UNIVERSITEIT TWENTE. connexxion

MASTER'S THESIS

PUBLIC TRANSPORT ON DEMAND

A better match between passenger demand and capacity

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PUBLIC TRANSPORT ON DEMAND

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MANAGEMENT SUMMARY

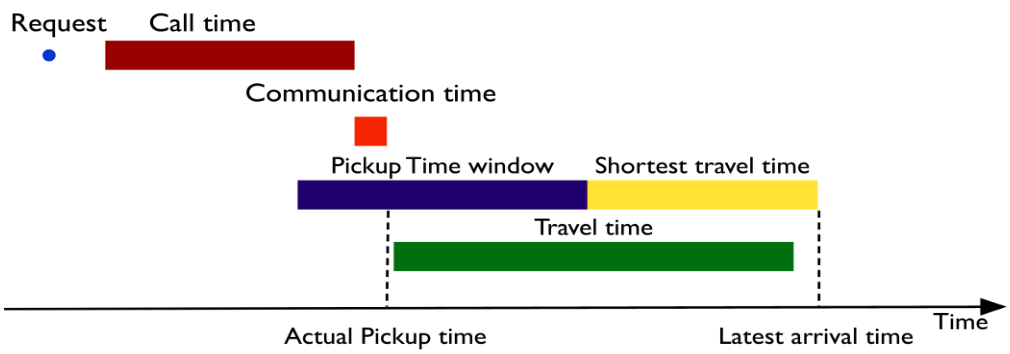
Public transport is becoming more and more important, especially in densely populated cities. The more citizen use public transport, the less congestions and greenhouse gas emissions, which all affect the living environment. But to motivate citizen to use public transport, the public transport service need to be fast, reliable, flexible, and cheap. That is why we formulated the following objective for our research:

Design a solution model that is able to combine and handle real-time DRT requests of customers, with an acceptable service level against minimal costs.

Connexxion is considering a new solution for the public transport that enables customers to order a ride based on their demand. The current operating bus lines, driving a fixed route, are replaced by a service that creates routes based on the customer demand. The customer has the benefit of no more changes between bus lines, and he or she is able to send a request on a preferred time. We suggest that this model uses predetermined stop locations that are only serviced on-demand. The customers is able to send in a request a short time before the actual start, containing an earliest pickup time. The customer receives a message containing information about the pickup time window, the latest arrival time. A short period before the actual pickup, the exact time of the pickup is communicated. The model is able to make a detour to combine more requests in the same vehicle.

THE TWO MODELS

Inspired by the dial-a-ride problem of Cordeau and Laporte (2003), who formulated a model, that provides a stop-to-stop service with allowed detours to combine rides, we develop a method that is able to handle requests that are only known a short time before the actual pickup. Our model is able to handle on-line requests, this process is explained the figure below.



A customer sends a request before the call time (the minimum time a request must be known), the model assigns the requests during the call time to a vehicle, as soon when a vehicle is going to serve a request, within the agreed pickup time window, the customer is noticed a short time before the actual pickup, the communication time. The latest arrival time is based on the latest pickup time plus the direct travel time. We bound the maximum ride time in two ways, the ride must arrive before the latest arrival time, or by a predetermined maximum detour time. For the determination of the maximum detour time, we formulate two models. Model 1 uses a fixed maximum detour time. Independent of the ride length the allowable detour time remains the same. Model 2 uses a detour factor, the allowable detour time is based on the direct ride time times the detour factor. This model results in that all rides have the same relative allowable detour time.

RESULTS

To evaluate the performance of our models, we collected data of the current situation in Helmond. The requests that are used as input for our models, are based on OV-chip card data of September 2015. We are only using requests that stay within Helmond, all requests using bus lines that leave the city are not used. Experiments show that changing parameters have a significant influence on the performances of our models. We see that in the current situation 20 large busses and 4 small vehicles are used. Our results show that only 9 small vehicles with a capacity of eight persons are needed, to serve all requests using one of our models. In the current situation an average distance of 33,452 km, with a corresponding 1,517 hours are needed to serve all requests in a month. Our model 2 serves all the request driving 36,714 km with a corresponding 1,464 hours in a month.

The results show us the effects when serving the customers on demand. Based on de results we believe that the use of on-demand transport is possible, and profitable for Connexxion. Although our model is not extensively tested, we believe if makes a valuable contribution in getting more insight of the possibilities of on-demand transport.

RECOMMEDATIONS AND FURTHER RESEARCH

For the implementation of our on-demand model, we recommend to implement the service in phases. First a combination with the current bus lines, while reducing the frequency of the busses. After a while the bus lines should stop operating and only the on-demand service is available. Since Connexxion already provides the social support transport, the system could combine these requests with the regular request served by on-demand vehicles. To make the service attractive to customers, we recommend to use a fixed fare price.

For further research, we suggest to find out the impact of using flexible vehicle locations instead of using one depot. We also suggest to find out the results of a combination of on-demand transport and bus lines. Another suggestion is to take online events into account (e.g., accidents, traffic jams, and rush hours) and use stochastic travel times. We suggest that a possible improvement of our model is achieved by reassigning the customers that did not already received an actual pickup time. To increase the possible service level for the customers, we suggest a case that allows the customers to change the parameters. We state that customers that cannot be served in within the given restrictions, are rejected, it might be helpful to see the effect of offering the rejected request an alternative pickup time.

CONTENTS

1 INTRODUCTION

"Problems are not stop signs, they are guidelines."
- Robert H. Schuller

This project is commissioned by the department Future Technology (FT) at Connexxion. Connexxion is part of the international shareholder Transdev. The goal of Connexxion is to be the best choice in the field of regional passenger and healthcare transport in the Netherlands. In this chapter, we introduce our research. Section 1.1 provides the context. In Section 1.2, formulates an introduction of our problem, followed by Section 1.3 where we break down the research.

1.1 CONTEXT

Public transport (PT) is getting more and more important in densely populated cities to reduce the number of vehicles on the road. To reduce congestion, citizens need to be stimulated to use PT, instead of using their private car. Congestions causes a lot of stress, loss of time, extra costs, more particulate matter, and accidents. A method to stimulate citizens from not using their private car is a fast, reliable, flexible, and cheap alternative transport mode from one location to another.

The people are expecting a certain level of service from the PT Company, higher service lead most of the times to higher costs, e.g. more buses per hour, increases service, but also increase operation expenses. So a trade-off between operating tasks and the service level must be made. Travelers that use PT want to travel as fast as possible between their pickup location and the destination. The ride of a traveller can be measured in total travel time. The total travel time consists of waiting time, the access and alight time, in-vehicle traveling time and transferring time. Beside the total travel time, the users expect reliable and comfortable rides (Cepeda et al. 2006, Raveau et al. 2011, Schmöcker et al. 2011). The operators are interested in a profitable system, where wages, and the costs of vehicle usage are low.

Constructing a public transit schedule in a bus company is a challenging process. The planning process, exists of several phases shown in Figure 1.1. When focusing on the column "Problem", all the phases are shown separately, since it is practically not possible to solve all the phases at the same time, some phases can be solved at once to get a better result. The vehicle scheduling phase and driver scheduling phase can be combined, as shown in Freling et al. (2003) and Zijp (2005). The planning process is known as the Transit Network Planning problem (TNP). The phases of the TNP can be divided in strategical, tactical and operational decisions, see Figure 1.1 (Ceder 2007, Desaulniers and Hickman 2007).

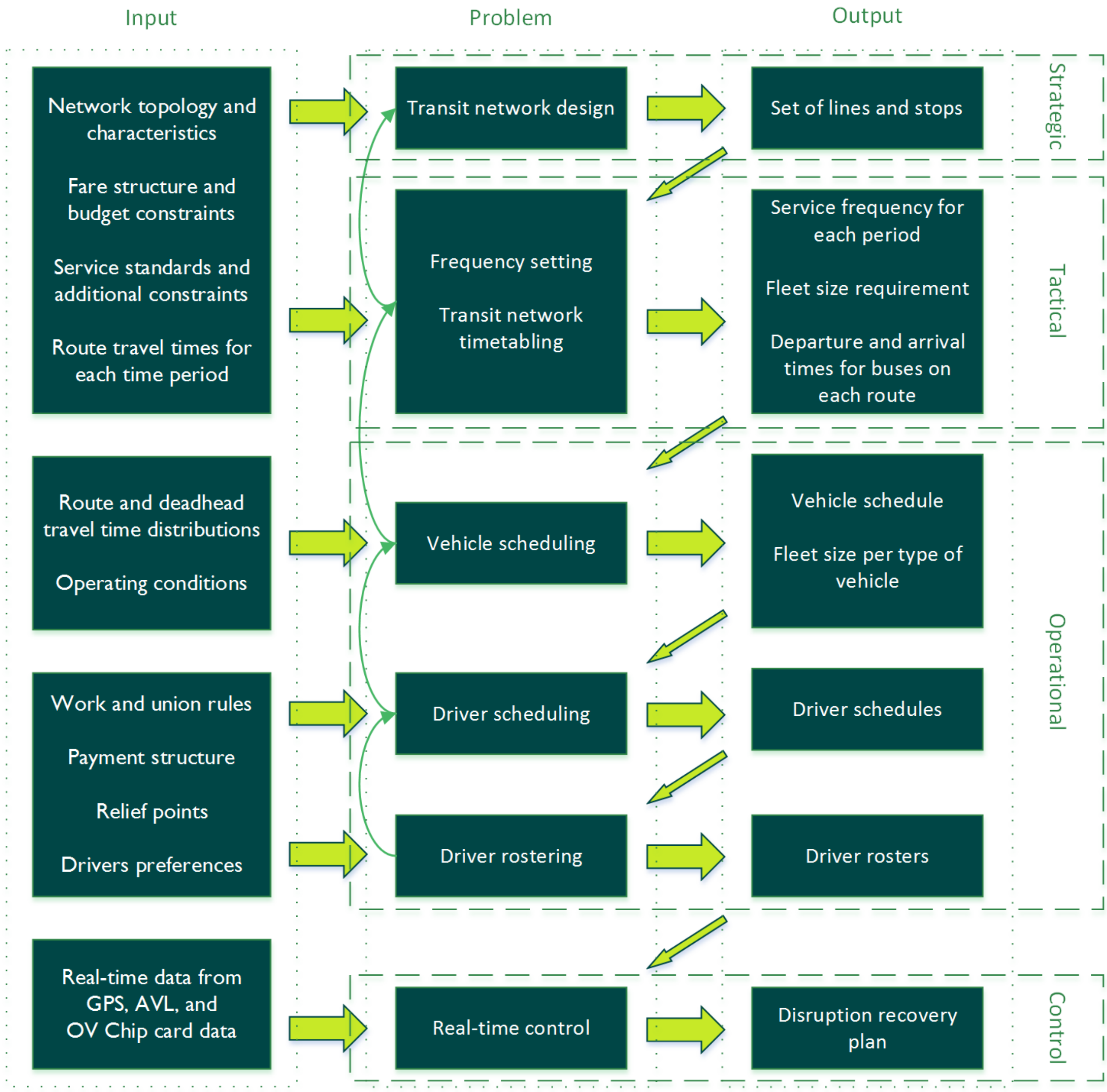


Figure 1.1: *Interactions between the phases of the planning process.*
(This figure is based on the work of Ibarra-Rojas et al. (2015))

We briefly discuss the phases of the planning process described by Ibarra-Rojas et al. (2015):

- Transit Network Design (TND): the strategic phase, which defines the lines layout with the operational characteristics, e.g. the choice of a vehicle and the space between the stops. In this phase the frequencies must be preliminarily set.
- Frequency Setting (FS): part of the tactical phase, the frequencies are determined based on demand patterns, e.g., the traffic peaks. So the number of trips per time period can be determined to satisfy the demand of the passengers.

- Transit Network Timetabling (TNT): part of the tactical phase, the times of arrival and departure are determined for all stops along the transit network, to achieve different goals, e.g., meet a given frequency, satisfy specific demand patterns, and maximize the number of well-timed passenger transfers.
- Vehicle Scheduling Problem (VSP): part of the operational phase, determines the assignment of vehicle types to cover all the planned trips with regard to minimizing the operational costs.
- Driver Scheduling Problem (DSP): part of the operational phase, defines the number of duties that cover all the scheduled trips, with regard to the labour regulations, e.g., minimum/maximum work length, while minimizing the cost of driver wages.
- Driver Rostering Problem (DRP): the last part of the operational phase. Given the number of available shifts created in the DSP. The DRP assigns the shifts to the drivers, while satisfying the labour regulations.

Solving the TNP is done in a certain order. Figure 1.1 shows the input data needed to complete a phase. These phases are mostly solved with the use of commercial support packages, such as HASTUS (Rousseau and Blais 1985), HOT II (Daduna and Völker 1995), and TRACS II (Fores et al. 2002). These packages solve the phases (partially) sequentially and can be altered or fine-tuned, by an algorithm or hand, to improve the outcome (Quak 2003).

The creation a complete bus schedule, is a complicated process based on a various number of factors to fulfil the transport demand. A disadvantage of this method is that the schedule is updated only once a year, and the route of the bus is predetermined until a possible new schedule update. Since the routes are set for a certain time period, it could occur that a customer needs to change between buses to get to their destination. The predetermined routes result in a lack of flexibility. If a customer wants flexibility, taxi services can be a better solution. This type of transport can be altered to satisfy the demand of the customer. Taxi services are fast, reliable, and flexible, but are quite expensive and the average number of passengers in the vehicle is low.

The predetermined schedule and lines, as named above, are based on average demand. The demand and supply of transport, can have a misfit in the following ways: the offered capacity is too small, so customers cannot be transported to their destination, or the offered capacity is not used, e.g., empty buses. To reduce this misfit a new approach of PT is needed.

Connexxion is considering a new solution of PT that is able to fulfil the demand. A system that can offer rides on demand makes use of a lot of stop places that are only serviced on demand, and can make agreements about the pickup and delivery times. This new method of PT could solve the misfit to the demand and possibly reduce the number of rides of private cars. The idea is to create a transport solution on demand in which a car or bus drives to the ordered place of the customer. In the literature several names are used for a service like this, namely Demand Responsive Transport (DRT), Demand Responsive Transit, Demand Responsive Service (DRS), Dial-a-ride problem (DARP), or Flexible Transport Services FTS. For the purpose of this research, PT can be categorized as DRT if:

- The service is available to the general public, and is not restricted to a particular group of users.

- The service uses small vehicles like cars or mini vans.
- The route is created between the requested pickup and drop-off location.
- A request is serviced by a vehicle, if a new request is combined in the same vehicle, the route is changed. If the request cannot be combined, the route is not changed.
- The request can be accepted instantly or pre-booked.

1.2 PROBLEM IDENTIFICATION

On demand transport is commonly only possible with taxi services that are costly for the passengers. A cheaper alternative is to use PT. But travelling to a boarding point to hop on a bus, tram or train is inevitable. Once in PT, the ride is not over the shortest route to the preferred destination, and a change might be needed to transfer to another PT service or line. This generally results in longer travel times compared to direct routes within a city.

The current PT system relies on the Transit Network Planning methodology. This methodology does not take the online demand into account. Hence, a misfit between the offered capacity and the demand may occur. When the bus starts the route it could happen that a lot of customers are travelling from a stop towards a stop in the middle of the route. This can lead to a low utilization of the vehicle, since in the second part of the route no customers are served. Another reason for a lower utilization of buses is that routes cannot be altered to the customer wishes. It could occur that some customers need transfers that can significantly increase the ride time. Customers using PT need, most of the times, extra time to travel towards a stop. The number and location of the stops are pre-set. Compared to a taxi service, where customers are pickup and dropped-off at their preferred address. Customers that want to use the new PT solution still need to travel towards a stop. It is not possible for a customer to enter or leave between stops. If a customer wants to travel, without transit, from and to a specific address, other options can be cycling, using the private car or using a taxi service cab.

Buses are facing big fluctuations in the demand. Although this demand fluctuations are not desirable, it is hard to prevent, since demand fluctuates and a stable schedule is desirable, e.g., a bus must have a frequency of four per hour. In a rural area were the demand is low, but a public transport service must be offered to the citizens, a fixed frequency is a way to service the small demand. In the urban areas with a high demand, the buses can be overcrowded. Especially during the rush hours buses are overcrowded, although this is profitable, the service for the customers is low. These limitations can reduce the profit or service of the bus line. Finding a balance in the use of vehicle capacity, the demand for PT and meeting the social obligations, can reduce the costs and improve the service. Replacement of high point-to-point demand transport, e.g., between a city centre and an airport, is not in the scope of this project. The same holds for the sparsely populated rural areas, were the use of a private car, shared rides, or the use of a bike is a justified solution, because the distances between several customers is large, and the stops are often located far from the address. So the challenge for the new method of PT lies in urban areas when the utilization of bus lines are low, and the travel time to a location is long while the shortest distances between the locations is small.

Connexxion is developing new methods to improve the service for customers, while increasing the utilization of the vehicles. An ultimate goal is to increase the number of travellers using PT. A new more flexible, on demand driven method could be the solution for this challenge.

1.3 RESEARCH PROBLEM

This section describes the research problem. We start with the objective of this research, followed by the scope of the project to finish with the research questions.

1.3.1 OBJECTIVE

The main objective of this research is to develop a solution model that is able to handle the online requests for DRT. The solution model is activated by an online request that is send by the customer. The customer requests the service at least T_r minutes before the start of the service. The T_r is to be small, to allow customers to order the service a short period before the actual start of the service. A request contains the time the customer wants to be picked-up and information about the latest arrival time at the drop-off location. Based on the request data the solution model calculates to which vehicle the customer should be assigned, while not violating the agreements of the customers already in the vehicle.

The solution model are tested with the use of real life, historical data of the Dutch city Helmond and compared to the current situation. In Helmond several scenarios are simulated, e.g., the number of vehicles needed and the capacity of the vehicles. These scenarios are simulated to find improvements or deteriorations and to find out if the new method is cost effective. The simulations are done in Helmond, since a new tender must be written for this area, and a new solution model can be suggested in the tender, if it can operate cost effective. Helmond has several benefits, the area that is covered is relatively small. The area contains, a hospital, a vocational school, and four train stations, this locations probably have a large demand.

The available data of Helmond contains all the rides that are paid with the use of the OV-chip card. This data contributes by the estimation of the demand in Helmond, the travel time within Helmond, and the locations that are often used by travellers. The estimations are used to solve the new solution model. All the simulations done with the new situation, are evaluated on costs effectiveness, to see if a new method for PT can be implemented.

Before we can test if a new solution model can be implemented, the current situation of Helmond is analysed. The analysis contains the current occupation of the all buses, the number of changes between lines, and the travel time between stops is determined with the given OV-chip card data of Helmond. The current situation enables us to determine, which bus lines can be replaced since they are not cost effective.

1.3.2 SCOPE

For the development of a solution model, we want to operate within a certain context, of which the boundaries and assumptions are described in this section.

- The pickup and drop-off locations are known. This research is not focussing on finding the optimal locations for the stops points.
- The determination of the shortest path is determined with the use of available software.
- The determination of the travel times is done with the use of a time matrix between stops. The time matrix is created with the use of the shortest path software.
- The vehicles that can be used for our problem, are already purchased. This means that we can only choose between vehicles with a capacity of 3 or 8 persons.

1.3.3 RESEARCH GOAL

In Section 1.3.1, we described the problem of a misfit between the demand and the available capacity. Therefore we define the following research goal:

Design a solution model that is able to combine and handle real-time DRT requests of customers, with an acceptable service level against minimal costs.

This solution model helps customers to use PT, without changes between lines. Although the solution model uses the current bus stops, these stops are only serviced on demand, and are not serviced in a predetermined order.

1.3.4 RESEARCH QUESTIONS

To achieve the research goal, a number of research questions are formulated. First we start in Chapter 2 by describing the current situation in Helmond. We answer the following questions.

- What is the current route situation in Helmond?
- What is the current demand for PT in Helmond?
- What are the costs for driving the routes and what is the utilization?
- How is the current performance measured, and what is the current performance?

Chapter 3 provides a literature study. The literature is used to create a new solution model for the demand responsive transport. We describe the history of the vehicle routing problem followed by the DRT with all restrictions that are needed to handle our case. Then a number of methods for solving routing problems are described.

- What relevant variations of the vehicle routing problem (VRP) are available in the literature?
- What solution models are available for DRT?
- What does the literature tell us about DRT?

Besides answers on the DRT related questions, Chapter 3 contains a study about factors that influence the service level of the PT, to see what factors are important to improve or maintain. We use the following questions:

- What kind of simulation models can be used for simulating the DRT in Helmond?
- How to measure customer satisfaction, and determine fare pricing?
- What can we learn from already implemented DRT systems, what are the advantages and drawbacks?

Chapter 4 describes the solution model, based on the literature discussed in Chapter 3. The following questions are about to be answered:

- How is the solution model formulated?
- What restrictions should be taken into account?
- What solution model is used to solve the model, and have a good performance?

Chapter 5 describes the experiments and the results of the two models.

- What is the performance of the new solution model, in terms of average occupation, driven distance?

Finally, in Chapter 6, we present our conclusions and recommendations.

2 CURRENT SITUATION

"In business, words are words; explanations are explanations, promises are promises, but only performance is reality"

- Harold S. Genee

This chapter describes the current situation of the Helmond in the Netherlands. The data used for the analysis is the OV chip card data, representing all the check-in/out data. We start this chapter with a Section with a description of Helmond. Section 2.2 describes all stop locations. Section 2.3 describes all the passenger flows in Helmond. Section 2.4 provides the current situation of the bus lines. Section 2.5 describes the utilization of the bus lines. We finalize this Chapter in Section 2.6 with a conclusion about the current situation.

2.1 DESCRIPTION OF HELMOND

Helmond is a historical city in the province of Noord-Brabant in the southern Netherlands. Helmond is one of the five largest cities in the province, with a population of around 90,000, living in an area of 54.75 square kilometre. The population can be divided into several categories as shown in Table 2.1.

Table 2.1: *Citizen information of Helmond compared to the province and the country (source: (CBS 2011))*

	Helmond	Noord-Brabant	Nederland
Citizen	88,291	2,444,158	16,574,989
Age Percentage			
-0-20 year	24.9%	23.4%	23.7%
-20-65 year	61.6%	60.9%	61.0%
-65-80+ year	13.3%	15.7%	15.3%

Table 2.1 shows a relative younger population that lives in Helmond, compared to the province and the Netherlands. When changes happen in the PT, younger people are generally able to accept changes faster compared to the elderly (e.g., the implementation of a new PT system).

The public transport provision in the community is one of the best in the Netherlands, there are four train stations, and 91 bus stops. The complete municipality of Helmond consists of the postal codes 5701 to 5709, as shown in Figure 2.1.

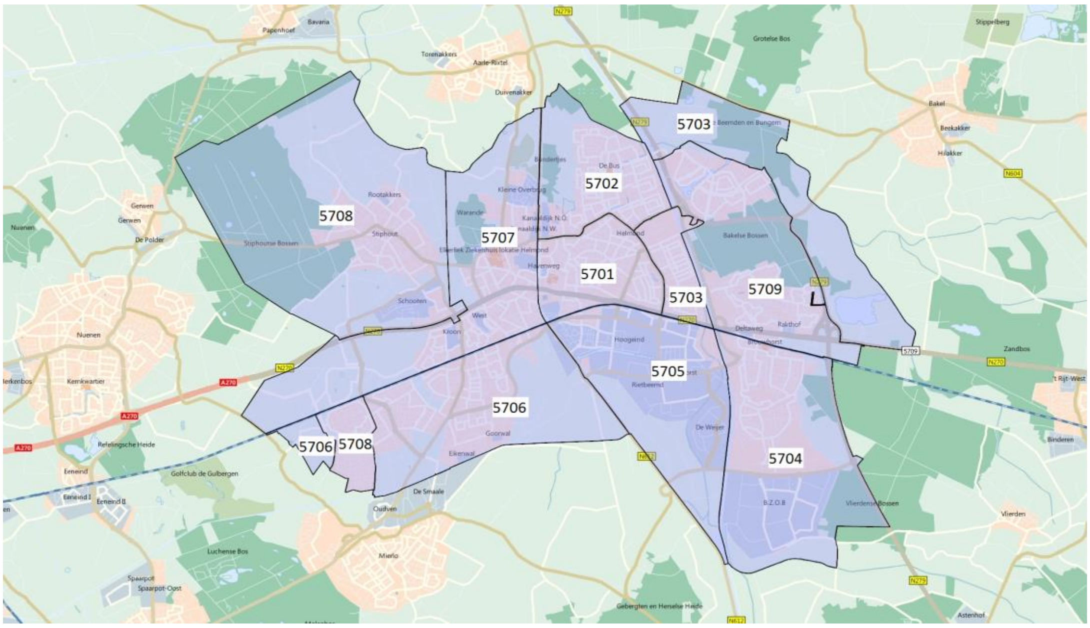


Figure 2.1: *Postal codes in Helmond*

2.2 CURRENT BUSSTOPS

Helmond has 91 bus stops, spread over the municipality. Figure 2.2 shows a map of Helmond where all the stops are shown with a red diamond.

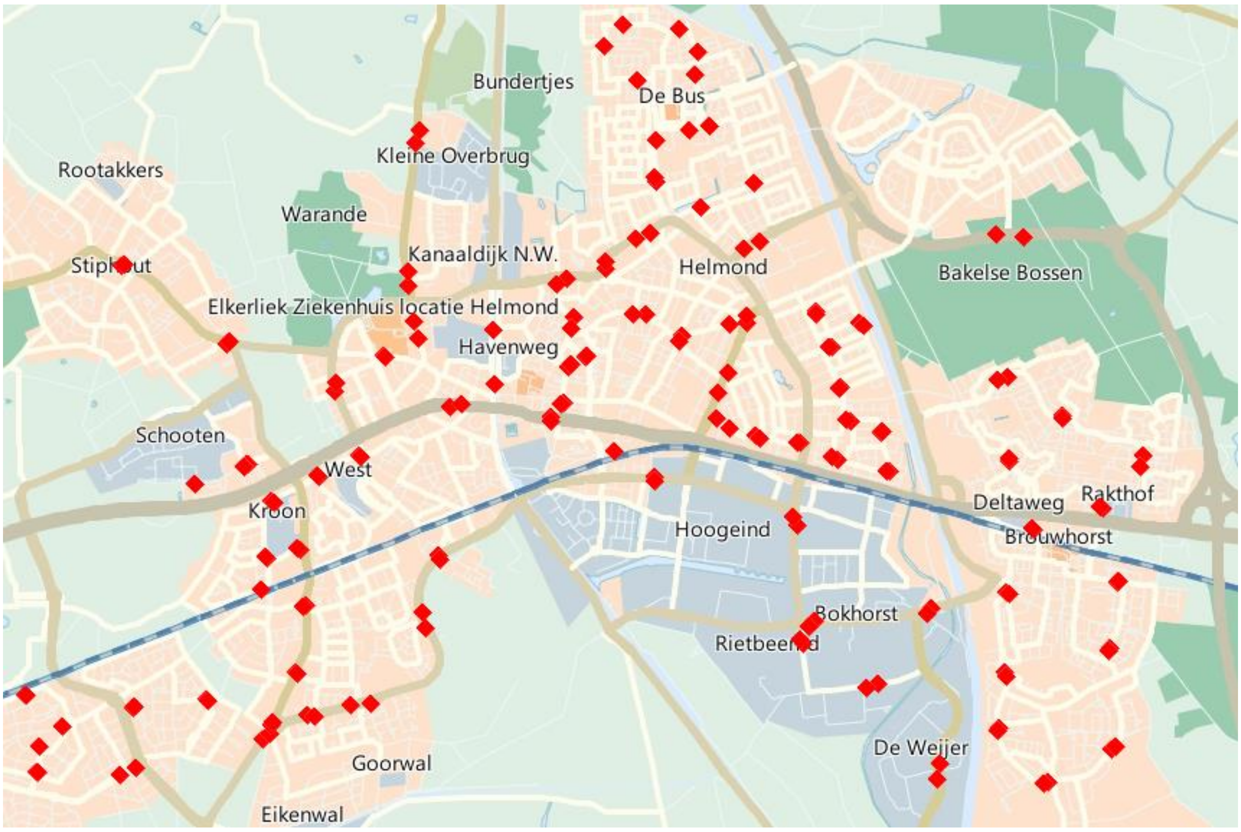


Figure 2.2: *Bus stops in Helmond*

From Figure 2.1, we see some areas are not covered with bus stops, especially the area above the 'Bakelse Bossen' and around 'Stiphout'. To increase the service level in these areas, transport on demand can be the solution.

2.3 CURRENT PASSENGER FLOWS

To get more insight into the current situation of the demand for public transport in Helmond, we analyse the OV-chip card data. The data is filtered on all the check-ins in Helmond, this also includes intercity bus lines. First we analyse the number of passengers per day, then the demand over the day, to finalize with the number of customers that use the bus lines.

2.3.1 NUMBER OF PASSENGERS PER DAY

To give more insight into the travel behaviour of the citizens of Helmond, we first analyse the number of travellers per day of the week, as shown in Figure 2.3.

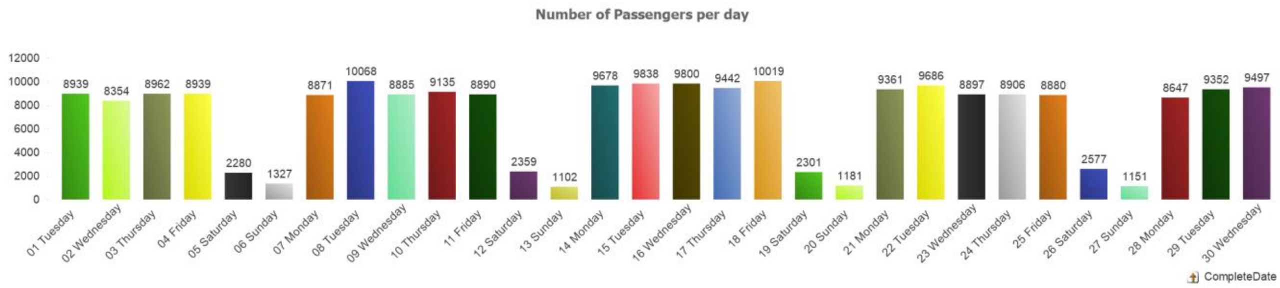


Figure 2.3: *Number of passengers per day*

The figure above clearly shows differences between the working days (Monday – Friday), Saturdays and Sundays. The demand during the workings days is significantly higher than during the weekend. In the first week of September, the demand is lower compared to follow up weeks, in the follow up weeks the demand remains relatively constant. A reason could be that the schools had a start up in the first week. In the weekend, a difference in demand on Saturday and Sunday is at least 41%, were the demand is the lowest at Sundays. In Section 2.3.2, we categorize the days as follows: the working days, Saturdays, and Sundays. We take a closer look at the differences in demand for these three categories.

2.3.2 NUMBER OF PASSENGER CHECK-INS PER HOUR

To analyse the travel behaviour of customers, the number of travellers is given per time unit. The data that is shown in Figure 2.4, is based on the data of a complete month (September 2015) that consists of 220,163 check-ins, including rides that go outside the municipality of Helmond.

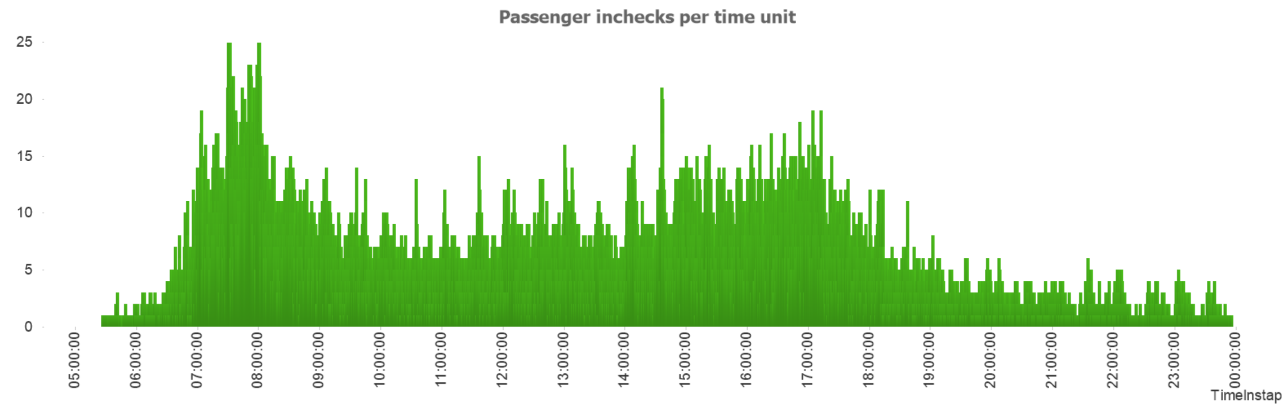


Figure 2.4: *Number of passengers traveling per time unit*

When we take a closer look at the picture, we clearly see that the customers are traveling in the morning between 6:00 and 9:00, a peak around 14:45, and an increase during from 15:00 to 18:00. After the morning rush the demand for bus transport is slowly increasing until 17:30, after 17:30 a clear drop in demand is noticed. The large peak around 14:45 is caused by students that finished their day at school. Figure 2.4 represents all the demand of September 2015 in Helmond. We analyse the data even further by separating the demand into the following categories: working days (Figure 2.5), Saturdays (Figure 2.6), and Sundays (Figure 2.7).

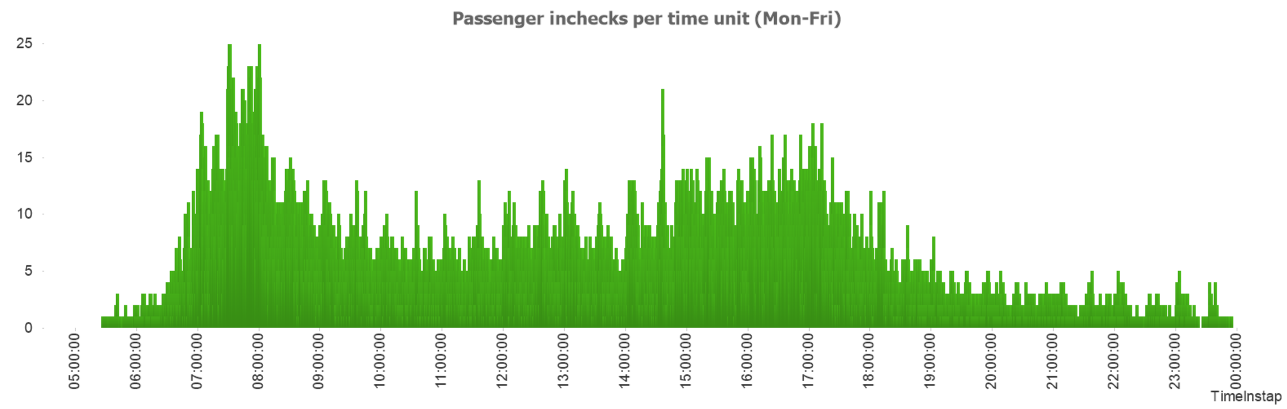


Figure 2.5: *Number of passengers traveling on Monday-Friday per time unit*

Figure 2.5 shows a similar pattern as Figure 2.4. The reason is that 92.2% of all the requests are done on working days, so the peaks can be explained in the same way.

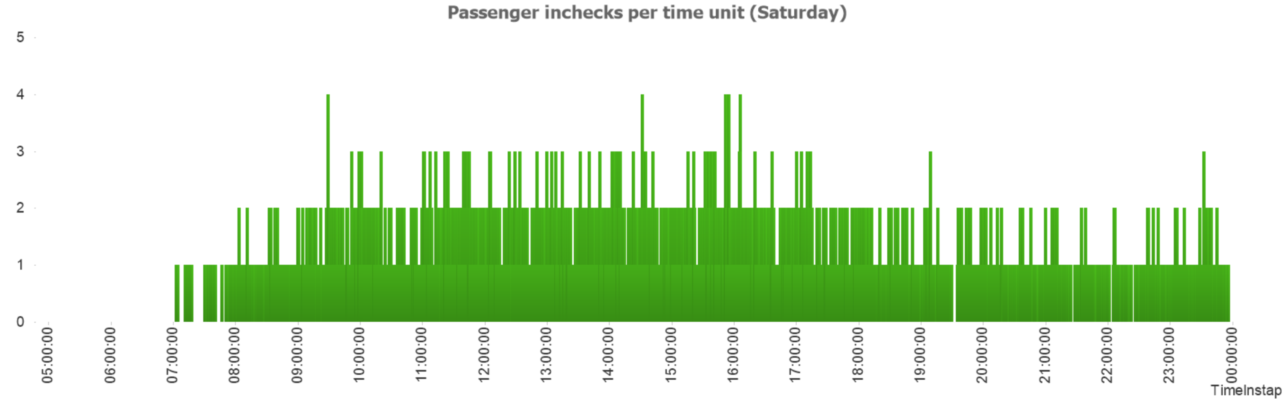


Figure 2.6: *Number of passengers traveling on Saturday per time unit*

Figure 2.6 (note that the scale is changed) is completely different and do shows a small increase in demand between 9:00 and 19:00. A small decrease of demand is shown before 9:00 and after 19:00. This figure is based on 9,517 check-ins in September 2015. So 4.3% of the rides are made on a Saturday.

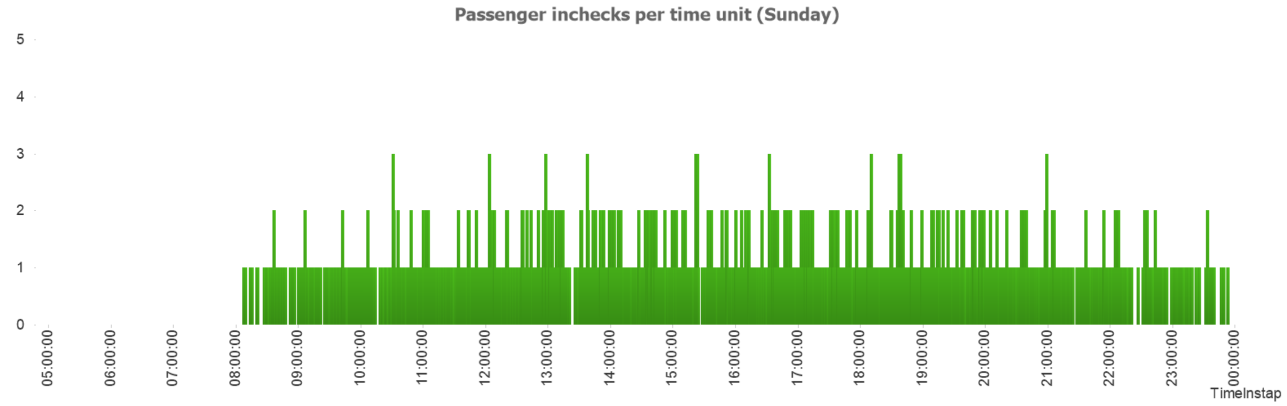


Figure 2.7: *Number of passengers traveling on Sunday per time unit*

Figure 2.7 shows an even further decrease in rides. No clear pattern can be noticed. The demand remains constant during the day. The figure is based on 4,761 check-ins, which equals 2.2% of the total rides done in September 2015.

