variety of experiments, making it a useful tool for analyzing multiple variables. This is especially useful when it comes to providing the company with possible solutions. To be able to obtain knowledge about the variables, it is critical that several tests are carried out with only a single variable changing for every passage of time. In this research, a standard dataset given by Hamer is chosen for testing. This dataset consists of data that resulted from real life situations Hamer faced and is explored in Section 5.1. Besides the answer to the following research question becomes clear: 'How to show and interpret the results?'.

To compare the results, the output is measured in the KPIs shown in Section 1.5. Subsequently, the problem is compared to the real-life scenario, in Section 5.4, to see whether improvements could be made. However, the routing heuristics must be reviewed in advance, in order for the test to run. An examination of the heuristics will be undertaken in order to check the influence of each heuristic and to ensure the right heuristic sequence is selected in the model, which is done in Section 5.2. In Section 5.3, a sensitivity analysis is performed to measure the relationship between penalty values and the KPIs, using the sensitivity analysis, the penalties can be adjusted to Hamer's wishes. The experiments are carried out using the custom made RPS for Hamer, for a more detailed description about how the model works, conduct appendix F.

5.1. Instances

To be able to conduct VRP experiments certain data is needed. This data has to be realistic and should therefore correspond as much as possible with the real situation. In this section, the data of a certain period provided by the databases of Hamer is analyzed and transformed into parameters used in the model, shown in Table 4. In this section the parameters of only one day are shown, so that a clear picture is given. The data of other days is also gathered and analyzed but not shown in this research for sake of brevity.

5.1.1. Data gathering

The data, which needs to be gathered for the model to run, is listed below.

- Locations of clients
- Available vehicles
- Location vehicles
- Distance between clients
- Service times
- Time windows
- Release times
- Cost per kilometer
- Due dates
- Penalties
- Available work hours
- Driving speed

Location of customers, available mechanics, location of mechanics, driving speed, time windows, release times, service times and due dates can be found in the databases of Hamer. The value for the cost per kilometer was obtained using semi-structured interviews and is estimated at a value of one in the model. To express the urgency of a malfunction, a penalty is associated with the malfunction. Determining the cost of a penalty cannot be easily quantified, therefore an estimate is made later in this section with help of the employees and experiments. The distance between locations is calculated using the coordinates of locations and the Pythagorean theory (Maor, 2010). In Appendix A the formula for the distances is more elaborated and an example of a distance matrix is given.

A problem Hamer is facing is that not everyone has the same experience and skills, which means that not every mechanic can handle and visit every malfunction. This leads to unlogical routes in some situations (a mechanic has to drive many kilometers to a location, which is close to another mechanic). To make sure this does not happen in the model, there has only been focus on the mechanics who are able to handle (almost) all malfunctions. Using semi-structured interviews, there are 11 out of the 14 mechanics, which can be sent towards (almost) all malfunctions.

Jobs

In this part, a map depicting Hamer's jobs is provided, shown in Figure 14. The blue circles represent a client's location, the darker the area, the more malfunctions in that area. These malfunctions represent a dataset, which will also be used in the experiments. From the map it can be obtained that planning for multiple mechanics, with different priorities without any assistance tool is difficult, which can lead to a loss of efficiency.

Figure 14: Locations of malfunctions given by the dataset, for a single day

Due dates, time windows and release times

As stated previously, Hamer has SLAs with different companies. Based on these, the service desk makes the notifications with a due date, on which the planners plan the malfunction for a mechanic. To express urgency in the model, every location is associated with a penalty, the higher the penalty, the more priority it has. These penalties were compiled through experimenting, consultation and observation with the company. In Section 5.3 a sensitivity analysis is conducted to assess the impact of penalty parameters on different KPIs.

To express the urgency, different categories are made. These categories are based on priority and are used to attach a penalty to malfunctions using the following formula: $150/C$. C Indicates the category of the priority, for example, $C = 1$ has more priority compared to $C = 2$. In Figure 15 the distribution of the categories are displayed, using the same dataset as the map of Figure 14.

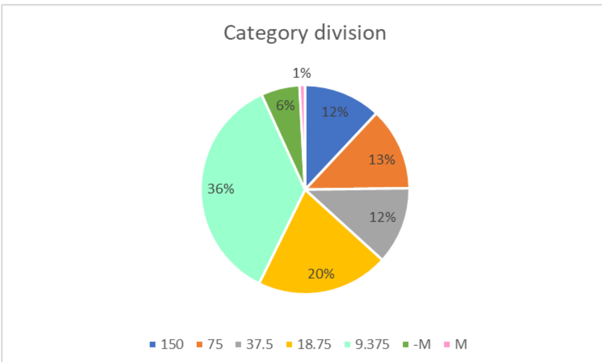

Figure 15. Single day penalty division

The urgency penalty is based on the category of a malfunction, which depends on how many days remain until the due date. Due to emergencies, a number of places must be visited that day; the penalty for these jobs is set to a high number M to ensure that they are always visited. Additionally, there are jobs that cannot be accessed, for instance when the supplies are not available. To make sure these locations will not be visited, a negative penalty is associated with it, $-M$.

For a small number of the malfunctions, time constraints are included, as shown in Figure 16. All dots are connected to a specific job and its time constraints. The orange dots indicate a moment, whereafter the associated job cannot be visited anymore. The blue dots indicate the release time, before this time a mechanic cannot travel to the associated job. If a job does not have an end time it is set to 23 and if a job does not have a release time it is set to 7, as shown in the figure.

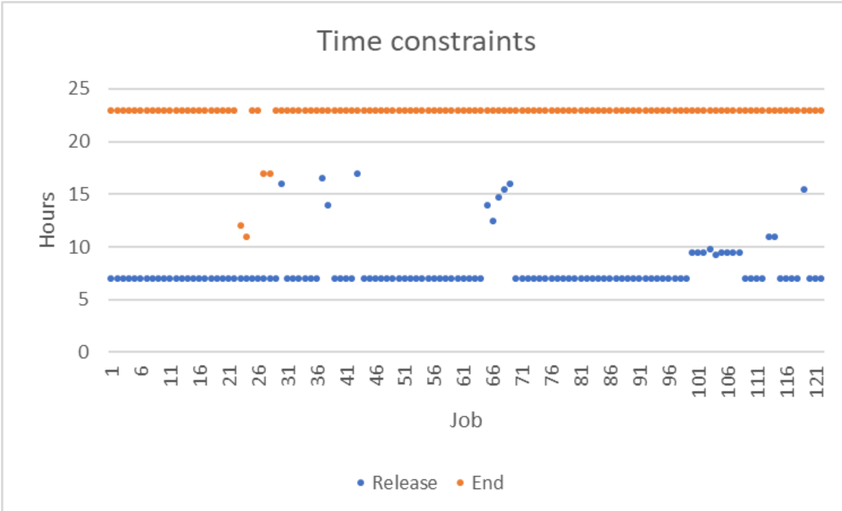

Figure 16. Overview of time restrictions given by the dataset

Service times

The service time can be different for every malfunction. Some malfunctions last a whole day and some take less than fifteen minutes. A rounded overview of the service times is given in Figure 17. The figure shows the distribution of several service times of malfunctions given by the dataset Hamer provided. Through experience and good communication, the service time of a job can be estimated well in advance. Therefore in the model, malfunctions are attached to different service times.

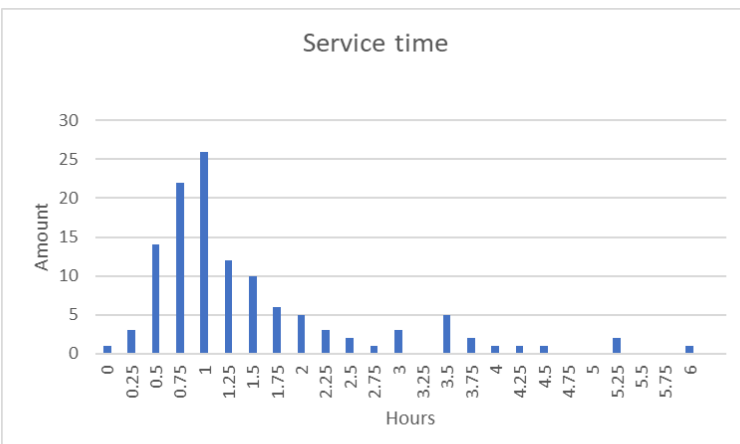

Figure 17. Overview of the service time given by the dataset

5.1.2. Model assumptions

Some assumptions and simplifications are necessary in order to solve the model. The first simplification has to do with the distance and travel time. The distance in the model is based on the coordinates and orthodromic line distance and the driving time is based on the average speed of 71 km/h. Without Application Programming Interface software or Add-ins it is not possible to obtain these variables, therefore the above approach is used.

The second simplification is the service times. In the model it is assumed to be deterministic but in reality it is stochastic. Although the service times can be well estimated, it could differ per mechanic and take longer or shorter than expected.

Lastly, Hamer's situation is a multi-period problem but the VRP is converted into a single-period problem in the model. However, priority is given to locations with earlier due-dates by means of penalties; this is done due to the preferences of the company.

5.2. Heuristic evaluation

An evaluation is done with several sets of improvement heuristics in order to measure the individual and group influence on the initial solution. Since Hamer is not able to visit every client, the constructive heuristics are used to see if more jobs can be added once the improved heuristics are executed. The combination of heuristics is tested with a fleet size of 5, 6, 7, 8, and 9 mechanics, since the heuristics can give different results based on the fleet size. The first five mechanics are once randomly selected and are supplemented with a random mechanic for all tests. The results of the different fleet sizes should be compared to gain more knowledge about the selected heuristics.

The order in which the heuristic algorithms are executed is of big importance for the result. First, the constructive heuristic is executed to link customers to routes using the PFIH algorithm. If no more location can be added due to constraints, the improvement heuristics will be executed. A combination of 2-interchange and cross-exchange algorithms are executed as the inter-route operators. Both try to switch the customers between routes to make the distance shorter. The intra-route heuristic used in the model is the 2-opt algorithm. For more detail about the heuristics see Section 5.2.2.

In the next experiment the sequence of the heuristics are adapted to evaluate their influence on the outcome. After the experiment, it can be decided which sequence of heuristics to use in the model of Hamer.

Heuristics \ Fleet size	5	6	7	8	9
PFIH	D: 654 C: 22 O: 16 WH: 8.5	D: 859 C: 25 O: 10.4 WH: 10	D: 1197 C: 26 O: 11 WH: 10.4	D: 1275 C: 29 O: 9 WH: 12.1	D: 1540 C: 33 O: 8 WH: 13.6
PFIH, λ-interchange, cross-exchange, 2-opt, PFIH	**D: 648** **C: 22** **O: 16** **WH: 8.6**	**D: 828** **C: 27** **O: 13** **WH: 9.9**	D: 1115 C: 29 O: 10 WH: 9.1	D: 1193 C: 32 O: 8 WH: 10.7	D: 1338 C: 35 O: 8 WH: 12.4
PFIH, cross-exchange , λ-interchange and 2 opt, PFIH	**D: 648** **C: 22** **O: 16** **WH: 8.6**	**D: 828** **C: 27** **O: 13** **WH: 9.9**	D: 1115 C: 29 O: 10 WH: 9.1	D: 1193 C: 32 O: 8 WH: 10.7	D: 1338 C: 35 O: 8 WH: 12.4

PFIH(2), interchange, cross-exchange, 2-opt, PFIH, interchange, cross-exchange, 2-opt, PFIH	**D: 648** **C: 22** **O: 16** **WH: 8.6**	D: 840 C: 26 O: 13 WH: 10.2	**D: 958** **C: 32** **O: 13** **WH: 11.1**	**D: 1036** **C: 35** **O: 11** **WH: 12.7**	**D: 1359** **C: 36** **O: 7** **WH: 14.1**
PFIH, 2-opt, PFIH	**D: 648** **C: 22** **O: 16** **WH: 8.6**	D: 853 C :25 O: 13 WH: 10.5	D: 1191 C: 26 O: 11 WH: 10.5	D: 1269 C: 29 O: 9 WH: 12.2	D: 1534 C: 33 O: 8 WH: 13.7
PFIH, interchange, cross-exchange	D: 654 C: 22 O: 16 WH: 8.5	D: 826 C: 25 O: 13 WH: 10.9	D: 1006 C: 26 O: 11 WH: 13.1	D: 1085 C: 29 O: 9 WH: 14.8	D: 1339 C: 33 O: 8 WH: 16.4
PFIH, interchange, cross-exchange, PFIH	D: 654 C: 22 O: 16 WH: 8.5	D: 875 C: 27 O: 13 WH: 9.2	D: 1147 C: 29 O: 10 WH: 8.6	D: 1226 C: 32 O: 8 WH: 10.3	D: 1371 C: 35 O: 8 WH: 12.0
PFIH, interchange, cross-exchange, 2-opt	**D: 648** **C: 22** **O: 16** **WH: 8.6**	D: 779 C: 25 O: 13 WH: 11.6	D: 974 C: 26 O: 11 WH: 13.6	D: 1052 C: 29 O: 9 WH: 15.2	D: 1306 C: 33 O: 8 WH: 16.8

Table 5: Heuristic evaluation
Meaning of letters in Table 5:

D = Distance
C = Locations
O = Due dates not visited
WH = Work hours remaining

Table 5 shows the solution of different heuristic combinations. The option, which is best according to Hamer per fleet size, is made italic and bold. The table shows the heuristics performance of the 2-opt operator and the combination of interchange and cross-exchange on the initial solution. The 2-opt operator shows an average decrease of 0.5% on the initial solution and 3.1% after the interchange and cross-exchange heuristics are executed. Secondly, the interchange and cross-exchange operators reduce the initial solution on average by 11.1%. Lastly, the interchange, cross-exchange and 2-opt operators combined decrease the initial solution by 13.9% on average.

The results show that not one combination of heuristics always provides the best solution. The following sequence is chosen for the model of Hamer and further research in this thesis:

PFIH(2), interchange, cross-exchange, 2-opt, PFIH, interchange, cross-exchange, 2-opt, PFIH

This sequence does not always show the best result but is still favorable. After experimenting and visualizing the results, it stood to reason that generally, mechanics would be divided better over the area when starting the sequence with PFIH for only 2 locations. Besides there is no difference between the sequence order of interchange and cross-exchange according to the results. In experiments with other datasets, different results were achieved between the sequences, but no significant sequence was preferred. For this research it is chosen to first use the interchange operators followed by cross-exchange.

5.3. Sensitivity analysis on the penalty parameter

In this section a sensitivity analysis is performed on the effect of the penalty parameter. The experiments are conducted with the same dataset used for the heuristic evaluation and seven random mechanics are chosen to run the model. As stated in Section 5.1, the penalties are based on their due date and are divided in different categories. In Figures 18 and 19 the results of the sensitivity analysis are visualized, the penalties are multiplied by a value, referred to as the µ-value. The yellow line shows that there is a relationship between the distance covered and the penalty values. The higher the value of the penalties, the higher the distance traveled. This can be easily explained by the fact that if the locations with high penalties are not close to each other, a longer distance is more likely to be covered to keep the objective value lower. Furthermore, the graph displays that the jobs that should have been visited but were not, i.e. the failed due dates, also decrease if the value attached to the penalties becomes bigger. This makes sense since the objective value is based on two parts, the distance and penalties. If a job is associated with a higher penalty, a mechanic is more likely to be sent there.

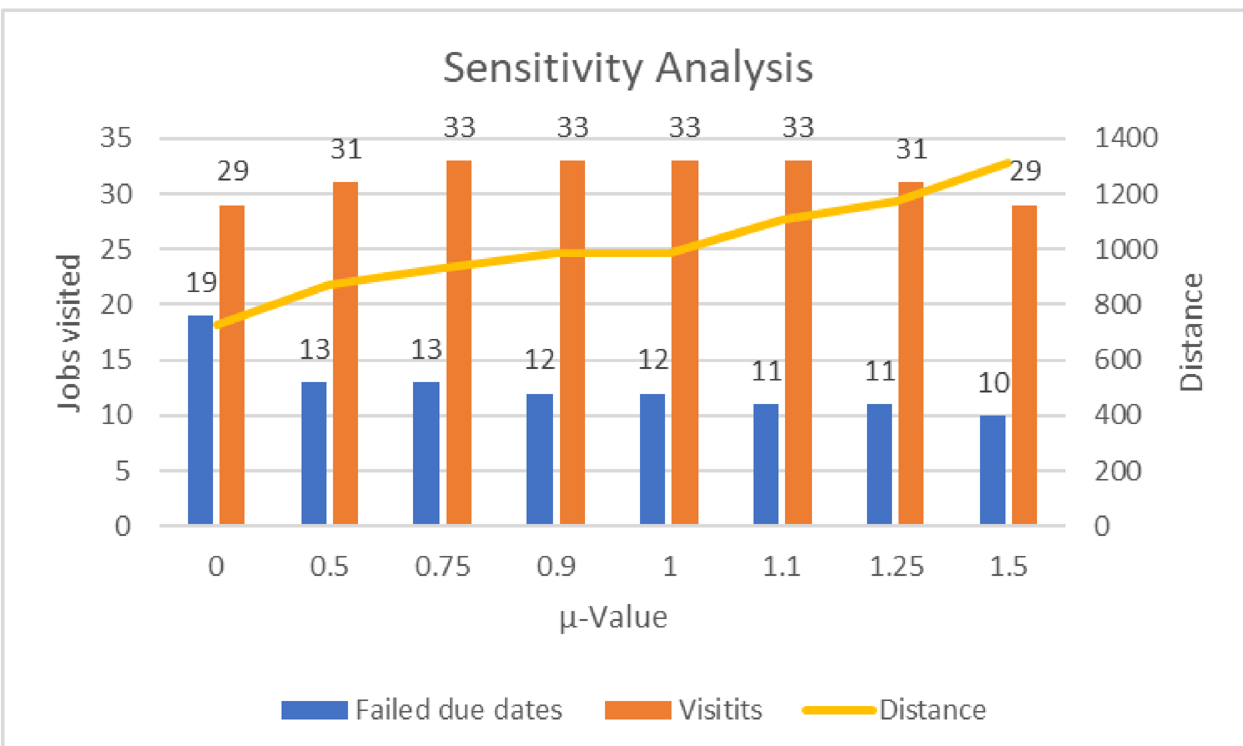

Figure 18. Sensitivity analysis on penalty parameter

It stands to reason that when the penalty's value is reduced and more emphasis is placed on distance, the number of jobs visited should simultaneously rise. However, this is not the case. The explanation being that in this dataset there are nodes with high service times and low urgency. If malfunctions are visited with long service time, logically, fewer malfunctions can be visited because less time is available. Research conducted over a longer period showed a negative relationship between the amount of visits and the value of the penalties. The last KPI considered in the sensitivity analysis is the working percentage. The working percentage is defined by the hours worked at jobs, divided by the total hours worked. Table 6 illustrates that the average working percentage decreases as the penalties value increases. So mechanics travel less and work more if less value is attached to the penalties.

μ-Value	0	0.5	0.75	0.9	1	1.1	1.25	1.5
Working Percentage	75	73	70	69	69	68	66	63

Table 6. Effect of μ-value on working percentage

The circumstances for the μ-value of 0.75, 0.9, 1 and 1.1 are all quite similar with their own pros and cons. The model is constructed in such a way that further nodes are always attempted to be added; as a result, nodes are added even when the μ-value is zero. Since there is no obvious pick in either of the circumstances, the μ-value of 1 is applied for the model of Hamer and the remainder of this study. This means the penalties stay the same as described in Section 5.1.1; this choice was based on the conducted experiments and the preferences of Hamer. For a visualization of the routes obtained using the μ-value of 0, 1 and 1.5, conduct Appendix C.