2.4 THE CURRENT BUS LINES

In this section we describe the current use of buses in Helmond. We start by describing the current bus lines with their frequencies, followed by the operating hours of the bus lines, and finally we describe the type of buses used.

2.4.1 BUS LINES

In the current situation, the municipality of Helmond is served by seven bus lines. A map containing the bus routes is shown in Figure 2.8. The lines and the number of fares per day are shown in Table 2.2.

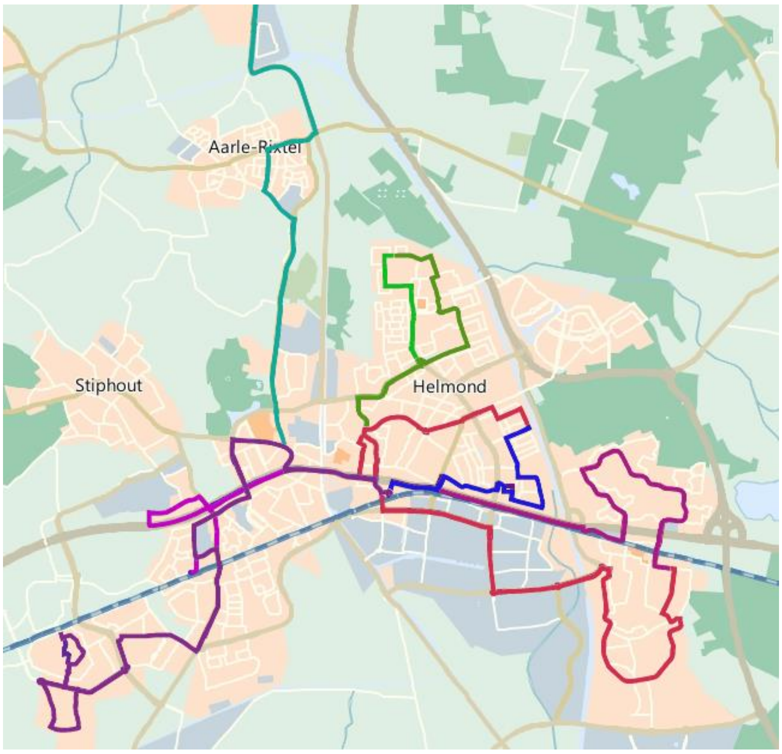


Figure 2.8: *Road map of Helmond showing the current bus lines*

Table 2.2: *Fares a day in the municipality of Helmond*

Bus lines	Route colour (Figure 2.8)	Mon/Fri	Sat	Sun
Line 25 Beek en Donk - Helmond busstation		13	11	4
Line 25 Helmond busstation - Beek en Donk		13	11	4
Line 50 Helmond busstation - Station 't Hout		15	0	0
Line 50 Station 't Hout - Helmond busstation		15	0	0
Line 51 Eeuwsels - Helmond busstation		26	19	0
Line 51 Helmond busstation - Eeuwsels		26	20	0
Line 52 Brouwhuis-Rijpelberg - Helmond busstation		13	9	0
Line 52 Helmond busstation - Brouwhuis-Rijpelberg		11	9	0
Line 53 Straakven - Helmond busstation		12	8	0
Line 53 Helmond busstation - Straakven		11	9	0
Line 54 Brouwhuis - Helmond busstation		14	10	0
Line 54 Helmond busstation - Brouwhuis		11	9	0
Line 54 Straakven - Helmond busstation		10	9	0
Line 54 Helmond busstation - Straakven		12	9	0
Line 552 Helmond busstation - Station Brandevoort		12	9	0
Line 552 Station Brandevoort - Helmond busstation		11	9	0

From Table 2.2 we see that bus line 51 is the most important line, since on weekdays and on Saturday it has the most fares back and forth. On Sundays we see that only one line is active, namely bus line 25, which is an intercity line. Although we excluded all intercity bus lines, we include line 25, because it has several stops in Helmond, and it is the only available bus on Sundays. Besides the most important bus line 51, the other lines are driven with almost equal frequency.

2.4.2 TIMETABLE HOURS

The operating time of a bus line is expressed in timetable hours. Table 2.3 shows the timetable hours of the bus lines and the total distance travelled during the timetable hours.

Table 2.3: *Timetable hours per bus line*

Line number	Timetable hours			Number of days in 2015			Total timetable hours a year	Total distance driven a year (KM)
	Mon/Fri	Sat	Sun	Mon/Fri	Sat	Sun		
25	9:37	8:09	4:32	255	52	58	3138:59	84,841
50	7:00	0:00	0:00	255	52	58	1785:00	37,426
51	11:58	8:56	0:00	255	52	58	3516:02	66,289
52	6:22	4:47	0:00	255	52	58	1872:14	46,175
53	4:13	3:07	0:00	255	52	58	1237:19	24,563
54	12:10	9:35	0:00	255	52	58	3600:50	73,845
552	10:20	8:06	0:00	255	52	58	3056:12	68,289
Total:	**61:40**	**42:40**	**4:32**				**18206:36**	**401,428**

The number of Sundays here is higher than 52 because national holidays also count as Sunday. As mentioned above bus line 51 is the most important line, but in the table above this line has not the most operating hours, this is due the length of the route.

2.4.3 TYPE OF BUSES

The bus lines are served by two type of buses, as shown in Table 2.4.

Table 2.4: *Type of buses*

Category Bus	Capacity	Used for Bus Lines	Total Number of buses
12 meter bus	45 seats	25, 51, 52, 53, and 54	20
small bus	8 seats	50 and 552	4

It is clear that in the current situation, almost all buses are in the category 12 meter. This bus type is responsible for 13,365 timetable hours, while the small buses are responsible for 4,841 timetable hours. This means that the average time for a 12 meter bus is 668 timetable hours, and 1,210 for a small bus. The small buses are used 44.7% more compared to a 12 meter bus.

The two categories of buses are having different costs. Since some figures are confidential, we use relative costs. We index the costs of the small bus by one. The costs of the 12 meter bus is expressed in the costs of a small bus. These costs are shown in Table 2.5.

Table 2.5: *Costs comparison between categories*

Category Bus	Wages	Purchase Costs	Depreciation a year	Cost per KM	Other
12 meter bus	1.58	2.6	3	2	2,5
Small bus	1	1	1	1	1

Table 2.5 shows several factors, the first is the wages. Due to the differences in the labour regulations, the driver of a 12 meter bus receives a higher salary. Second and third columns are the purchase costs, and the depreciation costs per year. A larger bus has higher purchase costs and has a depreciation that is three times as high compared to a small vehicle. The cost per kilometre represents the maintenance and fuel. The last column shows all the other costs, e.g., washing, parking, insurance, etc. Comparing the two buses, 2.27 small vehicles have the same costs as one 12 meter bus, if the current bus lines with the same frequency and distance are driven by the smaller vehicles. We conclude that, when more than 16 customers need transport, the 12 meter bus is the preferred solution, else it is cheaper to service the demand with two small vehicles.

2.5 UTILIZATION OF BUSES

We know which bus lines are operating in Helmond, this means that we can filter the OV-chip card data even further to only the trips that are done with bus lines in Helmond. All the intercity lines are left out, since the focus lies on travellers that travel within Helmond. Bus lines 50 and 552 are excluded because the small vehicles used for these lines do not have OV-chip card equipment on board, meaning that there is no available trip data. Figure 2.9 shows the number of passengers traveling by bus in Helmond in the month September 2015.

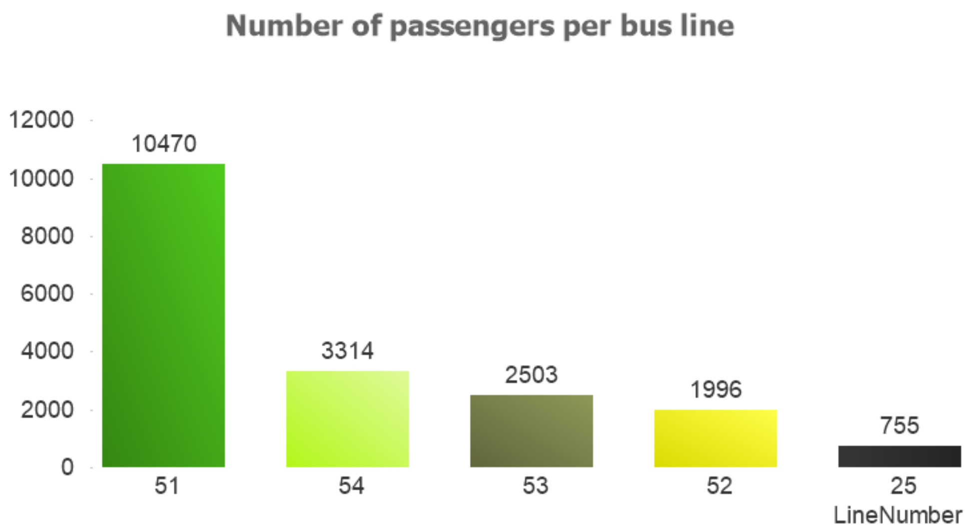


Figure 2.9: *Passengers per bus line*

Figure 2.9 shows that bus line 51 is the most important bus line, since it serves the most requests. Bus lines 25, and bus lines 51-54 are servicing 19,038 travellers together. Table 2.6 shows some performance figures per bus line, if no data is available the field is left blank.

Table 2.6: *Overview parameters per bus line*

Bus line	Total KM Sept.	Number of passengers	Passengers per KM	Revenue per Line	Revenue per KM	Season Tickets	Season Tickets/ Passengers	KM / stops
25	9,430	755	0.080	660.06	0.069989	248	32.8%	39.6 / 28
50	1,398	-	-	-	-	-	-	9.6 / 8
51	48,481	10,470	0.216	3761.68	0.077591	6,599	63.0%	8,7 / 24
52	17,215	1,996	0.116	1438.31	0.083549	825	41.3%	13.0 / 14
53	1,146	2,503	2.185	1321.06	1.153009	1,232	49.2%	8.0 / 22
54	20,585	3,314	0.161	2118.11	0.102895	1,464	44.2%	20.8 / 36
552	856	-	-	-	-	-		18.8 / 40

From Table 2.6 we see that, although bus line 51 is the most important bus line, the revenue per kilometre is not that high. However, the revenue is only based on customers that are not using a season ticket. The revenue generated by season tickets is not assignable to bus lines, because a season ticket gives a traveller the right to travel a certain number of zones. Bus line 51 has the highest percentage of travellers using a season ticket, resulting in a lower revenue per kilometre. When we take a look at the passengers per kilometre, we see that line 53 is the most effective, transporting 2,185 passengers per kilometre, and generating the most revenue per kilometre (excluding the seasonal tickets). Line 53 is effective, even with a relatively small number of travellers, because the complete bus route is only 8 km and contains 22 stops. Bus line 52 performs the worst on the performance indicator, revenue per kilometre.

The following subsections analyse the bus occupation per bus line even further by analysing the top 5 check-in and check-out stops. Since no OV-chip card data is provided from bus lines 50 and 552 no further analyses is done on these lines. Information about the utilization of the buses is described on the basis of average number of passengers in the bus (utilization) per time unit. Section 2.5.1 provides a complete analysis of bus line 25, the follow up section does not show all the graphs, only the noteworthy remarks are done. The graphs are shown in the Appendix B.

2.5.1 BUS LINE 25

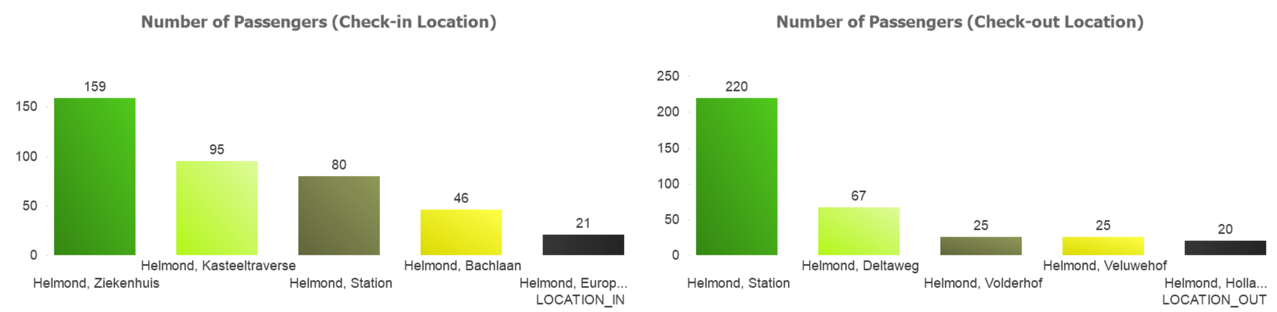


Figure 2.10: *Top 5 of Check-ins and Check-out locations in bus line 25*

Figure 2.10 shows a remarkable difference at Helmond Station between the check-in and check-out data, 220 of the 755 travellers are traveling towards the station, while only 80 travellers are traveling from Helmond

Station. Most travellers are checking in at Helmond Ziekenhuis, but only a small number are checking out at Helmond Ziekenhuis. A reason could be that a lot of patients use this bus line, and when they need treatment they travel with private transport, and when they are cured they use the bus.

The utilization of bus line 25 is shown in Figure 2.11.

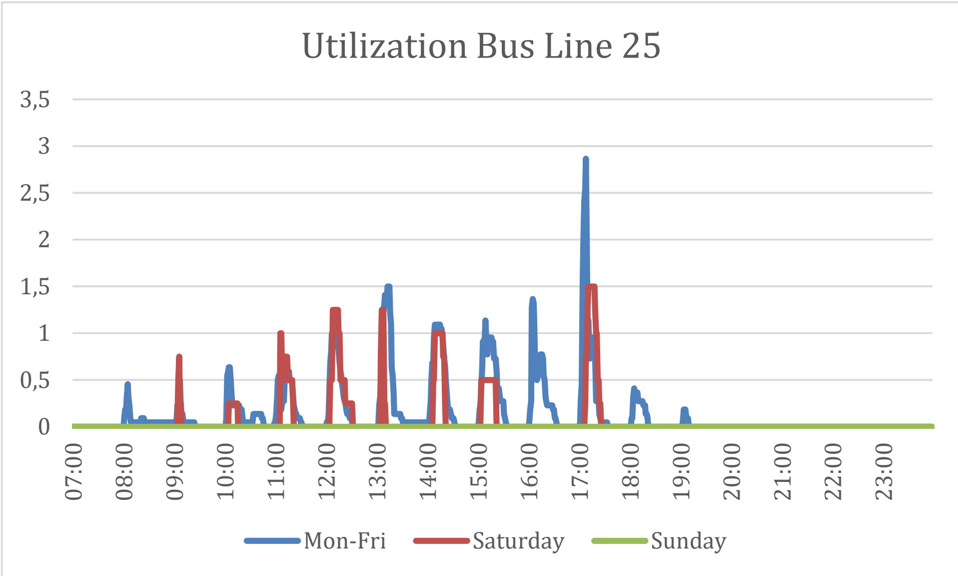


Figure 2.11: *Utilization of bus line 25*

Figure 2.11 shows that there is a small difference in utilization during the working days and Saturday. There is only a large peak shown around 17:00, the reason for this peak is the closing time of the stores, at this moment the shopping public uses the bus to go home. The utilization for all days is low. A small vehicle has enough capacity to serve all the customers. Since we take the average of the utilization of multiple days, it could happen that the capacity is violated, at certain moments (e.g., when a group of 30 persons are traveling only once a month at 13:00, while all the other days of the month no travellers are using the bus at 13:00. The average utilization at 13:00 is one, but the group cannot fit in the small bus).

2.5.2 BUS LINE 51

Bus line 51 has Helmond Station as most important location, handling a total 4,070 check-ins and 5,179 check-outs. This difference in travellers could be caused by the several train stations in Helmond, travels that had treatment at the hospital, or the use of intercity buses. Another important location is Helmond Noordende, with 1,460 check-ins and 1,266 check-outs. This stop lies in the city Centre of Helmond, where all stores are located. The shopping public explains the relatively high number of passengers using this stop.

Bus line 51 shows that the utilization during the working days is quite high. The utilization of bus line 51 shows similarities with Figure 2.4, namely the morning rush, an increase in demand around 14:45, and the evening rush. This bus line contains a stop nearby the school that explains the increase in demand at 14:45. We conclude that a 12 meter bus is the right equipment to service all requests during the working days. On

Saturday no clear pattern can be recognized, but the occupation of the bus is low, and most of the time a smaller bus can be used, but that could lead to rejecting passengers, which is not allowed.

2.5.3 BUS LINE 52

Bus line 52 shows again Helmond Station is the most important location, handling 799 check-ins and 758 of the 1,996 trips.. Another location noteworthy mentioning is Helmond, Deltaweg, since a significant number travellers are traveling towards and from this location. A reason could be that this bus stop is near the train station Helmond Brouwhuis.

Bus line 52 has clear peaks in the utilization, each peak equals a route that is driven by the bus. We see during working days, that the morning the frequency is higher. When comparing the working days with the Saturdays, the utilization remains almost the same. On the Saturdays around 13:00 an even higher utilization is measured. The peak in utilization can be explained by a large group of passengers traveling together around 13:00 using bus line 52. From the utilization data we conclude that the 12 meter bus is the right equipment for this bus line, because the utilization of this bus line is close to the maximum capacity of the small bus.

2.5.4 BUS LINE 53

Bus line 53 has Helmond Station as the most important stop. It handles 396 of the 2,503 check-ins and 412 of the 2,503 check-outs.

Bus line 53 shows an increase in demand on working days in the morning and evening. On the Saturdays, the demand starts high and is slowly decreasing during the day, a reason could be that travellers are leaving Helmond for the weekend in the morning. In this case a 12 meter bus could be the wrong equipment, since the maximum utilization lies around 5, while most of the times it is around 3. Although these numbers are utilization is an average of multiple days, a small bus might do the job.

2.5.5 BUS LINE 54

Bus line 54 shows again that Helmond Station is the most used bus stop, handling 1,496 check-ins, and 1,263 check-outs of 3,314 trips

Bus line 54 shows a unique pattern compared to the other bus lines. We cannot state why this increase in utilization occurs, a reason could be that travellers are traveling back to another train station and make use of bus line 54 to go back home. We see that the utilization is most of the time above 6 travellers. This holds for the working days as well as the Saturdays, only on Saturday mornings a small bus could be used, but the 12 meter bus is the right equipment to meet the demand for the rest of the day.

2.5.6 CONCLUSION

From the analysis of the bus lines, it becomes clear that Helmond station is the most important stop, handling a total of 6,841 check-ins, and 7,832 check-outs. From the occupation measurements almost at all times the 12 meter bus is the right equipment to serve the demand of travellers, except for bus line 53. But since these utilization numbers are averages, and rejecting travellers is not allowed, the 12 meter bus is a save solution. When analysing the bus lines, we conclude that most of the travellers are using bus line 51, nevertheless this bus line is not the most efficient per kilometre. Bus line 53 is the most efficient, but it handles less passengers. We already explained that bus line 51 handles the most season tickets, which is the reason why this bus line has a lower efficiency per kilometre.

2.6 CONCLUSION

From the analysis we see that 19,038 passengers (during a month) are traveling within Helmond. When we analyse the check-in data we clearly see that most transactions are done in the morning rush during the working days, after that period the demand remains steady, with a relatively small increase during the evening period. After the evening, demand declines further until the bus services stop operating. The demand during weekends is a lot smaller and steadier. No rush can be determined only a minor difference between the day shift and the night shift, where the night shows a reduced demand compared to the day.

We state that for some bus lines it is more effective to use smaller buses to service the requests. After 19:00 it is always better to use the small buses. Bus line 51 shows clear rush hours in the utilization of the bus. All the other bus lines do not suffer a significant increase in demand during the morning and/or evening rush, with exception of bus line 54 that only has an evening rush.

The performance of the bus lines varies per bus line, where bus line 53 is the most cost effective, which has 1.15 euro revenue per KM, and having 2,185 passengers per kilometre on board. The frequency of this line is twice per hour, with a total of 23 bus rides during weekdays and 17 bus rides on Saturday. The performance of bus line 51 is not as good as bus line 53, but it handles the most passengers, and it has the highest frequency of 52 busses during the weekdays and 39 busses on Saturdays, a reason for the poor performance is that travellers are only traveling a small part of the complete route.

3 LITERATURE REVIEW

"In theory, there is no difference between theory and practice. But in practice, there is."

- Yogi Berra

In this section of the research, a literature study is performed. We start in Section 3.1 by searching for various problems that are selected to our problem. In the literature our problem is known as the vehicle routing problem (VRP). The vehicle routing problem in general and several variants of the vehicle routing problem are described. Section 3.2 describes several performance indicators and the influence of the performance indicators on the overall customer satisfaction. In Section 3.3 some extensions on the VRP are shown, and the last section of this chapter describes several issues for implementing a demand responsive transport system.

3.1 VEHICLE ROUTING PROBLEMS

More than half a century ago, the VRP was introduced as the truck dispatching problem (Dantzig and Ramser 1959). The VRP is a generic name given to a class of problems involving optimizing vehicle routes. The goal of the VRP is to serve a number of customers with the least amount of vehicles given a set of restrictions, while minimizing the total route costs. Many companies face this problem on a daily basis, think for instance about the supply of stores, or the mail delivery.

The VRP is a combinatorial optimization problem. A combinatorial optimization problem deals with problems of maximizing or minimizing a function with a finite set of solutions. The function of variables subject to inequality and equality constraints and integrally restrictions on some or all of the variables (Wolsey and Nemhauser 2014).

A common formulation for the classical VRP is as follows (Dantzig and Ramser 1959): Let $G = (\mathcal{V}, \mathcal{A})$ be a directed graph where $\mathcal{V} = \{0, \dots, n\}$ is the vertex set and $\mathcal{A} = \{(i,j): i,j \in \mathcal{V}, i \neq j\}$ is the arc set. Vertex 0 represents the depot whereas the remaining vertices correspond to customers. A fleet of m identical vehicles with capacity Q is based at the depot. The fleet size is either given a priori or is a decision variable. Each customer i has a nonnegative demand q_i. A cost matrix c_{ij} is defined on $\mathcal{A}$. The problem consists of designing m vehicle routes such that each route starts and ends at the depot, each customer is visited exactly once by a single vehicle, and the total demand of each route does not exceed Q (Christofides 1976). A VRP is a generalization of the Traveling Salesman Problem (TSP). The key difference is that in the TSP only one 'vehicle' (the salesman) visits a given set of cities with no capacity constraints, while in the VRP a given fleet of m vehicles with a capacity Q that cannot be violated, must visit a given set of customers. In both problems the goal is to find the shortest route, or to minimize the total costs, or to minimize the number of vehicles.

In practice several problems arise, for example time windows, meaning the vehicle must visit the location within the time window. Since there are a lot of variants on the VRP, we address some of these variants in

Section 3.1.1, in Section 3.1.2 we discuss different solution methods for VRPs, the insertion of customers to known routes are addressed in Section 3.1.3. We end with a conclusion in Section 3.1.4.

3.1.1 VARIANTS OF THE VRP

In case of the classical VRP, some restrictions are not taken into account, this can lead to a mismatch with practice. So over the years new cases of the VRP are proposed. The next sections describe some variations of the classical VRP model.

Vehicle routing problem with time windows

A vehicle routing and scheduling problem with time windows (VRSPTW) or the vehicle routing problem with time windows (VRPTW), deals with allowable delivery times or time windows. The VRSPTW takes the allocations of customers in a present time window into account. In the VRPTW the customers are already allocated to a time window. These variations state that location i should be visited within a time interval $[E_i, L_i]$. A vehicle can arrive at location i before time E_i, this means that when vehicle (bus) b arrives too early, it should wait until the time is greater than E_i. If the vehicle arrives too late, i.e., the arrival time is greater than L_i, the solution is infeasible. The VRPTW can be solved with two objective functions: 1st minimize the fleet size m and the total costs, and 2nd minimize the total travel distance or duration of the routes (Solomon 1987, Bräysy and Gendreau 2005).

Multi-depot vehicle routing problem

The multi-depot vehicle routing problem (MDVRP) is a variation in which there are multiple depot locations. So vehicles can start from different depot locations. The MDVRP has a fleet of vehicles stationed at z depots to deliver specified quantities of a single type of product to n locations in such a manner that the total distance traveled by the vehicles is minimized (Gillett and Johnson 1976). Since the standard formulation of the MDVRP assumes an unlimited number of vehicles at a depot, a variant on the MDVRP is developed that is called the multi depot vehicle routing problem with fixed distribution of vehicles (MDVRPFD). This variant assigns a fixed number of vehicles to each depot in order to make the algorithm more realistic (Lim and Wang 2005). Another formulation of the MDVRP is with time windows (TW) formulated as a multi-depot heterogeneous fleet vehicle routing problem with TW by Dondo and Cerdá (2007).

Vehicle routing problem with pickup and delivery

A vehicle routing problem with pickup and delivery (VRPPD) is an extension on the classic VRP problem. In the classic VRP, the delivery or the pickup is considered. While the VRPPD handles pickup as well as delivery (e.g., delivering new goods and pickup the return goods). The goal of the VRPPD is to minimize the total distance travelled subject to the maximum capacity of the vehicles. In the VRPPD there are several categories of picking-up goods and delivering (Nagy and Salhi 2005):

- Delivery-first, pickup-second, with the assumption that customers can be divided in two categories: customers receiving goods and customers sending goods. Furthermore, the vehicles can only pickup goods when the truck is empty. The reason behind this strategy can be that the rearrangement of the vehicle might be hard and time consuming (Goetschalckx and Jacobs-Blecha 1989).

- Mixed pickups and deliveries, in this category pickups and deliveries can occur in any sequence while not violating the restrictions (e.g., vehicle capacity), but the customers can only send or receive goods. This is also known as the vehicle routing problem with backhauling (VRPB) (Salhi and Nagy 1999, Toth and Vigo 1999).
- Simultaneous pickups and deliveries, in this category both the pickup and delivery could be made concurrently at the same location. In practice the simultaneous pickup and deliveries can be compared with the public transport (PT), where people enter and leave the transport at a specified location (Min 1989).

Dial-a-Ride problem

The Dial-a-Ride problem (DARP) consists of designing vehicle routes and schedules for n users who specify pickup and drop-off locations in the request. In the DARP there are two variants, a static and a dynamic one. In the static case, requests are often known days beforehand, so a complete route can be created. In the dynamic case, the request are only known a short period before the actual pickup time. The goal for both DARP formulations is to minimize the operating costs while accommodating as many requests as possible. The key difference of the DARP to other variants of the VRP, is the human aspect. This results in not only finding the cheapest way to transport people, but finding a balance between user inconvenience and minimizing operating costs (Cordeau and Laporte 2003).

Demand responsive transport

Demand responsive transport (DRT), also known as demand responsive service (DRS) or flexible transport service (FTS), is a PT service that combines the benefits from bus transport with taxi transport (Brake et al. 2007). This combination leads to a relatively cheap, yet increasing the flexibility, particularly in low demand regions or the off rush hours. The customers are able to order their demanded ride short before their preferred departure time. The routes are created or adapted in real-time, when a customer request come in. A small or medium sized vehicle drives the created route to pickup and deliver the customers. The key point of this type of PT is that the vehicle routes are updated daily or in real time by using the requests of the customers. A similarity with the DARP is that DRT also uses requests that include pickup and drop-off locations. The DRT has a various variations as described below (Mulley and Nelson 2009, Wang et al. 2015):

- Many-to-one, is a model in which there are many pickup locations in a predetermined zone. In each zone only one vehicle operates, that vehicle picks up the requests and delivers them to a central location (Daganzo et al. 1977).
- One-to-many, is the reverse system of many-to-one. There is one central pickup location that services the drop-off locations within the predetermined area (Häme 2013).

- One-to-many-to-one, means that all drop-off demands start at the depot and all pickup demands should be transported to the depot. This is a combination of the many-to-one and the one-to-many (Gribkovskaia and Laporte 2008).
- Many-to-many, defines a certain service area in which one or more vehicles take customers from and to their destinations in the predetermined service area. This type differs from one-to-many-to-one, since a request of a customer is executed without a transfer. The many-to-many category has two main sub-categories (Daganzo 1978):
    - A taxi system, where one vehicle picks-up the customer and proceeds non-stop to the customer's preferred destination, also known as door-to-door transport. So at all times each vehicle services at most one request at a time (Daganzo 1978).
    - A Dial-a-Bus system, in comparison with the taxi system, it is allowed to deviate from the shortest route to pickup other requests. This enables an increase in the vehicle utilization (Daganzo 1978).

Mobility Allowance Shuttle Transit

Mobility Allowance Shuttle Transit (MAST) is a hybrid transportation system, where vehicles may deviate from a fixed path, with a predetermined range (e.g., a vehicle can service a customer, with a maximum deviation of one kilometre from the main route). The fixed path is based on a few mandatory checkpoints that need to be served. The fixed service points are mostly located at major transfer points or high density demand zones, these points are often located far from each other, to get more slack time for servicing customers located off the route. The idea behind the MAST system is to combine the flexibility of the DRT system and the fixed-route systems. This combination of systems can lead to more flexibility in a cost effective way (Quadrifoglio et al. 2006).

3.1.2 SOLVING VEHICLE ROUTING PROBLEMS

A VRP problem is a hard combinatorial optimization problem, which is non-deterministic polynomial-time complete (NP-complete) (Nemhauser and Trotter Jr 1975). This means that solving the mathematical problem is hard. Exact algorithms therefore have a slow convergence rate, since a nearly complete enumeration is necessary. Solving realistic problem sizes with a constant success rate within an acceptable time is impossible (Cordeau et al. 2002). The best known (exact) algorithm so far can handle about 100 customers (Fukasawa et al. 2006, Baldacci et al. 2008). In practice 100 customers is not enough, real instances often exceed this size and the solutions must be found quickly (Laporte 2009). The number of computations grows exponentially in the size of the problem (Goetschalckx and Jacobs-Blecha 1989). Due to this increase in computation time, many researchers are focused on developing heuristics. An extra advantage of heuristics is that they are easier to adapt (e.g., adding restrictions).

We structure and use the classification of solutions methods according to Laporte (2009). The following sections describe various ways of solving the VRP and variants of the VRP. We start with the conventional methods, divided in exact methods and classical heuristics. "Classical" refers to heuristics that do not contain mechanisms allowing to deteriorate the objective function from one iteration to the next. A meta-heuristic does allow this, and is treated at the end of the next section.

Exact Methods

A procedure that solves a VRP to optimality, in a limited time period, with a limited problem size, is called exact (Goetschalckx and Jacobs-Blecha 1989). The main disadvantage of an exact approach is the limitation on the problem size, since the problem size grows exponential. In the literature there are several ways to solve the VRP. Some well-known methods are treated below, respectively branch-and-bound algorithms, branch-and-cut algorithms, dynamic programming, commodity flow formulations, and set partitioning.

Branch-and-Bound algorithms One of the first exact solution methods for the VRP in the literature is the branch-and-bound (BB) algorithm. The BB algorithm gives an exact solution by searching in the complete solution space. The idea of the algorithm is to partition the solution space in disjunctive partitions, and then again partition the disjunctive partitions until the best feasible solution is found. The partitions can be visualized in a search tree, see Figure 3.1.

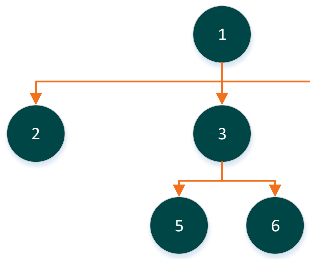


Figure 3.1: *Example of a search tree*

The branches in a branch and bound represent a possible solution. Each branch contains an upper and lower bound. These bounds can be used to discard other partitions that cannot produce a better solution. Christofides and Eilon (1969) developed one of the first algorithms that uses a branch-and-bound algorithm. Their solution method branches on arcs. The arcs can either be included or excluded in the solution. Later, Christofides (1976) developed a new way of branching: instead of branching on the arcs, he branched on the routes. That resulted in a wider but less deep search tree. Neither of these algorithms is capable of handling large instances. To handle some larger instances with the use of BB, new methods were developed that were able to derive sharp lower bounds. Christofides et al. (1981) were the first that successfully solved instances with $10 \leq n \leq 25$ using their lower bounds. Later, Fisher (1994) found a new way of determining a lower bound that is able to solve several real problem instances with $25 \leq n \leq 71$.

Branch-and-cut algorithms Branch-and-cut algorithms solve the VRP by executing two steps. The first step is to solve the linear relaxation, a relaxed form of the integer linear program (ILP). If the solution of the linear program (LP) is feasible the optimal solution is found, and no further steps are needed. If the solution contains one or more non-integer values that are supposed to be integer, a cutting plane scheme is used. A cutting plane helps to tighten the linear programming relaxations. The cutting plane tightens the inequalities until a feasible solution is found (Belenguer et al. 2011, Coelho and Laporte 2013).

Dynamic programming Dynamic programming (DP) is another exact optimization approach that is capable of dealing with complex problems. DP solves the problem by dividing the complete problem into a number of sub-problems. Then all the sub-problems are solved until there are no more options left to create sub-problems, this is the last stage of the DP in which the optimal solution is found. Eilon et al. (1971) provide a DP formulation for a VRP. Their formulation is as follows. Let $c(S)$ be the optimal cost of a single vehicle route through the vertices of $S \subseteq \mathcal{V} \backslash \{0\}$. The objective is to minimize (3.1) over all feasible partitions $\{S_1, \dots, S_m\}$ of $\mathcal{V} \backslash \{0]$. Let $f_v(\mathcal{U})$ be the least cost achievable using v vehicles and delivering to $\mathcal{U} \subseteq \mathcal{V} \backslash \{0\}$. Where $\mathcal{U}$ is a subset of $\mathcal{V} \backslash \{0\}$. The mathematical formulations is the following:

$$\min_{S_r \in S} \sum_{r=1}^{m} c(S_r) \tag{3.1}$$

$$f_v(\mathcal{U}) = \begin{cases} c(\mathcal{U}), k = 1 \\ \min\limits_{\mathcal{U}^* \subseteq \mathcal{U} \subseteq \mathcal{V} \backslash \{0\}} \{f_{v-1}(\mathcal{U} \backslash \mathcal{U}^*) + c(\mathcal{U}^*)\}, k > 1 \end{cases} \tag{3.2}$$

In all the stages, the partial solutions are extended with an extra node. The total number of stages is equal to the number of nodes that are formulated in the DP. The stages can have a various number of states, which are partial solutions that contribute to solve the main problem. The solution cost is $f_m(\mathcal{V} \backslash \{0\})$ and the optimal partition corresponds to the optimized subsets in the recurrent formula (3.2). Christofides et al. (1981) created a DP that could handle instances with $10 \leq n \leq 25$. In the last few years the number of article using DP is significantly reduced, Laporte (2009) and Kok et al. (2010) are one of the latest authors using this technique.

Commodity flow formulations A recent formulation that solves the VRP with the use of commodity flow formulation (CFF) is given by Baldacci et al. (2004). Their formulation is based on Finke et al. (1984) and is suitable for capacitated vehicle routing problem (CVRP): variable x_{ij} defines the load carried on arc (i, j), an extended graph $\overline{G} = \left(\overline{\mathcal{V}}, \overline{\mathcal{E}}\right)$, where $\mathcal{E}$ represents edges (undirected, and with symmetric distances), obtained from G by adding node $n + 1$, which is a copy of depot node 0. Given a vertex set $\overline{\mathcal{V}} = \mathcal{V} \cup \{n + 1\}$, and edges $\overline{\mathcal{E}} = \mathcal{E} \cup \{\{i, n + 1\}, i \in \mathcal{V}\}$. A vehicle route is represented by a path from node 0 to node $n + 1$ in $\overline{G}$. Let y_{ij} be a binary variable that has value 1 if edge $\{i, j\} \in \overline{\mathcal{E}}$ is in the solution and 0 otherwise. This formulation uses two flow variables x_{ij} and x_{ji} to represent an edge $\{i, j\} \in \overline{\mathcal{E}}$ of a feasible solution for the CVRP. If the vehicle travels from i to j, then the flow is represented by x_{ij}, and the available empty space is represented by x_{ji}.

It is reported that randomly generated instances with $30 \leq n \leq 60$ with $m = 3$ or $m = 5$ are solved. For larger instances the method becomes more inconsistently but it was able to solve up some instances with $n = 100$ and $m = 8$ (Baldacci et al. 2004).

Set partitioning Balinski and Quandt (1964) where the first to use a set partition (SP) formulation for the VRP with capacity restrictions, also known as the CVRP with an inhomogeneous vehicle fleet. The definition of SP is that all the feasibility is implicitly considered by the definition of the route set $\mathcal{R}$. A drawback of SP is that it cannot solve nontrivial CVRP instances, due to the large number of possible routes. Despite of the drawback, SP is part of two of the most successful VRP algorithms from Fukasawa et al. (2006) and Baldacci et al. (2008)

Classic Heuristics

Classic heuristics can be subdivided into two main categories, construction and improvement heuristics. The main difference between these categories is that the construction heuristics, a feasible solution is built by adding routes from "scratch", whereas the improvement heuristic, also known as local-search, starts with any feasible solution, which the heuristic tries to improve. The improvement heuristic, consists of two subcategories, intra- and inter-route moves. Intra-route moves improves each route separately, while with inter-routes moves of customers, the moves are analysed between different routes. It is possible that a heuristic uses both methods. We briefly discuss the heuristics mentioned by Laporte (2009): cluster-first route-second, the savings algorithm, the set partitioning heuristic (SPH), K-opt, and b-cyclic k-transfer scheme.

Cluster-first, route-second heuristics A cluster-first, route-second (CFRS) heuristic consist of two phases, namely clustering and routing. Fisher and Jaikumar (1981) formulated one of the famous CFRS heuristics, they first locate m seeds and construct a cluster for each seed. The assignment of each customers to a cluster is solved by the generalized assignment problem (GAP). Some procedures for selecting the seeds are described by Bramel and Simchi-Levi (1995), and Baker and Sheasby (1999). The second phase in the CFRS heuristic is solving the TSP for each cluster. The savings algorithm and the set partitioning are examples of a CFRS, both are treated in the next two paragraphs.