5.4. Comparison

In order to improve validity and reliability, experiments are carried out and compared to actual history. The comparison is based on the given dataset explained in Section 2.3 and is done to check whether improvements could be made using the model. The actual working hours are frequently exceeded in real life. To make the situation as realistic as possible, the hours are altered to reflect the amount of hours the mechanics were available for the department. Besides, not every mechanic is available every day throughout the chosen week and certain mechanics are therefore not selected for certain days. In Table 7 the KPI results of the real situation and the results utilizing the algorithm are displayed. Both results are measured using the model in order to maximize validity of the results. A complete overview of the routes constructed in this experiment can be found in Appendix D.

	Actual situation					Algorithm				
	Distance	Locations	Failed due dates	Working percentage	Hours worked	Distance	Locations	Failed due dates	Working percentage	Hours worked
Day 1	990	24	18	67.4	43.21	1061	28	12	63.7	41.21
Day 2	865	21	20	68.6	38.90	909	27	14	68.1	40.26
Day 3	1219	28	20	65.6	49.92	1425	26	10	56.7	45.31
Day 4	1673	24	18	58.3	56.56	1293	19	7	63.7	50.22
Day 5	1297	17	17	59.5	45.02	1133	21	7	63	42.17
Average	1208.8	22.8	18.6	63.88	46.7	1164.2	24.2	10	63.04	43.8
Total	6044	114			233.61	5821	121			219.17

Table 7. KPI score actual situation vs Algorithm

The outcomes indicate a positive shift; more locations are able to be reached with generally less distance traveled. In order to obtain these results, the sequence obtained in Section 5.2 was used. If Hamer wants to score better on certain KPIs, such as failed due dates or travel distance, the value of penalties can be adapted as shown in Section 5.3.

The comparison of the obtained period is discussed below. As stated earlier, the results depend on the value of the penalties. The experiments could also be runned with other penalty values to score better on certain KPIs, as shown in Section 5.2. In this research the values are as described in Section 5.1, which is done in agreement with Hamer.

Jobs visited

The company wants to visit as many clients as possible in order to earn more money, and likewise to build towards more satisfied clients as they would generally have to wait less. Since there are various service times, it is possible that more places are visited because, generally speaking, the problems requiring long service periods will not be visited. As a result, mechanics who spent the entire day at one place are not taken into account in this research; this is done in order to maintain the validity of the results. When looking at the real-life routes, 114 jobs were addressed, and using the algorithm, 121 jobs were visited. On average there were 5.6 mechanics available during the week, which means 1.25 more malfunctions on average can be tackled according to the model.

Distance traveled

Hamer's mechanics spend a lot of time traveling on the road. Naturally, Hamer wants to keep the cost as low as possible, therefore they want to spend as little time as possible on the road. The results show that less distance could be traveled by adjusting the planned routes. Comparing the results of the model with the real scenario, an improvement from 6044 to 5821 kilometers could be achieved in a week using the model. Logically, the average driving distance per job would decrease; it reduces from an average of 53.0 km per job to 48.1 km according to the model.

Failed due dates

Table 7 illustrates that more malfunctions could be visited before the due date according to the model. Some jobs cannot be visited before their due date and therefore the results cannot be zero. There are various reasons for this, such as resources available. The failed due dates are an ongoing process; the fewer due dates that need to be taken into account, the more freedom there is in planning the routes. This will ultimately improve other KPIs. According to the model, 8.6 more clients can be visited on average before their due date per week.

Work percentage and work hours

The work percentage is the KPI that lags the most, and the cause is straightforward. While it is impossible to usually work overtime in the model, this is frequently the case in reality. Then, malfunctions are tackled that last longer but do not significantly alter the driving time. In the observed period the tool gives a solution where 13.4 hours are worked less compared to the real situation. If these hours were worked extra, an improvement of approximately 2.1% on the work percentage is possible according to the model. Besides, less value to the penalties could be given, causing an increase in the working percentage as shown in Section 5.3.

5.5. Conclusion

To conclude, in Section 5.2 the heuristics are evaluated. After several experiments with different heuristics combinations and fleet sizes, the following heuristic combination was chosen for the model: **PFIH(2), interchange, cross-exchange, 2-opt, PFIH, interchange, cross-exchange, 2-opt, PFIH**. This combination generally provides the best solution and is therefore preferred. PFIH(2) indicates that the PFIH operator is executed for 2 locations. After experimenting, this caused the mechanics to be spread more successfully over the work environment. Section 5.3 explores the effect of the penalty parameter on certain KPIs, using a sensitivity analysis. The sensitivity analysis showed a positive correlation between the penalty values and the distance traveled. On the other hand, it showed a negative relation between the penalty values and the due dates not visited as well as the work percentage. Lastly, the model was tested on a real scenario in Section 5.4, to check whether improvements could be made on the KPIs using the model. The results showed a shift from 6044 to 5821 kilometers driven, while handling 1.25 more jobs on average per mechanic during the selected week. This ensured an average decrease from 53.0 km per malfunction to 48.1. Additionally, the results showed that in the period 13.4 hours less were needed in total to complete the routes. Finally, the model was able to visit 8.6 clients more on average before their due date. This shift will result in more jobs being visited before their due time, which means less sanctions for Hamer.

6. Summary and recommendations

In this chapter the last research question will be answered:

‘What conclusions and recommendations may be drawn from the research done at Hamer?’

The research approach is reflected, and the main findings of this research are discussed. Besides the recommendations, limitations and possible topics for future research are discussed. So, Hamer and other companies are able to use this paper as a foundation for further improvements in efficiency using RPS.

Conclusion

Hamer is an installation company, which also does repairs. The action problem Hamer had was that the amount of malfunction their current employees handled was too low. Every mechanic handled on average around 20 malfunctions per week during the time of conducting this research. Hamer wanted to increase this amount by one malfunction per mechanic. After doing research on the company and investigating their problems, it could be identified that the core problem was their route efficiency. Therefore the main goal was to answer the following research question:

‘**How can Hamer routes be more efficient?**’

In order to sufficiently answer this question, additional sub-questions were created (Section 1.6).

The first step of the approach was researching their current situation on how the routes are constructed. This analysis showed that the routes were not made in a structured way or using software to maximize the efficiency of the routes. This opens the gap for improvement. The routes made are based on two factors; driving distance and due time. Hamer wants to drive as little as possible to save costs, but at the same time they want to visit the clients before their due date. This requirement ensures that the routes cannot solely be based on the nearest jobs, because sometimes mechanics have to cover long distances to meet a client’s due time.

In order to find out how to improve the situation of Hamer, literature research was conducted. This showed that Hamer’s problem could be classified as an adapted Multi-Depot Vehicle Routing Problem with Time Windows (MDVRPTW) which could be solved using custom Route Planning Software (RPS). This software was made in Python and Excel. The software is capable of utilizing different algorithms, in this research it was decided to use heuristics because this problem is specific and heuristics can provide a good solution relatively quickly. Since not every job could be visited and the routes had to be based on distances and due times, a special algorithm was developed to create the initial solution for a single day. For creating the initial solution, the Push Forward Insertion Heuristic (PFIH) was chosen. The PFIH was considered the most suitable for Hamer’s situation since it is able to take into account different costs (Ghoseiri and Ghannadpour, 2010). The due dates had to be converted into measurable values, so the PFIH algorithm can take them into account. These values represent their due date: the higher the value of an associated job, the higher the priority and the earlier it is included in the routes.

Before the RPS could be made, a mathematical formulation must be constructed. A mathematical formulation consists of an objective function, which is tried to be optimized without violating the constraints. In the research of Li et al. (2014), a mathematical formulation was found, which could be adapted to Hamer's situation. After the mathematical formulation was constructed the heuristics could be chosen to solve the problem. An adapted 2-interchange combined with cross-exchange and the 2-opt algorithm were chosen to improve the initial solution obtained by the adapted PFIH. These algorithms were chosen because of their literature support and the problem Hamer is facing.

Using these heuristics, the model was created, which enabled the conducting of further experiments. In this research there were three experiments conducted. Firstly, the heuristics were evaluated to find the best sequence and to measure their influence. **PFIH(2)*, 2-interchange, cross-exchange, 2-opt, PFIH, interchange, cross-exchange, 2-opt, PFIH** gave the best results and were therefore used for the RPS. 2-Opt improves the initial solution by 0.5%, and 3.1% after the interchange and cross-exchange were executed. The interchange and cross-exchange operators reduce the initial solution on average by 11.1%, and the interchange, cross-exchange and 2-opt operators combined decrease the initial solution by 13.9% on average.

Secondly, a sensitivity analysis on the penalty parameter was conducted to analyze the relation between the penalty values and the KPIs. The sensitivity analysis showed a positive correlation between the penalty values and the distance traveled. On the other hand, it showed a negative relation between the penalty values and the due dates not visited as well as the work percentage.

Lastly, the results of actual history were compared to the model of Hamer. According to the findings, the number of kilometers driven decreased from 6044 to 5821, and each mechanic handled 1.25 more jobs on average for the selected period, with which the norm of Hamer is achieved. As a result, the average distance per malfunction decreased from 53.0 km to 48.1 km. The outcomes also demonstrated that in total 13.4 hours less were required to complete the routes, and that the model increased the average number of clients visited before the due date by 8.6.

Overall, the routes of Hamer could be more efficient using a custom-made RPS. RPS gives recommendations and handy insight, which can be used to plan routes for mechanics. According to the results, it is possible to tackle the standard of 21 malfunctions per technician in one week by using the RPS of this research. In addition, it is also possible to improve other KPIs, such as less time on the road, fewer hours worked and visiting more locations before their due date. As a result, Hamer can reduce costs by using custom-made RPS, since less driving is done, more faults can be addressed, and clients are more often visited before the due date.

The current RPS is specifically made for Hamer, but could also be used by other companies, which are facing a similar situation, as long as the parameters are adjusted to their situation and the input is static for determining the routes. In Hamer's situation, not every job can be visited in a day and therefore priority is taken into account for selecting which locations are visited. If all locations can be visited or if there is no priority between different locations, the RPS could still be used by excluding the penalties parameter.

*PFIH(2) = PFIH for two locations

Discussion and recommendation

The results of this study indicate that there is certainly potential for more efficiency in Hamer's route planning. With the use of an optimization algorithm, experiments were conducted to show that more malfunctions could be visited with more time- and cost-efficiency. The parameters can be adapted to Hamer's preference, in this way more value can be associated to distance or to penalties as shown in the sensitivity analysis. Different papers show multiple approaches to this kind of problem, among which, the paper of Ghoseiri and Ghannadpour (2010). In line with those papers is the aim to minimize the distance traveled to reach an efficient routing solution. However, the model of this research is also able to take into account the priority of certain locations. The use of RPS is different compared to Hamer's current work method. Currently, planners create routes by hand without assistance. With RPS assistance, it is possible to develop suggested routes that are frequently faster and more efficiently constructed compared to the current work method.

Needless to say, this research also has its limitations. Firstly, the computer program is dependent on the dataset and the inputs given. In order for the model to quantify the optimal choices and priority list, certain parameters are assumed to calculate the optimal outcome. However, Hamer may attribute more value to distance or due dates. Since the scale of priority is set by the user of the model, outcomes can be influenced by wrongly estimated inputs. Next to that, the current study tackles the problem of Hamer using a single day approach. Since the problem of Hamer is a continuous period problem, the results could be limited. Lastly, the estimated values of certain parameters outside the algorithm could deviate from reality and influence the model, such as travel time.

Future research on route planning software for Hamer can focus on improving the validity and reliability of the parameters and input variables of the model, such as travel time. This results in a better reflection of reality and thus more accurate route optimization. Also, multi-period planning can provide more suitable results when Hamer decides to use RPS for future route planning strategies. Currently the model only makes routes for a day but does not plan multiple days ahead. Thirdly, future research could be conducted in finding the best algorithms for Hamer's situation. The current RPS is based on different algorithms, which were chosen due to the situation and literature support. Since there are many different solving methods, there are situations in which other algorithms generate better solutions. Therefore, in the future Hamer could look at algorithms that provide more efficient solutions compared to the algorithm currently used. Lastly, the current RPS only takes the mechanics into account, which are able to handle (almost) all malfunctions for the department. In the future, Hamer could adapt the RPS to take into account more mechanics with different skills and abilities, which ensures that not every mechanic could visit every type of malfunction.

The final recommendation is to invest time and money into RPS because of its potential efficiency results. Currently the routes are made manually, which overall result in less optimized routes compared to optimization-based solutions in a software program. Route planning software gives a heuristic solution which is in general more efficient and faster. The RPS made in this research is able to evaluate the routes made by planners since it is able to take into account release times. In addition, Hamer can experiment to advance the custom-made RPS to calculate future situations, without having routes pre-made by planners. On this basis, Hamer is able to operate more efficiently, which results in time and cost reduction.

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8. Appendices

Appendix A: Distance matrix

In Figure 19 a small part of a distance matrix, used in the model, is given. These matrices are made for every day, but for the sake of brevity only one is partly shown to give a visualization. The distances are calculated using the following excel formulation:

*Distance =ACOS(SIN(lat1)*SIN(lat2)+COS(lat1)*COS(lat2)*COS(lon2-lon1))*6371000* (14)

Lat1 indicates the latitude coordinate location 1, lon1 indicates the longitude coordinate, the same goes for lon2 and lat2.

The latitude and longitude coordinates are based on the zip code of the malfunction. The formula assumes that distances of the routes are an orthodromic line, to make sure the results are not to the advantage of the researcher, the distance will be multiplied by a certain factor. This factor indicates the transition to road distances; according to research this factor lies around 1.3 (Hughes, 2017). According to Ekeris (2021), the factor with the least amount of deviation is around 1.28. The distance of the model is compared with GoogleMaps for certain routes of Hamer (Google, 2022). The factor 1.37 gave the lowest deviation and was therefore selected for this research. This means that the outcome of the formula (14) is multiplied by 1.37 to get the distances used in the model.

1		P07103	P04171	P07162	P07200	P07024	P07029	P07181	P90062	P90094	P07109	P07152	1126319-(	1126470-(	1125387-(	1128310-(	1126629-(	1126184-(	1127454-(	1127627-(	1127860-(	1129928-(	1129678-(	1130427-(	1117753-(	1127512-(	1130391-(	113(
2	P07103	0	107.077	0	35.3666	15.7426	60.5477	0	0	84.562	144.993	154.142	76.0546	54.5986	61.4229	139.765	76.8278	56.459	27.1483	20.5666	73.0336	144.723	94.2038	24.9886	70.3767	79.3852	72.2689	31
3	P04171	107.077	0	107.077	128.826	104.479	102.508	107.077	107.077	189.251	241.938	256.767	127.508	67.2752	47.7469	244.884	181.448	137.621	108.102	91.2178	125.856	248.699	124.938	83.119	135.52	138.017	48.3603	1
4	P07162	0	107.077	0	35.3666	15.7426	60.5477	0	0	84.562	144.993	154.142	76.0546	54.5986	61.4229	139.765	76.8278	56.459	27.1483	20.5666	73.0336	144.723	94.2038	24.9886	70.3767	79.3852	72.2689	31
5	P07200	35.3666	128.826	35.3666	0	50.6232	95.5793	35.3666	35.3666	62.3208	114.331	152.489	50.9048	64.4587	81.0883	134.236	77.7256	22.4986	20.7981	39.3048	48.1539	141.283	73.2281	48.7031	40.4328	50.272	102.695	44
6	P07024	15.7426	104.479	15.7426	50.6232	0	44.9729	15.7426	15.7426	93.8404	156.815	152.787	91.2143	61.3836	62.3921	140.405	76.9782	72.1076	42.3573	30.2606	88.1955	144.336	108.44	29.7226	86.0427	94.9529	64.3691	32
7	P07029	60.5477	102.508	60.5477	95.5793	44.9729	9.5E-05	60.5477	60.5477	131.445	197.155	164.962	133.563	88.9736	77.5869	158.309	99.3647	117.007	85.7804	68.805	130.59	159.467	148.147	62.8762	130.027	138.5	54.1523	66
8	P07181	0	107.077	0	35.3666	15.7426	60.5477	0	0	84.562	144.993	154.142	76.0546	54.5986	61.4229	139.765	76.8278	56.459	27.1483	20.5666	73.0336	144.723	94.2038	24.9886	70.3767	79.3852	72.2689	31
9	P90062	0	107.077	0	35.3666	15.7426	60.5477	0	0	84.562	144.993	154.142	76.0546	54.5986	61.4229	139.765	76.8278	56.459	27.1483	20.5666	73.0336	144.723	94.2038	24.9886	70.3767	79.3852	72.2689	31
10	P90094	84.562	189.251	84.562	62.3208	93.8404	131.445	84.562	84.562	0	66.7816	104.279	98.29	126.663	141.722	82.5649	52.0514	65.7972	82.7292	98.0388	96.6762	91.6779	121.351	106.445	83.3633	91.116	156.747	65
11	P07109	144.993	241.938	144.993	114.331	156.815	197.155	144.993	144.993	66.7816	0	137.252	126.286	175.242	194.548	114.901	114.917	104.916	134.453	153.605	126.245	125.151	144.261	162.926	112.898	115.637	216.377	1
12	P07152	154.142	256.767	154.142	152.489	152.787	164.962	154.142	154.142	104.279	137.252	0	198.653	208.075	214.658	22.9119	77.4636	164.871	168.074	174.141	196.541	12.8134	222.108	178.968	184.399	193.144	212.441	12
13	1126319-(	76.0546	127.508	76.0546	50.9048	91.2143	133.563	76.0546	76.0546	98.29	126.286	198.653	0	62.8408	85.9946	178.63	127.115	33.7932	48.923	64.9775	3.02122	186.725	23.4551	72.3553	15.0286	11.0977	120.406	9
14	1126470-(	54.5986	67.2752	54.5986	64.4587	61.3836	88.9736	54.5986	54.5986	126.663	175.242	208.075	62.8408	0	23.1922	192.562	130.612	70.5121	43.9518	34.11	60.7189	198.183	67.2028	31.6626	68.87	72.5418	59.6715	85
15	1125387-(	61.4229	47.7469	61.4229	81.0883	62.3921	77.5869	61.4229	61.4229	141.722	194.548	214.658	85.9946	23.1922	0	201.046	137.819	90.9333	60.3936	43.8763	83.8237	205.692	89.6761	36.5699	91.3987	95.5439	38.1817	92
16	1128310-(	139.765	244.884	139.765	134.236	140.405	158.309	139.765	139.765	82.5649	114.901	22.9119	178.63	192.562	201.046	0	63.4468	144.979	151.081	159.099	176.652	10.2946	202.048	164.754	164.115	172.579	202.435	1
17	1126629-(	76.8278	181.448	76.8278	77.7256	76.9782	99.3647	76.8278	76.8278	52.0514	114.917	77.4636	127.115	130.612	137.819	63.4468	0	93.9369	91.3411	96.6919	124.64	67.9117	150.228	101.758	114.134	123.679	139.658	45
18	1126184-(	56.459	137.621	56.459	22.4986	72.1076	117.007	56.459	56.459	65.7972	104.916	164.871	33.7932	70.5121	90.9333	144.979	93.9369	9.5E-05	34.1485	54.8109	31.6894	152.979	57.2449	64.1896	20.2016	29.8687	118.117	66
19	1127454-(	27.1483	108.102	27.1483	20.7981	42.3573	85.7804	27.1483	27.1483	82.7292	134.453	168.074	48.923	43.9518	60.3936	151.081	91.3411	34.1485	0	20.6748	45.9018	157.45	67.4695	30.1091	44.2671	52.7903	84.2672	50
20	1127627-(	20.5666	91.2178	20.5666	39.3048	30.2606	68.805	20.5666	20.5666	98.0388	153.605	174.141	64.9775	34.11	43.8763	159.099	96.6919	54.8109	20.6748	0	62.0437	164.436	79.7033	9.51138	63.2113	70.8173	63.7672	51
21	1127860-(	73.0336	125.856	73.0336	48.1539	88.1955	130.59	73.0336	73.0336	96.6762	126.245	196.541	3.02122	60.7189	83.8237	176.652	124.64	31.6894	45.9018	62.0437	0	184.668	25.6712	69.4971	13.9254	12.1947	117.914	92
22	1129928-(	144.723	248.699	144.723	141.283	144.336	159.467	144.723	144.723	91.6779	125.151	12.8134	186.725	198.183	205.692	10.2946	67.9117	152.979	157.45	164.436	184.668	0	210.174	169.667	172.359	180.996	205.285	11
23	1129678-(	94.2038	124.938	94.2038	73.2281	108.44	148.147	94.2038	94.2038	121.351	144.261	222.108	23.4551	67.2028	89.6761	202.048	150.228	57.2449	67.4695	79.7033	25.6712	210.174	0	85.3503	38.0406	30.6944	126.871	11
24	1130427-(	24.9886	83.119	24.9886	48.7031	29.7226	62.8762	24.9886	24.9886	106.445	162.926	178.968	72.3553	31.6626	36.5699	164.754	101.758	64.1896	30.1091	9.51138	69.4971	169.667	85.3503	0	71.7253	78.9044	54.2559	5
25	1117753-(	70.3767	135.52	70.3767	40.4328	86.0427	130.027	70.3767	70.3767	83.3633	112.898	184.399	15.0286	68.87	91.3987	164.115	114.134	20.2016	44.2671	63.2113	13.9254	172.359	38.0406	71.7253	0.00013	9.87534	123.18	85
26	1127512-(	79.3852	138.017	79.3852	50.272	94.9529	138.5	79.3852	79.3852	91.116	115.637	193.144	11.0977	72.5418	95.5439	172.579	123.679	29.8687	52.7903	70.8173	12.1947	180.996	30.6944	78.9044	9.87534	0	128.892	95
27	1130391-(	72.2689	48.3603	72.2689	102.695	64.3691	54.1523	72.2689	72.2689	156.747	216.377	212.441	120.406	59.6715	38.1817	202.435	139.658	118.117	84.2672	63.7672	117.914	205.285	126.871	54.2559	123.18	128.892	0	9
28	1130933-(	31.3635	136.13	31.3635	44.8711	32.1868	66.1121	31.3635	31.3635	65.3917	131.14	122.854	95.135	85.8194	92.0563	109.08	45.7624	66.6247	50.7657	51.7095	92.2579	113.649	116.401	56.114	85.3034	95.1413	96.396	
29	1130238-(	28.6162	134.811	28.6162	39.4147	32.0868	69.12	28.6162	28.6162	63.0114	128.064	125.687	89.7686	82.492	89.9265	111.161	48.2727	61.1593	46.0026	48.466	86.9027	116.133	111.16	53.5999	79.8451	89.6866	96.431	5.4
30	1130096-(	164.366	254.18	164.366	130.978	177.601	220.026	164.366	164.366	93.4935	31.2158	168.095	131.17	186.906	207.916	145.906	143.899	117.004	149.615	169.845	131.847	156.125	145.272	179.349	119.9	120.079	233.566	15
31	1128810-(	56.459	137.621	56.459	22.4986	72.1076	117.007	56.459	56.459	65.7972	104.916	164.871	33.7932	70.5121	90.9333	144.979	93.9369	9.5E-05	34.1485	54.8109	31.6894	152.979	57.2449	64.1896	20.2016	29.8687	118.117	66
32	1130521-(	64.7132	155.056	64.7132	29.8342	79.3921	123.987	64.7132	64.7132	48.1678	86.8913	150.147	50.1405	88.4367	107.77	129.407	83.529	19.1994	48.2495	68.3639	48.6093	137.911	73.1987	77.8681	35.1955	43.1966	132.097	65
33	1130353-(	178.416	271.827	178.416	146.334	190.824	231.86	178.416	178.416	101.881	35.1027	163.47	150.696	204.622	225.028	142.244	149.433	134.221	165.764	185.572	151.2	152.191	165.643	195.018	138.807	139.647	248.972	16
34	1130468-(	118.258	15.4045	118.258	142.048	114.087	106.343	118.258	118.258	201.584	255.739	265.039	142.716	81.8599	61.1908	254.142	190.878	151.856	121.473	103.699	141.016	257.478	140.34	95.1411	150.438	153.156	53.1771	14
35	1130513-(	169.299	258.614	169.299	135.814	182.581	225.053	169.299	169.299	98.4813	35.4762	171.831	135.111	191.347	212.469	149.766	148.77	121.593	154.346	174.62	135.856	159.957	148.751	184.127	124.077	124.014	238.357	15
36	1130463-(	41.7194	94.9868	41.7194	77.0615	26.7423	19.8115	41.7194	41.7194	118.236	182.577	164.1	113.758	71.0089	62.6662	154.812	92.9287	97.9915	66.1588	49.0079	110.788	157.232	128.467	43.3685	110.426	118.796	48.4695	53
37	1130200-(	61.4811	167.704	61.4811	60.2252	63.9135	92.7245	61.4811	61.4811	44.1111	110.404	94.0688	109.815	114.328	122.883	78.3959	17.504	76.8631	74.1453	80.7139	107.303	83.8693	132.85	86.4527	97.0609	106.693	127.948	31
38	1127640-(	118.62	218.615	118.62	89.9003	129.776	169.39	118.62	118.62	38.7471	28.0408	120.413	110.159	152.891	170.922	97.5125	87.9564	84.0255	110.528	128.753	109.538	107.75	130.621	137.872	95.6657	100.377	190.571	10
39	1130253-(	55.9796	148.64	55.9796	21.5004	70.5602	115.125	55.9796	55.9796	48.4845	93.5215	147.658	51.0717	82.655	101.093	127.563	78.3492	17.527	40.9463	60.5717	49.1037	135.673	74.5078	70.036	36.7668	45.8214	124.147	57
40	1127944-(	107.569	42.0533	107.569	137.591	99.0705	79.2013	107.569	107.569	191.994	251.548	243.164	150.702	87.9761	64.7861	234.66	172.72	151.982	118.594	98.3971	148.462	236.818	153.715	88.922	155.239	160.016	35.3119	13