The savings algorithm, probably the best-known heuristic for the VRP, is described by Clarke and Wright (1964). This heuristic starts with an initial (possibly infeasible) solution made up of n back-and-forth routes $(0, i, 0)(i = 1,2, \dots, n)$ where 0 represents the depot. The heuristic then evaluates all possible options to remove arcs $(i, 0)$ and $(0, j)$ and add arc (i, j) followed by a calculation of the savings $s_{ij} = c_{i0} + c_{0j} - c_{ij}$, these savings are calculated for all possibilities and the insertion that yields the largest savings is implemented. The heuristic iterates until there are no more possibilities for insertions. The heuristic is easy and it can handle extra restrictions with ease, which is probably the reason why this heuristic is still popular. Golden et al. (1977) proposed an improvement by multiplying c_{ij} by a positive weight λ, the route shape parameter that helps finding the shortest route. Another improvement is proposed by Altinel and Öncan (2005), they added the customers' demands impact while calculating the savings. They formulated the savings as follows:

$$s_{ij} = c_{i0} + c_{oj} - \lambda c_{ij} + \mu |c_{0i} - c_{j0}| + v \frac{d_i + d_j}{\bar{d}} \tag{3.3}$$

The savings parameters are explained as follows: d_i is the demand of customer i, d_j is the demand of customer j, $\overline{d}$ is the average demand of all customers, μ exploits the asymmetry information between customers i and j, and v is a non-negative parameter. The last part of (3.3) gives a placement priority to customers with larger demands. This improvement makes the heuristic faster and more accurate. Nevertheless this heuristic for solving the VRP, is still highly time consuming and is outperformed in time by all other heuristics described in this section.

Set Partition Heuristic (SPH), also known as "Petal Heuristic", is another well-known set of construction heuristics. An SPH normally assumes that the vertices are distributed on a plane. The most elementary version of a Petal Heuristic is the sweep algorithm of Gillett and Miller (1974). The sweep algorithm starts with a half-line rooted at the depot, then it rotates counter clockwise or clockwise, the customers are incorporated in increasing order of the angle. The cluster stops when the load/capacity is exceeded, in which the route returns to the depot. This algorithm does not allow intersecting routes (See Figure 3.2 for a simplified case). Other SPH do allow the intersecting of routes Ryan et al. (1993).

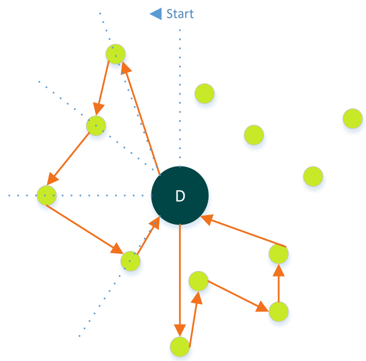


Figure 3.2: *Example of the sweep algorithm.*
Start at 12 o'clock with a capacity of four customers.

K-opt The k-opt heuristic is an intra-route improvement heuristic. Croes (1958) was the first describing a type of k-opt, the 2-opt. The 2-opt method generates a 2-optimal route, which is a route that cannot be improved by exchanging any two arcs. To accomplish a 2-opt, all the arcs that cross each other must be removed, since crossing of arcs is never optimal in the classical VRP with no capacity restrictions and a symmetric cost matrix. The 2-opt method is generalized to k-opt by Lin and Kernighan (1973). The k-opt move, changes a tour by replacing k edges from the tour by k other edges of the same tour, in such a way that a shorter tour is achieved.

b-cyclic, k-transfer scheme Thompson and Psaraftis (1993) formulated an inter-route improvement heuristic, b-cyclic, k-transfer scheme, wherein b routes are considered for relocation and k vertices from each route, are moved to the next route of in b. Computational results shows that combinations of variables $b = 2$ or b has a variable value, and $k = 1$ or 2 produce good results.

Metaheuristics

Over the last years various metaheuristics have been designed. All the current formulated metaheuristics allow the exploration of the solution space beyond the local minima. The classic heuristics can give a local minimum as result. Metaheuristics are formulated in such a way that they allow infeasible of inferior solutions to escape from local minima. Roughly all metaheuristics can be classified into three categories: local search, population search, and learning mechanisms. First we start with the local search metaheuristic, then population's search, to end with learning mechanisms.

Local search Local search (LS) methods start with an initial solution that might be infeasible. The methods explore the neighbourhood of the current solution and moves in each iteration to a solution in that neighbourhood. A various number of methods are defined in this category to explore the neighbourhood. According to Laporte (2009) the following LS methods are used often, tabu search (Glover 1986), simulated annealing (Kirkpatrick and Vecchi 1983, Černý 1985), and variable neighbourhood search (Mladenović and Hansen 1997). These LS methods are respectively described below.

Tabu search methods are using a memory function that keeps track of the properties of the previously visited solutions, to make sure that some solutions are not considered anymore for a certain number of iterations, the so called tabu-list. In each iteration the best solution in the neighborhood is selected and written to the tabu list. The tabu list is necessary to prevent the search from cycling. To apply the tabu method to the VRP, the metaheuristic TABUROUTE is formulated by Gendreau et al. (1994). The TABUROUTE works as follows: a solution is a set $\mathcal{S}$ of m routes $R_1, \dots, R_m$ where $m \in [1, M]$, $v_i \in R_r$ if v_i is a component of R_r, $(v_i, v_j) \in R_r$ if v_i and v_j are two consecutive vertices of R_r, and each vertex $v_i (i \geq 1)$ belongs to exactly one route. These routes may be (in)feasible with respect to the capacity and length constraints.

$$\mathrm{F}_1(S) = \sum_r \sum_{(v_i, v_j) \in R_r} c_{ij} \tag{3.4}$$

$$\mathrm{F}_2(S) = F_1(S) + \alpha \sum_r [(\sum_{v_i \in R_r} q_i) - Q]^+ + \beta \sum_r [(\sum_{(v_i, v_j) \in R_r} c_{ij} + \sum_{v_i \in R_r} \delta_i) - L] \tag{3.5}$$

Where $[x]^+ = \max(0, x)$ and α, β are two positive parameters. If the solution is feasible, $F_1(S)$ and $F_2(S)$ coincide. $F_2(S)$ incorporates two penalty terms for capacity and route duration. The TABUROUTE procedure is as follows: a neighbour solutions consists of removing a route R_j with $I \leq j \leq m$ of solutions set $\mathcal{S}$, the current route, and the reinsertion of R_m into another solution set $\mathcal{S}'$. Then the route R_m is declared tabu. Since intermediate infeasible solutions are allowed it is possible to escape from local minima.

Simulated annealing (SA) is a generic method to find an approximation for the global optimum. This method was independently presented by Kirkpatrick and Vecchi (1983) and Černý (1985). They were inspired by the statistical thermodynamics in a process called annealing in metallurgy, a technique that heats and cools steel in a controlled way to increase the size of its crystals and reduce their defects. SA works as follows, first select a random solution s from the neighbourhood $N(s_t)$ of the current solution s_t at iteration t. At each iteration an acceptance probability p_t decides whether to move to the neighbourhood solution of stay at the current solution. The p_t is a decreasing function of t and of $f(s) - f(S_t)$, the acceptance probability allows the solution to move to a new neighbourhood solution even if the solution is worse.

Variable neighbourhood search (VNS) is another branch of the local search metaheuristics. The VNS works with an ordered list of neighbourhoods, which are usually nested. The VNS starts with a neighbourhood and searches for local optima; if a local optimum is found, the heuristic switches to a new neighbourhood in the list. Hansen and Mladenović (2001) formulated the basic steps of a VNS. First a finite set of neighbourhood structures $\mathcal{N}_k$ must be formulated. Then an initial solution x is found in $N_k(x)$, the set of solutions in the k^{th} neighbourhood of x and choose a stopping condition. Then the VNS repeats the following steps until the stopping condition is met: **(1)** Set $k \leftarrow 1$. **(2)** Until $k = k_{\max}$ repeat the following steps: **(a)** *shaking*, generate a point x' at random from the k^{th} neighbourhood of $x(x' \in N_k(x))$. **(b)** *local search*, apply some local search method with x' as initial solution; denote with x'' the so obtained local optimum. **(c)** *move or not*, if this local optimum is better than the incumbent, move there $(x \leftarrow x'')$, and continue the search with $N_1(k \leftarrow 1)$, otherwise set $k \leftarrow k + 1$. The basics of the VNS are used in a various number of articles, Bent and Van Hentenryck (2004) expressed the two-stage hybrid algorithm, and Ergun et al. (2006) stated a very-large scale neighbourhood search algorithm, and Kytöjoki et al. (2007) formulated the two-phase VNS. All these above named methods are able to handle large VRPs with the use of VNS.

Population search Population search methods stimulate the process of natural selection by mutating the properties of parent solutions, which are randomly picked from the population of solutions. The parent solutions are recombined to create offspring, which replaces the worst elements in the solution. The mutation of the population eventually evolves towards a new generation of hopefully better solutions.

Genetic algorithms (GA) (Holland 1975), are good examples that use the populations search strategy. Baker and Ayechew (2003) applied the GA to the VRP. Figure 3.3 shows an example of feasible parent solutions that create the offspring solutions, by recombining. The recombination of the two parents mostly happens in the VRP with the use of LS (Mester and Bräysy 2007, Vidal et al. 2014). If one of the solutions violates a restriction it is denoted as unfit, and it is not used.

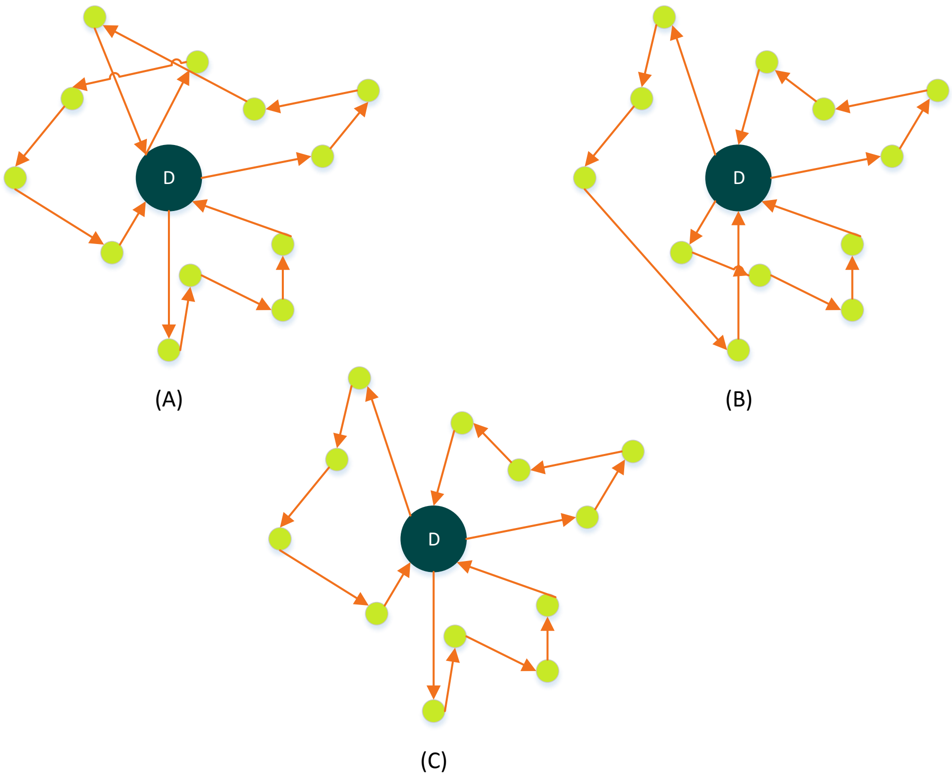


Figure 3.3: *Example of GA, (A) parent 1, (B) parent 2, (C) offspring solution*

Yet another way of recombining the GA and the LS is to start with LS and list all the feasible solutions found during the iteration. When LS is done, a list of solutions is saved in memory. Then parents are picked and recombined to hopefully create a better offspring solution. After each iteration the list is updated to reduce the number of solutions in the list. This way of combining LS with the GA is introduced by (Rochat and Taillard 1995), they reported great results with this way of combining these methods.

Learning mechanisms Learning mechanisms use data or experience from the past. With this data they can change the weights (e.g., increase or decrease the costs of an arc), in such a way that a good solution can be found. In this paragraph we discuss the ant colony optimization (ACO) as an example of a learning mechanism.

Biomimicry is a science that studies nature models, and uses these models to solve human problems. In the VRP a new approach is inspired on the behaviour of ants, the ACO. In nature, ants start by walking randomly, until they find food. Then they bring the food back to the colony, while laying down pheromone trails. When other ants find a pheromone trail, they likely follow the trail instead of wandering randomly. If other ants also find the food, they are likely to reinforce the pheromone trail, to make other ants more aware of this path. Heuristics based on ACO, assign scores to edges, if one edge appears often in multiple solutions, that edge is more likely to be included in other solutions. The heuristic is reported as successful by Bell and McMullen (2004).

3.1.3 INSERTION METHOD

The scheduling and routing of vehicles is a main-topic in the related literature. Several authors examined the handling of a request that should be inserted in a current route of a vehicle, the so called insertion procedure. Jaw et al. (1986) described, as one of the first, an insertion method. They modelled the insertion procedure as follows. Assume n customers and $\mathcal{B}$ vehicles are given: sort the available requests on the earliest pickup times. Then find all the feasible ways in which a customer can be inserted into the work-schedule of vehicle $b \in \mathcal{B}$. If it is infeasible to insert a customer, then examine the next vehicle $b + 1$. If the customer cannot be fitted in the current work-schedules, the algorithm creates a new route that results in minimum additional costs. The strength of this insertion method are the schedule-blocks, a schedule block is a continuous period of active vehicle time. Each schedule block has a sequence of pickup and drop-off locations, indicating the planned time and slack time per location within the block. To find feasible insertions, we need to identify feasible schedule sequences of pickup and drop-off locations, then for each feasible schedule sequence an upper and lower bound for the actual pick-up and drop-off times is needed. If the customer cannot be inserted in the current schedule block, due to for example violating a TW of another customer, a new schedule block is created. This method is a quick test to see if an insertion might be feasible. The number of possibilities are $(a + 2)(a + 1)/2$, with a the number of stops already in the schedule block. In a schedule block the requested pickup location must precede the requested drop-off location. The classic insertion method is a construction method that not result in an optimal solution. However the classic insertion method seems to produce a quick possible solution for the TW.

Häme (2011) formulated an advanced insertion method, in which all infeasible insertions found by the classical insertion method are not considered, and the feasible insertions are constructed one-by-one. This method is able to solve the problem to near optimality. They state that the insertion of a new customer should be tried in all the known routes with respect to existing customers. The second step is determining the set of feasible routes with respect to the new and existing customers. The biggest disadvantage of this insertion method is the computation time, especially if there are a high number of feasible routes. E.g., if no restrictions are used and the pickup of customer i must happen before the drop-off (the pickup is represented as i^+ and the drop-off i^-). If one customer needs service the route is $1^+, 1^-$ as the only feasible sequence. In case of two customers, there are six options:

$$A: 1^+, 1^-, 2^+, 2^- \quad B: 1^+, 2^+, 1^-, 2^- \quad C: 1^+, 2^+, 2^-, 1^-$$

$$D: 2^+, 1^+, 1^-, 2^- \quad E: 2^+, 1^+, 2^-, 1^- \quad F: 2^+, 2^-, 1^+, 1^-$$

If customer 2 need to be inserted in the existing route of customer 1 six routes can be created that all need calculations, when there are n customers, and each customer requests contains a pickup and a drop-off this means $2n!$ possible sequences, but due to the fact the pickup location must precedes the drop-off location, the number of possible sequences is divided by 2^n, resulting in $p_n = 2n!/2^n$ possible sequences. When using a strict TW as restriction, the number of feasible service sequences p_n is bounded to $p_n \leq \left(\frac{2(n-1)!}{2^{n-1}}\right) * n * (2n-1)$. In other words, the use of narrow TW reduce the possible sequences.

Problems involving a large number of customers are still computationally intensive. To reduce the number of solutions further, Häme (2011) uses the priori clustering method (PCM). Assuming that the time windows of the problem are relatively narrow, the PCM can eliminate a significant number of solutions, before the actual insertion process is started. The PCM can be explained as follows, create clusters of customer's pick-ups and drop-offs. Cluster C_k precedes cluster C_ℓ if and only if the transition $i \rightarrow j$ is a priori infeasible for all $i \in C_\ell$ and $j \in C_k$. Assuming that a feasible solution exists, the relation of clusters is a partial ordering (Knuth 1997):

(1) $C \nprec$ C for all clusters

(2) $C_a \prec C_b$ implies $C_b \nprec$ C_a

(3) $C_b \prec C_c$ and $C_a \prec C_b$ implies $C_a \prec C_c$.

From the adjacency matrix the clusters can be determined. The matrix $\boldsymbol{F}$ is created by the following rules: $F_{ij} = 1$ if $i \rightarrow j$ is feasible and $F_{ij} = 0$ otherwise. Arranging the rows and columns, that a right upper triangular matrix is created. Each block in the matrix corresponds to a cluster see Table *3.1*.

Table 3.1: *An example with involving four customers, an example of a priori adjacency matrix*

	1^+	1^-	3^+	2^+	2^-	3^-	4^+	4^-
1^+	1	1	1	1	1	1	1	1
1^-	0	1	1	1	1	1	1	1
3^+	0	1	1	1	1	1	1	1
2^+	0	1	1	1	1	1	1	1
2^-	0	0	0	0	1	1	1	1
3^-	0	0	0	0	0	1	1	1
4^+	0	0	0	0	0	1	1	1
4^-	0	0	0	0	0	0	0	1

From the matrix shown in Table *3.1*, five clusters are identified, namely $\{1^+\} \prec \{1^-, 3^+, 2^+\} \prec \{2^-\} \prec \{3^-, 4^+\} \prec \{4^-\}$. From these clusters we conclude that the positions of the nodes $1^+, 2^-$ and 4^- compared to the other nodes are fixed, so only the other pickup or drop-off customers should be considered in finding the optimal ordering of nodes. The use of PCM reduces the amount of insertions significantly, meaning these insertions do not have to be checked for feasibility.

3.1.4 CONCLUSION

After studying the VRP literature, we conclude that our problem is characterized as a many-to-many demand responsive transport problem or a dial-a-ride problem. This is based on the fact that we want to create a new way of on-demand transport which is available for all citizens in the specified area.

In our on-demand dial-a-ride problem, we want to use narrow time windows to make the service more attractive for the customers. The customers are not know beforehand, so the insertion of customers in routes is the method of handling the customer requests. After an insertion of a customer it is possible to assign the customer to another vehicle. But reassignment is only allowed if a customer is not picked up by a vehicle. The reassignment could possibly lead to in a better solution, the better solution could be found with the use of a metaheuristic. The effects of the reassignment are not treated in this research, but are recommend for future research

3.2 PERFORMANCE INDICATORS FOR CUSTOMER SATISFACTION

To motivate citizens to make use of the PT, instead of their private car, the PT sector needs to satisfy the travellers in some way. Key performance attributes can help in how to measure customer satisfaction. An attribute is a characteristic of an object that can be operationalized. In the related literature, several proposals are made on how to measure the performance of PT. Redman et al. (2013) state that the attributes can roughly be divided into two categories: physical and perceived. The attributes linked to the physical category can be measured without the input of the users of PT, and are made about the impact on the users of PT. The perceived attributes are measured using PT users experience. We created Figure 3.4 that defines the most commonly studied PT attributes, where the overall customer satisfaction of all the attributes are represented in the figure.

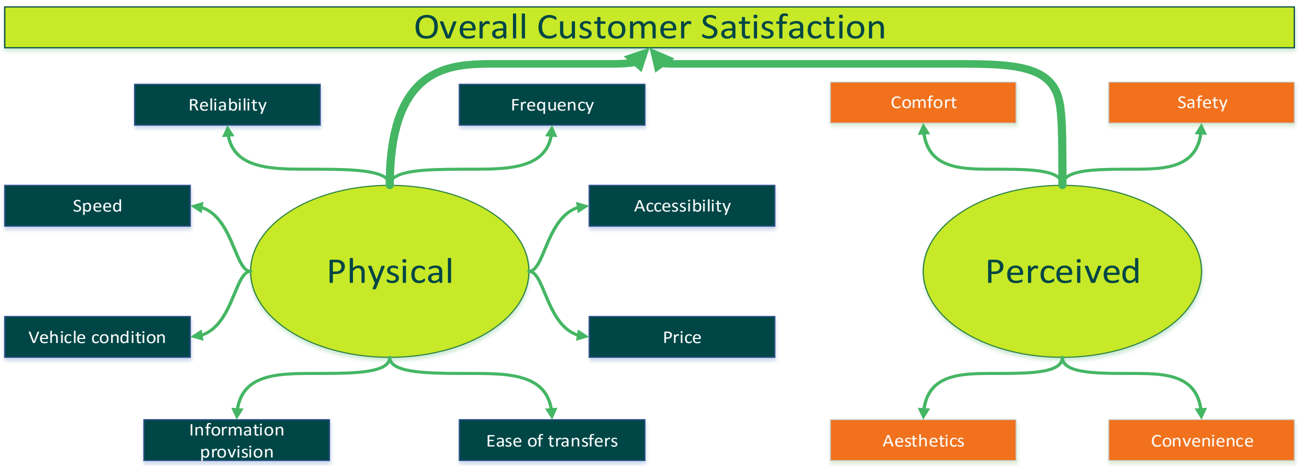


Figure 3.4: *The service attributes related to PT*

We follow Redman et al. (2013) in the explanation of the attributes, and describe the Pearson correlation that is reported by Mouwen (2015) based on performance measures of PT in the Netherlands. The Pearson correlation coefficient is a common measure in statistics for correlation between attributes. It can answer questions like: (I) is the attribute data showing a linear relationship with the overall customer satisfaction? (II) to what percentage can the attribute explain the overall customer satisfaction? Figure 3.5 shows various Pearson correlations with fictive data. If the Pearson correlation is 1, the data is completely explained by the attribute. If the Pearson correlation is 0 it is not explained by the attribute.

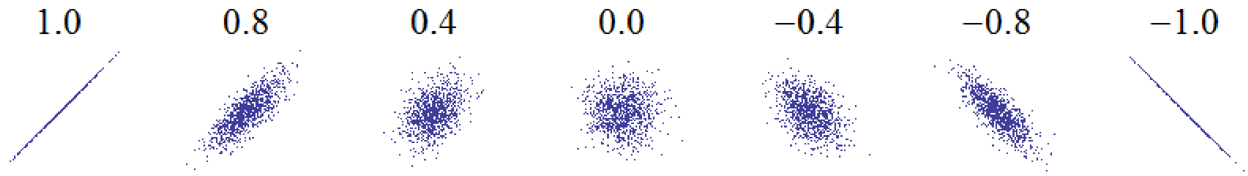


Figure 3.5: *Pearson correlations*

3.2.1 RELIABILITY

Reliability in PT means that the actual departure and arrival times do not deviate from the official timetable (Rietveld et al. 2001). In the literature, reliability seems to be the key attribute in determining the quality of the PT (Filipović et al. 2009, Van Oort 2014). Nevertheless reliability is measured in various ways. Van Oort (2014) states that in the Netherlands 46% of the time measurements is done at all stops, 32% at main stops, 11% at the last stop and 11% at the first stop. These various ways of measurement are showing different results. The Pearson correlation with the overall customer satisfaction is 0.361.

3.2.2 FREQUENCY

The attribute frequency has the meaning of how often the service operates during a given period (e.g., how often a bus arrives at a bus stop). Balcombe et al. (2004) described, when large buses with a frequency of three times an hour were replaced by smaller ones with a frequency of ten times an hour, resulted in a significant increase in demand. Later, Wall and McDonald (2007) confirmed an significant increase in another research. This attribute measures the number of arrival times according the timetable. The Pearson correlation is 0.468 with the overall satisfaction.

3.2.3 ACCESSIBILITY

Accessibility is the degree to which PT is reasonably available to as many people as possible. The effect of accessibility is hard to measure. Chien and Qin (2004) have found that the optimal number of stops is not affected by the length of the route, but by the user's valuation of time, speed of accessing the stop, and demand. Later, Loader and Stanley (2009) described a case in Melbourne Australia. They stated that an extension in routes and providing more service in weekends and evenings results in a growing demand for PT. They noticed that a minimum level of service quality must be provided to motivate citizens to use PT. In the literature above, definitions of accessibility can only be measured with the use of surveys among the citizens. Both authors state that accessibility is important for the demand, The Pearson correlation is 0.364 with the overall satisfaction (note the definition used by Mouwen (2015) is only about the ease of boarding and alighting).

3.2.4 PRICE

The attribute price is defined as the monetary cost of travel. Pricing has a great influence on the demand. The demand for PT decreases when ticket prices increase. Several experiments with free fares during one month are done by Fujii and Kitamura (2003) and Thøgersen (2009) to see the effect on PT use. Both reported a higher demand in the free period, and when the free period expired, the demand remained higher than before the intervention. Besides making the PT free, a lot of pricing mechanisms are described in the literature. A well-known one is the integrated tariff system (ITS) (e.g., one ticket for intercity, buses, subway, etc. that can be used for a short period of time). The ITS increases the demand for PT on the long-term according to Matas (2004) and Abrate et al. (2009). The Pearson correlation is 0.366 with the overall satisfaction.

3.2.5 SPEED

The attribute speed is the time spent traveling between specified points. This attribute is critical when it comes to improving customer satisfaction. In Seoul, Korea an enormous increase in demand is created by introducing a special lane for a bus, so increasing the bus travel speed. Reducing the waiting times for the Los Angeles Metro Orange Line, a bus rapid transit system, resulted in a tripled demand compared to the old situation (Pucher et al. 2005). The Pearson correlation is 0.560 between the attribute speed and customer satisfaction.

3.2.6 COMFORT

Comfort is how comfortable the journey is regarding access to seat, noise levels, and vehicle tidiness. The suppliers of PT often address the comfort attribute by improving standards for vehicles or stations. Wall and McDonald (2007) did their research after the introduction of a new low-floor bus, they concluded that the improvement of comfort is noticed by the travellers but the number of travellers using PT service did not increase. Unlike Foote (2004) who found an increase in the demand by improving the comfort of the ride. Mouwen (2015) did not treat the attribute comfort as one, but defined it in separate attributes, seating capacity, vehicle tidiness, and on-board noise. The Pearson correlations towards overall satisfaction, respectively are 0.361, 0.456 and 0.381.

3.2.7 INFORMATION PROVISION

The attribute information provision is how much information is provided about routes, and interchanges, and how often this information is updated. Brons et al. (2009) found that the provision of information helps in motivating travellers to use PT. Besides that, the provision of accurate information is valued as one of the important attributes that affect customer satisfaction (Nathanail 2008, Aydin et al. 2015). Mouwen (2015) formulated the provision of information in two separate attributes, on-board information on delays and information provision on stops. The Pearson correlation is respectively 0.356 and 0.423.

3.2.8 EASE OF TRANSFERS

In the literature this part is not separately discussed. Probably because the attribute “ease of transfers” is covered by the attributes comfort and speed, because the ease of transfers is related to the speed, frequency, information provision, and the distance that is achieved.

3.2.9 SAFETY

Safety is defined as how safe from accidents (e.g., criminality, aggression, collisions, etc.) passengers feel during the journey. From the analysis of Mouwen (2015), safety is not the number one customer satisfaction attribute. However he described that passengers who had experience with a negative critical incident value the attribute safety significantly more than passengers without a negative critical incident experience. Mouwen (2015) divided the attribute safety into two attributes, safety on board and safety at stops. These attributes are mildly correlated with each other, and have respectively a Pearson correlation with the overall satisfaction of 0.398 and 0.312.

3.2.10 CONVENIENCE

Convenience is how simple the PT service is to use and how well it adds to one's case of mobility. While it might be related to other attributes, it can differentiate more on the ease and simplicity of paying for and planning a PT trip. Sharaby and Shiftan (2012) reported an increase of up to 25% in the first year when a simple zone fare system is implemented, with free transfers. Mouwen (2015) did not treat the attribute convenience, but we assume that his attribute ticket-selling network that is defined as: "ease of obtaining a ticket from on- and off-board selling points" is the definition that is closest to our chosen definition. The Pearson correlation with the overall satisfaction is 0.368.

3.2.11 AESTHETICS & VEHICLE CONDITION

Aesthetics is defined as the appeal of vehicles, stations and waiting areas to users' senses, and vehicle condition as the physical and mechanical condition of vehicles, including frequency of breakdowns. Like the attribute convenience, these attributes are somehow related to other attributes. We think that the definition of these two attributes are covered by the attributes: comfort, reliability, and safety. If a vehicle is not well maintained, we assume the score is about to be lower on the previous named attributes. When a PT vehicle looks poor, the safety experience of passengers is lower. Mouwen (2015) did not treat this attribute, so no Pearson correlation van be given.

3.2.12 CONCLUSION

The key performance indicator of user satisfaction in PT, is often discussed in the literature. To potential PT users, the attributes above need to score as high as possible to get a high level of customer satisfaction. In Table 3.2 a summary of the Pearson correlation of the attributes is given.

Table 3.2: *Summary of attributes with the Pearson correlation score (according Mouwen (2015))*

Attribute	Pearson correlation
Reliability	0.361
Frequency	0.468
Accessibility	0.364
Price	0.366
Speed	0.560
Comfort	0.364/0.456/0.381
Information provision	0.356/0.423
Ease of transfers	-
Safety	0.398/0.312
Convenience	0.368

From the Pearson correlations we conclude that the strength of association between the attributes and the customer satisfaction are medium correlated, only the attribute speed is highly positively correlated. For all the attributes the P-value is 0.000 which means that the correlation coefficient is significantly different from zero.

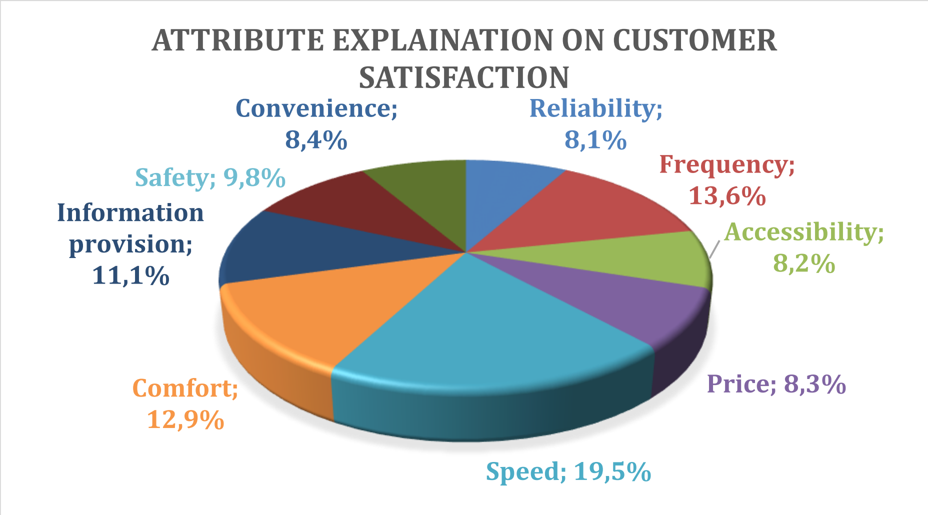


Figure 3.6: *Attribute explanation on customer satisfaction*

Figure 3.6 shows the percentage that explain the influence of the attribute in customer satisfaction. The influences of the attributes are calculated using the highest Pearson correlation if multiple correlation values are known, the percentage is calculated as follows $\%\ of\ attibute = Pearson\ Correlation^2/Total\%$. Figure 3.6 shows that speed and frequency are the two attributes that have the most influence in the customer satisfaction. From the correlation we see that the pricing of PT is not as important as others. We conclude that customers are willing to accept a higher price, if the attributes with a higher percentage improve (e.g., Speed).

3.3 EXTENTIONS FOR THE DARP

The basic version of the DARP (Cordeau and Laporte 2003) does not handle all the restrictions related to our problem. This section describes additional constraints that make the DARP more realistic, although any model is still a simplified version of the real-world situation, but it can represent reality. First we treat the various resource capacities, followed by drive time related constraints, then driver constraints, followed by the fare price constraint, to finalize with an extension for the objective value.

3.3.1 VARIOUS RESOURCE CONSTRAINTS

When a customer is picked up at its preferred location it could occur that the customer need a special transport mode, e.g., a front seat for travel sickness, or the customer has a wheelchair. To make sure that these needs can be taken into account, the following constraints need to be added to the model (Parragh et al. 2012):

$$x_{ij}^b = 1 \rightarrow Q_j^{r,b} \geq Q_i^{r,b} + q_j^r \qquad \forall i,j \in \mathcal{V}, b \in \mathcal{B} \qquad (3.6)$$

$$Q_i^{r,b} \leq Q_b^r \qquad \forall i \in \mathcal{V}, b \in \mathcal{B}, r \in \mathcal{R} \qquad (3.7)$$

The various transport modes are represented by $r \in \mathcal{R}$. Where $\mathcal{R}$ denotes a set of integer numbers that represent the various number of transport modes. The x_{ij}^b is a binary variable, which is 1 if vehicle b goes immediately from location i to location j, 0 otherwise. The $Q_i^{r,b}$ represents the load of transport mode r on location i in vehicle b. The Q_b^r denotes the capacity of resource r in vehicle b. Constraint (3.6) ensures that if the route is driven, the load of request j is added to the load of vehicle b. Constraint (3.7) ensures that the capacity restriction of all resources are not violated.

In practice several vehicles have a flexible layout. This could lead to a loss of regular seats in the vehicle when a wheelchair needs to be transported. E.g., a vehicle can transport six regular customers without big luggage, but when a wheelchair request comes in, the capacity for regular customers is only three since the wheelchair takes three regular seats. Flexible capacity is not taken into account in our case.

3.3.2 DRIVE TIME CONSTRAINTS

In the Netherlands, there are several regulations for the work time of drivers. The Dutch government uses the regulations formulated by the European Parliament and of the Council (2006). These rules state that the maximum driving time is nine hours with at least a break of 45 minutes (separable into 15 minutes followed by 30 minutes) that should be taken after four and half hours at the latest. To handle these regulations, the following constraints should be added to the model (Parragh et al. 2012):

$$v_{2n+2}^b = 0 \rightarrow Z_{2n+2}^b - Z_0^b \leq T_l \qquad \forall b \in \mathcal{B} \tag{3.8}$$

$$v_{2n+2}^b = 1 \rightarrow Z_{2n+2}^b - Z_0^b + H \leq T \qquad \forall b \in \mathcal{B} \tag{3.9}$$

$$x_{ij}^b = 1 \ \wedge v_i^b = 0 \rightarrow Z_j^b \geq Z_i^b + t_{ij} \qquad \forall i,j \in \mathcal{V}, b \in \mathcal{B} \tag{3.10}$$

$$x_{ij}^b = 1 \ \wedge v_i^b = 1 \rightarrow Z_j^b \geq Z_i^b + t_{ij} + H \qquad \forall i,j \in \mathcal{V}, b \in \mathcal{B} \tag{3.11}$$

$$v_i^b = 1 \rightarrow e_H \leq Z_i^b \leq l_H \qquad \forall i \in \mathcal{V}, b \in \mathcal{B} \tag{3.12}$$

$$v_i^b = 1 \rightarrow Q_i^b = 0 \qquad \forall i \in \mathcal{V}, b \in \mathcal{B} \tag{3.13}$$

First the maximum shift duration for all drivers (due to regulations) is defined as T, and T_l denotes the maximum worktime without a lunch break. H is the duration of a break, and v_i^b is a binary variable that is 1 if the lunch break is held before location i by vehicle b. The t_{ij} represents the real driving time to form location i to location j. The Z_i^b denotes the arrival time of using vehicle b at location i, and d_0^b is a binary variable, 1 if a driver is assigned to vehicle b, 0 otherwise. The depot at the end of the shift is represented by $(2n+2)$. We choose $(2n+2)$ since an additional situation constraint a noon depot, represented by $(2n+1)$. Constraint (3.8) states that if no lunch break has occurred, the maximum shift duration must be smaller than the maximum work time without a break. Constraint (3.9) states if a lunch break has occurred, the maximum work time cannot exceed the maximum working time T. Constraint (3.10) ensures, the start time at location j is later than the start time in location i plus the pickup, drop-off, and travel time. Constraint (3.11) states if a lunch break is held at location i the start time at location j is calculated in the same way as constraint (3.10), only the duration of the lunch break is now added. Constraint (3.12) states, if a lunch break is held at location i, then the lunch break must start within the time window of the lunch break. Constraint (3.13) handles that no break can start at location i if the vehicle is not empty.

The constraints above are still a simplified version of reality, since not only the European regulations are taken into account, but also company policies and collective agreements. For our solution method a simplified version of the regulations is used that can calculate solutions that are legal according the European regulations.

3.3.3 DRIVER CONSTRAINTS

When dealing with large vehicle fleets, with a various types of vehicles, the number of drivers can limit the number of vehicles that can be used. For including the number of drivers, the following constraints can be added to the model:

$$\sum_{b \in \mathcal{B}} d_0^b \leq m^d \tag{3.14}$$

Where the given number of drivers is denoted as m^d.

3.3.4 TIME AND COST RELATED OBJECTIVE

In most cases the service is an important factor that is not considered in the objective function of the basic DARP. The way that the service is measured can be done in several manners. We choose to use the minimization of the detour time. This can be done with the use of the following objective function:

$$\min \sum_{b \in \mathcal{B}} \sum_{i \in \mathcal{V}} \sum_{j \in \mathcal{V}} w(c_{ij}^b x_{ij}^b) + (1 - w)(T_i^b - t_{ij}) x_{ij}^b \tag{3.15}$$

In the objective function (3.15) a weight factor w is introduced: $(0 \leq w \leq 1)$. Variable T_i^b represents the travel time from location i to location j, and t_{ij} represents the direct (without detours or delays) travel time. We can adjust the weight factor to determine the importance of costs or service.

In the above objective function only two factors are taken into account, but it is possible to add more factors that can be minimized or maximized. If a factor must be maximized in a minimization objective function, that factor must be reformulated into a minimization function.

3.3.5 CONCLUSION

From the mathematical models described before, we can create a formulation that can help solving our problem. Constraints, for various capacities, driver restrictions, and time windows, are given for the DARP with driver-related and specified capacity constraints.