Figure 19. Example of a used distance matrix

Appendix B: Heuristics evaluation

Appendix B-1: Heuristics

Push-Forward Insertion Heuristic (PFIH) implementation:

Figure 20 shows the main part of the PFIH algorithm. For every route, the algorithm loops over all the available locations in the Excel data, then for every location, it calculates the cheapest way to insert this location into the route without violating constraints. The cost of this route is then compared to the cheapest route so far, if the new route is cheaper, it becomes the new cheapest route. Initially the cheapest route is set to minus infinity.

```
for i in range(len(drivers) + 2, max_loc):  # loop over all locations in the Excel file
    elem = sh_data[order_col + str(i)].value  # the order number of the location
    if elem not in visited:  # if element is already in a route -> skip
        options = insert_options(routes[x], elem)  # list of all possible places 'elem' can be added to a route
        for route in options:  # loop over every possible new route

            if elem in starts:  # check if location has a required start time
                time_so_far = calc_working_hours_for_route_so_far_start(route, elem)
                s = sh_orders[start_col + str(find_row_ord(elem))].value  # look up start time in Excel file
                if time_so_far < s - start_work_day:  # if route so far finishes before start time -> skip location
                    continue

            if elem in ends:  # check if location has a required end time
                time_so_far = calc_working_hours_for_route_so_far_end(route, elem)
                e = sh_orders[end_col + str(find_row_ord(elem))].value  # look up start time in Excel file
                if time_so_far > e - start_work_day:  # if route so far ends after end time -> skip location
                    continue

            temp_cost = calc_costs_for_route_with_pen(route, elem)
            temp_dist = calc_costs_for_route_no_pen(route)

            if temp_cost > highest_cost:
                workload = calc_working_hours_for_route(route)
                if work_hours[x] - workload >= 0:
                    highest_cost = temp_cost
                    highest_route = route
                    highest_elem = elem
                    highest_workload = workload
                    highest_dist = temp_dist
```

Figure 20. Python code PFIH operator

This algorithm can be used in two different ways:

The first one is letting it add a specified number of locations for each route, allowing each route to add two locations for example. This can be useful for generating a small starting route.

The second option is letting the algorithm add locations until no change is detected. Eventually, each route will be ‘full’ once it approaches the maximum allowed working hours for a driver.

Flowchart

In Figure 21 the flowchart shows the constructive algorithm. The first customer is selected with a different calculation. The algorithm for the first customer has more reach in distance compared to if the second algorithm would be used. After experimenting these results were more appropriate.

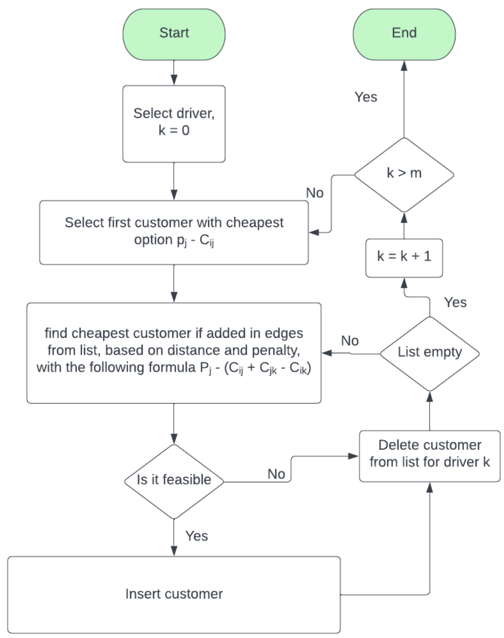

Figure 21. Flowchart PFIH operator

Interchange and cross-exchange implementations:

Since all interchange ((0,1), (1,0), (1,1), (2,0) and (0,2)) and cross-exchange ((2,1),(1,2) and (2,2)) algorithms work on the same principle, all implementations are very similar as well. For the sake of brevity only the (2,1) implementation is discussed. Figure 22 shows the main part of the (2,1)-switching algorithm and it works as follows:

The algorithm takes two routes as input, with one route having at least 2 elements and the other one having at least 1 (otherwise the 2-1 switch is not possible). Then for the first route, two subsequent elements are temporarily removed from the route, whereas for the second route one element is removed. Then these three elements are 'switched' by inserting the element from the second route into the first route and vice versa for the two elements from the first route.
The cost of the adapted routes are calculated and if it is cheaper and feasible the adapted routes become the new routes, otherwise the routes stay the same.

```python
for i in range(1, len(routes[x]) - 2):  # loop to find two elems to switch from route1 (except start / finish)
    temp_switch11 = routes[x][i]  # first element
    temp_switch12 = routes[x][i+1]  # second element
    test1 = copy.deepcopy(routes[x])  # copy original route
    test1.remove(temp_switch11)  # remove first element
    test1.remove(temp_switch12)  # remove second element

    for j in range(1, len(routes[y]) - 1):  # loop to find elem to switch from route2 (except start / finish)
        temp_switch2 = routes[y][j]  # element
        test2 = copy.deepcopy(routes[y])  # copy original route
        test2.remove(temp_switch2)  # remove element

        options1 = insert_options(test1, temp_switch2)  # list with all possible ways to insert elem into route1
        options2 = insert_options_two(test2, temp_switch11, temp_switch12)  # "" to insert two elems into route2

        for op1 in options1:  # loop over all new route1 options
            for op2 in options2:  # loop over all new route2 options
                if op1 not in empty_routes and op2 not in empty_routes:  # if one route is empty -> skip
                    c_option1 = calc_costs_for_route_no_pen(op1)  # calculate cost for new route1
                    c_option2 = calc_costs_for_route_no_pen(op2)  # calculate cost for new route2
```

Figure 22. Python code interchange and cross-exchange operators

Flowchart

In Figure 23, the flowchart of the interchange and cross-exchange operators are displayed.

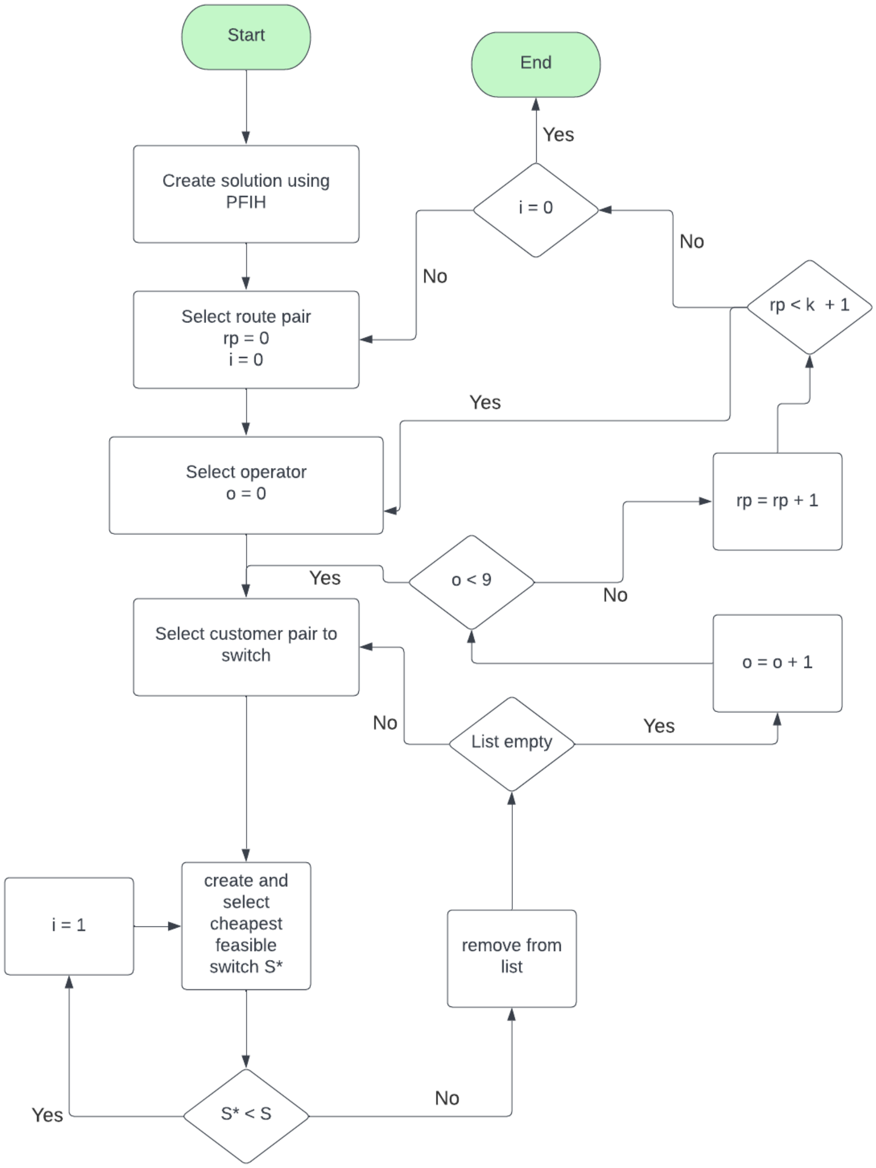

Figure 23. Flowchart interchange and cross-exchange operators

2-opt implementation:

Figure 24 shows the main part of the 2-opt algorithm. This algorithm is run on every route generated thus far and for every route it essentially cuts and adds edges of all routes, in order to find improvements. If the adapted routes are cheaper and do not violate constraints, the adapted routes become the new routes.

```python
for i in range(1, len(route) - 2):  # loop over (n-2) locations in route (so skip start / finish)
    for j in range(i + 1, len(route) - 1):  # loop over all locations that come after location i (without finish)
        if not (i == 1 and (j == len(route) - 2)):  # skip i == 0 & j == (n-2) -> this case changes nothing
            temp_route = [route[0]]  # array used to temporarily store the new route that is explored

            for k in range(1, i):  # just copy the first (i-1) locations from the route
                temp_route.append(route[k])

            k = j  # set k to j and decrement until k == i
            while k >= i:  # add locations between i and j (i <= k <= j) to new route in reverse order
                if k in starts:  # first check if this location has a required start time
                    time_so_far = calc_working_hours_for_route_so_far_start(temp_route, k)
                    s = sh_orders[start_col + str(find_row_ord(k))].value  # look up start time in Excel file
                    if time_so_far < s - start_work_day:  # if route so far finishes before start time -> skip
                        continue

                if k in ends:  # also check if location has a required end time
                    time_so_far = calc_working_hours_for_route_so_far_end(temp_route, k)
                    e = sh_orders[end_col + str(find_row_ord(k))].value  # look up end time in Excel file
                    if time_so_far > e - start_work_day:  # if route so far finished after end time -> skip
                        continue

                temp_route.append(route[k])
                k = k - 1

            for k in range(j + 1, len(route)):  # copy locations at index k > j to new route
                temp_route.append(route[k])

            workload = calc_working_hours_for_route(temp_route)  # calculate new workload for route
            cost = calc_costs_for_route_no_pen(temp_route)  # calculate new cost for route
```

Figure 24. Python code 2-Opt operator

Flowchart

The flowchart of the 2-Opt algorithm is given in Figure 25.

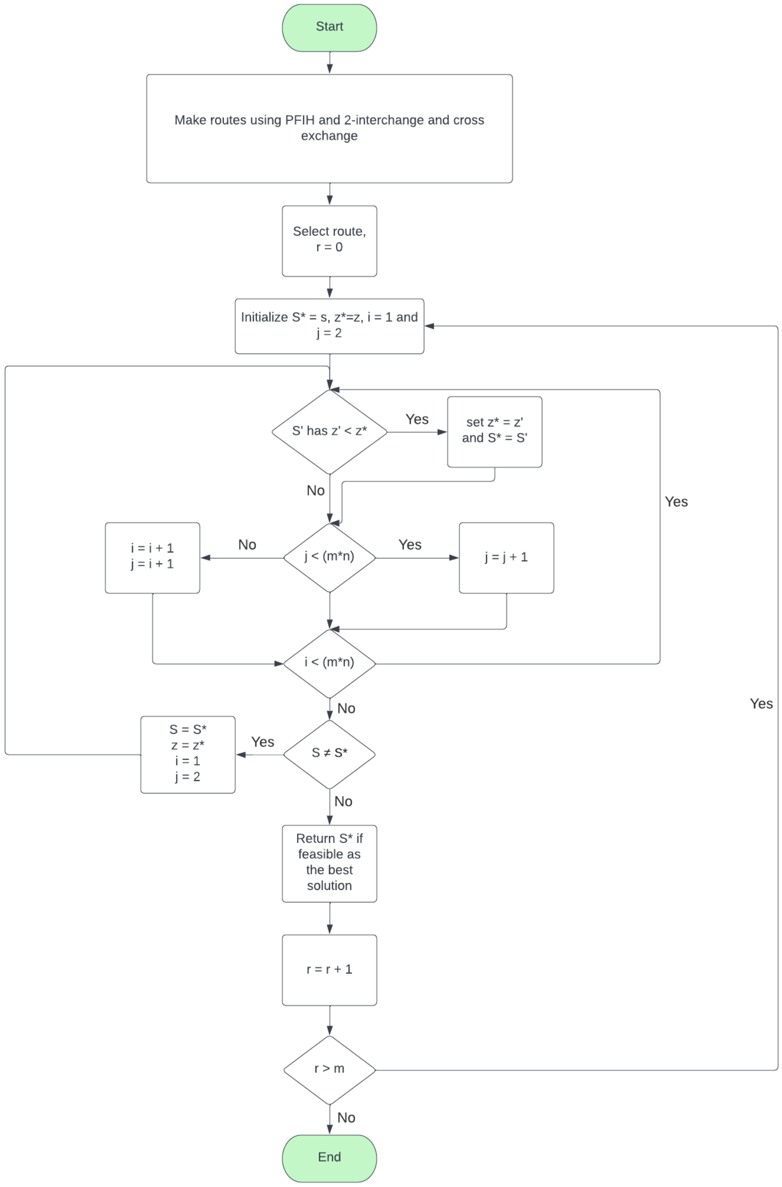

Figure 25. Flowchart 2-opt operator

Appendix B-2: Heuristics combination

In Figure 26 the flowchart of the heuristic combination used in Section 6.3. is displayed. This combination gave the result, which was preferred the most.