3.4 DEMAND RESPONSIVE TRANSPORT IN PRACTICE

This section describes some DRT systems that are already implemented, and some implementation issues that could occur. We start with introducing systems that are already been implemented, followed by some implementation issues in Section 3.4.2.

3.4.1 EXISTING SYSTEMS

MetroAccess Washington

MetroAccess is a shared ride PT service for customers that are unable to use the regular PT. The service can pickup and drop-off customers within a predetermined range from a metro or bus stop. If the preferred location is within the range, a door-to-door service can be provided, outside the range the service drops the customer off at the maximum allowable range. The service only operates on requests done between one and seven days in advance (Washington Metropolitan Area Transit Authority 2015).

Kutsuplus Helsinki

Helsinki adapted an on-demand minibus service, called Kutsuplus (Finnish for call plus). This PT system, is more expensive than a regular bus service but cheaper than a taxi. A customer can order a ride with the use of a smart phone, to select the pickup stop and the drop-off stop. The departure time of a ride can be maximum 45 minutes from the moment of ordering. The algorithm calculates the direct route between the chosen locations and to determine the ride fare. The start price is €3,50 and additional costs of €0,45 per kilometre. A discount on the fare price is given when the ride is ordered between 10:00 and 14:00, and for groups. When a customer accepts the ride, he/she needs to pay the trip in advance. Once the trip is ordered it cannot be cancelled anymore (Barray 2013, Kutsuplus 2015).

CallConnect Lincolnshire

Lincolnshire introduced the CallConnect service. This service is based on two methods: an entirely demand responsive service, which serves an area of 11 to 16 kilometre from a large stop, and has no fixed routes or timetables. Or the semi-flexible service, which operates using a timetable but can deviate off the route to serve other locations. The service area is a lot smaller compared to the entirely demand responsive service. The timetables and the routes for both services are not fixed but are altered by the customer requests. Customers can book a ride up to one week ahead and with a minimum of one hour notice on the day. The service is designed to improve the PT opportunities in rural areas and some market towns where there is an infrequent conventional bus service. The service is not available in areas where a frequent bus service is active. The CallConnect service performs pickups and drop-offs at designated locations, and is not limited to only disabled customers but can service all citizen (InterConnect 2015).

Texel Hopper

The Texel Hopper is a pilot that operates on Texel in the Netherlands. The Texelhopper system is a combination of a fixed bus line with fixed times, and smaller vehicles. The smaller vehicles serve customers on demand, where the request of a customer must be done at least one hour in advance. The vehicle has a vast network of stops over the entire island, that are only served if requested by a customer. This system operates similar to the Kutsuplus in Helsinki Finland.

3.4.2 IMPLEMENTATION ISSUES

DRT is promoted as a PT solution in areas where the traditional services are not economical. Earlier in this chapter, we described the VRP, how to solve the VRP, and what the important satisfaction factors are for passengers. In this last part of the literature review, we describe some possible challenges and factors that affect the operational ability. First we describe how to make transport more demand responsive, followed by costs and revenues, operational issues, institution issues, economic issues, and cultural issues.

The concept of DRT exists several years and is implemented in a number of cities. In most cases the DRT is implemented in a rural area, where regular bus transport may not be viable. In some cases the DRT is only available to elderly or disabled passengers. In the case of social support transport systems, the DRT is fully or partially funded by authorities. From the experience of the DRT implementation, key elements are formulated and recommendations are given to make the DRT viable. First it is important to determine the flexible forms of DRT. This can be determined on various elements. Figure 3.7 shows for each element how to increase the demand responsiveness. It also shows that not only the route, or vehicle should be taken into account, but also the time availability of the service, type of passengers, and payment. We disagree with Brake et al. (2007), we think the demand responsiveness is not dependent on type of passengers, and payment as shown in Figure 3.7.

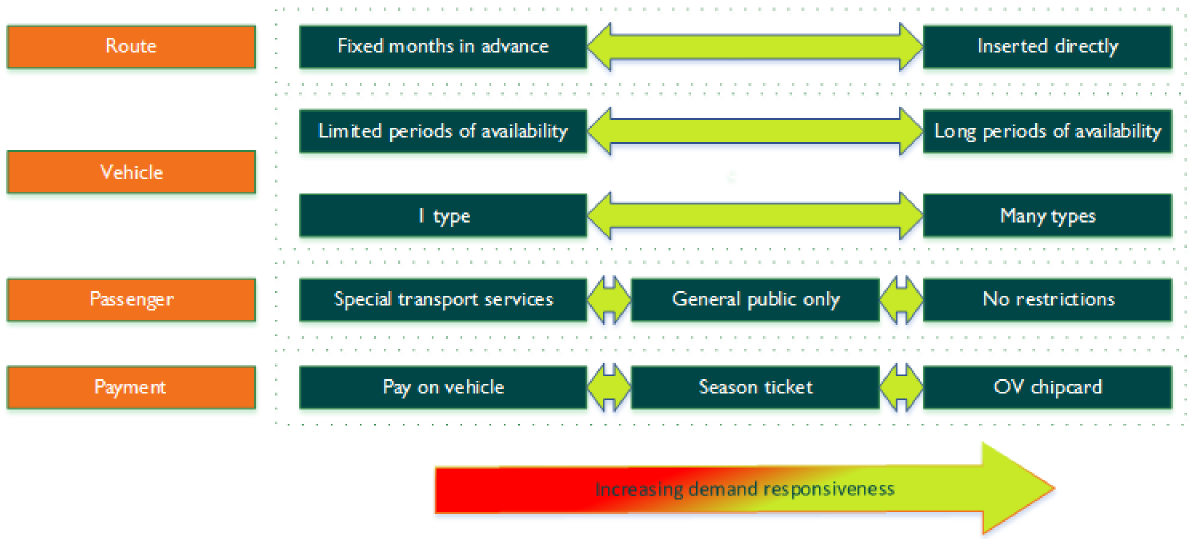


Figure 3.7: *Level of demand responsive transport of PT (based on Brake et al. (2007))*

Costs and revenue issues

One of the most important factors to make DRT viable is the balance between revenues and costs. Brake et al. (2007) state from the current experience in provision of DRT that the service is only sustainable with subsidy. As shown in the performance indicators, the price has a little influence the travel behaviour of the passengers. The costs of the DRT should be divided into: administrative costs (e.g., advertising), capital costs (e.g., office supplies), and operation costs (e.g., driver wages).

Operational issues

For the service related factors, Wang et al. (2015) described several challenges, the first category involves the operational issues, e.g. improving the booking methods, and routing efficiency. One of the biggest operational issues is related to the fleet and vehicle types. Most of the conventional bus operators are driven by their core business and this may lead to unsuitable vehicles for a DRT service. Procuring new vehicles could lead to extra costs, not only the depreciations costs but also cost for maintenance, and other vehicle related costs. These extra costs for accessible vehicles are a potential issue (Mulley et al. 2012).

Institutional issues

Institutional factors can determine the ease of implementation of DRT. Under institutional issues, Mulley et al. (2012) reported policies, legislation and regulation. The core challenge is the complex array of stakeholders and regimes, in terms of licensing, tax, and insurances. It can become a challenge when one of the important stakeholders is not co-operating, which can lead to an impossible implementation of a DRT service.

Economic issues

As mentioned earlier, costs and revenues are an important part to make DRT viable. Funding issues can create a new barrier. A DRT service is often seen as an innovation that requires funding for the long term. If this funding only happens for a short period, this could lead to an introduction of a DRT service, and a short period of time later the fall of the DRT service. The subsidy payment for DRT is hard to determine, since the level of subsidy cannot be determined beforehand, because the demand and distance travelled are unknown. The operators could risk higher costs per km than expected, e.g., due to lower demand (Mulley et al. 2012).

Cultural issues

The introduction of a new DRT service brings in some cultural issues. On the operator side, it introduces uncertainty in the outcome. The service only responds to the demand, which may produce more or less funding, and may require more or less subsidy from the government. On the demand side, attitudes and cultural views on DRT can create barriers. The general perception of travellers is the need for a certain fixed scheduled service, instead of services that need to be initiated by the traveller (Martikke and Jeffs 2009). The time needed to change this travellers' behaviour is posed as another barrier (Mulley et al. 2012).

Information issues

Information and awareness can be a barrier for both operators and the public. Most of the operators are comfortable with their core business and are unfamiliar with a DRT service. Not only the operators have a lack of knowledge, passengers also have a lack of understanding how a DRT might function and what the benefits are for them as passengers. To create awareness of the opportunities DRT has to offer, the need for appropriate marketing is essential (Mulley et al. 2012).

Conclusion

To make the DRT system function properly, a number of barriers need to be overcome. One of the most important barriers are the institutional barrier, if no license or insurance is given, the implementation is impossible, and the economic barrier, without subsidy from the government the project is not affordable. The other barriers need time and investments, but do not block implementation.

3.5 CONCLUSION

From the literature we state that our problem can be characterized as a many-to-many DRT or a DARP. For solving the problem we prefer to use a metaheuristic due to the ability to handle a very large number of customers, and to find good solutions in limited time. When the number of locations is small, an exact algorithm can help solving the problem. We use the DRT and DARP, to create a formulation that could handle our problem. Important customer satisfaction attributes are speed, frequency, and comfort. These attributes are important for implementation, to satisfy the customer's needs. Besides the customer's needs there are other barriers to overcome, especially the institutional barriers (licenses and insurance), and the economic barriers (subsidy).

4 SOLUTION DESIGN

"Beware of bugs in the above code; I have only proved it correct, not tried it"

- Donald Knuth

This chapter contains several sections to formulate our solution model. We start by formulating the foundation of our problem in Section4.1, followed by the assumptions for our model in Section 4.2. In Section 4.3 we formulate our model, and in Section 4.4 two different interpretations of the detour time are formulated and explained. We finalize in Section 4.5 with conclusions.

4.1 FOUNDATION

In this section two type of decisions are described. First the high level decisions that determine the way the DRT should operate i.e., strategical decisions. In Section 4.1.2 the low level decisions, like the operational and planning decisions, are described.

4.1.1 HIGH LEVEL DECISIONS

Connexxion wants to provide a "when you want and where you want service". Customers can send in a request that contains a pickup location and a drop-off location. The request of the customer is fulfilled by one vehicle, so no transfers in the predetermined area are needed. The route of a DRT service vehicle is created on demand, so no predetermined routes are driven. These points make the DRT service a flexible service.

The DRT variant that Connexxion wants to use, is restricted by the use of pickup and drop-off points. These pick-up and drop-off points are predetermined and are only visited when a customer requests a ride from one location to another. The location of the pickup and drop-off points are the same as the current bus stops, shown in Figure 2.2. The number of stops remains the same as the current situation. The vehicles that could be used should be identical. The reason for Connexxion is buying an adjusting the same type of vehicles reduces the total investment.

A vehicle always starts and finishes at the depot, located near the train station Helmond. All the vehicles used are driving until the maximum work time is violated or when there are no more assigned requests. The stop Helmond Station has the benefit that it is located in the centre of Helmond, and all other stops are reached within fifteen minutes.

In PT, all the prices for traveling should be known beforehand. If a customer sends a request, the fare price is based on the shortest path. So the customer does not pay extra for an eventual detour. This method of pricing is transparent and fair for a customer. Another option is a fixed price that is independent of the ride length.

4.1.2 LOW LEVEL DECISIONS

In contrast with the current models in the literature, our model only accepts requests, if the customer orders T_r (Call time) minutes before the requested earliest pickup time. Requests that are done earlier, are known and stored but cannot be immediately assigned to a vehicle.

The customer receives a TW with the earliest pickup time, the preferred pickup time and the latest pickup time. The customer also receives the latest arrival time of his or her request. The latest arrival time is the time that the customer must be dropped-off at the requested location. The exact time of arrival is not given since it is possible that a new customer sends a request that could be fitted in the same vehicle by making a detour.

The customer receives at least O_i (communication time) minutes before the actual pickup a message that states the actual pickup time at location i, this is the moment were it is not allowed to insert a request before the location that is communicated.

Figure 4.1 shows the process that starts by ordering and ends when the requested trip is served.

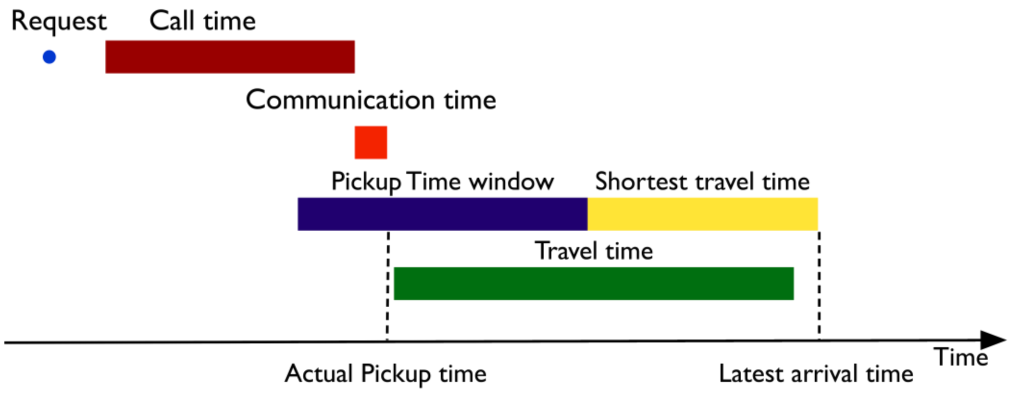


Figure 4.1: *Time windows of a ride*

Figure 4.1 shows a schematic representation of the times of the process. It starts with a request (the blue dot), the request must be done before the call time starts. The call time is the time, the model assigns the request to a route. The request contains the earliest pickup time, and the latest pickup time (the dark blue bar). At a certain moment the actual pickup time is communicated (the red square), and the customer enters the vehicle. The time that a customer is in the vehicle is the travel time (the dark green bar). The customer must arrive at the requested location before the latest arrival time, the latest arrival time is determined by the latest pickup time plus the shortest travel time.

4.2 ASSUMPTIONS

In this section several assumptions are formulated.

4.2.1 REQUEST TIME

When a customer sends a request, he/she can determine the earliest pickup time. The customer orders the ride with a minimum of T_r minutes (Call time) before the earliest pickup time.

4.2.2 ACTUAL PICKUP TIME

The actual pickup time is communicated if the pickup location of the customer request is the first in the route, meaning it is possible to have a communications time larger then O_i. When the pickup location has predecessor locations, the actual pickup time is communicated at least O_i minutes before the vehicle arrives. As soon as the actual pickup time is communicated the model considers the route of the vehicle to be fixed up to the communicated time.

4.2.3 RIDE COMBINATIONS

When a customer orders a ride, the customer is assigned to the most suitable vehicle. If an insertion is not possible the customer is rejected. In real-life it is not allowed to reject customers, so all customers rejected by our model must be outsourced to a third party.

4.2.4 DRIVE TIMES

The drive times between the locations are considered to be deterministic and are not affected by real life events e.g., an accident.

4.2.5 AGREEMENTS

A customer can order a ride at any time the service is active. When the customer orders a ride, he or she must be waiting at the preferred pick-up point in the time window. If the vehicle arrives and the customer is not at the agreed location (no-show), the vehicle continues the route without servicing the drop-off location of the no-show request.

4.2.6 ARRIVAL TIME VEHICLE

The vehicle can only service a stop within the time window, when the vehicles arrives before the earliest arrival time of the requested ride, it must wait until the earliest arrival time of the time window is met. In the model the route is infeasible if the arrival time at the drop-off locations is past the latest arrival time.

4.2.7 MAXIMUM RIDE TIME

The maximum ride time is determined beforehand. The maximum ride time is determined in two different ways. 1st the maximum ride time is the shortest path ride time plus a fixed detour time. 2nd the maximum ride time is the shortest path ride time times a factor.

4.2.8 BOARDING TIME

The boarding time for each customer is assumed to be very short since the customer must stand at the boarding location, and the use of small vehicles allows to customer to quickly get out of the vehicle. We assume that customers using the service are physically healthy and do not need any help in boarding or leaving the vehicle, that is why we assume the boarding time is included in the travel time matrix.

4.2.9 ROUTE

The route is created based on demand, and always starts at the depot and ends at the depot. The route can be extended by new requests until, the driving time of the driver is ended or when there is are no more requests assigned to the vehicle. The vehicle returns to the depot since the depot location is chosen such that it is able to reach any predetermined stop within fifteen minutes.

4.2.10 LUGGAGE

Some travellers carry large pieces of luggage, the needed extra space for luggage can be requested by adding an extra seat. We assume if a customer carries a regular piece of luggage it causes no problems.

4.2.11 TIME WINDOW VIOLATIONS

When customers receive the time of actual pickup they are assigned a vehicle. In practice it could happen that a vehicle gets delayed, e.g., due to traffic jams. In our model, real life events that result in delays are not taken into account. So all assigned requests are serviced within the time windows.

4.3 MODEL FORMULATION

This section starts with a mathematical presentation for our construction models. In Section 4.3.2 we explain how we handle the online requests by the insertion method.

4.3.1 DARP FORMULATION

We make use of a mathematical formulation to set strict boundaries for our research. The mathematical model is not directly used, since we do not solve and the mathematical formulation. All the restrictions shown in the model are actually implemented in our program. The DARP formulation is described in Appendix C.

4.3.2 INSERTION

In Section 3.1.3 the idea of inserting a new request in an existing route is explained. The idea of the insertion algorithm is to construct the route iteratively by performing an insertion for each request. All infeasible solutions are removed from the solution set. The procedure involves one step for each request (Häme 2011):

- Perform insertion of the new request to all feasible service sequences with respect to existing customers. The current sequence of locations assigned to a bus cannot be changed.

Objective

The main objective of the insertion method is to minimize the total costs, and reduce the detour time. To achieve this, only feasible insertions are considered. All infeasible insertions are eliminated to reduce the computation time. Narrow time windows result in less computations, so a good solution can be generated fast. Besides reducing the number of computations, another goal is to find a feasible sequence if one exists, and to decide whether or not a request can be accepted by our model.

Formulation

To check whether or not a customer request can be accepted, the insertion checks the feasibility in two phases. The first phase checks if the current sequence, on the precedence, time, and capacity constraints are satisfied. In the second phase, the remaining locations that are not in the sequence are determined by considering the possibilities of adding a remaining location to the sequence.

4.4 TWO MODELS

In this section, we formulate two models that are both based on mathematical formulations in Appendix C. Connexxion wants to see the effects when using fixed detour time. This means no matter the duration of the ordered ride, the detour time remains the same. The second model uses a factor, in this case de detour time is the shortest ride time times the factor. This means short rides have a relative short detour time, and longer rides a relative longer detour time. In Section 4.4.1 the model with a fixed detour time is explained, while in Section 4.4.2 the second model with detour factors is explained.

4.4.1 EXPLANATION OF MODEL 1

Times of a request

Model 1: Here we use the concept of a fixed detour time. The latest pickup time is equal to the earliest pickup time plus flexibility time (TW size). The latest arrival time is equal to the latest possible pickup time plus the direct ride time. Hence the planning flexibility might be 'considered in two ways, either by waiting at the pickup location or by the detour time.

Example

The basic idea of the multi vehicle DARP, is serving all the customer requests. The routes are not fixed but are created based on the customer requests. Below a simplified example is shown of Model 1. The example has the following parameters: a maximum detour of 10 minutes, a maximum call time of 5 minutes, and a flexibility of 15 minutes.

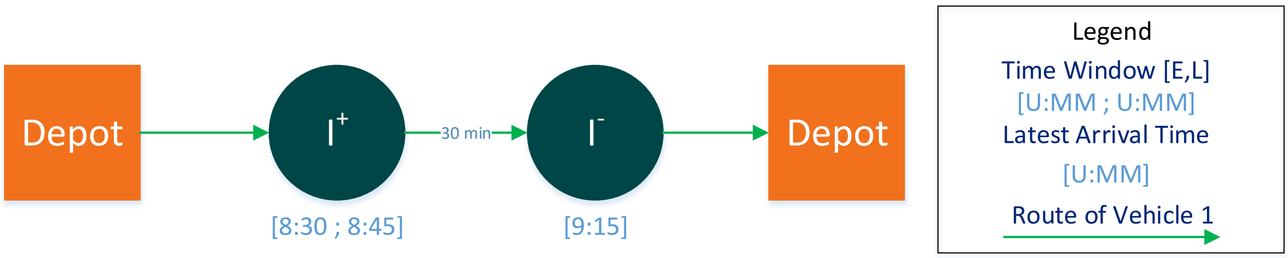


Figure 4.2: *Model 1 with one customer*

Figure 4.2 shows the route of vehicle 1 servicing only one customer request, since no more requests are known. Vehicle 1 starts the route to service customer 1. At 8:29 another customer sends a request, see Figure 4.3.

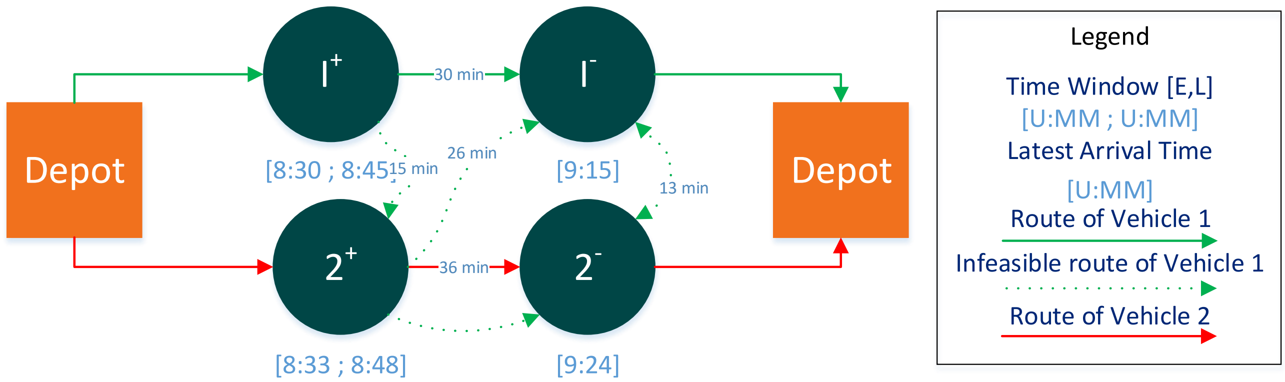


Figure 4.3: *Model I with two customers*

Figure 4.3 shows that a second vehicle is needed to serve the second request, since the agreed latest arrival time, and the maximum detour time of customer 1 are violated, if vehicle 1 arrives at 8:30 at the pickup location of customer 1, then vehicle 1 can pickup customer 2 at 8:45, so the time windows of both customers are feasible. To check if customer 2 can be inserted in the current route we check the following sequence options before visiting the drop-off location 1, the sequences and the time of arrival in the drop-off location is calculated (assuming pickup location (1^+) is visited at 8:30): $1^+, 1^- = 9{:}00$; $1^+, 2^+, 1^- = 9{:}11$; $1^+, 2^+, 2^-, 1^- = 9{:}34$; $1^+, 2^+, 1^-, 2^- = 9{:}24$. The sequence $1^+, 2^+, 2^-, 1^-$ is infeasible due to the violation of the latest arrival time of customer 1. The sequence $1^+, 2^+, 1^-, 2^-$ is not violating the pickup TW or the latest arrival times of both request, but this sequences is infeasible due to violating the maximum detour time. The detour for customer 1 is 11 minutes, while the maximum detour time is 10 minutes. So a second vehicle is needed to accept the request of customer 2. In Figure 4.4, the model is extended with a third customer.

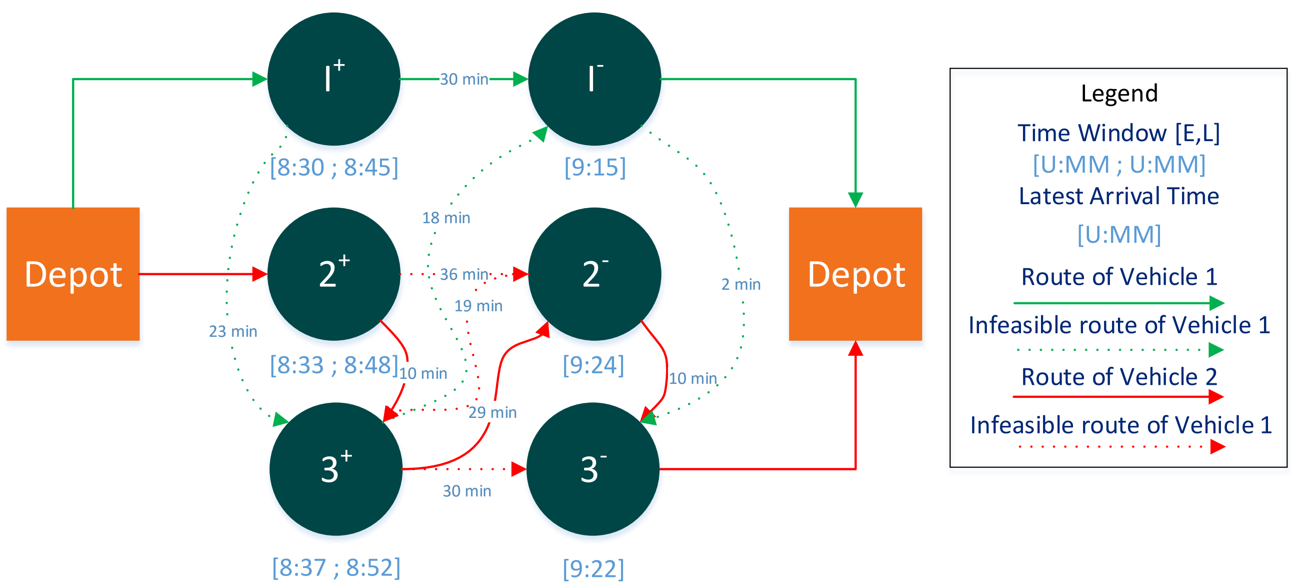


Figure 4.4: *Model I with three customers*

Figure 4.4 shows that the third customer sends in a request at 8:33, the current situation consists of two routes $1^+, 1^-$ and $2^+, 2^-$, driven by two vehicles. If we add customer 3 to the route of vehicle 1. The pickup time of customer 3 is violated, so an insertion in route 1 is infeasible. When we add customer 3 in the route of vehicle 2, the pickup TW, and the maximum detour time are not violated. The following route sequence is possible $2^+, 3^+, 2^-, 3^-$ without violating any restriction. Customer 3 is inserted in vehicle 2. It is also possible to pickup customer 3 before customer 2, the route then becomes $3^+, 2^+, 2^-, 3^-$, but the request of customer 3 is done at 8:33, exactly the moment that vehicle 2 arrives at the pickup location of customer 2. So this sequence is rejected, since customer 2 is already in the vehicle. The option of using a new vehicle, if available, is also considered, but using a new vehicle comes with high start costs, so this option is only considered when a request cannot be assigned to one of the current routes.

4.4.2 EXPLANATION OF MODEL 2

Times of a request

Model 2: Here we use the concept of using a factor. The maximum detour is determined by multiplying the direct driving time with the detour factor. All the other parameters determined in the same manner as model 1.

Example

Model 2 uses another TW strategy, using a detour factor. The maximum detour time is the shortest path time times the detour factor. The model is explained with the use of a simplified example given below. The insertion of the first request is the same as shown in Figure 4.2, the insertion of the second customer is different. The example has the following parameters: a detour factor of 1.5, a maximum call time of 5 minutes, and a TW size of 15 minutes.

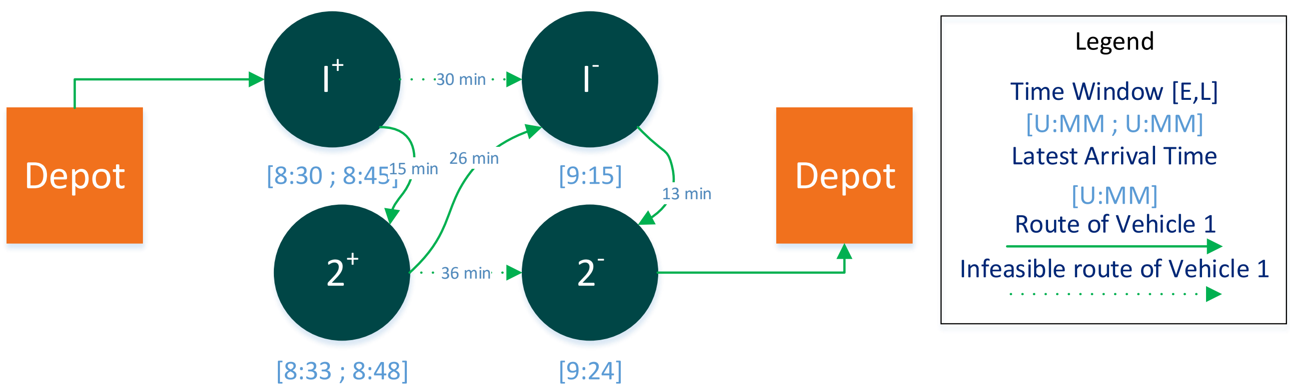


Figure 4.5: *Model 2 with two requests*

Figure 4.5 shows a second customer has send a request. Compared to the Figure 4.3 it is possible to service both requests with one vehicle. Since the detour time of customer 1 is 15 minutes, and the latest arrival times are not violated. The feasible route shown in Figure 4.5, shows that the arrival time at the drop-off location of the second request is 9:24.

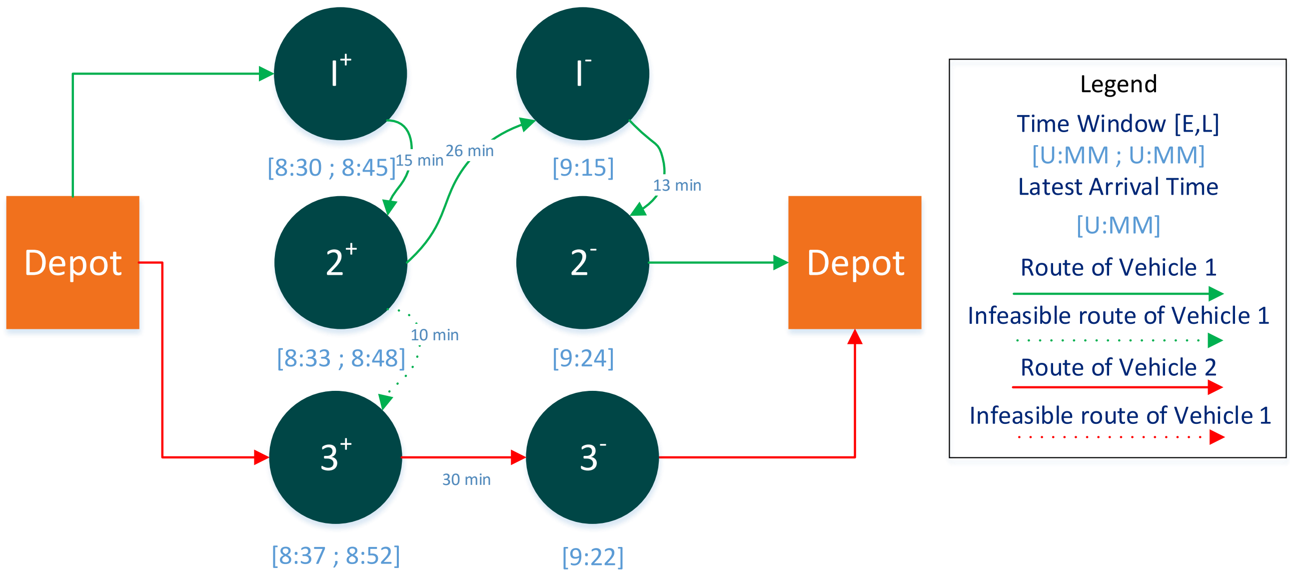


Figure 4.6: *Model 2 with three requests.*

In Figure 4.6 a third request is made by customer 3. Since the actual pickup time is already communicated to customer 2, it is not allowed to insert customer 3 before customer 2. If we insert customer 3 after the pickup location of customer 2, the pickup TW of customer 3 is violated. If an extra vehicle is available the request is assigned to that vehicle, else if no more vehicles are available the request is outsourced to a third party.

4.4.3 CONCLUSION

From the examples we see both models handle the requests differently. In the first model, customer 2 is assigned to a new vehicle, and customer 3 inserted in the route of the second vehicle. The second model shows that customer 2 is inserted in the route of the first vehicle while the customer 3 is assigned to a new vehicle.

4.5 CONCLUSION

This chapter introduced an insertion method that incorporates all restrictions mentioned in the mathematical model. The insertion method assigns the requests that are known to a vehicle with the lowest costs. The narrow time windows reduces the number of possible insertions drastically.

In this chapter we formulated two construction models, the first model makes use of a fixed maximum ride time. The second model uses a maximum ride time that is based on a factor times the direct driving time. The next chapter simulates both models and report the results.

5 PERFORMANCE EVALUATION

"An ounce of performance is worth pounds of promises."
- Mae West

In this chapter, we test our solution models, and present the results. We start by describing the experiments in Section 5.1, followed by the results of the experiments in Section 5.2. Section 5.3 provides an overall conclusion.

5.1 EXPERIMENTS

To find out the effects of several parameters and the differences between our models, we first analyse the requests that are used as input data. In Section 5.1.2 the experiments are shown for our two models.

5.1.1 INPUT DATA

To compare the new situation with the current situation in Helmond, the passenger requests of September 2015, analysed in Section 2.3, are used as input for the model. We take all customer requests that stay within Helmond as input. In the new situations customers do not have the opportunity to use a bus line. The stop locations are located at the same locations as the current bus stops.

By analysing the input requests even further, we see that 21,736 trips stay within Helmond (our service area), with a total distance of 57,069 KM, and an average distance of 2.68 KM. The total shortest travel time of all the requests is 2153:39 hours with an average shortest travel time of 6:05 minutes. The longest trip within Helmond has a distance of 6.65 KM with a corresponding longest trip duration of 13:57 minutes.

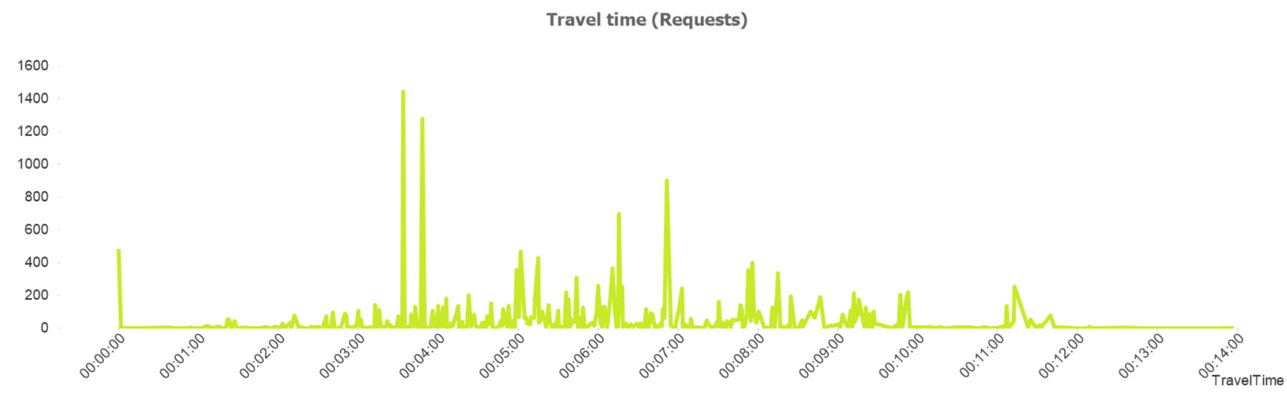


Figure 5.1: The shortest travel time of the trips

Figure 5.1 shows large peaks around a shortest travel time of 3:45. We think these peaks are caused by the travelers using bus line 51, traveling from Helmond Station to Helmond Noordende and the other way around. The peak shown at 0:00 are the requests that are checked in and checked out at the same location at the same time. These requests are not served by our model and ignored in all calculations. The other peaks are caused by the other top 5 check-in and check-out locations as shown in Section 2.5.

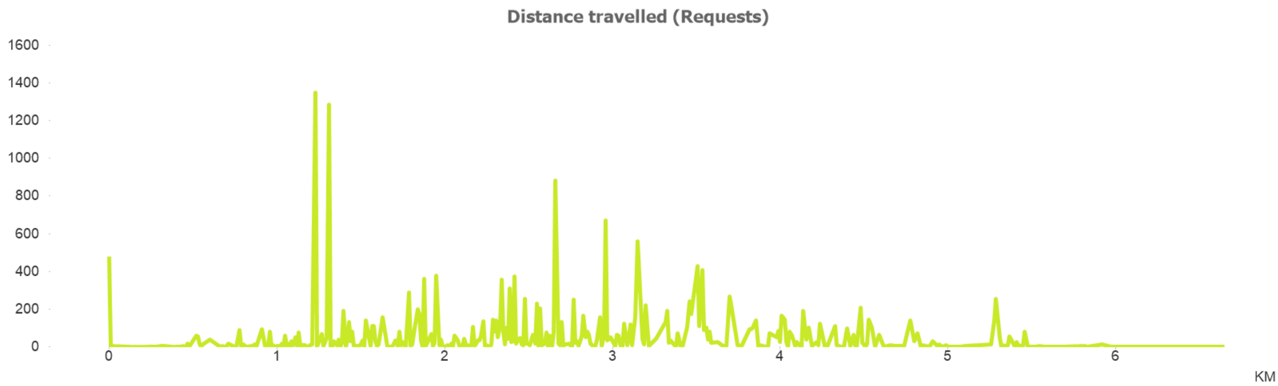


Figure 5.2: *The distance traveled by the requests*

Figure 5.2 shows the distance travelled by the requests. These distances are determined using our distance matrix. Again we see two large peaks around 1.3 kilometre, these peaks correspond with the peaks mentioned before. Although we expect the pattern to be the same as Figure 5.1, Figure 5.2 is showing more peaks.

The use of a fixed number of bus stops allows us to create a pre-calculated distance matrix. Events, like roadworks, that cause detours are not taken into account. The distance between stops is based on the fastest route supplied by TomTom Maps. Since the fastest route is not always the shortest, and most cities contain one-way streets, the distance matrix is not symmetrical.

Travel times between the stops are determined in the same way as the distance matrix. Due to the fact that we do not consider online events, and use a fixed number of stops, we are able to use a pre-calculated time matrix. The travel times between locations are determined with TomTom Maps, these travel times are calculated with the use of average speeds on various types of roads. These average speeds are lower than the allowed speed, creating a bit of slack time. The slack time handles uncertainty (e.g., waiting for a red light, turn time) in the travel time.

5.1.2 MODEL SETTINGS

In Section 4.4 we mentioned two models, model 1 uses a fixed detour time, and model 2 uses a factor to determine the maximum detour time. We programmed both models in Delphi XE7. Our simulation program enables the variation of the following parameters: call time, capacity of the vehicle, the maximum number of available vehicles, the maximum detour time or factor, and finally the pickup flexibility (TW size).

Table 5.1 represents the cases for model 1, and Table 5.2 for model 2. In each case only one parameter is adjusted, this parameter is recognized by the arrow and the brackets. The parameter goes from the value before the arrow to the value after the arrow with the step size shown between the brackets. In each table the last row, is a combination of several parameters. For all instances, either a vehicle fleet of nine vehicles with a capacity of three persons (vehicle fleet A), or a vehicle fleet of six vehicles with a capacity of eight persons (vehicle fleet B) is used.

Table 5.1: *Cases for Model 1*

Model 1: Fixed Time Window with a fixed detour time				
	Vehicles	TW Size	Detour time	Call time
Case 1	Vehicle Fleet A or B	15	5	0 → 50 (5 min)
Case 2	Vehicle Fleet A or B	15	0 → 10 (1 min)	30
Case 3	Vehicle Fleet A or B	5 → 30 (5 min)	5	30
Case 4	1→ All requests are served by the 3 or 8 persons vehicles	15	5	30
Case 5	Vehicle Fleet A or B	15	0 → 10 (1 min)	0 → 50 (5 min)

Table 5.2: *Cases for model 2*

Model 2: Fixed Time Window with a detour factor				
	Vehicles	TW Size	Detour factor	Call time
Case 6	Vehicle Fleet A or B	15	1.5	0 → 50 (5 min)
Case 7	Vehicle Fleet A or B	15	0 → 2 (0.1)	30
Case 8	Vehicle Fleet A or B	5 → 30 (5 min)	1.5	30
Case 9	1→ All requests are served by the 3 or 8 persons vehicles	15	1.5	30
Case 10	Vehicle Fleet A or B	15	0 → 2 (0.2)	0 → 50 (5 min)

To measure the performance of each case, we use several measurements. We divide the performance into two categories, performance measures related to the operation (Connexxion), and to customer service. First we treat the performance measures related to the operation, followed by the performance measures related to the customers.

The performance measures for the operation:

- Number of served requests; all the requests that are served by our system.
- Number of not served requests; the requests that could not be served, given the restrictions.
- Total driven distance; the distance that is driven to serve the requests.
- Total driving time; the time needed to serve all the requests.
- Average occupation; the average number of customers in the vehicle.

The performance measures for the customers:

- Average detour time; the average extra time that is needed to transport customers towards their destination.
- Average waiting time; the average time that a customer needs to wait at the pickup location.

5.2 RESULTS

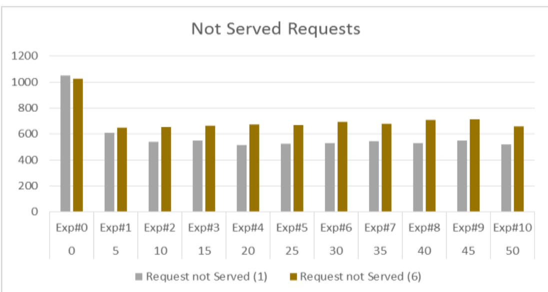
As mentioned in Section 5.1.2, in each case the results found are split into results for nine times a three person vehicle (vehicle fleet A), and six times an eight person vehicle (vehicle fleet B). The standard parameters settings are: 30 minute call time, 15 minute time window, detour time of 5 minutes for model 1, or detour factor of 1.5 for model 2. The minimum communication time is always set to 5 minutes. The following subsections describe the results when a parameter is changed. We start with changing the call time, followed by detour time, then the TW size, and the number of available vehicles, to finalize with changing the call and detour time.

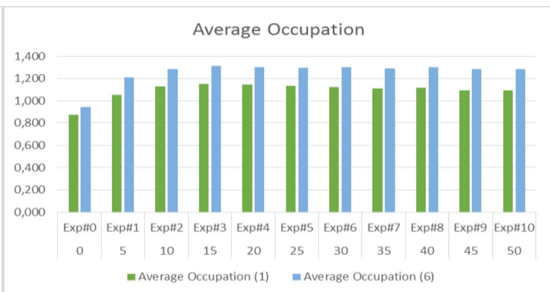
In the following sections we discuss the results. The cases are represented between brackets, e.g., (1) means case 1. Each case contains multiple runs, we call a single run an experiment, shown in the tables and graphs as 'Exp#'. The graphs for all cases are shown in Appendix D, and the detailed data of cases 5 and 10 are stated in Appendix E. For cases 2-5 and 7-10 we only treat what is extraordinarily or worth mentioning. Cases 1 and 6 are explained extensively. For each case we write a conclusion containing a table with the experiment results, except for cases 5 and 10. The shown table for cases 5 and 10 only contains experiments where at least one performance indicator is in the top 5 best performing indicators.

Cases 1 and 6 (Call time)

In cases 1 and 6 the parameter call time is changed, the call time is the maximum time up front in which a request of a customer must be known. The call time is the time where all the requests need service are known, the models use this time to find the best possible insertion for each request. The results for a vehicle fleet A and B are respectively shown in Figure 5.3, and Figure 5.4.

Vehicle Fleet A





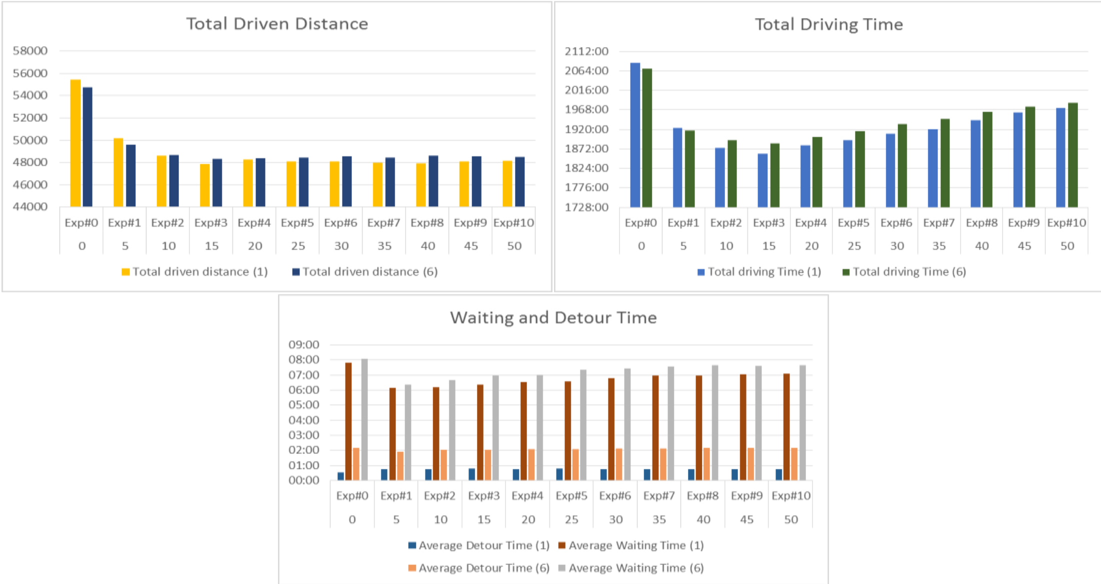


Figure 5.3: *Cases 1 and 6 with vehicle fleet A*

Figure 5.3, shows the results for vehicle fleet A. The chart of "Not-Served Requests" shows that a call time only with a call time of zero the number of not served request is high, when the call time set on 5 minutes the not served requests remain constant.

The chart "Average Occupation" shows that the average occupation is always higher when we use model 2. We see that a small call time results in a lower average occupation, but when the call time becomes larger than 10 minutes the average occupation remain almost the same for both models.

The chart "Total Driven Distance" shows that when a small call time is used, the driven kilometres are significantly more compared to a larger call time. This is due to the fact that a small call time results in an immediately departure of the bus to service the request, reducing the number of possible combinations, and hence resulting in a lower average occupation. The influence of a call time larger than 15 minutes on the total driven distance is minimal.

The chart "Total Driving Time" shows a remarkable pattern. First there is a decline in driving time, but when the call time passes the 15 minutes, the total driving time is increasing, while the total distance driven remains constant, as well as the number of not served requests. We state this increase is caused by routes that are time consuming, requests that have a short distance, with a long travel time between the pickup and drop-off locations.

The last chart "Waiting and Detour Time", shows that a longer call time results in a slightly higher average waiting and detour time. We think this is caused due to the increase in travel time.

Vehicle Fleet B

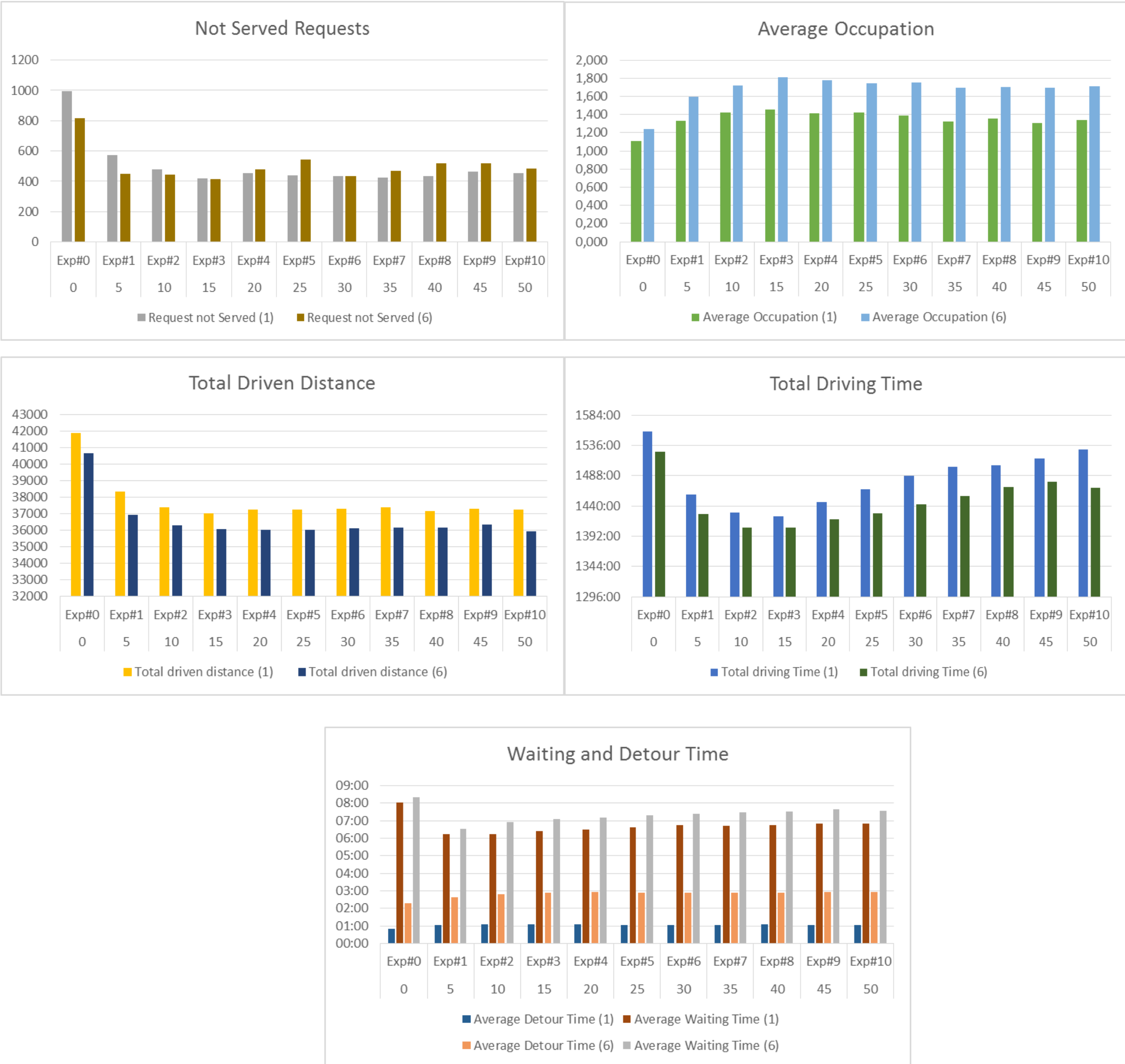


Figure 5.4: *Cases 1 and 6 with vehicle fleet B*

Figure 5.4 shows the results for vehicle fleet B. The patterns shown are quite similar to the patterns shown in Figure 5.3. We describe the deviations of the patterns. The chart "Not Served Requests" shows a small increase in the middle, this is caused by requests that are inserted in a route, but due to the insertion of other requests the sequence is performing worse.

The chart "Total Driven Distance", shows a completely different pattern compared to the three person vehicle case. Here model 2 always outperforms model 1, with at least 800 kilometres. This significant reduction is explained by the higher average occupation of the vehicles, meaning more rides are combined, which leads to a reduction in kilometres.

Conclusion

The best five results found are highlighted in red. All results, when using vehicle fleet A, are shown in Table 5.3.

Table 5.3: *Results of cases 1 and 6 for vehicle fleet A*

Cases 1 and 6 (call time)	0	5	10	15	20	25	30	35	40	45	50
(3 Person vehicles)	Exp#0	Exp#1	Exp#2	Exp#3	Exp#4	Exp#5	Exp#6	Exp#7	Exp#8	Exp#9	Exp#10
Request served (1)	20684	21125	21198	21188	21221	21209	21205	21192	21205	21184	21216
Request not Served (1)	1052	611	538	548	515	527	531	544	531	552	520
Total driven distance (1)	55469,39	50149,03	48594,63	47836,21	48281,69	48109,83	48104,76	47980,85	47931,43	48083,58	48167,87
Total driving Time (1)	2084:19	1923:47	1873:43	1860:02	1880:37	1893:57	1908:47	1920:10	1941:46	1962:07	1972:11
Average Occupation (1)	0,872	1,053	1,127	1,155	1,148	1,136	1,125	1,113	1,117	1,094	1,093
Average Detour Time (1)	00:33	00:44	00:45	00:46	00:46	00:46	00:46	00:46	00:46	00:46	00:45
Average Waiting Time (1)	07:49	06:08	06:12	06:21	06:32	06:34	06:48	06:58	06:57	07:04	07:05
Request served (6)	20712	21089	21083	21070	21062	21069	21044	21056	21027	21021	21077
Request not Served (6)	1024	647	653	666	674	667	692	680	709	715	659
Total driven distance (6)	54776,81	49574,01	48658,65	48310,71	48379,16	48456,46	48575,44	48417,23	48602,07	48560,43	48487,68
Total driving Time (6)	2068:54	1916:51	1892:38	1885:19	1900:33	1915:02	1932:44	1946:07	1963:37	1975:59	1985:44
Average Occupation (6)	0,942	1,208	1,283	1,314	1,302	1,299	1,304	1,294	1,301	1,282	1,284
Average Detour Time (6)	02:10	01:53	02:01	02:03	02:05	02:04	02:08	02:07	02:10	02:10	02:09
Average Waiting Time (6)	08:05	06:22	06:39	06:58	07:01	07:21	07:26	07:33	07:40	07:36	07:40

Table 5.3 shows that in case 1 a kind of diamond is created, when the call time is short the higher the performance for the customers, a longer call time leads to a better performance for Connexxion. We think a balance between the performance for the customers and Connexxion is the best. We conclude that a call time of 15 minutes, in case of model 1, has the best performance.

When we analyse case 6, we see that a call time of 15 or 25 minutes, results all the six performance indicators are in the top 5 best performing indicators. Although both experiments are showing a good performance, the performance in the experiment with a call time of 15 minutes shows a slightly better result on all indicators.

If we compare both models, we see that the best performance for both models is with a call time of 15 minutes. We see that model 2 shows a higher average occupation of the vehicles, but this result in more time in a vehicle for the customer, due to a higher average detour time. When all the other performance measures are compared, we see that model 1 shows the best performance, accept on the average occupation. That is why we state in this case model 1 has the best overall performance when using vehicle fleet A, and a call time of 15 minutes.

The results for vehicle fleet B are shown in Table 5.4.

Table 5.4: *Results of cases 1 and 6 for the 8 person vehicles*

Cases 1 and 6 (Call time) (8 person vehicles)	0 Exp#0	5 Exp#1	10 Exp#2	15 Exp#3	20 Exp#4	25 Exp#5	30 Exp#6	35 Exp#7	40 Exp#8	45 Exp#9	50 Exp#10
Request served (1)	20741	21164	21256	21314	21280	21294	21303	21309	21303	21273	21283
Request not Served (1)	995	572	480	422	456	442	433	427	433	463	453
Total driven distance (1)	41878,77	38355,31	37412,43	37023,55	37241,78	37277,61	37330,12	37407,64	37169,64	37323,48	37257,21
Total driving Time (1)	1558:02	1458:23	1429:20	1423:43	1446:04	1466:49	1487:16	1501:49	1504:19	1515:22	1529:24
Average Occupation (1)	1,110	1,331	1,426	1,456	1,415	1,420	1,393	1,323	1,357	1,311	1,339
Average Detour Time (1)	00:51	01:03	01:05	01:04	01:04	01:04	01:04	01:04	01:04	01:03	01:04
Average Waiting Time (1)	08:02	06:15	06:15	06:23	06:29	06:37	06:45	06:43	06:44	06:50	06:50
Request served (6)	20921	21286	21291	21323	21259	21194	21302	21267	21215	21219	21251
Request not Served (6)	815	450	445	413	477	542	434	469	521	517	485
Total driven distance (6)	40673,01	36938,73	36301,71	36071,62	36036,76	36039,08	36139,06	36162,85	36158,51	36369,43	35956,58
Total driving Time (6)	1525:36	1427:21	1406:07	1405:31	1418:38	1428:38	1442:03	1456:02	1469:32	1477:59	1468:49
Average Occupation (6)	1,237	1,600	1,722	1,809	1,782	1,747	1,753	1,696	1,702	1,694	1,710
Average Detour Time (6)	02:17	02:39	02:49	02:53	02:55	02:54	02:54	02:53	02:53	02:56	02:55
Average Waiting Time (6)	08:19	06:31	06:56	07:06	07:11	07:18	07:23	07:30	07:31	07:39	07:33

Table 5.4 shows almost a similar diamond as in case 1 using vehicle fleet A. Due to the same reasons as mentioned before, a call time of 15 shows the best result, for both models. Comparing the models, we see that model 2 is again better in combining requests, but in the case we vehicle fleet B, we see that model 2 has the best performance for the operation when using a call time of 15 minutes, when the service level is more important model 1 is the preferred choice. Although the service level is important, we think the operational performance is more important, that is why we choose model 2 in case of using vehicle fleet B.

Cases 2 and 7 (Detour Time)

In cases 2 and 7 we alter the maximum allowed detour time/factor. The detour times bounds the maximum time for a customer in a bus. In model 1, the maximum time for a customer in a bus is determined by the shortest path time plus the fixed detour time. In model 2 the maximum time in a bus is determined by the shortest path time plus the shortest path time times the detour factor. The graph are shown in Appendix D.1.

Vehicle Fleet A

The performance indicator "Not Served Requests" shows us that, if a detour is not allowed the not served requests is larger than 3000, a small detour reduces the number of not served requests drastically. When the detour time becomes larger than 5 minutes, or in case of a detour factor of 0.5, the not served requests are increasing. This increase eventually results in a more rejected requests, compared to a small detour time. We state that the phenome is due to the position of the vehicles in Helmond. A larger detour prevents vehicles from returning to the depot. So the travel time to a new request location is too large to service the request on time.

The performance indicators detour and waiting time shows that a small maximum detour lead to higher average waiting times. When increasing the maximum detour time or factor, we see that the average detour keeps increasing, while the waiting times at the stops remain the same. Increasing the maximum detour time do not lead to lower waiting times, but results in more time in the bus. The other performance indicators are showing logical patterns, a higher detour time leads to more request combinations. More request combination leads to less driving time and distance. When increasing the detour time we see that the performance indicators: total distance driven and total driving time, are showing similar patterns. The less kilometres driven, the shorter the total driving time.

Vehicle Fleet B

When we use vehicle fleet B. We notice that a detour factor greater than 1 does not reduce the driven kilometres any further, but causes a slight increase. The effects of an increasing detour time creates a slightly increased difference between the two models.

Conclusion

All results, when using a vehicle fleet A, are shown in Table 5.5, and using vehicle fleet B are shown in Table 5.6.

Table 5.5: *Results of cases 2 and 7 for vehicle fleet A*

Cases 2 and 7 (Detour time)	0 or 0	1 or 0.1	2 or 0.2	3 or 0.3	4 or 0.4	5 or 0.5	6 or 0.6	7 or 0.7	8 or 0.8	9 or 0.9	10 or 1.0
(3 person vehicles)	Exp#0	Exp#1	Exp#2	Exp#3	Exp#4	Exp#5	Exp#6	Exp#7	Exp#8	Exp#9	Exp#10
Request served (2)	18467	21024	21179	21187	21172	21205	21187	21165	21118	21133	21116
Request not Served (2)	3269	712	557	549	564	531	549	571	618	603	620
Total driven distance (2)	62888,52	52594,82	50152,33	49097,91	48361,08	48104,76	47847,02	48043,03	48219,12	48123,95	48129,97
Total driving Time (2)	2436:28	2056:27	1980:48	1942:42	1917:05	1908:47	1904:36	1916:08	1920:37	1923:23	1916:29
Average Occupation (2)	0,663	0,918	0,991	1,038	1,086	1,125	1,153	1,179	1,217	1,239	1,266
Average Detour Time (2)	00:00	00:04	00:14	00:26	00:36	00:46	00:57	01:09	01:23	01:33	01:40
Average Waiting Time (2)	08:48	07:28	07:09	07:01	06:53	06:48	06:40	06:39	06:40	06:37	06:38
Request served (7)	18467	20911	21061	21199	21235	21221	21244	21181	21238	21163	21190
Request not Served (7)	3269	825	675	537	501	515	492	555	498	573	546
Total driven distance (7)	62888,52	54092,32	51462,91	50074,82	49120,3	48521,11	47950,93	47759,12	47515,98	47584,32	47571,3
Total driving Time (7)	2436:28	2108:04	2013:49	1978:08	1944:33	1930:05	1908:51	1909:03	1896:18	1903:26	1901:37
Average Occupation (7)	0,663	0,883	0,952	0,985	1,031	1,066	1,091	1,112	1,150	1,155	1,184
Average Detour Time (7)	00:00	00:02	00:08	00:14	00:23	00:31	00:39	00:47	00:57	01:06	01:17
Average Waiting Time (7)	08:48	07:43	07:31	07:24	07:14	07:18	07:15	07:15	07:09	07:07	07:11
Cases 2 and 7 (Detour time)	1.1	1.2	1.3	1.4	1.5	1.6	1.7	1.8	1.9	2.0	
(3 person vehicles)	Exp#11	Exp#12	Exp#13	Exp#14	Exp#15	Exp#16	Exp#17	Exp#18	Exp#19	Exp#20	
Request served (7)	21175	21166	21120	21091	21044	21012	20996	21023	20918	20796	
Request not Served (7)	561	570	616	645	692	724	740	713	818	940	
Total driven distance (7)	47715,2	48038,63	48191,08	48472,66	48575,44	48795,66	48865,92	49109,95	49517,11	49644,97	
Total driving Time (7)	1903:11:59	1915:29:47	1920:52:06	1923:34:51	1932:44:13	1948:26:59	1942:35:53	1955:19:06	1967:01:10	1967:54:22	
Average Occupation (7)	1,220	1,241	1,269	1,287	1,304	1,319	1,341	1,354	1,379	1,414	
Average Detour Time (7)	01:26	01:38	01:48	01:58	02:08	02:20	02:24	02:35	02:48	03:06	
Average Waiting Time (7)	07:15	07:18	07:24	07:23	07:26	07:24	07:29	07:28	07:30	07:31	

Table 5.5 shows an unexpected pattern for case 2, we expected a longer detour time should lead to a better performance for the operation, since the planning flexibility is increased. We see that a detour time of 6 minutes shows the best performance for model 1, having all most all performance indicators in the top 5.

In case 7 more experiments are done. We see test a maximum detour that is twice the ride length. This long detour shows the highest average occupation, but also results in a high number of rejected requests. We see that experiment 8 shows four performance indicators in the top 5, with a corresponding detour factor of 0.8. When using model 2, a detour factor of 0.8 shows the best results.

Comparing the best performances of the models, we see that model 2 with a detour factor of 0.8 is outperforming model 1 with a detour time of 6 minutes. We conclude model 2 with a detour factor of 0.8 is the best choice, using vehicle fleet A.

Table 5.6: *Results of cases 2 and 7 for vehicle fleet B*

Cases 2 and 7 (Detour time)	0 or 0	1 or 0.1	2 or 0.2	3 or 0.3	4 or 0.4	5 or 0.5	6 or 0.6	7 or 0.7	8 or 0.8	9 or 0.9	10 or 1.0
(8 person vehicles)	Exp#0	Exp#1	Exp#2	Exp#3	Exp#4	Exp#5	Exp#6	Exp#7	Exp#8	Exp#9	Exp#10
Request served (2)	15584	20250	20872	21062	21143	21303	21326	21394	21385	21393	21384
Request not Served (2)	6152	1486	864	674	593	433	410	342	351	343	352
Total driven distance (2)	47820,26	42570,09	40242,26	38966,94	37901,02	37330,12	36659,84	36491,63	36026,11	35817,21	35733,86
Total driving Time (2)	1815:57	1657:16	1575:39	1539:21	1501:01	1487:16	1459:28	1452:06	1434:18	1432:33	1427:59
Average Occupation (2)	0,687	1,006	1,143	1,255	1,330	1,393	1,490	1,555	1,623	1,662	1,702
Average Detour Time (2)	00:00	00:06	00:20	00:34	00:49	01:04	01:20	01:38	01:56	02:09	02:23
Average Waiting Time (2)	09:42	07:59	07:32	07:07	06:53	06:45	06:25	06:23	06:14	06:07	06:02
Request served (7)	15584	19778	20476	20783	21058	21213	21245	21305	21344	21356	21345
Request not Served (7)	6152	1958	1260	953	678	523	491	431	392	380	391
Total driven distance (7)	47820,26	43865,75	41888,92	40759,81	39254,67	38452,61	37895,56	37228,07	36762,29	36704,32	36450,86
Total driving Time (7)	1815:57	1692:46	1632:48	1594:30	1552:41	1526:34	1510:17	1480:18	1467:32	1468:49	1458:19
Average Occupation (7)	0,687	0,950	1,050	1,120	1,176	1,271	1,302	1,359	1,422	1,478	1,528
Average Detour Time (7)	00:00	00:03	00:10	00:19	00:31	00:42	00:52	01:04	01:17	01:31	01:46
Average Waiting Time (7)	09:42	08:21	08:07	07:51	07:34	07:34	07:28	07:21	07:19	07:19	07:13
Cases 2 and 7 (Detour time)	1.1	1.2	1.3	1.4	1.5	1.6	1.7	1.8	1.9	2.0	
(8 person vehicles)	Exp#11	Exp#12	Exp#13	Exp#14	Exp#15	Exp#16	Exp#17	Exp#18	Exp#19	Exp#20	
Request served (7)	21368	21338	21295	21313	21302	21258	21247	21160	21193	21104	
Request not Served (7)	368	398	441	423	434	478	489	576	543	632	
Total driven distance (7)	36209,28	36007,58	36078,52	36082,4	36139,06	36259,65	36160,66	36431,13	36528,67	36694,71	
Total driving Time (7)	1443:53:54	1437:27:29	1446:35:26	1444:14:48	1442:03:20	1447:28:17	1448:11:10	1453:01:31	1451:36:19	1459:25:59	
Average Occupation (7)	1,607	1,619	1,669	1,722	1,753	1,754	1,843	1,861	1,919	1,939	
Average Detour Time (7)	02:00	02:13	02:27	02:41	02:54	03:10	03:27	03:41	03:55	04:15	
Average Waiting Time (7)	07:16	07:04	07:23	07:17	07:23	07:25	07:24	07:33	07:28	07:31	

Table 5.6 shows that in case 2, the best performances are all located with larger detour times, with exception of the average detour time. The average waiting time is slightly decreasing while the average detour is increasing almost twice as fast. We think the best balance in performance for case 2 is found with a detour time of 7 minutes, when using vehicle fleet A.

Case 7 does not show the best performance with the largest detour factors. In case 7 only experiment 12 has four performance indicators in the top 5. This experiment shows us that not only the performance of the operation is good, but the average waiting time for the customers is the lowest, compared to the other experiments in case 7. We think the best performance for case 7 with the use vehicle fleet B is with a detour factor of 1.2.

Comparing both models, we see that model 2 has a slight advantage when we look at the operational performance: it has a shorter total driven distance, a shorter total driven time, and a higher occupation. Model 1 has a better score for the customer service, and it serves more requests. That is the reason why we prefer model 1 with a detour time of 7 minutes, when using vehicle fleet B.

Cases 3 and 8 (TW Size)

In this experiment we variate the size of the TW. The TW is the time that bounds the earliest pickup possibility and the latest pickup possibility. The graphs are shown in Appendix D.2.

Vehicle Fleet A

Cases 3 and 8 both show a remarkable pattern on the total driven distance. While the total driven time is decreasing, the total driven distance starts increasing, when increasing the TW size. We think this is caused by the way customers are inserted into the routes. A TW size of 15 minutes creates the worst sequence when only looking to the total distance driven. When the TW size becomes larger than 15 minutes the total distance driven is declining again.

The larger the TW size, the more time the models have to create better sequences of the requests, increasing the planning flexibility, but this is at the expense of the average waiting time. The average detour remains constant for all TW size larger than 5. The TW size of 5 minutes shows a slightly reduced average detour time compared to the other TW sizes.

Vehicle Fleet B

The performance patterns of changing the TW size for vehicle fleet B, show similar patterns. The remarkable patterns are explained in the same way, when using vehicle fleet A. Only the performance values have changed.

Conclusion

The best performance measurements for cases 3 and 8, when using vehicle fleet A the results are shown in Table 5.7, using vehicle fleet B the results are shown in Table 5.8. Note that in tables containing results of the cases 3 and 8, only the best two performance measures are highlighted, since only six experiments are made.

Table 5.7: *Results of cases 3 and 8 with vehicle fleet A*

Cases 3 and 8 (TW Size)	5	10	15	20	25	30
(3 person vehicles)	Exp#0	Exp#1	Exp#2	Exp#3	Exp#4	Exp#5
Request served (3)	19990	20803	21205	21391	21485	21601
Request not Served (3)	1746	933	531	345	251	135
Total driven distance (3)	47737,21	48189,04	48104,76	47854,72	46797,73	45634,19
Total driving Time (3)	2140:40:39	1997:22:53	1908:47:59	1875:12:27	1827:13:58	1784:12:56
Average Occupation (3)	0,933	1,046	1,125	1,156	1,211	1,262
Average Detour Time (3)	00:40	00:46	00:46	00:47	00:49	00:52
Average Waiting Time (3)	01:20	03:42	06:48	09:59	12:48	15:21
Request served (8)	20057	20743	21044	21266	21458	21541
Request not Served (8)	1679	993	692	470	278	195
Total driven distance (8)	47887,55	48066,19	48575,44	48620,83	47502,3	46856,74
Total driving Time (8)	2104:24:16	1972:55:33	1932:44:13	1912:47:50	1871:54:58	1839:48:55
Average Occupation (8)	1,071	1,240	1,304	1,333	1,383	1,446
Average Detour Time (8)	01:52	02:04	02:08	02:09	02:09	02:13
Average Waiting Time (8)	01:33	04:16	07:26	10:42	13:26	16:16

Table 5.7 shows the best performance for the operation when the TW size is large, and the best performance for the customers when using a small TW. Both models show practically the same best pattern. Again it is important to find a balance in performance for both stakeholders. We think that the balance is found with a TW size of 20 minutes for both models.

Comparing the results of the best performance of each model, we directly see that model 1 outperforms model 2 on all performance indicators. Thus, we prefer model 1 when using vehicle fleet A.

Table 5.8: *Results of cases 3 and 8 with vehicle fleet B*

Cases 3 and 8 (TW Size)	5	10	15	20	25	30
(8 person vehicles)	Exp#0	Exp#1	Exp#2	Exp#3	Exp#4	Exp#5
Request served (3)	19605	20825	21303	21484	21598	21692
Request not Served (3)	2131	911	433	252	138	44
Total driven distance (3)	37041,87	37397,1	37330,12	36837,46	35874,28	34448,56
Total driving Time (3)	1631:49:01	1541:29:16	1487:16:40	1440:49:35	1400:03:42	1344:15:50
Average Occupation (3)	1,120	1,310	1,393	1,464	1,532	1,649
Average Detour Time (3)	00:51	01:01	01:04	01:06	01:09	01:12
Average Waiting Time (3)	01:24	03:46	06:45	09:44	12:42	15:04
Request served (8)	20265	20946	21302	21428	21576	21660
Request not Served (8)	1471	790	434	308	160	76
Total driven distance (8)	36385,33	36260,83	36139,06	36132,18	35136,06	33899,99
Total driving Time (8)	1596:28:21	1488:57:27	1442:03:20	1426:05:50	1379:02:11	1336:23:15
Average Occupation (8)	1,386	1,659	1,753	1,787	1,935	2,009
Average Detour Time (8)	02:33	02:49	02:54	03:02	03:03	03:06
Average Waiting Time (8)	01:44	04:23	07:23	10:35	13:47	15:39

Table 5.8 shows almost the same best performances as Table 5.7. In this case we choose again a TW size of 20 minutes, and prefer using model 1 when using vehicle fleet A.

Cases 4 and 9 (Vehicles)

In this experiment we add vehicles to the fleet until all requests are served, this allows us to see the effect of adding more vehicles to the fleet. We start with cases 4 and 9 adding three person vehicles. The graphs are shown in Appendix D.3.

Adding three person vehicles

We see an exponential decrease in the not served requests when adding more vehicles to the vehicle fleet. We state that serving 100% of the requests within the given restrictions is expensive. The last 252 request require 5 extra vehicles, while the other 10 vehicles are serving 21,484 requests. We need a total of 15 vehicles using model 1, and 14 vehicles using model 2 to serve all the requests.

The indicators "average occupation", "total driven distance", and the 'total driving time" show a square root increase. Adding vehicles to a small fleet have a higher impact, than adding the last vehicle to serve the last requests. The performance of the "Detour and Waiting Time", shows a small linear decrease in the average waiting time and average detour time, when more vehicles are added. After adding the 11th vehicle, the average detour and waiting time remain almost the same.

Adding eight person vehicles

Using vehicle fleet B a drastical reduction in the number of vehicles needed to serve all the requests is shown. Both models need 9 vehicles to serve all the requests. Again we see similar the patterns of the performance indicators, when using vehicle fleet A or B. We see that the last 76 requests for model 1, and 93 requests for model 2, need 3 extra vehicles..

Conclusion

The best performance measurements for cases 3 and 8, when using vehicle fleet A are shown in Table 5.9, and using vehicle fleet B are shown in Table 5.10.

Table 5.9: *Results of cases 4 and 9 with vehicle fleet A*

Cases 4 and 9 (Vehicle)	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
(3 person vehicles)	Exp#0	Exp#1	Exp#2	Exp#3	Exp#4	Exp#5	Exp#6	Exp#7	Exp#8	Exp#9	Exp#10	Exp#11	Exp#12	Exp#13	Exp#14
Request served (4)	4318	7998	11262	14237	16676	18498	19790	20609	21205	21484	21626	21688	21722	21734	21736
Request not Served (4)	17418	13738	10474	7499	5060	3238	1946	1127	531	252	110	48	14	2	0
Total driven distance (4)	9222,73	17392,03	24994,76	31866,72	37658,95	42021,39	44790,03	46991,62	48104,76	48761,1	49113,9	49288,9	49446,27	49421,3	49423,11
Total driving Time (4)	352:56	661:04	954:22	1230:15	1469:40	1660:50	1774:05	1868:35	1908:47	1936:44	1949:56	1952:27	1955:01	1955:34	1956:09
Average Occupation (4)	0,741	0,823	0,871	0,907	0,966	1,021	1,068	1,098	1,125	1,138	1,153	1,154	1,157	1,161	1,160
Average Detour Time (4)	00:35	00:39	00:39	00:41	00:42	00:43	00:44	00:47	00:46	00:47	00:47	00:47	00:46	00:47	00:47
Average Waiting Time (4)	10:01	09:53	09:40	09:12	08:37	08:07	07:36	07:08	06:48	06:29	06:15	06:03	06:00	05:56	05:55
Request served (9)	3683	7198	10516	13537	16124	18087	19491	20416	21044	21398	21594	21688	21725	21736	
Request not Served (9)	18053	14538	11220	8199	5612	3649	2245	1320	692	338	142	48	11	0	
Total driven distance (9)	9108,63	17330,54	24913,32	31752,75	37616,06	42063,94	45111,52	47167,25	48575,44	49233,35	49434,33	49768,58	49973,69	49947,8	
Total driving Time (9)	352:35	662:13	956:37	1234:09	1473:39	1659:40	1792:08	1872:07	1932:44	1967:25	1966:17	1978:49	1985:07	1984:12	
Average Occupation (9)	0,870	0,959	1,031	1,069	1,145	1,223	1,258	1,289	1,304	1,323	1,332	1,327	1,330	1,330	
Average Detour Time (9)	02:46	02:42	02:35	02:27	02:22	02:18	02:12	02:11	02:08	02:06	02:04	02:03	02:03	02:04	
Average Waiting Time (9)	10:48	10:29	10:17	09:44	09:13	08:41	08:16	07:49	07:26	07:04	06:45	06:36	06:32	06:30	

Table 5.9 shows that not serving customers results in less kilometres and driving time. But rejecting more than 5% of all the requests is not acceptable. We do not consider experiments 0 to 7, we need at least 9 vehicles for both cases. Since the purchase costs of a vehicle are high, we want to use as less vehicles as possible, while serving the most requests, in the shortest possible time. We state a balance for model 1 is found with the use of 11 vehicles, since three performance indicators are in the top 5. The best performance for model 2 is found with the use of 10 vehicles.

When comparing both models, we see that model 1 serves significantly more requests, and has a better performance on all performances indicators, with exception of the average occupation than model 2. We state that using 11 times a three person vehicle, model 1 provides the best performance.