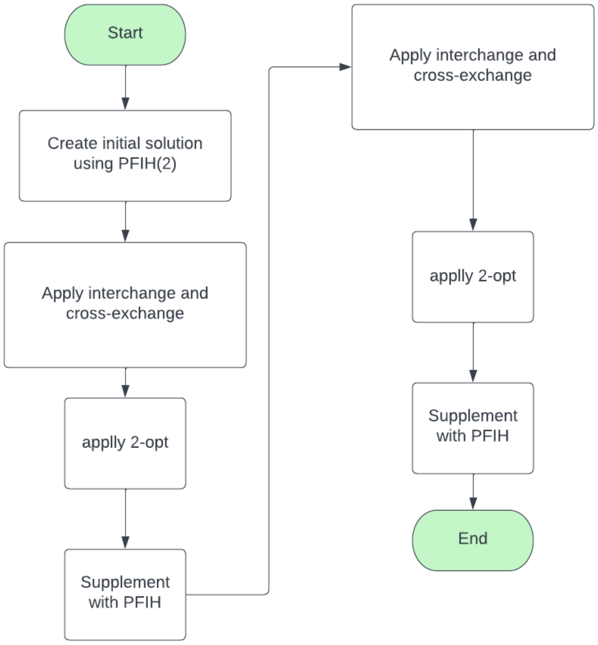

Figure 26. Flowchart of chosen heuristic combination

Appendix C: Sensitivity analysis

Below the visualization of a couple of the sensitivity experiments can be found, the higher the µ-value, the more value is attached to penalties. Which makes the model more likely to create routes with longer distances as shown.

µ-value = 1.5

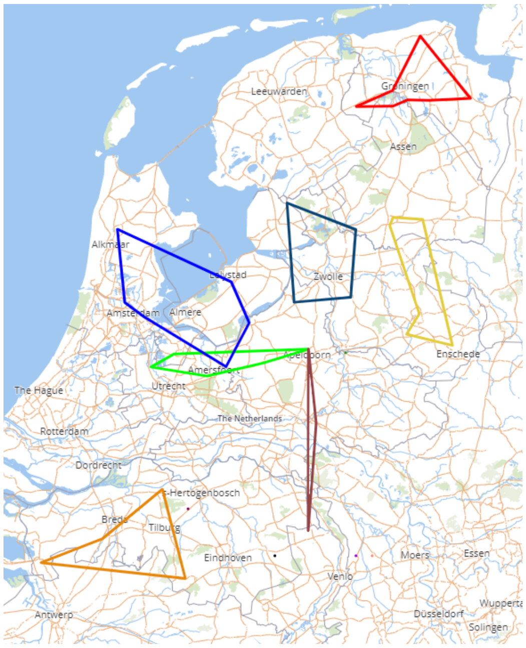

Figure 27. Map with µ-value multiplied by 2

µ-value = 1

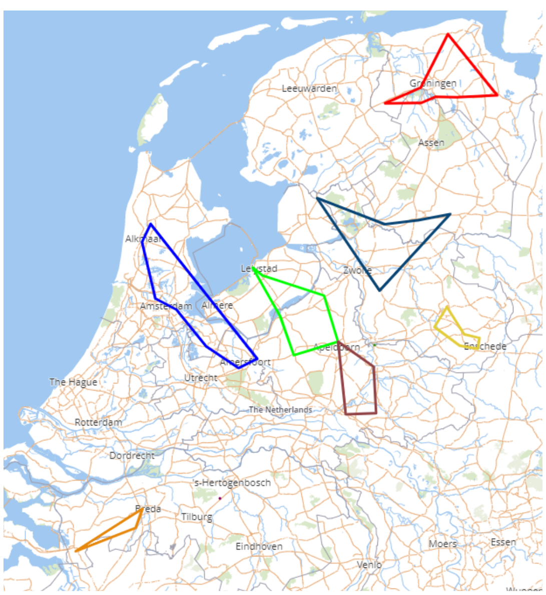

Figure 28. Map with µ-value multiplied by 1

µ-value = 0

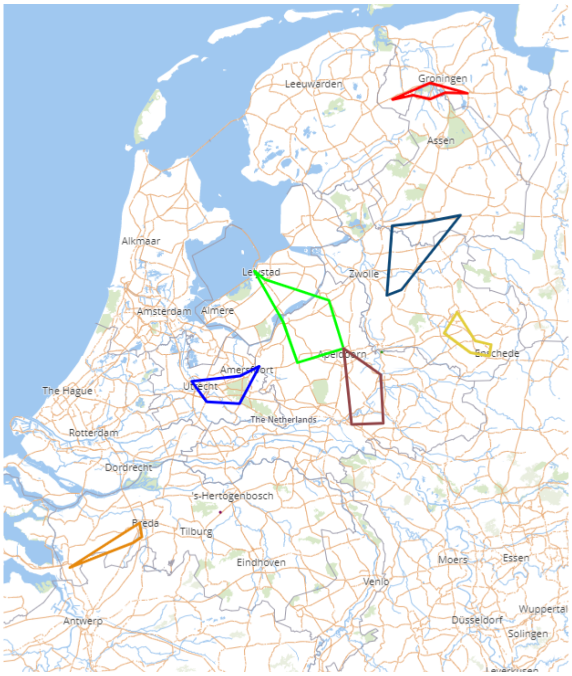

Figure 29. Map with μ-value multiplied by 0

Appendix D: Algorithm evaluation

In Appendix D the driven routes are compared to the routes given by the algorithm. It occurs sometimes that a certain location must be visited by a certain mechanic. This is assigned in the model; an example is shown in Figure 30 to 34. In this example the red and blue routes cross each other because locations are assigned to a certain mechanic.

Reality

Day 1

Figure 30. Driven routes reality (left), routes according the model (right), day 1

Day 2

Figure 31. Driven routes reality (left), routes according the model (right), day 2

Day 3

Figure 32. Driven routes reality (left), routes according the model (right), day 3

Day 4

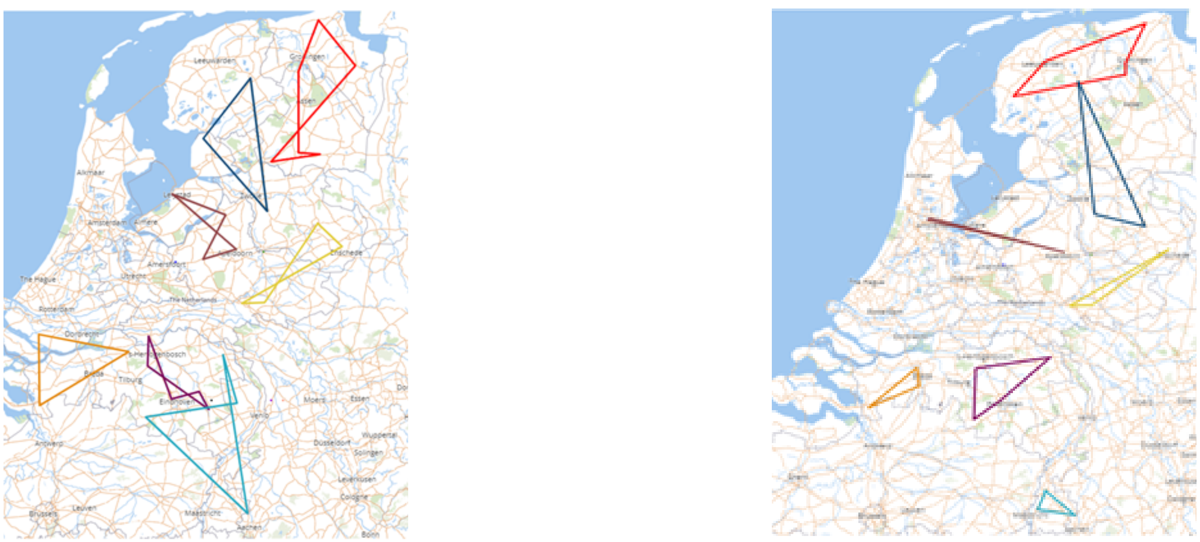

Figure 33. Driven routes reality (left), routes according the model (right), day 4

Day 5

Figure 34. Driven routes reality (left), routes according the model (right), day 5

Appendix E: Further route explanation

Most of the locations visited on a day are known beforehand; no clear image is given to show the constraint which makes sure the routes are not adapted before a malfunction is visited which occurs the same day.

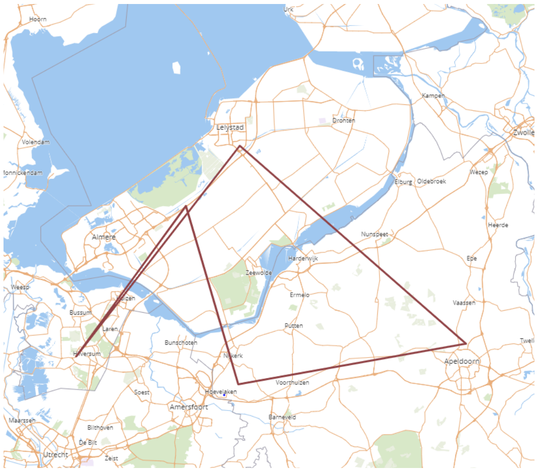

Figure 35: Route with malfunction occuring during the day

The route displayed in Figure 35 is obtained using the model and another gathered dataset; it shows the route is not quite optimal by only looking at the sequence. The reason for this is because of the constraints, so the model does not allow the order of locations in a route to change after a malfunction is added, which occurs the same day.

Appendix F: User manual RPS

This section focuses on how to use the model made for Hamer. The model is made using Python and Excel. In figure 36 is the beginning of the code given, where "EXCEL" is now filled, enter the name of the excel file. There are two Excel sheets needed in order to let the model work and must be entered after the file name; the sheet with the vertex set and its parameters and the concerned arc sheet, containing the distance matrix. Thereafter the parameters of the vertex sheet are connected to the concerned column and some fixed values are addressed.

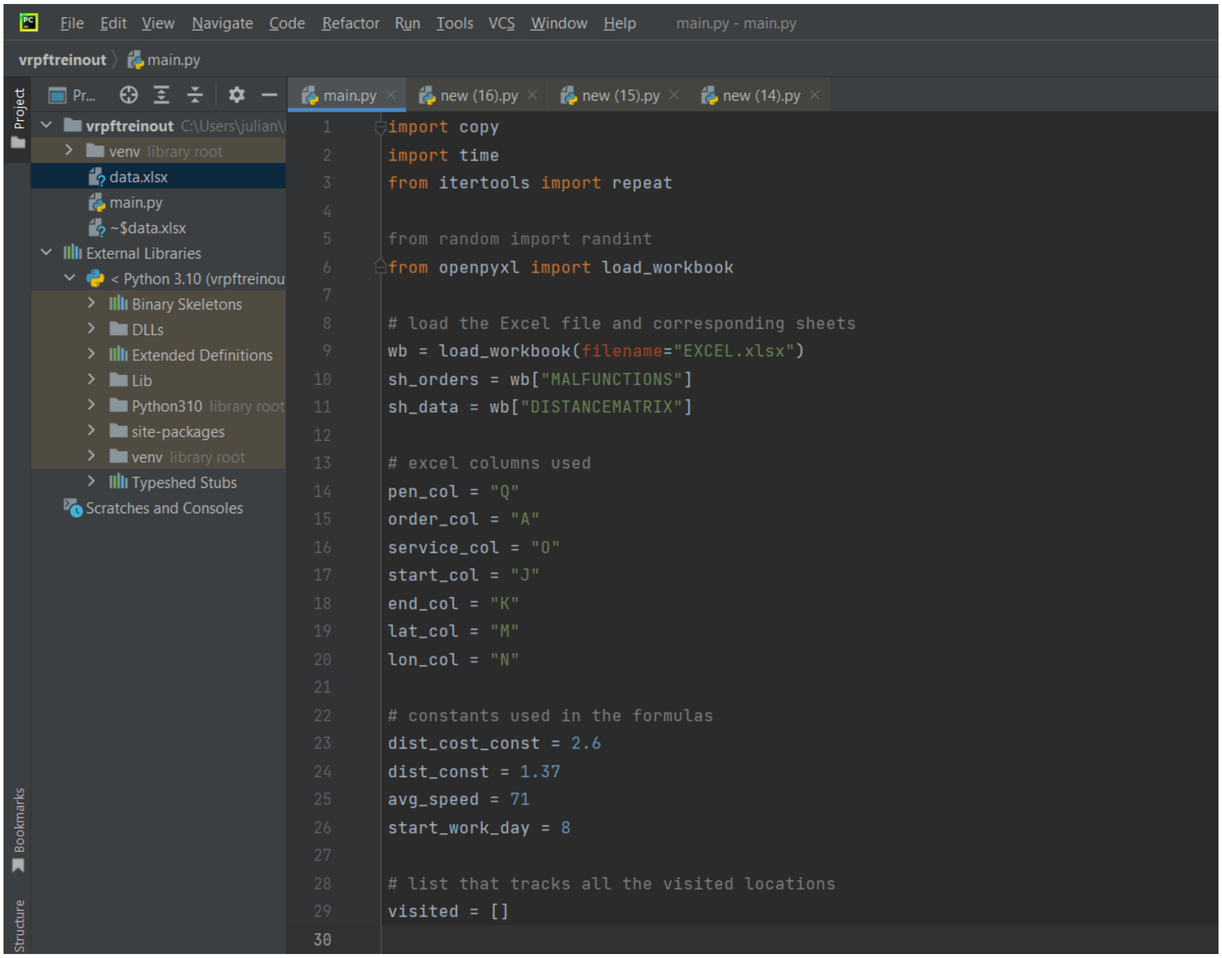

Figure 36. Beginning of the code

Later in the code the heuristics are called, as shown in Figure 37. The order in which the heuristics are called in this part of the code is also the order in which they are executed in the model. For more information about the codes of heuristics, see Appendix B.

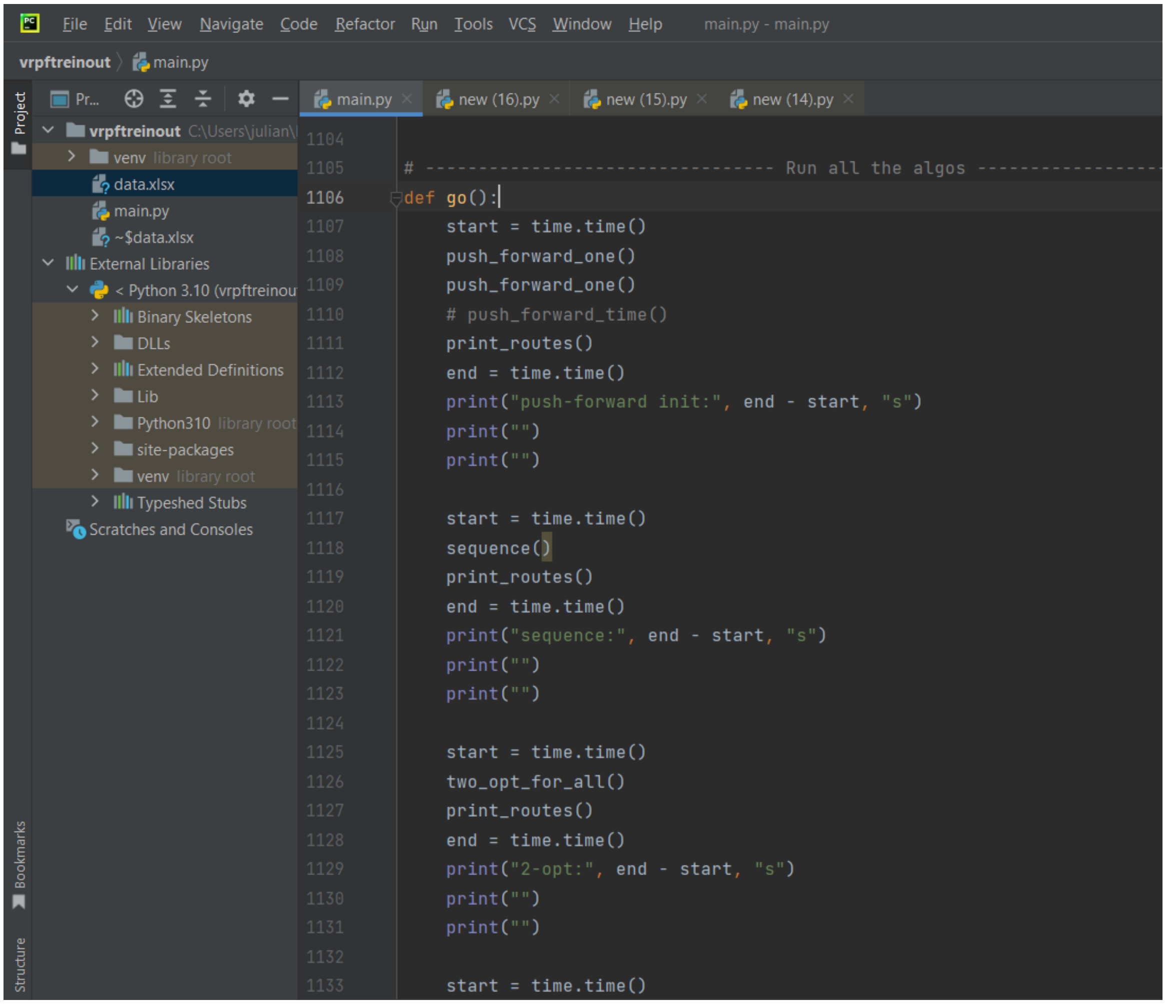

Figure 37. Heuristic sequence in the code

Lastly, the mechanics are selected and their availability as shown in Figure 38. All mechanics are in the Excel sheet, but not all are available in reality. The mechanics can be deactivated and the number of available hours can be adjusted, in the figure an example is given to show how it is done.

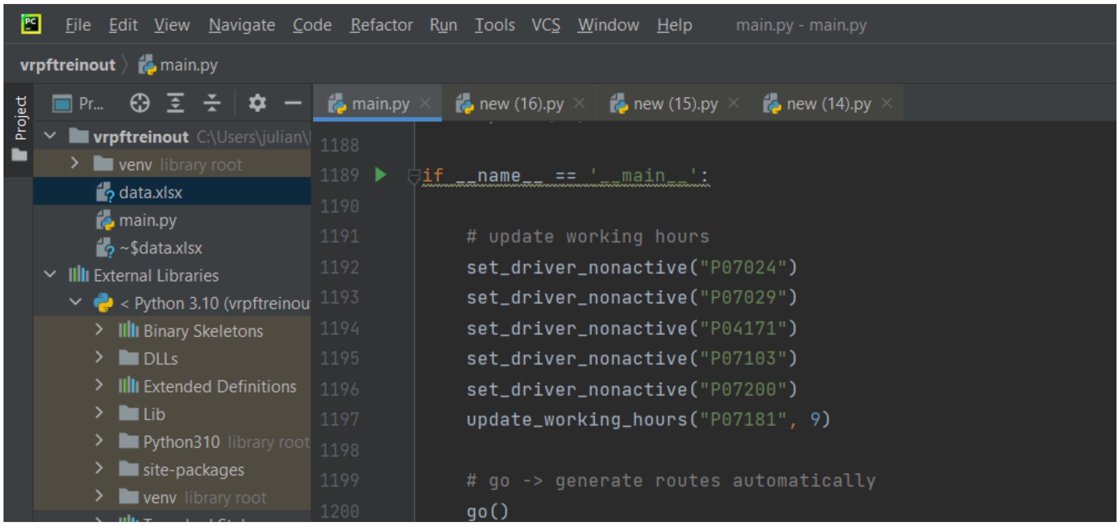

Figure 38. Selecting mechanics and availability