Table 5.10: Results of cases 4 and 9 with vehicle fleet B

Cases 4 and 9 (Vehicle)	1	2	3	4	5	6	7	8	9
(8 person vehicles)	Exp#0	Exp#1	Exp#2	Exp#3	Exp#4	Exp#5	Exp#6	Exp#7	Exp#8
Request served (4)	5707	10669	14791	18064	20219	21303	21660	21729	21736
Request not Served (4)	16029	11067	6945	3672	1517	433	76	7	0
Total driven distance (4)	9192,72	17248,99	24590,74	30849,35	35109,43	37330,12	38162,32	38308,41	38301,02
Total driving Time (4)	352:11	657:05	945:18	1205:14	1389:15	1487:16	1515:33	1520:06	1517:31
Average Occupation (4)	0,914	1,024	1,096	1,164	1,320	1,393	1,428	1,462	1,466
Average Detour Time (4)	00:53	00:57	00:57	01:01	01:02	01:04	01:05	01:06	01:07
Average Waiting Time (4)	09:30	09:12	08:47	08:07	07:26	06:45	06:13	06:04	06:01
Request served (9)	5019	9799	14327	17701	20112	21302	21643	21731	21736
Request not Served (9)	16717	11937	7409	4035	1624	434	93	5	0
Total driven distance (9)	9004,1	17023,22	24364,18	30407,56	34355,49	36139,06	36604,6	36760,09	36716,97
Total driving Time (9)	352:04	657:53	944:43	1193:37	1366:43	1442:03	1463:19	1463:30	1463:41
Average Occupation (9)	1,145	1,289	1,405	1,471	1,619	1,753	1,810	1,852	1,845
Average Detour Time (9)	03:37	03:31	03:20	03:10	03:01	02:54	02:57	02:57	02:56
Average Waiting Time (9)	10:30	10:04	09:26	08:56	08:09	07:23	06:51	06:42	06:40

Table 5.10 shows the same pattern as Table 5.9. We do not consider the experiments 0 to 5, due to the high number of rejected requests. For both models the use of six vehicles show the best acceptable results. Comparing the models we see that using 6 eight person vehicles in combination with model 2, results in the best performance for Connexxion, while the performance for the customers is the best when using model 1. In this case we choose for model 2, due to the lower operational costs, while having an acceptable service level.

Cases 5 and 10 (Call time and Detour time)

Vehicle Fleet A

In cases 5 and 10 all combination of varying the call and detour time are done, resulting in 264 experiments. Table 5.11 shows the best results for cases 5 and 10 using vehicle fleet A, and Vehicle Fleet B

Table 5.12 shows the result using vehicle fleet B. Note that all experiments without any performance indicator in the top 5 are left out, they are shown in the Appendix E.

Table 5.11: *Results of cases 5 and 10 with vehicle fleet A*

Cases 5 and 10 (3 person)	Exp#0	Exp#1	Exp#2	Exp#3	Exp#4	Exp#5	Exp#13	Exp#19	Exp#20	Exp#21	Exp#23	Exp#25	Exp#26	Exp#27	Exp#28	Exp#29	Exp#31
Call time	0	10	20	30	40	50	10	10	20	30	50	10	20	30	40	50	10
Detour time	0 or 0	0 or 0	0 or 0	0 or 0	0 or 0	0 or 0	2 or 0.4	3 or 0.6	3 or 0.6	3 or 0.6	3 or 0.6	4 or 0.8	4 or 0.8	4 or 0.8	4 or 0.8	4 or 0.8	5 or 1
Request Served (5)	17946	18469	18512	18467	18465	18515	21164	21207	21159	21187	21178	21173	21176	21172	21176	21144	21198
Request Not Served (5)	3790	3267	3224	3269	3271	3221	572	529	577	549	558	563	560	564	560	592	538
Total Driven Distance (5)	63806,22	62932,84	63006,53	62888,52	62879,2	62995,58	50677,33	49511,59	49210,98	49097,91	48871,05	48793,51	48357,06	48361,08	48361,11	48149,82	48594,63
Total Driving Time (5)	2375:31	2365:20	2398:48	2436:28	2464:23	2496:38	1931:28	1897:42	1907:17	1942:42	2001:30	1878:02	1886:06	1917:05	1956:06	1982:26	1873:43
Average Occupation (5)	0,632	0,686	0,678	0,663	0,657	0,651	0,999	1,049	1,071	1,038	1,011	1,090	1,104	1,086	1,071	1,059	1,127
Average Detour Time (5)	00:00	00:00	00:00	00:00	00:00	00:00	00:14	00:25	00:26	00:26	00:25	00:36	00:36	00:36	00:35	00:36	00:45
Average Waiting Time (5)	08:55	08:23	08:39	08:48	08:56	08:58	06:33	06:19	06:49	07:01	07:19	06:15	06:43	06:53	07:09	07:14	06:12
Request Served (10)	17946	18469	18512	18467	18465	18515	21236	21253	21252	21244	21246	21243	21226	21238	21202	21207	21209
Request Not Served (10)	3790	3267	3224	3269	3271	3221	500	483	484	492	490	493	510	498	534	529	527
Total Driven Distance (10)	63806,22	62932,84	63006,53	62888,52	62879,2	62995,58	49569,23	48798,34	48226,27	47950,93	47987,67	48256,65	47593,94	47515,98	47395,33	47300,04	47967,69
Total Driving Time (10)	2375:31	2365:20	2398:48	2436:28	2464:23	2496:38	1904:11	1881:12	1886:54	1908:51	1968:54	1870:25	1869:16	1896:18	1922:42	1953:42	1867:18
Average Occupation (10)	0,632	0,686	0,678	0,663	0,657	0,651	1,034	1,085	1,103	1,091	1,057	1,133	1,154	1,150	1,123	1,120	1,186
Average Detour Time (10)	00:00	00:00	00:00	00:00	00:00	00:00	00:22	00:37	00:38	00:39	00:38	00:55	00:56	00:57	00:56	00:57	01:14
Average Waiting Time (10)	08:55	08:23	08:39	08:48	08:56	08:58	06:35	06:37	06:56	07:15	07:30	06:26	06:54	07:09	07:20	07:27	06:30

Cases 5 and 10 (3 person)	Exp#32	Exp#33	Exp#34	Exp#35	Exp#37	Exp#39	Exp#41	Exp#43	Exp#44	Exp#49	Exp#55	Exp#56	Exp#61	Exp#62	Exp#63	Exp#64	Exp#65
Call time	20	30	40	50	10	30	50	10	20	10	10	20	10	20	30	40	50
Detour time	5 or 1	5 or 1	5 or 1	5 or 1	6 or 1.2	6 or 1.2	6 or 1.2	7 or 1.4	7 or 1.4	8 or 1.6	9 or 1.8	9 or 1.8	10 or 2.0	10 or 2.0	10 or 2.0	10 or 2.0	10 or 2.0
Request Served (5)	21221	21205	21205	21216	21220	21187	21176	21174	21185	21164	21159	21132	21174	21133	21116	21104	21103
Request Not Served (5)	515	531	531	520	516	549	560	562	551	572	577	604	562	603	620	632	633
Total Driven Distance (5)	48281,69	48104,76	47931,43	48167,87	48420,43	47847,02	47951,09	48206,17	47932,11	48386,77	48445,51	47875,43	48360,33	48353,72	48129,97	48086,94	48435,28
Total Driving Time (5)	1880:37	1908:47	1941:46	1972:11	1872:57	1904:36	1969:29	1866:24	1875:28	1875:14	1879:26	1880:21	1876:54	1892:46	1916:29	1939:56	1996:01
Average Occupation (5)	1,148	1,125	1,117	1,093	1,157	1,153	1,120	1,201	1,212	1,226	1,248	1,272	1,263	1,286	1,266	1,240	1,218
Average Detour Time (5)	00:46	00:46	00:46	00:45	00:56	00:57	00:55	01:09	01:10	01:22	01:32	01:32	01:40	01:40	01:40	01:40	01:40
Average Waiting Time (5)	06:32	06:48	06:57	07:05	06:01	06:40	07:00	06:04	06:24	06:00	06:00	06:23	05:59	06:25	06:38	06:47	06:54
Request Served (10)	21186	21190	21175	21169	21171	21166	21153	21098	21142	21074	20959	21031	20843	20795	20796	20801	20773
Request Not Served (10)	550	546	561	567	565	570	583	638	594	662	777	705	893	941	940	935	963
Total Driven Distance (10)	47649,92	47571,3	47545,3	47517,01	48280,08	48038,63	48014,88	48496,94	48377,3	48606,5	49332,1	49002,99	49773,68	49664,73	49644,97	49870,89	50134,36
Total Driving Time (10)	1869:53	1901:37	1936:06	1959:09	1877:24	1915:29	1969:51	1886:03	1901:41	1888:45	1910:35	1923:40	1930:20	1946:00	1967:54	1995:53	2046:38
Average Occupation (10)	1,211	1,184	1,168	1,151	1,222	1,241	1,203	1,262	1,296	1,306	1,333	1,371	1,355	1,397	1,414	1,394	1,360
Average Detour Time (10)	01:16	01:17	01:16	01:17	01:33	01:38	01:38	01:51	01:57	02:10	02:30	02:34	02:52	03:01	03:06	03:05	03:08
Average Waiting Time (10)	06:51	07:11	07:21	07:29	06:34	07:18	07:39	06:36	07:10	06:39	06:42	07:13	06:49	07:18	07:31	07:45	07:52

Table 5.11 shows that case 5 has only experiment 37 with three performance indicators in the top 5. For case 10 we see experiment 25 is the only experiment with three performance indicators in the top 5. If we compare the results we see that using model 2, results in serving more requests, while having a lower total driving time and total distance, and the performance for the customer is only slightly decreased. That is why we choose to use model 2 with a call time of 10 minutes and a detour factor of 0.8, while using vehicle fleet A.

Vehicle Fleet B

Table 5.12: *Results of cases 5 and 10 with vehicle fleet B*

Cases 5 and 10 (8 person)	Exp#0	Exp#1	Exp#2	Exp#3	Exp#4	Exp#5	Exp#25	Exp#26	Exp#31	Exp#32	Exp#33	Exp#35	Exp#37	Exp#38	Exp#39
Call time	0	10	20	30	40	50	10	20	10	20	30	50	10	20	30
Detour time	0 or 0	0 or 0	0 or 0	0 or 0	0 or 0	0 or 0	4 or 0.8	4 or 0.8	5 or 1	5 or 1	5 or 1	5 or 1	6 or 1.2	6 or 1.2	6 or 1.2
Request Served (5)	15170	15519	15557	15584	15626	15625	21184	21175	21256	21280	21303	21283	21340	21316	21326
Request Not Served (5)	6566	6217	6179	6152	6110	6111	552	561	480	456	433	453	396	420	410
Total Driven Distance (5)	47420,86	47899,5	47873,88	47820,26	47915,46	47888,99	38150,36	37970,88	37412,43	37241,78	37330,12	37257,21	36856,58	36709,28	36659,84
Total Driving Time (5)	1751:22	1783:00	1797:21	1815:57	1829:44	1839:01	1453:03	1473:36	1429:20	1446:04	1487:16	1529:24	1415:14	1434:45	1459:28
Average Occupation (5)	0,671	0,675	0,678	0,687	0,661	0,663	1,351	1,354	1,426	1,415	1,393	1,339	1,506	1,481	1,490
Average Detour Time (5)	00:00	00:00	00:00	00:00	00:00	00:00	00:50	00:49	01:05	01:04	01:04	01:04	01:24	01:23	01:20
Average Waiting Time (5)	09:51	09:33	09:39	09:42	09:43	09:45	06:26	06:43	06:15	06:29	06:45	06:50	05:55	06:16	06:25
Request Served (10)	15170	15519	15557	15584	15626	15625	21364	21354	21294	21387	21345	21353	21283	21321	21338
Request Not Served (10)	6566	6217	6179	6152	6110	6111	372	382	442	349	391	383	453	415	398
Total Driven Distance (10)	47420,86	47899,5	47873,88	47820,26	47915,46	47888,99	37315,09	36951,96	36873,91	36357,59	36450,86	36399,27	36502,75	35887,59	36007,58
Total Driving Time (10)	1751:22	1783:00	1797:21	1815:57	1829:44	1839:01	1437:08	1442:51	1423:16	1427:10	1458:19	1498:52	1414:13	1408:00	1437:27
Average Occupation (10)	0,671	0,675	0,678	0,687	0,661	0,663	1,420	1,444	1,504	1,554	1,528	1,496	1,596	1,654	1,619
Average Detour Time (10)	00:00	00:00	00:00	00:00	00:00	00:00	01:16	01:17	01:43	01:46	01:46	01:47	02:10	02:13	02:13
Average Waiting Time (10)	09:51	09:33	09:39	09:42	09:43	09:45	06:58	07:08	06:54	07:12	07:13	07:28	06:48	07:09	07:04

Cases 5 and 10 (8 person)	Exp#43	Exp#44	Exp#45	Exp#49	Exp#50	Exp#53	Exp#55	Exp#56	Exp#57	Exp#59	Exp#61	Exp#62	Exp#63	Exp#64
Call time	10	20	30	10	20	50	10	20	30	50	10	20	30	40
Detour time	7 or 1.4	7 or 1.4	7 or 1.4	8 or 1.6	8 or 1.6	8 or 1.6	9 or 1.8	9 or 1.8	9 or 1.8	9 or 1.8	10 or 2.0	10 or 2.0	10 or 2.0	10 or 2.0
Request Served (5)	21352	21386	21394	21389	21382	21402	21375	21441	21393	21394	21419	21400	21384	21333
Request Not Served (5)	384	350	342	347	354	334	361	295	343	342	317	336	352	403
Total Driven Distance (5)	36431,77	36196,77	36491,63	36118,73	36210,09	35960,2	36063,41	35756,19	35817,21	35829,21	35941,15	35726,34	35733,86	35706,45
Total Driving Time (5)	1403:11	1411:43	1452:06	1389:56	1412:49	1484:46	1392:53	1397:34	1432:33	1482:35	1389:04	1397:50	1427:59	1447:03
Average Occupation (5)	1,579	1,595	1,555	1,636	1,656	1,527	1,654	1,733	1,662	1,611	1,729	1,754	1,702	1,670
Average Detour Time (5)	01:40	01:39	01:38	01:55	01:55	01:56	02:09	02:11	02:09	02:09	02:23	02:25	02:23	02:24
Average Waiting Time (5)	05:57	06:12	06:23	05:56	06:05	06:21	05:47	05:54	06:07	06:13	05:51	05:56	06:02	06:06
Request Served (10)	21300	21273	21313	21311	21255	21226	21260	21256	21160	21252	21097	21155	21104	21173
Request Not Served (10)	436	463	423	425	481	510	476	480	576	484	639	581	632	563
Total Driven Distance (10)	36289,29	35863,02	36082,4	36208,57	36157,89	36255,66	36425,3	36249,83	36431,13	36459,69	36720,83	36410,74	36694,71	36525,61
Total Driving Time (10)	1407:19	1407:20	1444:14	1404:53	1420:48	1491:26	1413:50	1422:40	1453:01	1504:15	1423:33	1427:53	1459:25	1472:51
Average Occupation (10)	1,690	1,773	1,722	1,794	1,827	1,704	1,843	1,874	1,861	1,789	1,910	2,010	1,939	1,881
Average Detour Time (10)	02:37	02:41	02:41	03:01	03:09	03:12	03:32	03:34	03:41	03:40	04:05	04:09	04:15	04:12
Average Waiting Time (10)	06:50	07:10	07:17	06:44	07:15	07:33	06:54	07:19	07:33	07:41	07:04	07:20	07:31	07:38

Vehicle Fleet B

Table 5.12 shows the best performance for case 5 in experiment 56, with five performance indicators in the top 5. The best performance for case 10 is hard to find, the highest number of performance indicators in the top 5 is two. Nevertheless, we think the best performance is reached in experiment 38, the first experiment containing two performance indicators in the top 5, while having the smallest allowable detour time. Comparing the models, we see that model 1 outperforms model 2 on all performance indicators, with exception of the average occupation. Thus we choose model 2, while using vehicle fleet B.

5.3 CONCLUSION

From our experiments we conclude that both models have a different performance, where model 2 perform better in combining requests, model 1 has a better performance for the customers. One of the highest costs are the wages of drivers and the purchase of vehicles. Although the purchase price of the three person vehicle is cheaper, the wage remains the same. In all situations, the performance vehicle fleet B is better compared to the vehicle fleet A. The less vehicles needed to serve the requests, the higher the revenue becomes while reducing the operating costs, due to the limited number of drivers. To compare both the models, we have summarized the results in Table 5.13. The cells containing a bold font, are the cases with the best performance. Cases 1 to 5 are using model 1, and cases 6-10 are using model 2.

Table 5.13: Summary of the best settings for each case

Case	Vehicle fleet A	Vehicle fleet B
	Parameter	Parameter
Model 1		
1	**Call time:15 minutes**	Call time: 15 minutes
2	Detour time: 6 minutes	**Detour time: 7 minutes**
3	**TW size: 20 minutes**	**TW size: 20 minutes**
4	11 vehicles	6 vehicles
5	Call time: 10 minutes; Detour time: 6 minutes	**Call time: 20 minutes; Detour time: 9 minutes**
Model 2		
6	Call time: 15 minutes	**Call time: 15 minutes**
7	**Detour factor: 0.8**	Detour factor: 1.2
8	TW size: 20 minutes	TW size: 20 minutes
9	**10 vehicles**	**6 vehicles**
10	**Call time: 10 minutes; Detour factor: 0.8**	Call time 20 minutes; detour factor: 1.2

Cases 1 and 6 are showing the best performance using a call time of 15 minutes. A 15 minutes call time, is enough to service the most requests, a longer call time result in assigning request in sequences with less performance.

Case 2 shows a small increase in the maximum detour time, results in a better performance for both the vehicle fleets. When we vehicle fleet B is used the detour time one minute higher. This is due to the capacity of the vehicles, the larger vehicles are able to combine more requests, and combining requests require planning flexibility. Case 7 shows a similar higher detour factor for vehicle fleet B.

Cases 3 and 7 are showing the best balanced performance using a pickup TW of 20 minute, independent of the vehicle fleet. More planning flexibility result in a better performance for the Connexxion, but reduces the performance for the customers.

Cases 4 and 7 show large difference in the number of vehicles to serve the same number of requests. An acceptable performance for vehicles with a capacity of eight persons is achieved, using six vehicles, while at least ten vehicles with a capacity of three persons are needed to achieve an acceptable result. Using less vehicles are drastically reducing the operating costs, but we must keep in mind that we service at least 95% of all request.

Case 5 shows that the best performance is found with a call time of 10 minutes and a detour time of 6 minutes using vehicle fleet A. Using vehicle fleet B a call time of 20 minutes and a detour time of 9 minutes are showing the best performance. Vehicle fleet A shows a smaller call and detour time. We state this is due the higher number of available vehicle, increasing the planning flexibility. The same reason holds for case 10.

Table 5.13 shows, that in some cases the choice for a model varies between the cases. When we use vehicle fleet A, we see that in 3 cases model 2 has the better performance. When we use vehicle fleet B, we see the opposite result. We think the best overall performance is found using a vehicles with a capacity of eight persons. Due to the fact that in all cases the eight person vehicles, are out performing the three person vehicles on all the performance indicators for the operation. The performance for the customers is slightly reduced.

6 CONCLUSION AND RECOMMENDATIONS

"Mathematics is the science which draws necessary conclusions."
- Benjamin Peirce

In this chapter, we provide the conclusions of our research in Section 6.1, followed by the limitation of our model in Section 6.2. In Section 6.3 we describe the recommendations for implementing our model in Helmond. In Section 6.4 we suggest areas for further research.

6.1 CONCLUSION

This section provides the conclusion of our research. We give answers on the research question formulated in Section 1.3.4.

The reason for conducting this research is to see the effect of replacing the existing bus lines by smaller vehicles that only service requests on-demand. We setup a simulation using several restrictions for servicing the customers based on their request. Connexxion wants to get more insight in servicing the existing stops on-demand, and creating flexible routes based on the requests. The model should provide information about the average occupation, the vehicles used, the total operating time and total distance travelled by the vehicles.

Helmond has a service area of 54.75 square kilometre, with a population around 90,000. The area is covered by 91 bus stops serviced by seven bus lines. These bus lines are have a total of 18,206:36 hours, and travel 401,428 kilometres a year. The OV-chip card data shows us that 21,736 requests stay within Helmond. The current utilization of the busses is relatively low, especially outside the rush hours. We conclude that the larger busses should be replaced by smaller vehicles outside the rush hours, with exception of bus line 51.

From the literature we conclude that the DARP formulation is the best formulation for our problem. We added some extensions to make the formulation more suitable for our situation. We found that price is not the most important performance indicator for the customers, but speed is the most important followed by the frequency and the comfort of the ride. We see that the current implementation of DRT systems have different approaches. The Kutsuplus in Helsinki is the best comparison with our problem, only the service area is much bigger in case of Kutsuplus.

In contrast to prevailing methods in literature, we use a small service area, in which all the stops can be served from one depot location without violating any restriction. In the small service area, all customers that request a ride within the area are serviced on-demand. When a customer wants to leave the service area he or she can be transported towards a public transport hub (e.g., a train station). Another difference compared to the literature is the way the latest arrival time is determined. In our model the latest arrival time is determined by using the latest possible pickup time plus the shortest travel time. This method of determining the latest arrival time reduces the system flexibility but, it improves the speed of transport for the customers.

When we compare our result (using model 2 with vehicle fleet B), to the current situation we see that in the current situation 20 large busses and 4 small vehicles are used. Our results show that only 9 vehicles are need, to serve all requests. The current total driven distance is 401,428 kilometres a year, meaning an average of 33,452 km a month. Our results shows that if all requests are served, 36,716 kilometres must be driven in the month September 2015. Although the distance is slightly larger, the customer do not need to change between lines anymore, and we serve the customer using smaller (cheaper) vehicles. In the current situation the busses are operating 18,206 hours a year, meaning an average of 1,517 hours a month, while our results show an operating time of 1,464 hours. We conclude that a possible saving in operating hours is possible when implementing our new PT model.

The result of this research is a simulation model that shows the effects of transport on-demand in Helmond. Our model uses a new approach on handling the requests, and uses an existing method to insert the customers. Although our model is not extensively tested, we believe it makes a valuable contribution in getting more insight of the possibilities of on-demand transport.

6.2 LIMITATION OF THE MODEL

In this section, we discuss the limitations of our models. First we discuss the drawback of our travel times, followed by the limitations of our model.

6.2.1 TRAVEL TIMES

To design our model we had to determine the travel times between any pair of stops. We choose to use fixed travel times including slack time. A drawback of fixed travel times is that the model is not capable of using varying travel times during the day. E.g., during the morning and evening rush, it is likely that the travel time is larger compared to the rest of the day. This may lead to misleading results for the real life situations. An advantage is that all the fixed travel times are determined in the same way enabling us to provide a consistent input for our models.

6.2.2 LIMITATION OF OUR MODEL

The first limitation of our model, is that the model is tested in an off-line environment that runs all the request of one month. The model inserts the customer to the best route available at that moment. This could lead to a poor performance of our models.

One limitation is the assumption that all requests that stay within Helmond are served by our new model, this means the request pickup times are not changed, compared to the current pickup time by the bus. While in real life customers might not feel comfortable with the new way ordering a ride, and will possibly use alternatives. It could also mean that all customers are planning their rides at the same moment, resulting in far more customers at the same time at the stop than the capacity of the vehicle. On the other hand, the new type of transport might attract people that use alternative transportation until now.

6.3 RECOMMENDATIONS

This section describes the recommendations for implementing our model in Helmond.

Implementation of a complete new way of public transport, requires some time. Customers need to get familiar with the sending of a request, and getting served with by a smaller vehicle. We suggest for the implementation to start combining the on-demand feature while reducing the frequency of the current bus lines. In the final phase after a certain period, all fixed routes are removed, and only an on-demand system is available.

In Helmond, Connexxion provides the social support act, a regulation that allows elderly and disabled persons to travel within the city, using a door-to-door service. Combining the social support service with the on-demand public transport, might increase the revenue, since more requests need service within the relatively small service area. A drawback for combining the social support act with the on-demand system, is that most customers are not able to enter the vehicle without help, or the customers need a wheelchair. The extra time (boarding and un-boarding) needed to service these type of customers can result in a decreasing service level for the customers using the regular on-demand PT.

The increase in flexibility and provision of an on demand service, comes at a price. Due to more uncertainty in demand, and finding a balance in the operating hours. Especially if the service is not used by the customers. But the use of the smaller vehicles results in less operating costs, as the driver number remains the same.

In Section 3.2, we found that pricing of fares is one performance indicator that can help to make the system a success. We think a fixed pricing is the most suitable strategy for our model in Helmond, since the fixed price strategy is always transparent for the customers.

6.4 FURTHER RESEARCH

To the best of our knowledge, no models in literature exist that approach our problem in the way our model does. Because our new approach in providing an on-demand service in a relative small area, further research should be done in order to adapt it to other regions. In this section we discuss the issues for further research.

In our model we are assume a fixed location for the depot. We did not take into account flexible vehicle locations, especially when the area becomes larger, and the call time is small, it might be necessary to relocate the empty buses over multiple stop locations/depots in such a way that all locations can be service within a short period of time.

In our model we do not implement a hybrid system, in which bus lines are combined with the on-demand system. We suggest that combining both systems together might reduce the travel distance. It is also possible to use the on-demand system outside the rush hours, where in the rush hours the bus lines are used to serve the requests.

Our model does not handle online situations that cause delays, and requests that cannot be served within the restrictions are rejected. We state that requests are rejected when they are unable to serve within the given restrictions. It might be possible to serve these requests, but not at the requested moment. We suggest to see the effect of sending an alternative pickup time to the customer to service the request instead of rejecting the send request.

We choose to use fixed travel times, meaning the travel times over the whole day are the same, while it is likely that the travel times increase during the rush periods, and decrease in the weekend. We ignored the possible effect of the using flexible travel time. We suggest to find out the effects of using variable times during the days, and maybe using stochastic travel times.

Our model handles a call time, the time in which all the customer requests are stored. Our model assigns the request once to a vehicle. A potential improvement phase could be reassigning the known requests to other vehicles as long as the actual pickup is not communicated, and hopefully find better solutions. We recommend to do the reassigning with the use of a metaheuristic, since the number of request that could be reassigned is could be large, and the heuristic is used after each new request.

We use in our models fixed parameters that hold for all requests. It could be that customers are willing to pay more for their ride if the TW size is reduced, or to have an earlier latest arrival time. A future research could study the effects of allowing customers to determine their own parameters.

Our model does not take the planning of staff into account, our models shows only the maximum number of vehicles needed during certain days and the hours the vehicles are needed. Similar to the current bus line planning, drivers must be assigned to vehicles. We suggest a research on the planning of staff while using our on-demand model.

Our proposed models are only tested on the set of requests of September 2015 in Helmond. Further research should assess the models validity and performance on other requests data (increasing/decreasing the number of requests on a day, a request data of one year) than the ones we used.

In this research we used predetermined stops that are served on-demand. These locations are based on the current bus stop locations. Changing the public transport by removing the predetermined routes could lead to poor locations for the stops, since these stop locations are located based on the route of the bus line. Further research should assess new stop location data (increasing the number of stops, or finding better locations for the stops) than the assumption we did of using the current bus stops .

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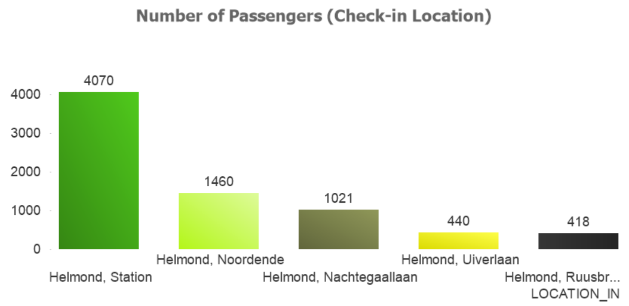
APPENDIX

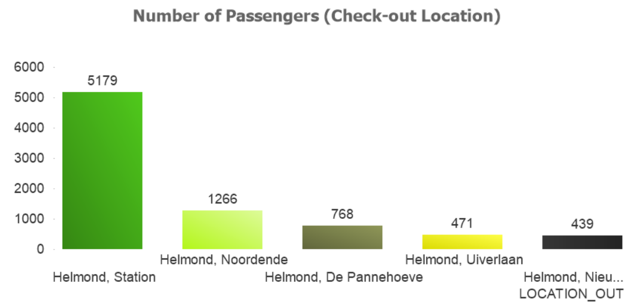
A. LIST OF ABBREVIATIONS

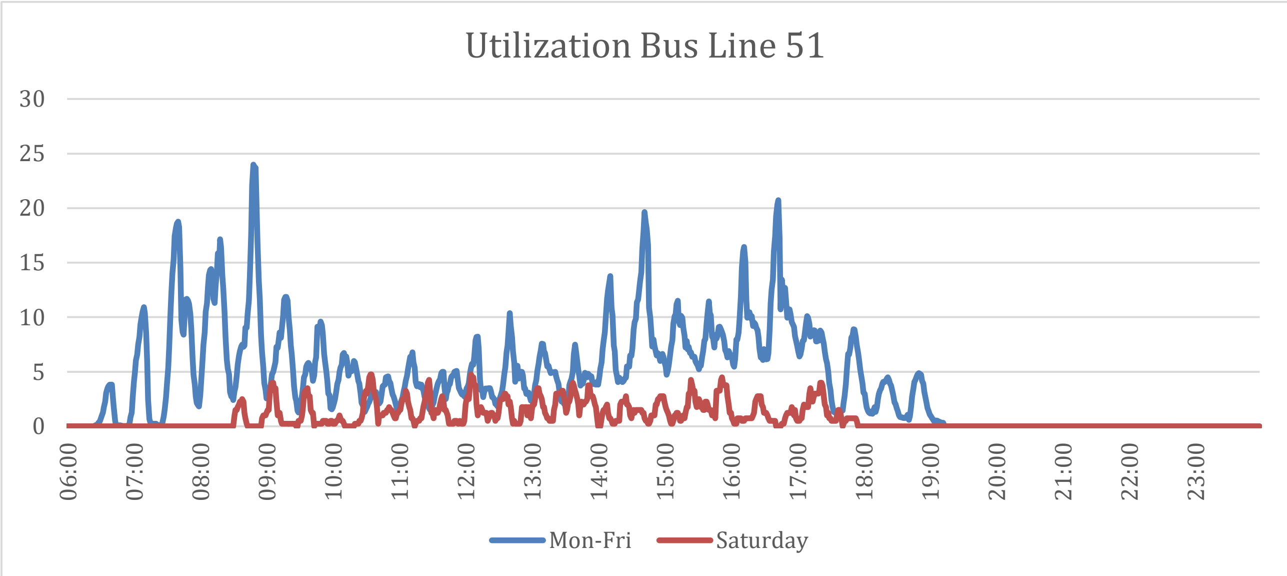
BB	Branch-and-Bound
CFF	Commodity Flow Formulations
CFRS	Cluster-First, Route Second
CVRP	Capacitated Vehicle Routing Problem
DARP	Dial-a-ride Problem
DP	Dynamic Programming
DRP	Driver Rostering Problem
DRS	Demand Responsive Service
DRT	Demand Responsive Transport
DSP	Driver Scheduling Problem
FS	Frequency Setting
FT	Future Technology
FTS	Flexible Transport Services
GAP	General Assignment Problem
ILP	Integer Linear Program
LP	Linear Program
LS	Local Search
MDVRP	Multi-Depot Vehicle Routing Problem
MDVRPFD	Multi-Depot Vehicle Routing Problem with Fixed Distribution
NP-complete	Nondeterministic Polynomial time Complete
PT	Public Transport
SA	Simulated Annealing
SP	Set Partition
SPH	Set Partition Heuristic
TND	Transit Network Design
TNP	Transit Network Planning
TNT	Transit Network Timetabling
TSP	Traveling Salesman Problem
TW	Time Windows
VNS	Variable Neighbourhood Search
VRP	Vehicle Routing Problem
VRPB	Vehicle Routing Problem with Backhauling
VRPPD	Vehicle Routing Problem with Pickup and Delivery
VRPTW	Vehicle Routing Problem with Time Windows
VRSPTW	Vehicle Routing and Scheduling Problem with Time Windows
VSP	Vehicle Scheduling Problem
PCM	Priori Clustering Method
MAST	Mobility Allowance Shuttle Transit

B. ANALYSE OF BUS LINES

B.1 BUS LINE 51







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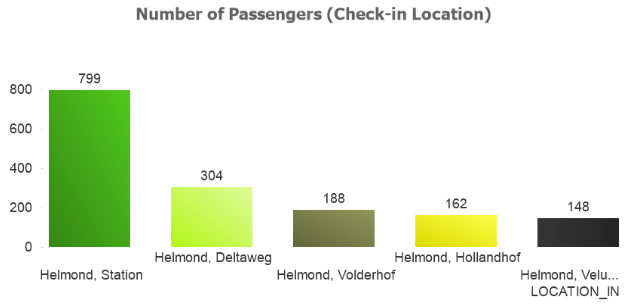

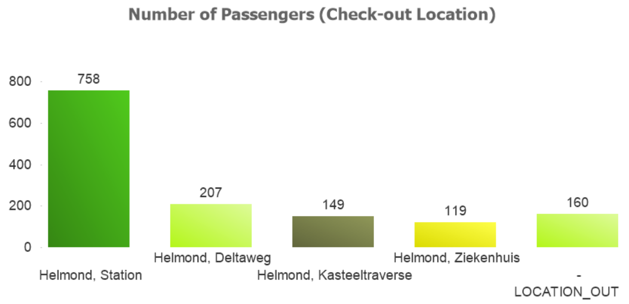

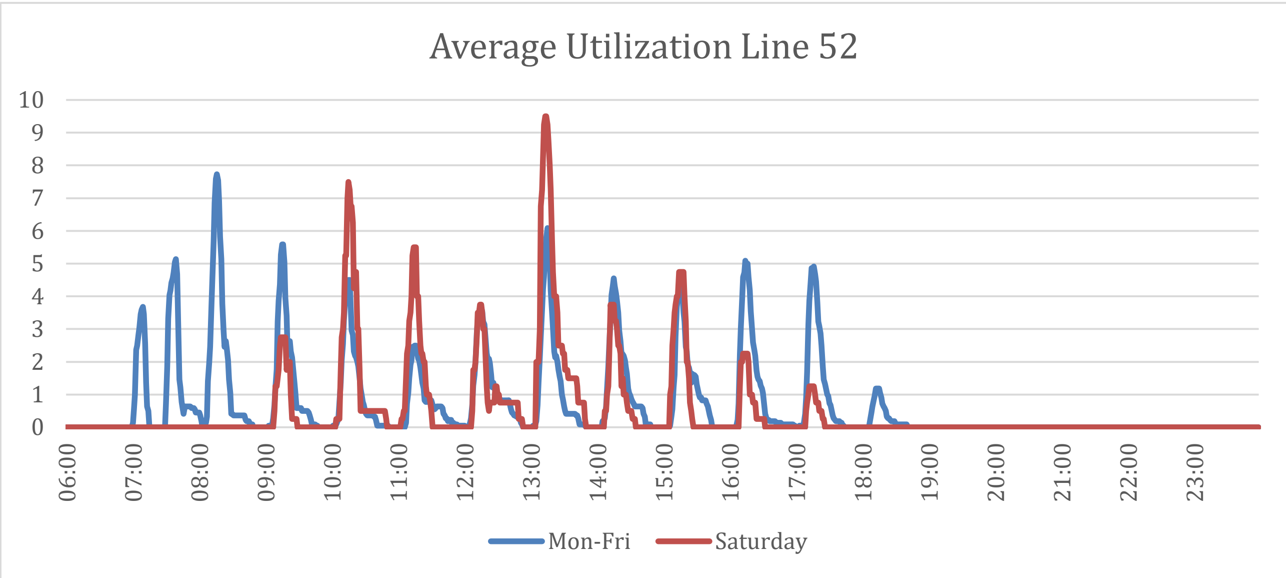

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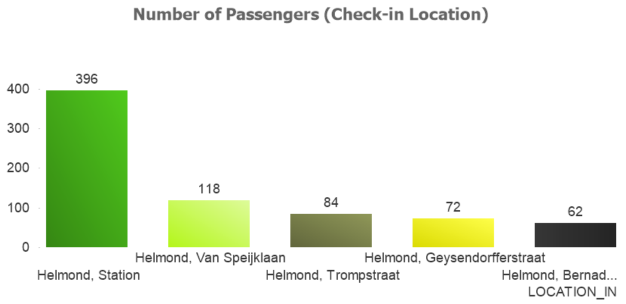

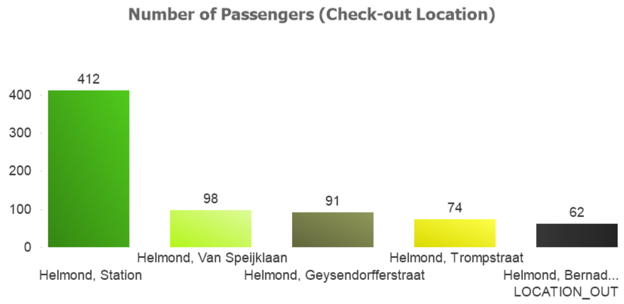

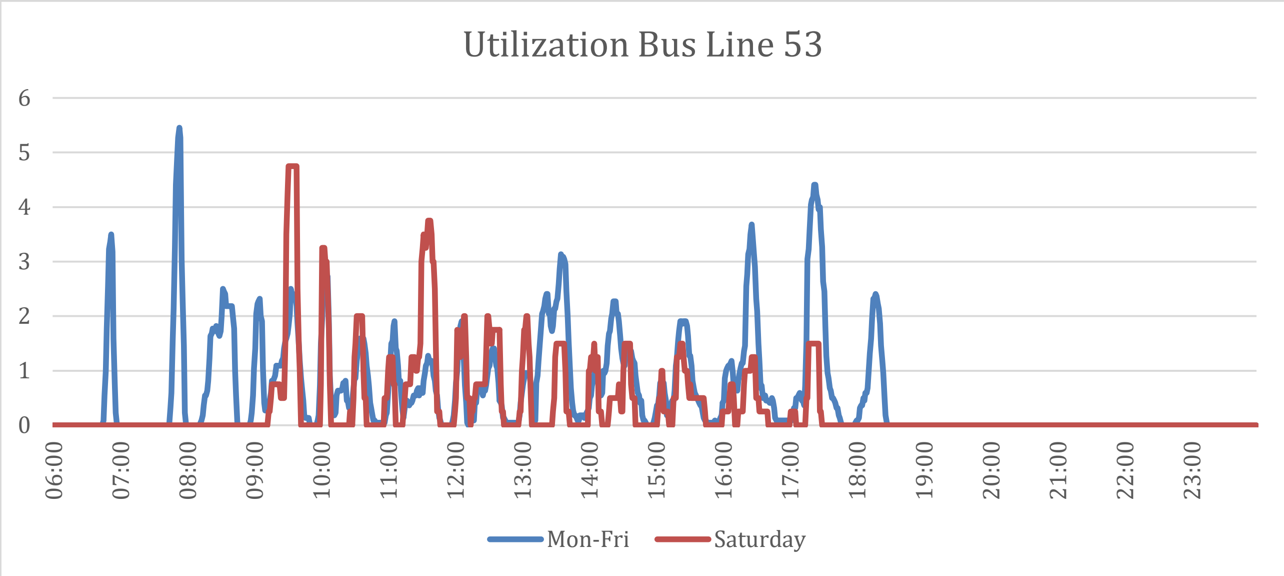

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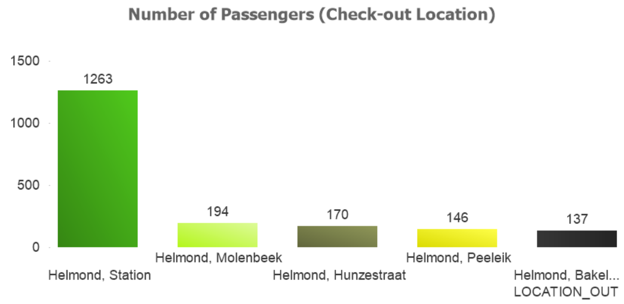
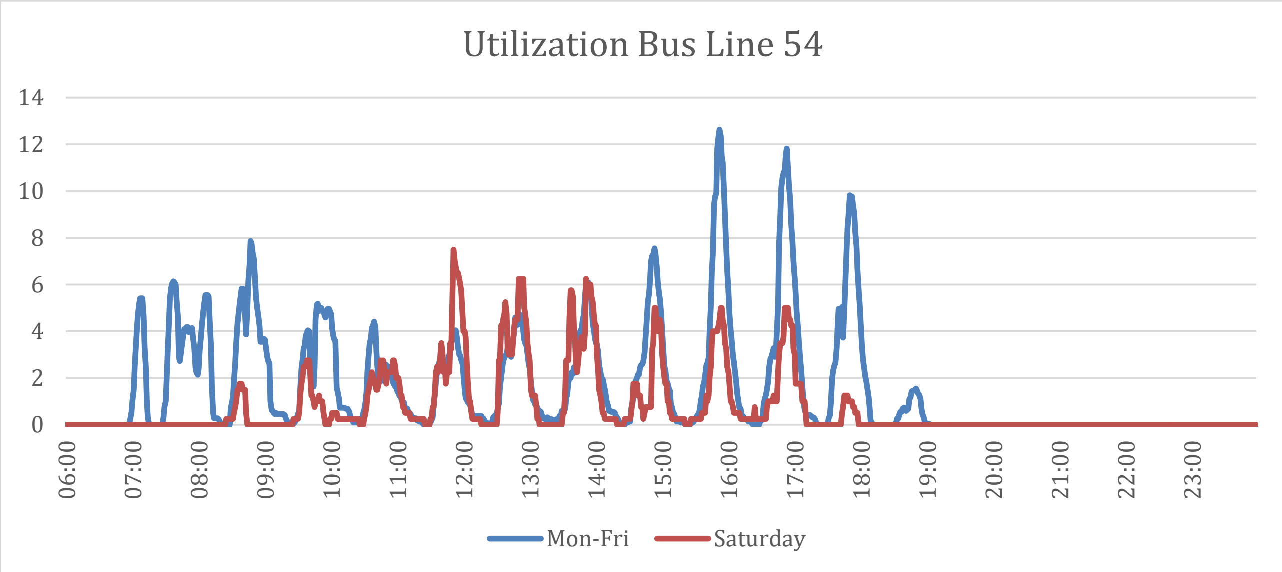




C. DARP FORMULATION

Mathematical formulation

The mathematical formulation is divided into blocks. Each block represent an extension that is explained in section 3.3. Model 1 contains a directed graph $G = (\mathcal{V}, \mathcal{A})$ with $\mathcal{A}$ the set of all arcs, and $\mathcal{V} = \{0, 2n+1, 2n+2\} \cup \mathcal{P} \cup \mathcal{D}$. The pickup locations are represented by $\mathcal{P} = \{1, \dots, n^+\}$, and $\mathcal{D} = \{1, \dots, n^-\}$ are the drop-off locations. The start depot is represented by $\{0\}$, the noon depot by $\{2n+1\}$, and the end depot by $\{2n+2\}$. A customer request is given by $i \in \{1, \dots, n\}$ with $i = \{i^+, i^-\}$. It is important to notice that the locations i are not unique, and are visited when requested by a customer.

Decision variables:

- x_{ij}^b is a binary variable, which is 1 if vehicle b goes immediately from location i to location j, 0 otherwise.

Auxiliary variables

- T_{ij}^b is a fractional variable that represents the ride time of traveling from location i to location j using vehicle b.
- $Q_i^{r,b}$ is a fractional variable that represents the load of resource r in vehicle b immediately after visiting location i.
- Z_i^b is a fractional variable that represents the arrival time of vehicle b on location i.

Parameters

- c_{ij}^b represents the costs of traveling from location i to j, with vehicle b.
- e_i is the earliest arrival time at location i.
- e_H is the earliest start time of the lunch break.
- H the duration of the break.
- l_i represents the latest arrival time at location i.
- l_H is the latest start time of the lunch break.
- n denotes the total number of request.
- O_i represents the communication time for location i.
- q_i^r number of persons that are traveling using resource r at location i.
- Q_b^r denotes the available load of resource r, in vehicle b.
- T the maximum allowable working time with a break.
- $T_i^{\max}$ maximum ride time for customer i.
- T_l the maximum allowable working time without a break.
- t_{ij} represents the time needed for traveling from location i to j.
- v_i^b a binary number that is 1 if a break is held before location i, 0 otherwise.

- w is a fractional variable, that represents the weight factor for cost minimization.

$$\min \sum_{b\in\mathcal{B}} \sum_{i\in\mathcal{V}} \sum_{j\in\mathcal{V}} w(c_{ij}^b x_{ij}^b) + (1-w)(T_i^b - t_{ij}) x_{ij}^b \tag{B.16}$$

Basic DARP constraints

s.t.
$$\sum_{b\in\mathcal{B}} \sum_{j\in\mathcal{V}} x_{ij}^b = 1 \qquad \forall i \in \mathcal{V} \cup \{0\} \tag{B.17}$$

$$\sum_{j\in\mathcal{V}} x_{ji}^b - \sum_{j\in\mathcal{V}} x_{ij}^b = 0 \qquad \forall i \in \mathcal{V} \cup \{0\}, b \in \mathcal{B} \tag{B.18}$$

$$\sum_{j\in\mathcal{V}} x_{i^+ j}^b - \sum_{j\in\mathcal{V}} x_{i^- j}^b = 0 \qquad \forall i \in \mathcal{P}, b \in \mathcal{B} \tag{B.19}$$

$$x_{ij}^b \in \{0,1\} \qquad \forall i \in \mathcal{V}, j \in \mathcal{V}, b \in \mathcal{B} \tag{B.20}$$

Various resource constraints

$$x_{ij}^b = 1 \rightarrow Q_j^{r,b} \geq Q_i^{r,b} + q_j^r \qquad \forall i,j \in \mathcal{V}, b \in \mathcal{B}, r \in \mathcal{R} \tag{B.21}$$

$$Q_i^{r,b} \leq Q_b^r \qquad \forall i \in \mathcal{V}, b \in \mathcal{B}, r \in \mathcal{R} \tag{B.22}$$

$$Q_i^{r,b} \geq 0 \qquad \forall i \in \mathcal{V}, b \in \mathcal{B}, r \in \mathcal{R} \tag{B.23}$$

Drive time constraints

$$v_{2n+2}^b = 0 \rightarrow Z_{2n+2}^b - Z_0^b \leq T_l \qquad \forall b \in \mathcal{B} \tag{B.24}$$

$$v_{2n+2}^b = 1 \rightarrow Z_{2n+2}^b - Z_0^b + H \leq T \qquad \forall b \in \mathcal{B} \tag{B.25}$$

$$x_{ij}^b = 1 \wedge v_i^b = 0 \rightarrow Z_j^b \geq Z_i^b + t_{ij} \qquad \forall i,j \in \mathcal{V}, b \in \mathcal{B} \tag{B.26}$$

$$x_{ij}^b = 1 \wedge v_i^b = 1 \rightarrow Z_j^b \geq Z_i^b + t_{ij} + H \qquad \forall i,j \in \mathcal{V}, b \in \mathcal{B} \tag{B.27}$$

$$v_i^b = 1 \rightarrow e_H \leq Z_i^b \leq l_H \qquad \forall i \in \mathcal{V}, b \in \mathcal{B} \tag{B.28}$$

Time Windows

$$O_i \leq E_{i^+} \qquad \forall i \in \mathcal{V}, b \in \mathcal{B} \tag{B.29}$$

$$E_{i^+} \leq Z_i^b \leq L_{i^+} \qquad \forall i \in \mathcal{V}, b \in \mathcal{B} \tag{B.30}$$

$$Z_j^b \leq L_{i^-} \qquad \forall i \in \mathcal{V}, b \in \mathcal{B} \tag{B.31}$$

$$T_i^b \leq T_i^{\max} \qquad \forall i \in \mathcal{V}, b \in \mathcal{B} \tag{B.32}$$

$$T_i^b = Z_{i^-}^b - Z_{i^+}^b \qquad \forall i \in \mathcal{P}, b \in \mathcal{B} \tag{B.33}$$

Domain constraints

$$x_{ij}^b \in \{0,1\} \tag{B.34}$$

$$a_i \in \{0,1\} \tag{B.35}$$

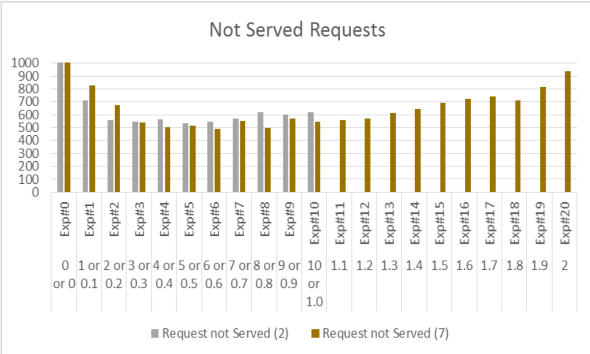
$$v_i^b \in \{0,1\} \tag{B.36}$$

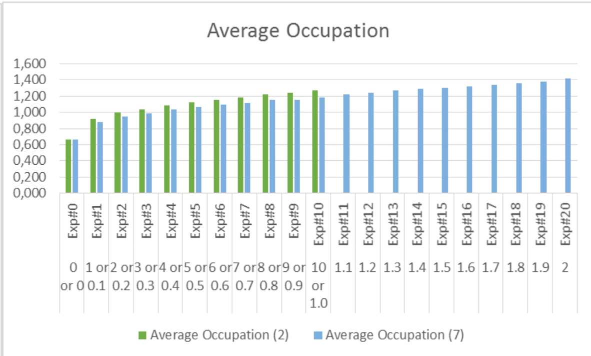
$$0 \leq w \leq 1 \tag{B.37}$$

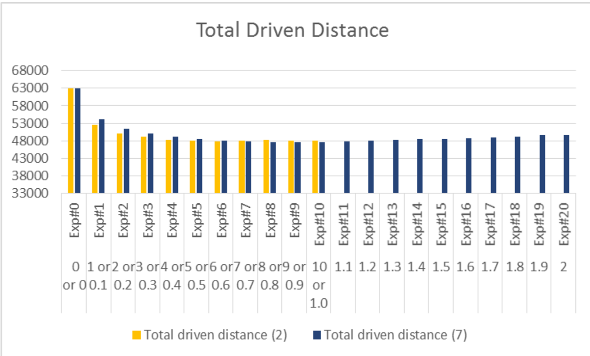
D. RESULTS OF CASES IN GRAPHS

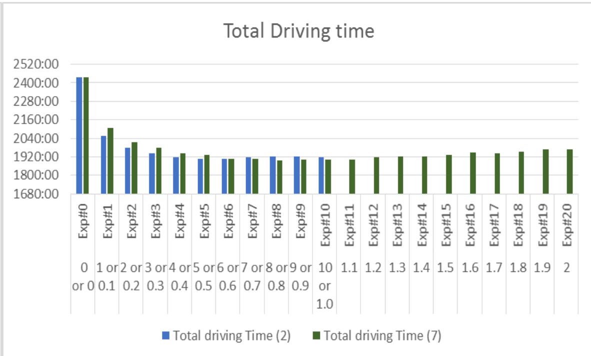
D.1 CASES 2 AND 7 (DETOUR TIME)

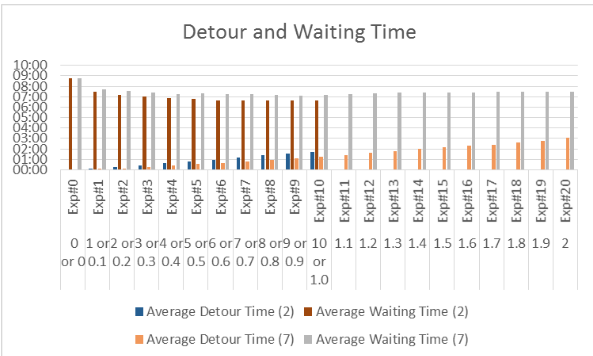
Nine times three person vehicles



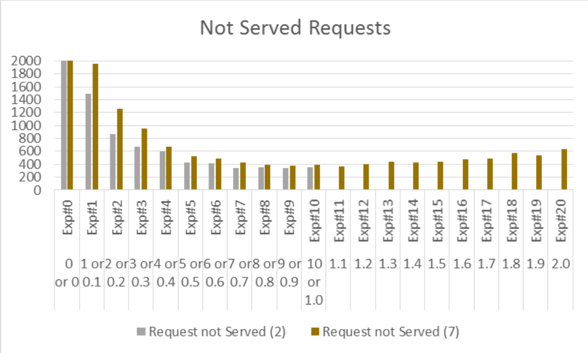


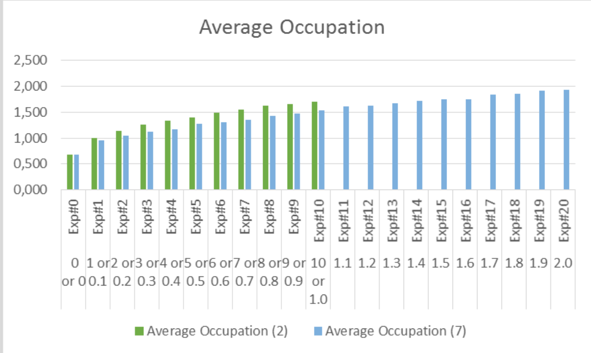


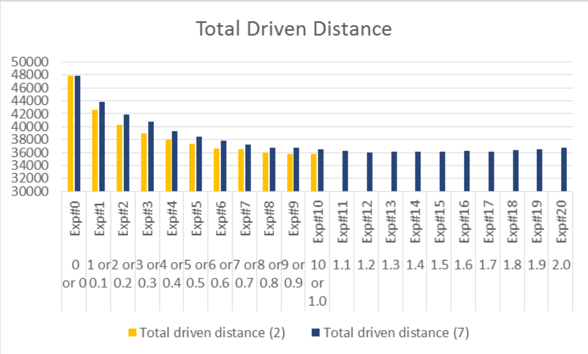


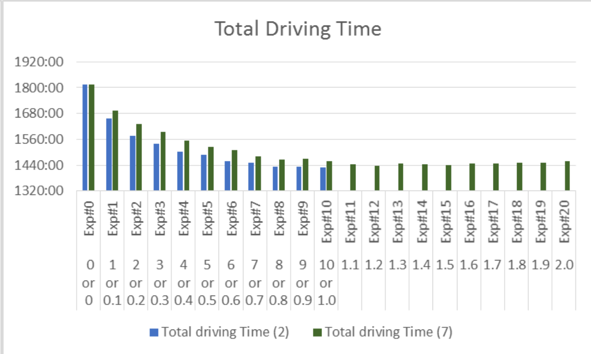


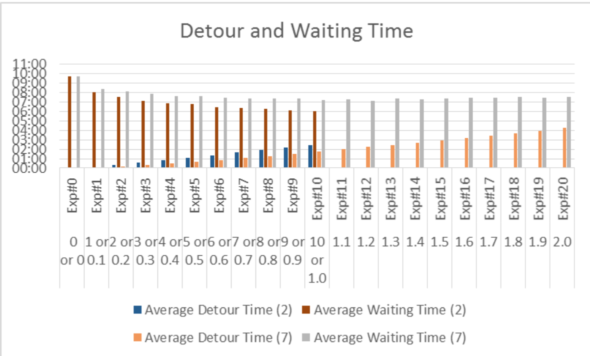
Six times eight person vehicles





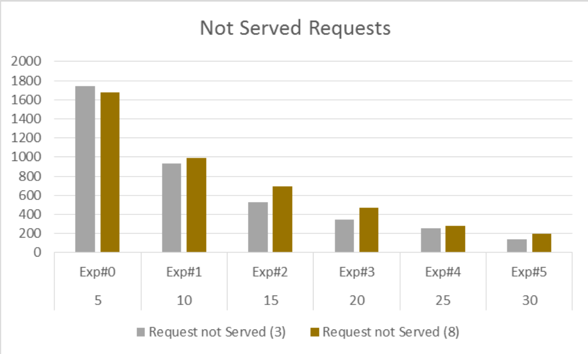


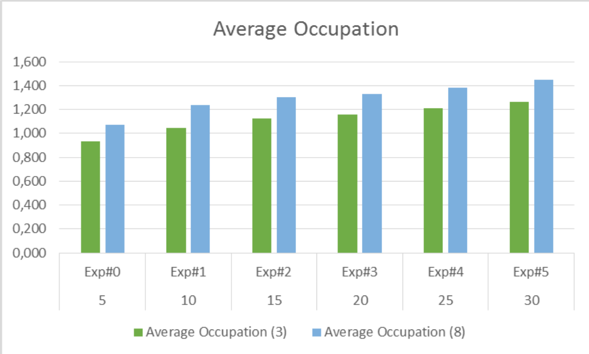


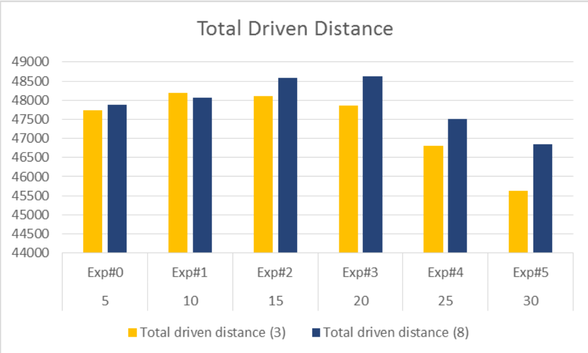


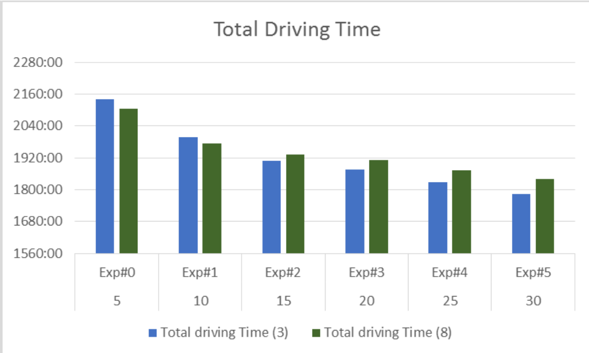
D.2 CASES 3 AND 8 (TW SIZE)

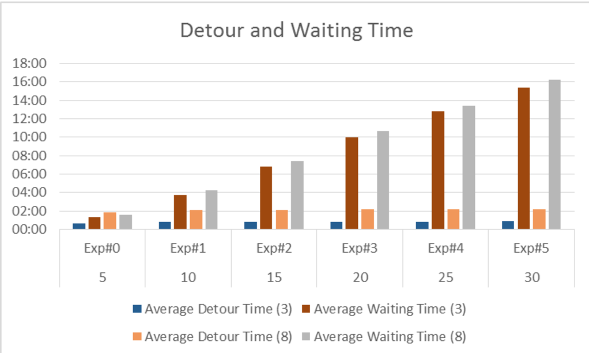
Nine times three person vehicles



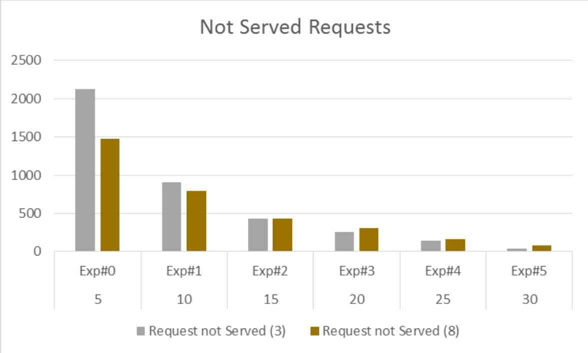


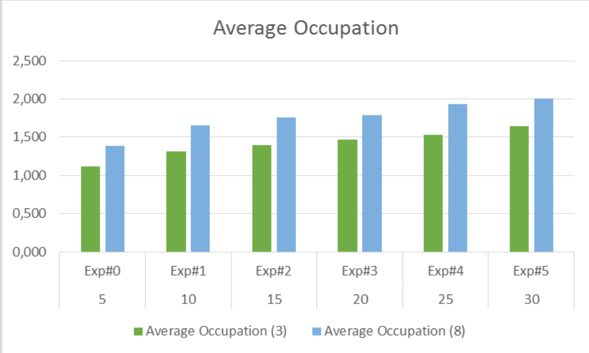


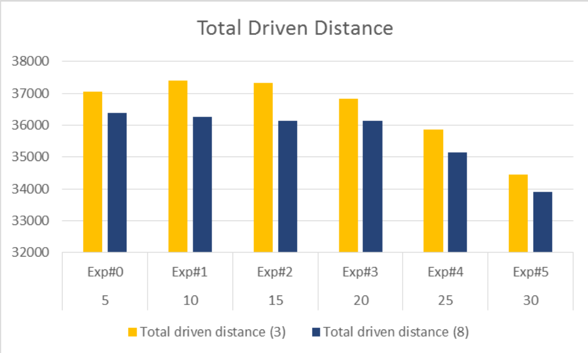


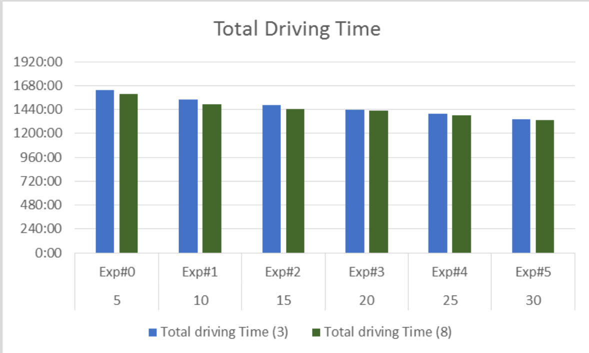


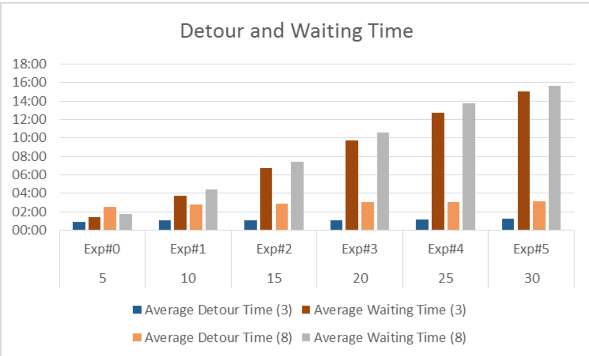
Six times eight person vehicles





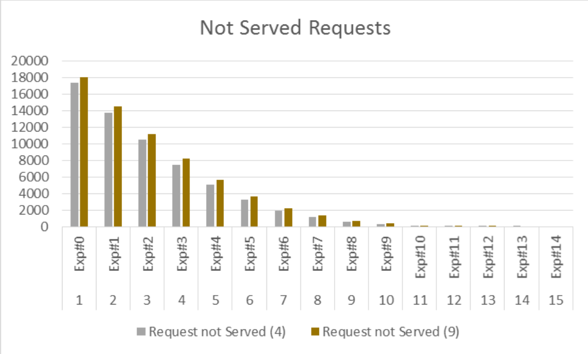


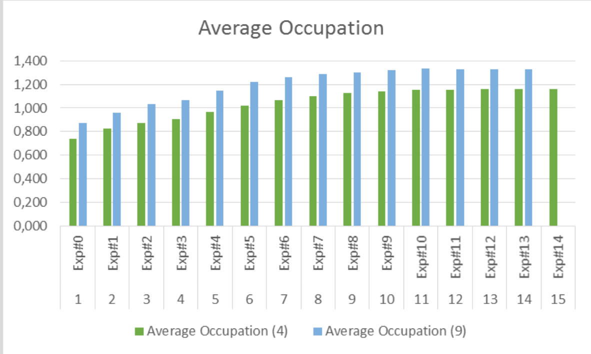


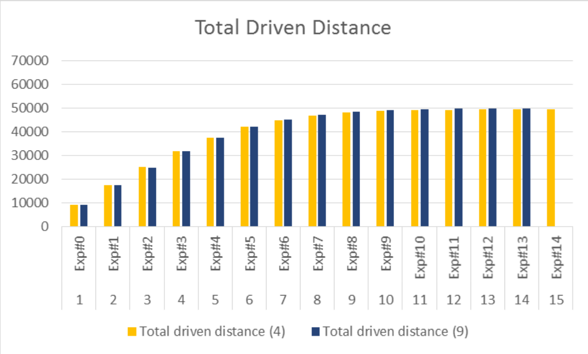


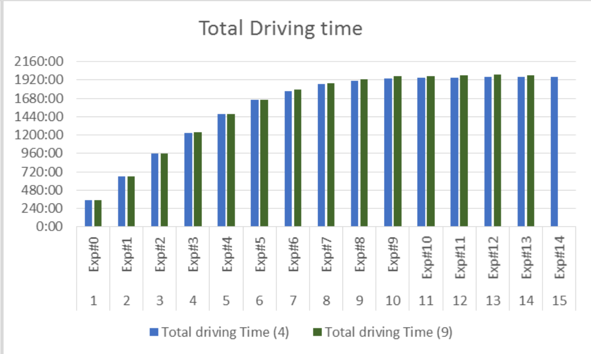
D.3 CASES 4 AND 9 (VEHICLES)

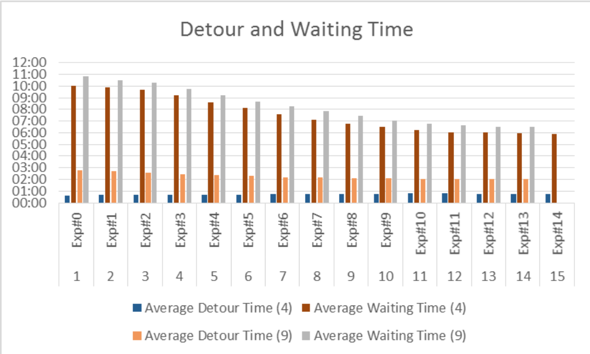
Adding three person vehicles



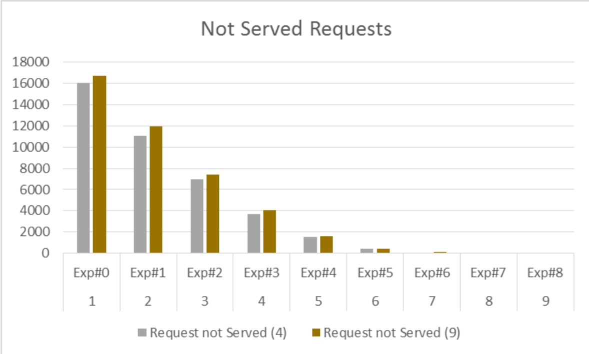


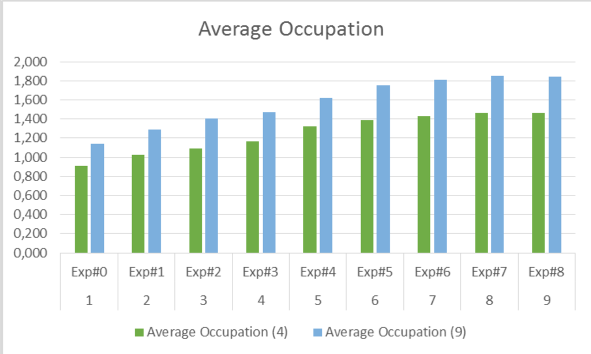


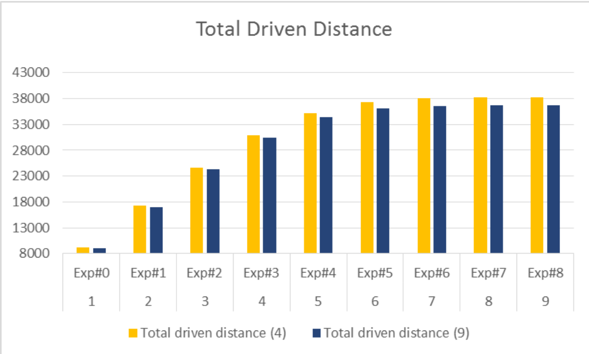


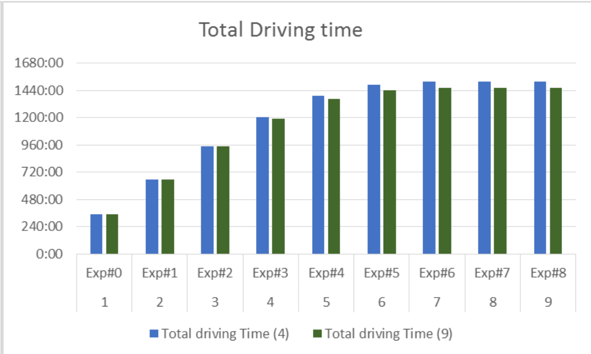


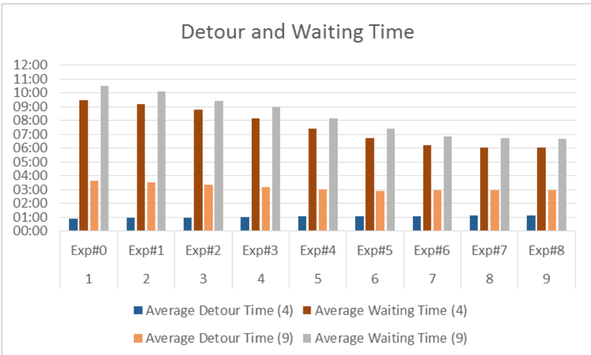
Adding eight person vehicles





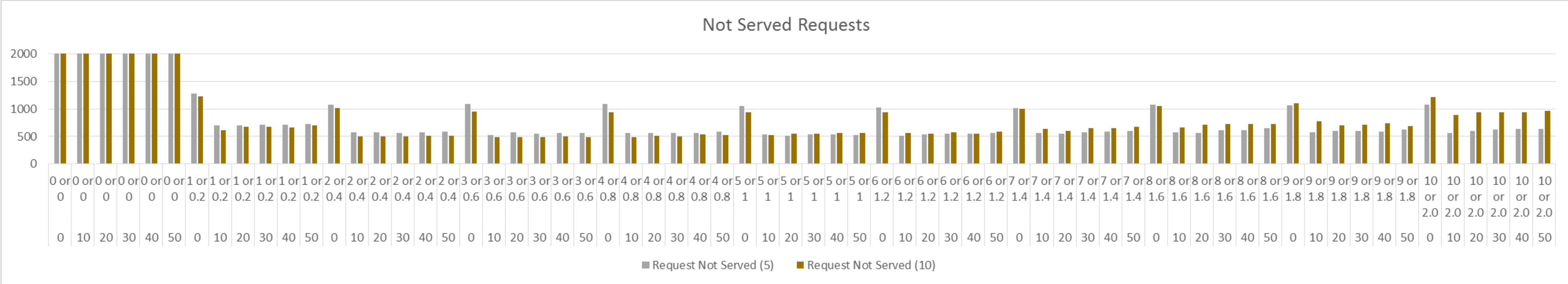


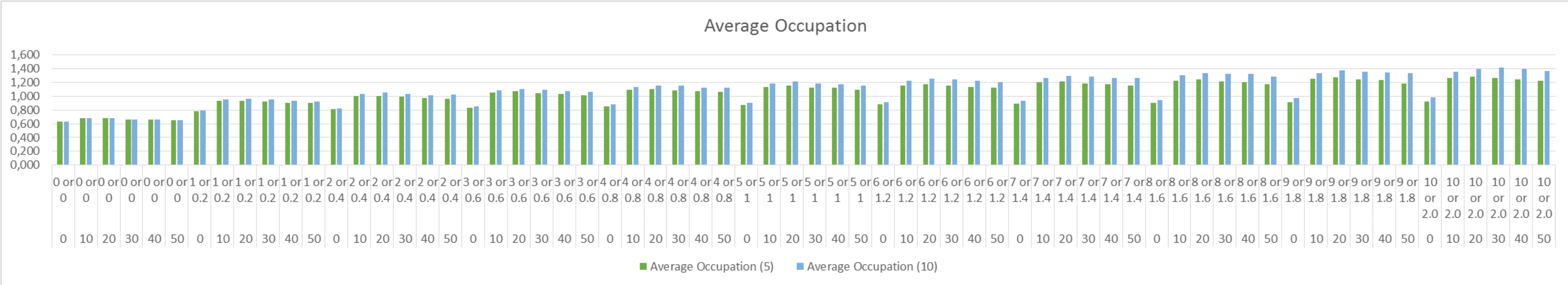


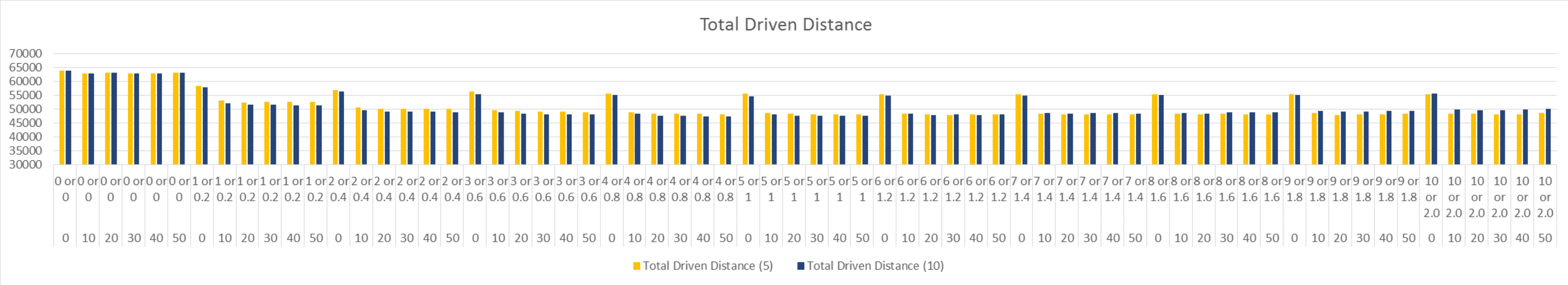


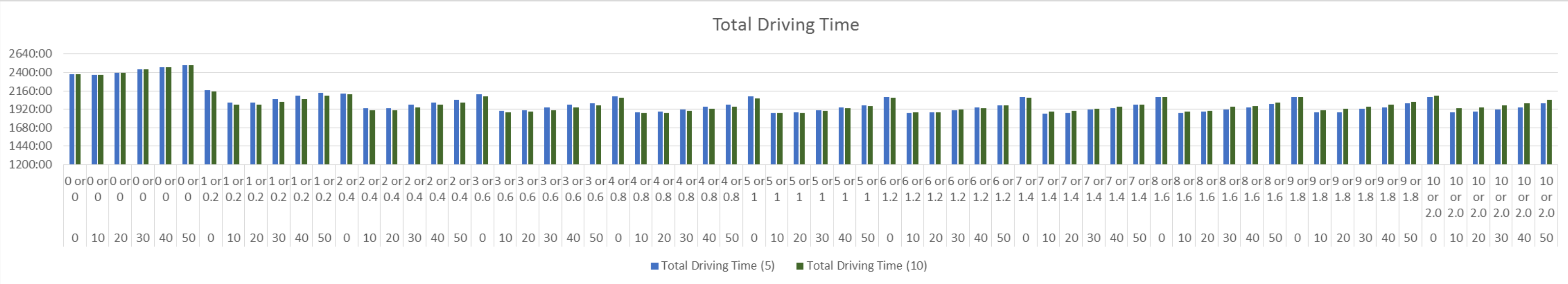
D.4 CASES 5 AND 10 (CALL AND DETOUR TIME)

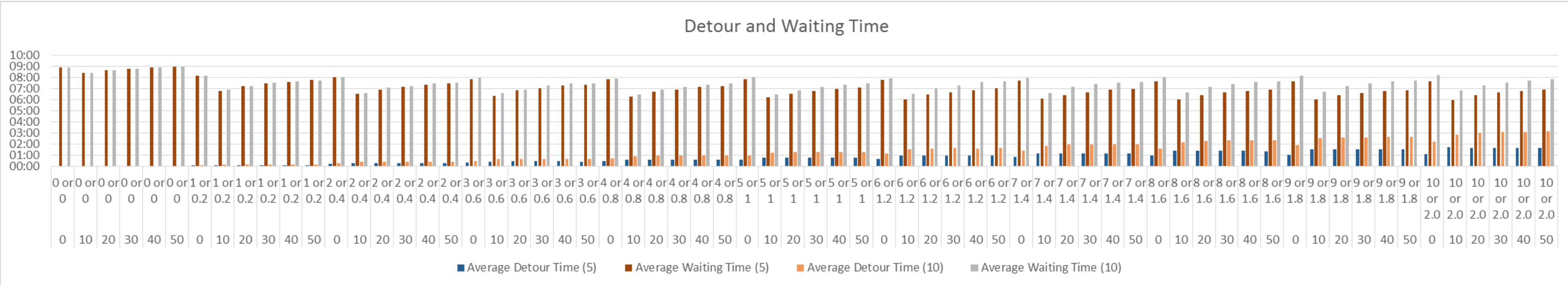
Nine times three person vehicles



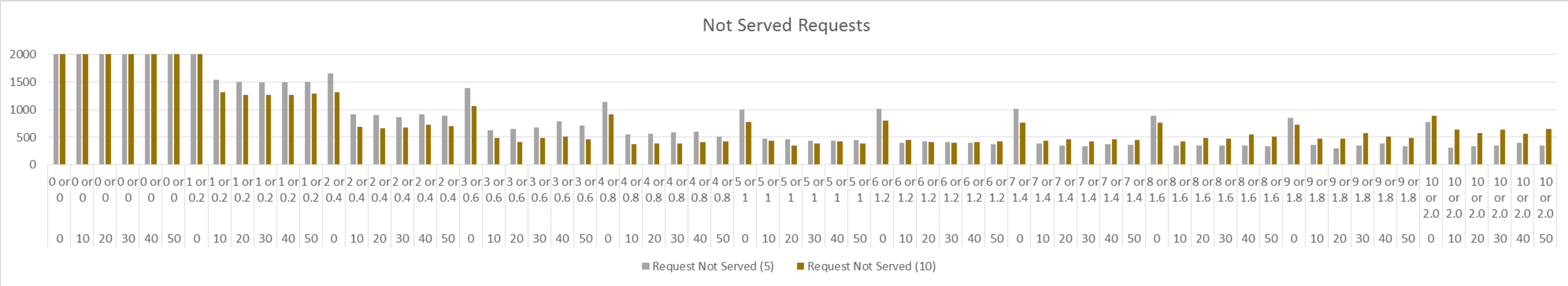


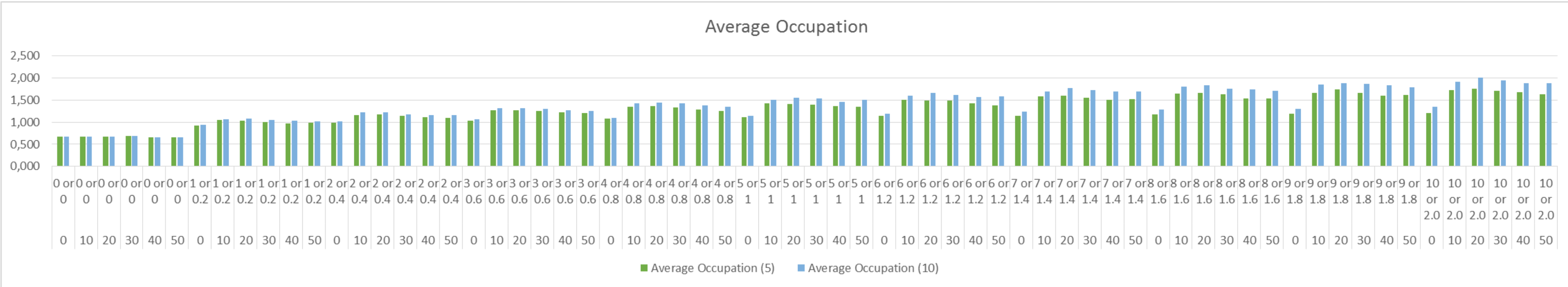

Total Driven Distance
70000
65000
60000
55000
50000
45000
40000
35000
30000
Total Driven Distance (5)
Total Driven Distance (10)

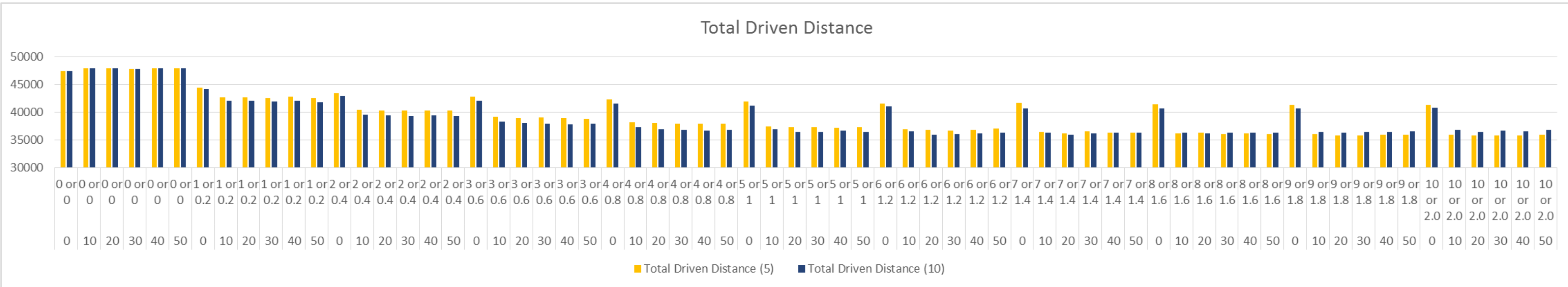

Total Driving Time
2640:00
2400:00
2160:00
1920:00
1680:00
1440:00
1200:00
Total Driving Time (5)
Total Driving Time (10)

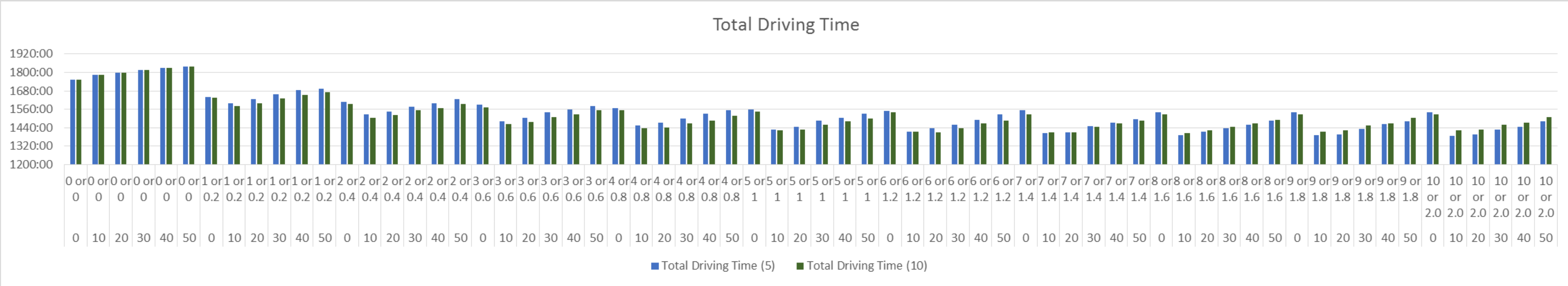

Detour and Waiting Time
10:00
09:00
08:00
07:00
06:00
05:00
04:00
03:00
02:00
01:00
00:00
Average Detour Time (5)
Average Waiting Time (5)
Average Detour Time (10)
Average Waiting Time (10)

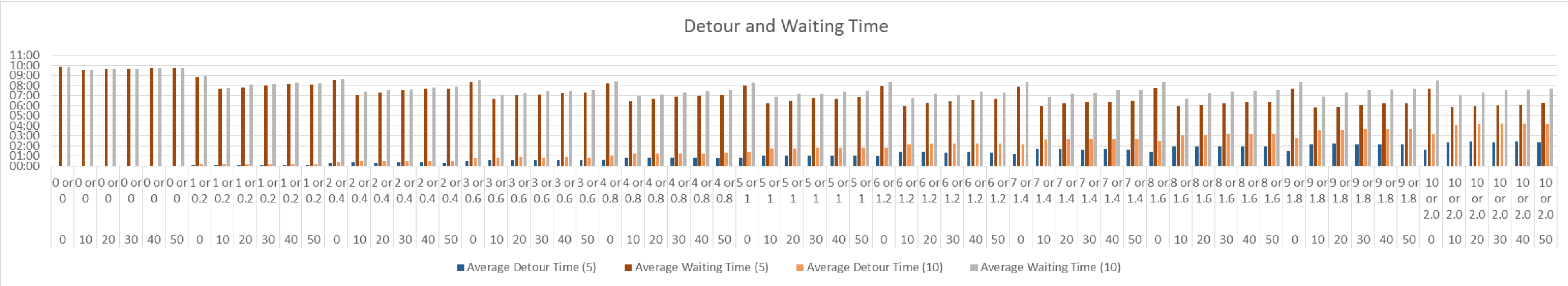
Six times eight person vehicles








Total Driving Time
Total Driving Time (5)
Total Driving Time (10)


Detour and Waiting Time
Average Detour Time (5)
Average Waiting Time (5)
Average Detour Time (10)
Average Waiting Time (10)

E. RAW DATA OF CASES 5 AND 10

Cases 5 and 10 (3 person)	Exp#0	Exp#1	Exp#2	Exp#3	Exp#4	Exp#5	Exp#6	Exp#7	Exp#8	Exp#9	Exp#10	Exp#11	Exp#12	Exp#13	Exp#14	Exp#15	Exp#16	Exp#17	Exp#18	Exp#19	Exp#20	Exp#21
Call time	0	10	20	30	40	50	0	10	20	30	40	50	0	10	20	30	40	50	0	10	20	30
Detour time	0 or 0	0 or 0	0 or 0	0 or 0	0 or 0	0 or 0	1 or 0.2	1 or 0.2	1 or 0.2	1 or 0.2	1 or 0.2	1 or 0.2	2 or 0.4	2 or 0.4	2 or 0.4	2 or 0.4	2 or 0.4	2 or 0.4	3 or 0.6	3 or 0.6	3 or 0.6	3 or 0.6
Request Served (5)	17946	18469	18512	18467	18465	18515	20463	21035	21041	21024	21022	21008	20666	21164	21163	21179	21157	21154	20649	21207	21159	21187
Request Not Served (5)	3790	3267	3224	3269	3271	3221	1273	701	695	712	714	728	1070	572	573	557	579	582	1087	529	577	549
Total Driven Distance (5)	63806,22	62932,84	63006,53	62888,52	62879,2	62995,58	58251,45	52976,74	52399,56	52594,82	52587,22	52559,2	56859,7	50677,33	50081,38	50152,33	50065,6	50026,03	56305,65	49511,59	49210,98	49097,91
Total Driving Time (5)	2375:31	2365:20	2398:48	2436:28	2464:23	2496:38	2172:53	2007:22	2010:11	2056:27	2097:55	2131:56	2128:00	1931:28	1934:31	1980:48	2006:02	2039:30	2112:55	1897:42	1907:17	1942:42
Average Occupation (5)	0,632	0,686	0,678	0,663	0,657	0,651	0,781	0,931	0,935	0,918	0,906	0,899	0,813	0,999	1,006	0,991	0,975	0,963	0,834	1,049	1,071	1,038
Average Detour Time (5)	00:00	00:00	00:00	00:00	00:00	00:00	00:03	00:04	00:04	00:04	00:04	00:04	00:11	00:14	00:14	00:14	00:14	00:14	00:20	00:25	00:26	00:26
Average Waiting Time (5)	08:55	08:23	08:39	08:48	08:56	08:58	08:09	06:49	07:14	07:28	07:37	07:47	08:01	06:33	06:56	07:09	07:20	07:29	07:52	06:19	06:49	07:01
Request Served (10)	17946	18469	18512	18467	18465	18515	20511	21118	21065	21061	21075	21037	20724	21236	21234	21235	21228	21219	20782	21253	21252	21244
Request Not Served (10)	3790	3267	3224	3269	3271	3221	1225	618	671	675	661	699	1012	500	502	501	508	517	954	483	484	492
Total Driven Distance (10)	63806,22	62932,84	63006,53	62888,52	62879,2	62995,58	57704,66	52052,6	51493,55	51462,91	51379,97	51370,42	56352,87	49569,23	49113,68	49120,3	49000,35	48903,44	55398,04	48798,34	48226,27	47950,93
Total Driving Time (10)	2375:31	2365:20	2398:48	2436:28	2464:23	2496:38	2155:38	1980:59	1982:10	2013:49	2051:46	2093:25	2116:36	1904:11	1910:32	1944:33	1979:13	2005:42	2088:02	1881:12	1886:54	1908:51
Average Occupation (10)	0,632	0,686	0,678	0,663	0,657	0,651	0,789	0,948	0,962	0,952	0,931	0,919	0,823	1,034	1,050	1,031	1,007	1,021	0,849	1,085	1,103	1,091
Average Detour Time (10)	00:00	00:00	00:00	00:00	00:00	00:00	00:06	00:07	00:08	00:08	00:08	00:08	00:17	00:22	00:23	00:23	00:23	00:23	00:28	00:37	00:38	00:39
Average Waiting Time (10)	08:55	08:23	08:39	08:48	08:56	08:58	08:11	06:53	07:14	07:31	07:41	07:45	08:02	06:35	07:04	07:14	07:29	07:32	07:57	06:37	06:56	07:15

Cases 5 and 10 (3 person)	Exp#22	Exp#23	Exp#24	Exp#25	Exp#26	Exp#27	Exp#28	Exp#29	Exp#30	Exp#31	Exp#32	Exp#33	Exp#34	Exp#35	Exp#36	Exp#37	Exp#38	Exp#39	Exp#40	Exp#41	Exp#42	Exp#43
Call time	40	50	0	10	20	30	40	50	0	10	20	30	40	50	0	10	20	30	40	50	0	10
Detour time	3 or 0.6	3 or 0.6	4 or 0.8	4 or 0.8	4 or 0.8	4 or 0.8	4 or 0.8	4 or 0.8	5 or 1	5 or 1	5 or 1	5 or 1	5 or 1	5 or 1	6 or 1.2	6 or 1.2	6 or 1.2	6 or 1.2	6 or 1.2	6 or 1.2	7 or 1.4	7 or 1.4
Request Served (5)	21179	21178	20648	21173	21176	21172	21176	21144	20684	21198	21221	21205	21205	21216	20711	21220	21194	21187	21192	21176	20719	21174
Request Not Served (5)	557	558	1088	563	560	564	560	592	1052	538	515	531	531	520	1025	516	542	549	544	560	1017	562
Total Driven Distance (5)	49102,12	48871,05	55692,45	48793,51	48357,06	48361,08	48361,11	48149,82	55469,39	48594,63	48281,69	48104,76	47931,43	48167,87	55331,52	48420,43	47958,57	47847,02	48039,24	47951,09	55263,15	48206,17
Total Driving Time (5)	1976:46	2001:30	2090:21	1878:02	1886:06	1917:05	1956:06	1982:26	2084:19	1873:43	1880:37	1908:47	1941:46	1972:11	2080:15	1872:57	1878:53	1904:36	1939:32	1969:29	2079:27	1866:24
Average Occupation (5)	1,031	1,011	0,851	1,090	1,104	1,086	1,071	1,059	0,872	1,127	1,148	1,125	1,117	1,093	0,880	1,157	1,172	1,153	1,129	1,120	0,896	1,201
Average Detour Time (5)	00:26	00:25	00:27	00:36	00:36	00:36	00:35	00:36	00:33	00:45	00:46	00:46	00:46	00:45	00:40	00:56	00:57	00:57	00:56	00:55	00:48	01:09
Average Waiting Time (5)	07:17	07:19	07:49	06:15	06:43	06:53	07:09	07:14	07:49	06:12	06:32	06:48	06:57	07:05	07:48	06:01	06:27	06:40	06:52	07:00	07:42	06:04
Request Served (10)	21238	21246	20792	21243	21226	21238	21202	21207	20795	21209	21186	21190	21175	21169	20792	21171	21181	21166	21192	21153	20737	21098
Request Not Served (10)	498	490	944	493	510	498	534	529	941	527	550	546	561	567	944	565	555	570	544	583	999	638
Total Driven Distance (10)	48058,57	47987,67	54968,16	48256,65	47593,94	47515,98	47395,33	47300,04	54644,07	47967,69	47649,92	47571,3	47545,3	47517,01	54776,64	48280,08	47824,02	48038,63	47790,75	48014,88	54864,86	48496,94
Total Driving Time (10)	1940:30	1968:54	2074:36	1870:25	1869:16	1896:18	1922:42	1953:42	2065:22	1867:18	1869:53	1901:37	1936:06	1959:09	2069:13	1877:24	1879:55	1915:29	1931:20	1969:51	2071:23	1886:03
Average Occupation (10)	1,073	1,057	0,878	1,133	1,154	1,150	1,123	1,120	0,896	1,186	1,211	1,184	1,168	1,151	0,914	1,222	1,256	1,241	1,226	1,203	0,931	1,262
Average Detour Time (10)	00:38	00:38	00:41	00:55	00:56	00:57	00:56	00:57	00:57	01:14	01:16	01:17	01:16	01:17	01:09	01:33	01:34	01:38	01:36	01:38	01:24	01:51
Average Waiting Time (10)	07:29	07:30	07:56	06:26	06:54	07:09	07:20	07:27	08:00	06:30	06:51	07:11	07:21	07:29	07:55	06:34	07:02	07:18	07:35	07:39	07:59	06:36

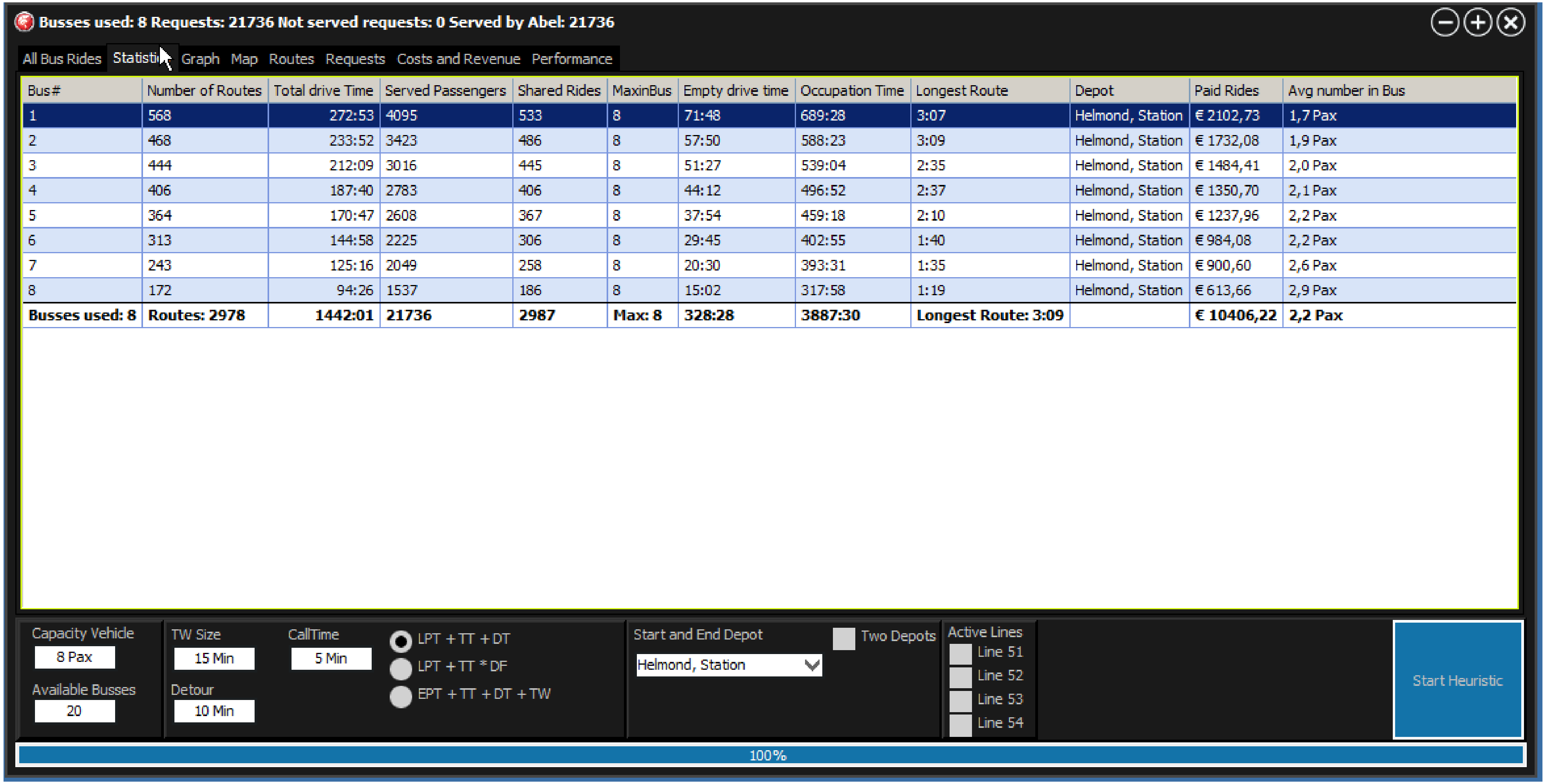
Cases 5 and 10 (3 person)	Exp#44	Exp#45	Exp#46	Exp#47	Exp#48	Exp#49	Exp#50	Exp#51	Exp#52	Exp#53	Exp#54	Exp#55	Exp#56	Exp#57	Exp#58	Exp#59	Exp#60	Exp#61	Exp#62	Exp#63	Exp#64	Exp#65
Call time	20	30	40	50	0	10	20	30	40	50	0	10	20	30	40	50	0	10	20	30	40	50
Detour time	7 or 1.4	7 or 1.4	7 or 1.4	7 or 1.4	8 or 1.6	8 or 1.6	8 or 1.6	8 or 1.6	8 or 1.6	8 or 1.6	9 or 1.8	9 or 1.8	9 or 1.8	9 or 1.8	9 or 1.8	9 or 1.8	10 or 2.0	10 or 2.0	10 or 2.0	10 or 2.0	10 or 2.0	10 or 2.0
Request Served (5)	21185	21165	21143	21137	20654	21164	21175	21118	21129	21092	20669	21159	21132	21133	21147	21116	20660	21174	21133	21116	21104	21103
Request Not Served (5)	551	571	593	599	1082	572	561	618	607	644	1067	577	604	603	589	620	1076	562	603	620	632	633
Total Driven Distance (5)	47932,11	48043,03	48015,5	47961,75	55304,31	48386,77	48132,98	48219,12	48009,45	48105,39	55284,11	48445,51	47875,43	48123,95	48067,32	48238,76	55197,13	48360,33	48353,72	48129,97	48086,94	48435,28
Total Driving Time (5)	1875:28	1916:08	1936:45	1979:04	2082:39	1875:14	1885:11	1920:37	1944:34	1984:39	2082:06	1879:26	1880:21	1923:23	1944:35	1995:30	2078:00	1876:54	1892:46	1916:29	1939:56	1996:01
Average Occupation (5)	1,212	1,179	1,171	1,151	0,903	1,226	1,245	1,217	1,202	1,170	0,914	1,248	1,272	1,239	1,229	1,187	0,921	1,263	1,286	1,266	1,240	1,218
Average Detour Time (5)	01:10	01:09	01:09	01:08	00:57	01:22	01:23	01:23	01:22	01:20	01:01	01:32	01:32	01:33	01:32	01:31	01:05	01:40	01:40	01:40	01:40	01:40
Average Waiting Time (5)	06:24	06:39	06:53	06:57	07:41	06:00	06:25	06:40	06:47	06:54	07:38	06:00	06:23	06:37	06:46	06:52	07:39	05:59	06:25	06:38	06:47	06:54
Request Served (10)	21142	21091	21087	21060	20691	21074	21018	21012	21014	21013	20641	20959	21031	21023	20998	21046	20525	20843	20795	20796	20801	20773
Request Not Served (10)	594	645	649	676	1045	662	718	724	722	723	1095	777	705	713	738	690	1211	893	941	940	935	963
Total Driven Distance (10)	48377,3	48472,66	48443,02	48323,3	55153,46	48606,5	48420,41	48795,66	48699,49	48790,49	55113,84	49332,1	49002,99	49109,95	49266,76	49323,94	55539,74	49773,68	49664,73	49644,97	49870,89	50134,36
Total Driving Time (10)	1901:41	1923:34	1956:47	1978:35	2080:20	1888:45	1899:17	1948:26	1960:13	2005:29	2078:51	1910:35	1923:40	1955:19	1978:54	2015:15	2092:56	1930:20	1946:00	1967:54	1995:53	2046:38
Average Occupation (10)	1,296	1,287	1,259	1,266	0,937	1,306	1,333	1,319	1,319	1,282	0,966	1,333	1,371	1,354	1,344	1,335	0,984	1,355	1,397	1,414	1,394	1,360
Average Detour Time (10)	01:57	01:58	01:56	01:59	01:36	02:10	02:16	02:20	02:20	02:20	01:52	02:30	02:34	02:35	02:39	02:40	02:11	02:52	03:01	03:06	03:05	03:08
Average Waiting Time (10)	07:10	07:23	07:33	07:37	08:04	06:39	07:08	07:24	07:35	07:40	08:08	06:42	07:13	07:28	07:38	07:45	08:12	06:49	07:18	07:31	07:45	07:52

Cases 5 and 10 (3 person)	Exp#0	Exp#1	Exp#2	Exp#3	Exp#4	Exp#5	Exp#6	Exp#7	Exp#8	Exp#9	Exp#10	Exp#11	Exp#12	Exp#13	Exp#14	Exp#15	Exp#16	Exp#17	Exp#18	Exp#19	Exp#20	Exp#21
Call time	0	10	20	30	40	50	0	10	20	30	40	50	0	10	20	30	40	50	0	10	20	30
Detour time	0 or 0	0 or 0	0 or 0	0 or 0	0 or 0	0 or 0	1 or 0.2	1 or 0.2	1 or 0.2	1 or 0.2	1 or 0.2	1 or 0.2	2 or 0.4	2 or 0.4	2 or 0.4	2 or 0.4	2 or 0.4	2 or 0.4	3 or 0.6	3 or 0.6	3 or 0.6	3 or 0.6
Request Served (5)	15170	15519	15557	15584	15626	15625	19408	20194	20238	20250	20242	20239	20088	20819	20830	20872	20822	20842	20341	21114	21082	21062
Request Not Served (5)	6566	6217	6179	6152	6110	6111	2328	1542	1498	1486	1494	1497	1648	917	906	864	914	894	1395	622	654	674
Total Driven Distance (5)	47420,86	47899,5	47873,88	47820,26	47915,46	47888,99	44467,06	42693,15	42622,72	42570,09	42733,31	42573,11	43415,02	40443,43	40257,75	40242,26	40280,28	40308,5	42842,38	39095,45	38901,04	38966,94
Total Driving Time (5)	1751:22	1783:00	1797:21	1815:57	1829:44	1839:01	1641:18	1600:22	1625:40	1657:16	1683:20	1695:16	1608:29	1525:16	1546:24	1575:39	1598:20	1626:33	1589:09	1480:34	1501:59	1539:21
Average Occupation (5)	0,671	0,675	0,678	0,687	0,661	0,663	0,929	1,045	1,034	1,006	0,962	0,979	0,981	1,160	1,168	1,143	1,112	1,097	1,035	1,262	1,274	1,255
Average Detour Time (5)	00:00	00:00	00:00	00:00	00:00	00:00	00:05	00:06	00:06	00:06	00:06	00:06	00:17	00:20	00:19	00:20	00:20	00:19	00:29	00:35	00:35	00:34
Average Waiting Time (5)	09:51	09:33	09:39	09:42	09:43	09:45	08:52	07:42	07:49	07:59	08:07	08:05	08:35	07:02	07:21	07:32	07:39	07:40	08:21	06:44	07:03	07:07
Request Served (10)	15170	15519	15557	15584	15626	15625	19625	20419	20478	20476	20475	20443	20421	21047	21069	21058	21013	21035	20672	21255	21328	21245
Request Not Served (10)	6566	6217	6179	6152	6110	6111	2111	1317	1258	1260	1261	1293	1315	689	667	678	723	701	1064	481	408	491
Total Driven Distance (10)	47420,86	47899,5	47873,88	47820,26	47915,46	47888,99	44168,91	42082,62	41979,11	41888,92	41987,96	41826,66	42896	39577,24	39436,4	39254,67	39386,72	39230,94	42040,5	38305,82	37961,9	37895,56
Total Driving Time (10)	1751:22	1783:00	1797:21	1815:57	1829:44	1839:01	1634:19	1581:56	1599:21	1632:48	1654:44	1670:51	1595:50	1502:22	1523:11	1552:41	1569:22	1595:41	1572:35	1465:48	1479:24	1510:17
Average Occupation (10)	0,671	0,675	0,678	0,687	0,661	0,663	0,942	1,071	1,076	1,050	1,026	1,013	1,015	1,214	1,215	1,176	1,161	1,157	1,071	1,319	1,313	1,302
Average Detour Time (10)	00:00	00:00	00:00	00:00	00:00	00:00	00:09	00:10	00:10	00:10	00:10	00:10	00:26	00:30	00:31	00:31	00:31	00:31	00:45	00:52	00:53	00:52
Average Waiting Time (10)	09:51	09:33	09:39	09:42	09:43	09:45	08:59	07:45	08:04	08:07	08:16	08:14	08:39	07:22	07:30	07:34	07:46	07:51	08:32	07:04	07:17	07:28

Cases 5 and 10 (3 person)	Exp#22	Exp#23	Exp#24	Exp#25	Exp#26	Exp#27	Exp#28	Exp#29	Exp#30	Exp#31	Exp#32	Exp#33	Exp#34	Exp#35	Exp#36	Exp#37	Exp#38	Exp#39	Exp#40	Exp#41	Exp#42	Exp#43
Call time	40	50	0	10	20	30	40	50	0	10	20	30	40	50	0	10	20	30	40	50	0	10
Detour time	3 or 0.6	3 or 0.6	4 or 0.8	4 or 0.8	4 or 0.8	4 or 0.8	4 or 0.8	4 or 0.8	5 or 1	5 or 1	5 or 1	5 or 1	5 or 1	5 or 1	6 or 1.2	6 or 1.2	6 or 1.2	6 or 1.2	6 or 1.2	6 or 1.2	7 or 1.4	7 or 1.4
Request Served (5)	20949	21018	20595	21184	21175	21143	21141	21230	20741	21256	21280	21303	21303	21283	20719	21340	21316	21326	21337	21367	20726	21352
Request Not Served (5)	787	718	1141	552	561	593	595	506	995	480	456	433	433	453	1017	396	420	410	399	369	1010	384
Total Driven Distance (5)	38840,86	38726,78	42227,77	38150,36	37970,88	37901,02	37935,13	37947,14	41878,77	37412,43	37241,78	37330,12	37169,64	37257,21	41575,28	36856,58	36709,28	36659,84	36802,37	37004,81	41693,92	36431,77
Total Driving Time (5)	1558:07	1580:21	1569:13	1453:03	1473:36	1501:01	1529:39	1553:43	1558:02	1429:20	1446:04	1487:16	1504:19	1529:24	1547:18	1415:14	1434:45	1459:28	1489:53	1525:34	1551:57	1403:11
Average Occupation (5)	1,217	1,197	1,076	1,351	1,354	1,330	1,290	1,247	1,110	1,426	1,415	1,393	1,357	1,339	1,136	1,506	1,481	1,490	1,424	1,369	1,148	1,579
Average Detour Time (5)	00:34	00:34	00:40	00:50	00:49	00:49	00:49	00:48	00:51	01:05	01:04	01:04	01:04	01:04	01:00	01:24	01:23	01:20	01:22	01:21	01:13	01:40
Average Waiting Time (5)	07:17	07:21	08:11	06:26	06:43	06:53	06:58	07:02	08:02	06:15	06:29	06:45	06:44	06:50	07:57	05:55	06:16	06:25	06:35	06:40	07:54	05:57
Request Served (10)	21228	21269	20823	21364	21354	21344	21330	21317	20955	21294	21387	21345	21308	21353	20937	21283	21321	21338	21326	21317	20979	21300
Request Not Served (10)	508	467	913	372	382	392	406	419	781	442	349	391	428	383	799	453	415	398	410	419	757	436
Total Driven Distance (10)	37766,5	37907,01	41469,38	37315,09	36951,96	36762,29	36701,78	36806,06	41141,84	36873,91	36357,59	36450,86	36586,38	36399,27	41059,14	36502,75	35887,59	36007,58	36174,22	36249,03	40705,8	36289,29
Total Driving Time (10)	1525:02	1555:13	1553:15	1437:08	1442:51	1467:32	1486:11	1518:12	1544:51	1423:16	1427:10	1458:19	1479:32	1498:52	1539:34	1414:13	1408:00	1437:27	1466:33	1484:33	1528:53	1407:19
Average Occupation (10)	1,274	1,258	1,102	1,420	1,444	1,422	1,379	1,347	1,148	1,504	1,554	1,528	1,459	1,496	1,191	1,596	1,654	1,619	1,563	1,580	1,241	1,690
Average Detour Time (10)	00:53	00:52	01:03	01:16	01:17	01:17	01:16	01:18	01:25	01:43	01:46	01:46	01:47	01:47	01:46	02:10	02:13	02:13	02:14	02:14	02:10	02:37
Average Waiting Time (10)	07:29	07:34	08:24	06:58	07:08	07:19	07:27	07:31	08:18	06:54	07:12	07:13	07:24	07:28	08:21	06:48	07:09	07:04	07:23	07:20	08:20	06:50

Cases 5 and 10 (3 person)	Exp#44	Exp#45	Exp#46	Exp#47	Exp#48	Exp#49	Exp#50	Exp#51	Exp#52	Exp#53	Exp#54	Exp#55	Exp#56	Exp#57	Exp#58	Exp#59	Exp#60	Exp#61	Exp#62	Exp#63	Exp#64	Exp#65
Call time	20	30	40	50	0	10	20	30	40	50	0	10	20	30	40	50	0	10	20	30	40	50
Detour time	7 or 1.4	7 or 1.4	7 or 1.4	7 or 1.4	8 or 1.6	8 or 1.6	8 or 1.6	8 or 1.6	8 or 1.6	8 or 1.6	9 or 1.8	9 or 1.8	9 or 1.8	9 or 1.8	9 or 1.8	9 or 1.8	10 or 2.0	10 or 2.0	10 or 2.0	10 or 2.0	10 or 2.0	10 or 2.0
Request Served (5)	21386	21394	21360	21369	20853	21389	21382	21385	21387	21402	20884	21375	21441	21393	21353	21394	20959	21419	21400	21384	21333	21381
Request Not Served (5)	350	342	376	367	883	347	354	351	349	334	852	361	295	343	383	342	777	317	336	352	403	355
Total Driven Distance (5)	36196,77	36491,63	36286,76	36325,53	41416,85	36118,73	36210,09	36026,11	36164,5	35960,2	41304,21	36063,41	35756,19	35817,21	35920,16	35829,21	41295,63	35941,15	35726,34	35733,86	35706,45	35926,66
Total Driving Time (5)	1411:43	1452:06	1472:37	1493:37	1542:20	1389:56	1412:49	1434:18	1459:59	1484:46	1541:25	1392:53	1397:34	1432:33	1463:06	1482:35	1541:29	1389:04	1397:50	1427:59	1447:03	1483:19
Average Occupation (5)	1,595	1,555	1,507	1,511	1,177	1,636	1,656	1,623	1,527	1,527	1,183	1,654	1,733	1,662	1,590	1,611	1,200	1,729	1,754	1,702	1,670	1,630
Average Detour Time (5)	01:39	01:38	01:38	01:37	01:23	01:55	01:55	01:56	01:56	01:56	01:29	02:09	02:11	02:09	02:08	02:09	01:36	02:23	02:25	02:23	02:24	02:22
Average Waiting Time (5)	06:12	06:23	06:23	06:30	07:45	05:56	06:05	06:14	06:21	06:21	07:41	05:47	05:54	06:07	06:12	06:13	07:41	05:51	05:56	06:02	06:06	06:16
Request Served (10)	21273	21313	21274	21284	20967	21311	21255	21258	21182	21226	21007	21260	21256	21160	21230	21252	20844	21097	21155	21104	21173	21083
Request Not Served (10)	463	423	462	452	769	425	481	478	554	510	729	476	480	576	506	484	892	639	581	632	563	653
Total Driven Distance (10)	35863,02	36082,4	36206,4	36214,98	40710,19	36208,57	36157,89	36259,65	36222,88	36255,66	40711,12	36425,3	36249,83	36431,13	36338,58	36459,69	40747,27	36720,83	36410,74	36694,71	36525,61	36799,23
Total Driving Time (10)	1407:20	1444:14	1466:01	1487:41	1528:34	1404:53	1420:48	1447:28	1466:42	1491:26	1527:05	1413:50	1422:40	1453:01	1470:20	1504:15	1526:20	1423:33	1427:53	1459:25	1472:51	1507:56
Average Occupation (10)	1,773	1,722	1,685	1,685	1,275	1,794	1,827	1,754	1,735	1,704	1,305	1,843	1,874	1,861	1,829	1,789	1,342	1,910	2,010	1,939	1,881	1,873
Average Detour Time (10)	02:41	02:41	02:44	02:43	02:28	03:01	03:09	03:10	03:13	03:12	02:45	03:32	03:34	03:41	03:41	03:40	03:13	04:05	04:09	04:15	04:12	04:11
Average Waiting Time (10)	07:10	07:17	07:33	07:30	08:22	06:44	07:15	07:25	07:30	07:33	08:20	06:54	07:19	07:33	07:36	07:41	08:29	07:04	07:20	07:31	07:38	07:41

F. SCREENSHOT PROGRAM



Bus#	Number of Routes	Total drive Time	Served Passengers	Shared Rides	MaxinBus	Empty drive time	Occupation Time	Longest Route	Depot	Paid Rides	Avg number in Bus
1	568	272:53	4095	533	8	71:48	689:28	3:07	Helmond, Station	€ 2102,73	1,7 Pax
2	468	233:52	3423	486	8	57:50	588:23	3:09	Helmond, Station	€ 1732,08	1,9 Pax
3	444	212:09	3016	445	8	51:27	539:04	2:35	Helmond, Station	€ 1484,41	2,0 Pax
4	406	187:40	2783	406	8	44:12	496:52	2:37	Helmond, Station	€ 1350,70	2,1 Pax
5	364	170:47	2608	367	8	37:54	459:18	2:10	Helmond, Station	€ 1237,96	2,2 Pax
6	313	144:58	2225	306	8	29:45	402:55	1:40	Helmond, Station	€ 984,08	2,2 Pax
7	243	125:16	2049	258	8	20:30	393:31	1:35	Helmond, Station	€ 900,60	2,6 Pax
8	172	94:26	1537	186	8	15:02	317:58	1:19	Helmond, Station	€ 613,66	2,9 Pax
Busses used: 8	**Routes: 2978**	**1442:01**	**21736**	**2987**	**Max: 8**	**328:28**	**3887:30**	**Longest Route: 3:09**		**€ 10406,22**	**2,2 Pax**